Can 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 economic damage depending on whether new technology is on average a substitute for or complement to favorable climatic conditions. To study the technological response to climate change empirically, we combine data on the geography of agricultural production, shifting temperature distributions, and crop-specific temperature tolerance to estimate crop-specific exposure to damaging extreme temperatures; we then use a database of crop-specific biotechnology releases and patent grants to measure technology development. We find that new technology has systematically re-directed toward crops with increasing exposure to extreme temperatures, and that county-level exposure to new innovation significantly dampens the local economic damage from extreme temperatures. Our estimates imply that directed innovation has offset 20% of the damage from climate change on US agriculture since 1960 and could, based on current trends, offset 15% of the damage from projected climate change over the 21st century. The results, taken together, highlight the vital importance, but incomplete effectiveness, of endogenous technological change as a systemic adaptive response 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 empirical focus is 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-ubquitous high-yielding and genetically modified plant varieties.[1] The same period has also seen rising temperatures dramatically alter agricultural productivity (Lobell and Field, 2007; Schlenker and Roberts, 2009; Lobell, Schlenker and Costa-Roberts, 2011). Yet little is known about how the pace and focus of agricultural innovation has been affected by climate change or shaped the economic consequences of an increasingly extreme environment. Understanding the process by which technological solutions have emerged in response to shifting and increasingly extreme temperatures 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 key 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).[2] Today, ag-tech research firms employ a similar narrative to promote their investments in climate-resistent technology.[3] The most prominent item on Syngenta's website reads "*Helping farmers. Fighting climate change.*" and links to a "growth plan" that includes 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 report, 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). Indeed, during the 2012-13 US mega-drought, farmers credited modern biotechnology with limiting production losses, and, on cue, multiple new drought-resistent seeds hit the market immediately afterward.[4]

The extent to which innovation is rapidly and effectively "helping farmers and fighting climate

[1] Kloppenburg (2005) provides a detailed history of these trends.

[2] Moscona (2019a), moreover, studies how induced innovation in biotechnology helped mitigate the long-run consequences of the American Dust Bowl, a period of severe drought and erosion that ravaged the Plains states in the 1930s.

[3] In 2019 Syngenta invested over $2 billion in technologies that will help farmers "prepare for and tackle the increasing threats posed by climate change," according to its press release (https://www.syngenta.com/ru/node/1518). Monsanto similarly invested $1.5 billion. The idea that technology developers are laser focused on threats posed by climate change is apparent. Gustin (2019) writes, "[P]owerful corporations in agribusiness have been very clear: The climate challenge presents a business opportunity [...] Agri-chemical companies, including the newly merged Monsanto-Bayer, are committing billions to finding the next generation of drought-resistant crops."

[4] Appendix C contains detailed discussion of this and other anecdotal points. For farmer testimony about the drought, see the NPR Report, "This Drought's No Dry Run" (Schaper, 2012). Two examples of drought-resistent seeds released shortly after the drought are Monsanto's Genuity DroughtGard Hybrid and DuPont's Optimum AQUAMax. These and other examples are discussed in a CNBC report, "Ag giants look to plant a seed to fight the drought" (Daniels, 2015).

change" may critically shape the economic impact of an increasingly extreme climate. This paper empirically investigates of how technological progress has reacted to modern climate 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, if so, how has the 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 technology.

We begin with an organizing theoretical framework. The model describes the equilibrium of a single market (e.g., the agricultural sector) with spatially heterogeneous production, centralized technology development by a profit-seeking monopolist, and a *climate shock* that reduces aggregate production posibilities.[5] Our results describe the equilibrium response of technology to the shock and convey, perhaps surprisingly, that endogenous technological change could *either mitigate or exacerbate* the climate shock's economic damage depending on competing forces. Whenever biotechnological advances *substitute* for favorable climatic conditions on average—for example, by making crops increasingly heat and drought resistant—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, so the role of prices as a hedge against negative shocks is intensified by directed innovation. On the other hand, the redirection of technology can exacerbate climate damages if biotechnological advances *complement* favorable climatic conditions on average—for example, by increasing productivity on average at the cost of making environmental requirements less forgiving—and price responses are sufficiently muted.[6] Here, profit incentives guide innovators away from propping up ecological "losers" and toward pushing forward ecological "winners." This second narrative lines up with the conventional wisdom that innovation concentrates in the largest sectors (Schmookler, 1966), formalized as the market size effect in modern models of directed technical change (Acemoglu, 2002).

To determine the role of technological progress in shaping the economic consequences of modern climate change, it is essential then to turn to empirical analysis. We combine comprehensive data on changing temperature realizations and biotechnology development to establish correct story. The first part of our empirical design compares technology development since the mid-20th century across crops that have different crop-specific productivity shocks associated with changing temperature realizations. We measure variation in crop-specific productivity shocks owing both to geography—the differential exposure of crops to temperature changes—and to crop biology—the differential sensitivity of each plant species to the same underlying temperature changes. Specifically, we start with county-level data on daily temperature realizations and crop-specific planting patterns. We

[5]The specific structure builds on Acemoglu (2007) and Acemoglu (2010). Models of directed technological change have been applied to agricultural innovation since the classic work of Griliches (1957) and Hayami and Ruttan (1970).

[6]This is consistent with the field-level study of Lobell et al. (2014), which shows increasing sensitivity of corn years to drought conditions over time (and flat or non-decreasing trends for soybeans) in Iowa, Illinois, and Indiana.

combine these data with expert-elicited estimates of the maximum temperature of an "optimum range" 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.[7] Focusing on temperature extremes is consistent with the state-of-the-art literature, following Schlenker and Roberts (2009), that identifies the increased likelihood of extreme heat as the dominant channel through which climate change has affected agricultural output in modern times.[8] Finally, we average local crop-specific extreme heat exposure over the locations in which a given crop was planted in the pre-analysis period to obtain a given crop's aggregate exposure to extreme heat.

As our primary technological outcome, we compile a comprehensive dataset 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 by Moscona (2019b). This measure has the benefits of (i) an unambiguous mapping to our productivity shocks, which are measured at the plant species level, and (ii) homogeneous coverage over a period of heterogeneous intellectual property rights for plant biotechnology.[9] We complement the *Variety Name List* with data on all issued Plant Variety Protection (PVP) certificates, a (weak) form of intellectual property protection for seeds introduced in 1970. Finally, to explore the redirection of innovation across types of technology, we also measure crop-specific patents in patent classes related to crop agriculture.[10] While plant biotechnology has anecdotally been the source of innovation most useful for adaptation to temperature change, the patent data make it possible to directly compare the response of innovation across types of technology that could be differentially useful for adapting to environmental stress.

Our first main empirical result is that plant biotechnology development since 1960 has been strongly directed toward crops that were more exposed to increases in extreme heat. The mean crop in our sample sees about a 20% increase in variety development caused by the shifting temperature. This result is robust to controlling directly for crop-level proxies for market size, pre-period innovative activity, pre-period climatic characteristics, and crop-specific linear trends, and it is driven by crops that command a large market size in the US. These findings firmly convey that biotechnology has re-directed toward distressed crops and are a first indication that technology may be a key source of resilience in the face of climate change.

We next probe the mechanisms that underpin the baseline finding. To better understand the timing of technology's response to extreme temperature, we show in a panel data model that the largest effects of extreme temperature appear within the decade, with some lagged effects and no evidence of anticipation. Moreover, innovation is more responsive to persistent, rather than transitory,

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

[8] Recent developments in agricultural science identify, as a physiological mechanism, that temperature both directly damages plant tissue via heat stress as well as hinders plant photosynthesis (see Lobell et al., 2013, on maize plants).

[9] For discussion of the second point, see Moscona (2019b) which deals directly with this issue.

[10] We link individual patents to crops in our data set by searching for crop names in the title and abstract of each patent.

crop-specific extreme heat exposure. We then investigate the relationship between the reallocation of production and innovation. While exposure to extreme temperature predicts declines in planted area, the extent of crop switching in response to extreme temperature has relatively limited to date, in our specification that conditions on crop and county fixed effects, and does not mediate the relationship between temperature change and innovation. Finally, when we study patterns of innovation across technology classes in the patent data, we find that technology development is concentrated in biological, chemical, and planting technologies that may be expected to combat environmental distress and absent, up to statistical precision, in harvesting and post-processing technologies that may not be.[11] This evidence, interpreted via the model, favors a story in which market forces that boost incentives for technology that improves climate resistance—rather than price effects—drive the baseline result.

Having established the direction of technology's response to temperature change, we turn next toward quantifying the extent to which technology has mitigated its economic harms. Previous studies have tried to tease apart direct versus adaptive effects of climate change by comparing short and long-run responses (Dell, Jones and Olken, 2012; Burke and Emerick, 2016).[12] This timing-based approach, apart from conflating all margins of adjustment, assumes that adjustment cannot occur in the relatively short run (i.e., within the decade) and ignores heterogeneity in adaptation across space and sub-industries. Our first set of results, however, documents that the re-direction of technology begins to occur within the decade and that it necessarily differs markedly across locations and crops.

For these reasons, we leverage a different strategy motivated by our model: to measure whether a given county's exposure to innovation, as predicted by the average damage across the US for that county's crop mix, dampens the negative effects of local extreme heat. We operationalize this in the data by constructing: (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 biotechnology documented that counties with higher "innovation exposure" have more climate-induced technology at their disposal. Our regression model allows innovation exposure to affect the sensitivity of local agricultural outcomes to county-level extreme heat exposure via an interaction term.[13]

We find that extreme heat has negative impacts on agricultural land value that are significantly muted by innovation exposure. 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)

[11] Indeed, mechanical technology (as opposed to biotechnology) has long been considered less relevant for increasing productivity in the face of land supply or ecological constraints (Hayami and Ruttan, 1971; Ruttan and Hayami, 1984).

[12] Keane and Neal (2020), building on the latter's framework, use a panel data model with time-varying coefficients but do not directly model the economic mechanism that may cause such changes.

[13] Our specification is related to influential analysis by Deschênes and Greenstone (2007) and Fisher et al. (2012) but differs in two respects. The first is that, leaving aside innovation exposure, our measurement of "direct exposure" takes into account the different climate sensitivity for different crops in a warming climate. The main specifications of aforementioned papers use either (i) raw changes in temperature or (ii) growing-degree-days relative to a crop-independent cut-off, which also scale linearly with temperature for average temperatures above that cut-off. Second, our model takes into account innovation exposure.

median exposure to extreme heat elsewhere compared with -0.003 percent at the 75th percentile of the same distribution and -0.015 percent at the 25th percentile.[14] That is, the heterogeneity in the effect attributed to innovation exposure is the same order of magnitude as the direct effect itself. The results are very similar using agricultural revenues and profits, rather than land values, as the outcome variable and are robust to directly controlling for changes in output prices and county-level average temperatures, and to a range of sample restrictions, regression weighting schemes, and control strategies discussed below. 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 interprets these magnitudes to study 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 a more heuristic interpretation. A world without innovation has the same heat-to-damage relationship today as it did in the mid 20th century, while a world with innovation sees a significant "flattening" of this relationship in proportion to induced innovation, which varies across crops and time. Our baseline estimate is that innovation has mitigated 19.9% (95% confidence interval: 15.3% to 24.5%) of the economic damage from temperature change in agriculture over the last 50 years. This result is not overly sensitive to alternative assumptions about resource constraints for research investment and crop switching. Quantitatively, the economic damage mitigated by technology development amounts to about $24 billion in current USD or 1.7% total US agricultural land value.

We repeat the same analysis for future climate scenarios in order to estimate the extent to which climate damages over the 21st century might be dampened by technological progress. Our projections use the model ensemble method of Rasmussen, Meinshausen and Kopp (2016), which averages the predictions of a number of leading climate models that are forced by the same standardized pathway for greenhouse gas concentrations (the IPCC's Representative Concentration Pathways). Under the model ensemble forecast forced by RCP 4.5, an intermediate scenario, innovation mitigates 15.1% of damage by mid-century (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 are economically significant. But they are far from suggesting that technology is capable of absorbing *all* the risks associated with climate change, even in a large and wealthy country like the United States, which may be a best case scenario for adaptation via technological progress.

This paper is at the intersection of several areas of research. Existing work pinpointing specific mechanisms of adaptation to climate change has focused the extent to which on production reallocation across different goods or space could theoretically mitigate economic losses from climate

[14]The median county in our sample in the modern period was exposed to to 1052 degree days. So average effects for a "typical" county with a 1052 degree-day exposure in our linear model, are respectively: -10.9%, -15.3%, and -2.9%.

change. Costinot, Donaldson and Smith (2016), Rising and Devineni (2020), and Sloat et al. (2020), in particular, study these questions in the context of agriculture.[15] Our approach by contrast focuses on the response of *production technology* itself, in theory and in practice, while also investigating the interaction between innovation and production reallocation in the context of our framework. A broader literature in environmental economics has studied adaptation to climate change by comparing short-run and long-run effects of climate shocks.[16] Our study focuses on technology development as a key mechanism of adaptation and bridges the gap empirical work on adaptation and theoretical literature on technological change in response to environmental change, which has focused mostly on incentives to develop low-emission technology instead of damage-mitigating technology (Newell, Jaffe and Stavins, 1999; Popp, 2002, 2004; Acemoglu et al., 2012, 2016; Aghion et al., 2016).

There has been a long-standing interest in the impact of temperature change on the agricultural sector, in large part because agriculture is particularly vulnerable to environmental change. Mendelsohn, Nordhaus and Shaw (1994), Schlenker, Hanemann and Fisher (2005), Schlenker, Hanemann and Fisher (2006), Deschênes and Greenstone (2007) and Fisher et al. (2012) estimate reduced-form relationships between changing temperatures on agricultural economic outcomes. A more recent literature, spearheaded by Schlenker and Roberts (2009)'s study of US corn, soybeans, and cotton, pinpoints the incidence of extremely hot days as an important mechanism for effects on production.[17]

This paper also adds to a large literature on the role of innovation in shaping US agricultural productivity (e.g., Griliches, 1957; Hayami and Ruttan, 1970; Olmstead and Rhode, 1993, 2008).[18] We extend this literature to study the response of agricultural innovation to modern climate change. Case studies for particular crops, including Roberts and Schlenker (2010) (corn and soybeans), Roberts and Schlenker (2011) (corn), Tack et al. (2016) (wheat), Burke and Emerick (2016) (corn and soybeans), and Keane and Neal (2020) (corn and soybeans), investigate fluctuations in the relationship between extreme heat and yields in order to infer the potential importance of adaptation.[19]

Finally, by providing evidence on adaptation and endogenous technological progress in a key sector, our findings may help inform a large literature developing quantitative models of re-allocation and adaptation in response to climate change (e.g., Nordhaus, 2010; Desmet and Rossi-Hansberg, 2015; Hsiang et al., 2017; Alvarez and Rossi-Hansberg, 2021). Our empirical results could aid in realistic calibration for the role of climate-mitigating technology development.

[15] A number of other studies, including Desmet and Rossi-Hansberg (2015), Alvarez and Rossi-Hansberg (2021), and Conte et al. (2020) study this question in multi-sector models.

[16] See Hornbeck (2012), Moore and Lobell (2014), Burke and Emerick (2016), and Auffhammer (2018) in the context of agriculture; and Barreca et al. (2016), Heutel, Miller and Molitor (2017), and Carleton et al. (2018) for a methodologically similar literature discussing the relationship between heat and mortality. See also Lemoine (2018) for a semi-structural approach to tease out delayed adaptation responses in panel regressions.

[17] A follow-up literature that extends the previous agronomic work and combines it with scientific modeling (e.g., Lobell et al., 2013; Schauberger et al., 2017) corroborates this story.

[18] This paper also relates our previous work on the response of biotechnology development to intellectual property expansion (Moscona, 2019b) and the technological response to the American Dust Bowl (Moscona, 2019a).

[19] Auffhammer and Schlenker (2014) reviews the related literature on this topic for agricultural economics. A different literature in agronomics and geography, including Rodima-Taylor, Olwig and Chhetri (2012) and Zilberman et al. (2018), has highlighted the potential for adaptation through new technology but not been able to quantify its effects.

Table 1: **Summary of Model Cases**

	In response to damaging climate change:	
	If technology **substitutes for** good weather,	If technology **complements** good weather,
and if price effects are **weak**,	(a) then directed innovation increases in the damaged sector and increases resilience.	(b) then directed innovation decreases in the damaged sector but increases resilience.
and if price effects are **strong**,		(c) then directed innovation increases in the damaged sector but reduces resilience.

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, both in the historical sample and over the course of the 21st century using projections of future temperature change. 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 Table 1. The theoretical results fill in the logic of these results and structure our subsequent empirical investigations and quantification. All detailed derivations and proofs are provided in Appendix A.

2.1 Set-up

Consider a static model economy consisting of one consumption good, which is an agricultural crop, and a numeraire, which stands in for the unmodeled remainder of the economy. The crop is produced by a unit measure of farms indexed $i \in [0, 1]$. 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 $F(\cdot)$ across locations $i \in [0, 1]$.

There is a single crop-specific *technology* in our model, which as a leading example we think of as

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 $\alpha \in [0,1]$ parametrizes the relative importance of the technological input (and the normalization $\alpha^{-\alpha}(1-\alpha)^{-1}$ is entirely for convenience); and $G(\cdot) : \mathbb{R}^2 \to \mathbb{R}_+$ captures the productivity of the technological input as a function of the climate and quality of the technology. We assume that $G(\cdot)$ is concave in θ and twice continuously differentiable, and normalize $G_1 \geq 0$ 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 directly shifted by the productivity function $G(\cdot)$.

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 technology development cost $C : \mathbb{R} \to \mathbb{R}_+$ for quality. 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 over quality θ:

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

That is, the innovator chooses θ to maximize aggregate demand across locations net of costs.

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 distributions. 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. In 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 Key Condition: Climate Substitutes and Complements

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

Definition 1. *Technological advances are climate substitutes if* $G_{12} \leq 0$ *and climate complements if* $G_{12} \geq 0$.

We state these conditions *globally*, or for all $(A, \theta) \in [\underline{A}, \overline{A}] \times \mathbb{R}$, in anticipation of deriving global comparative statics results later; but we could also state both the assumption and results locally, or evaluated at specific values of (A, θ).

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. This case corresponds to the left column of Table 1. 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.[20] This case corresponds to the right column of Table 1.

In the main model we define technological advances as either climate substitutes or climate complements; this embodies the idea that, in a given sector, technological possibilities are likely to be more climate substituting or climate complementing on average. In practice, this feature of technology may itself be (partly) endogenous. In Appendix B.2, we explore a version of the model in which the innovator can *choose* whether to develop climate-complementing or climate-substituting technology.

2.3 Main Results

2.3.1 The Equilibrium Direction of Innovation

Our main result shows how the direction of technology depends on the case in Definition 1. We first state the result in a *small open economy* variant of the model, which fixes the crop price at $\overline{p}$ and isolates the complements versus substitutes channel:

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.*

[20] 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.

In the more informal language used earlier, and in Table 1, the substitutes case corresponds to innovation *increasing* in the agricultural sector and the complements case to innovation *decreasing*.[21] The proof is a comparative static on the first-order condition associated with the innovator's choice in Equation 2.3. The innovator sets the marginal cost of technology development equal to the marginal benefit of shifting out technological input demand across locations. Since the cost structure is fixed in the comparative static, the direction of innovation depends solely on the movement of the marginal benefits curve (i.e. whether farmers are more or less willing to pay for technological improvements). This is, in turn, determined by whether technology is a climate substitute or complement. In the climate substitutes case, farmers are more willing to pay for technological improvements in the poorer climate because such improvements are more useful; in the climate complements case, the opposite is true. Note that in *both* cases the partial-equilibrium (i.e., fixed θ) effect of the damaging climate shock on production and technological input demand is negative. Thus the climate substitutes case allows innovation to concentrate in a "shrinking" market because the market nonetheless becomes more receptive on the margin to technological improvement. The climate complements case embodies the idea that the smaller market is *also* less receptive to new technology.[22,23]

We now allow for price adjustment. A damaging climate shock, holding fixed technology and inputs, creates crop scarcity and increases prices.[24] This is, from the farmer's perspective, a *price hedge* against the negative shock. It also increases the *value* marginal product of technology and hence the marginal return to technology improvement from the innovator's perpsective. In an endogenous technology equilibrium, this leads to a *technology hedge* against the shock that operates regardless of the considerations in Proposition 1. In the following result, 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.*

[21] A careful reader may observe that the general results of Acemoglu (2007) ensure that in an appropriately convex economy, like this one, the effect of directed innovation on *consumer welfare* is always mitigating. Practically, in the climate substitutes case, this means that directed innovation increases overall surplus by pulling resources out of the struggling agricultural sector. Throughout, we adopt the stance of assessing welfare (and climate damage and resilience) only within the single sector, as our modeling of other sectors is very reduced-form.

[22] In Acemoglu (2002, 2007), 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. See, in particular, the discussion in Acemoglu (2010).

[23] In our baseline model, there is one technological input that can be either climate-substituting or climate-complementing. While this simple set-up articulates all the key economic forces at play, in Appendix B.2 we introduce a variant of the model with two types of technology—one climate-substituting and the other climate-complementing—and an innovator who can choose to switch focus between technology types. An analogous set of results holds.

[24] That this effect is uniform across crops relies on our assumption that the crop-specific demand is separable, or depends only on the price and quantity of the given crop.

The proof encapsulates the previous logic by studying the two-equation fixed point of the equilibrium technology choice and the equilibrium price determination. To prove the first case, we show that either prices go down and intensify the push for technology to increase, or technology increases sufficiently to cause a net increase in production and decrease in prices. To prove the second, we provide examples in either direction.[25]

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 Resilience$(A, p, \hat{\theta})$ as the negative of profits' sensitivity to the weather:

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

When Resilience increases, the same climate shock has a smaller absolute-value effect on profits. Our result signs the change in Resilience between equilibria as a function of the model case.

Corollary 1. *Consider, in 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. *Resilience$(A, p, \theta') \geq$ Resilience(A, p, θ) if technology is a climate substitute.*
2. *Resilience$(A, p, \theta') \geq$ Resilience(A, p, θ) if technology is a climate complement and $\theta' \leq \theta$.*
3. *Resilience$(A, p, \theta') \leq$ Resilience(A, p, θ) if technology is a climate complement and $\theta' \geq \theta$.*

The proof of this result is a straightforward combination of the equilibrium comparative statics of Proposition 2 and the assumed monotonicities of marginal products embedded in Definition 1. Here, we describe the underlying economic intuition.

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. Quite literally, 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, as established in Proposition 2. If technology

[25]The case of Proposition 1 is the example of decreasing technology. We then construct a case with highly inelastic demand in which the price response overwhelms the marginal product effect and leads to technology growth that meets an emerging need in dollar terms even though, in terms of physical production, the marginal product of technology has gone down.

contracts, under weak price effects, climate change has magnified direct effects on the agricultural economy but reduced 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: better seeds, while they help reduce the level of climate damage, increase the agricultural sector's sensitivity to additional climate change.

This result emphasizes that fully understanding the role of innovation as a mediating force for climate damage requires independently measuring 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 Table 1, which is the level of precision required for quantification.

2.4 Extensions: Welfare and Endogenous Focus

The baseline model has simple normative properties driven by a single market failure: the innovator's monopoly power. In Appendix B.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; that is, the comparative statics of the planner's solution follow the same directional pattern as those of the equilibrium outcomes. Moreover the optimal policy which implements 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 B.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.[26] Thus the key driver of the sign prediction for "total" technology is which margin is more elastic. Finally, when interacted with the dynamic externality, this model allows also for the climate-focus of innovation to be inefficient due to the inherent "myopia" of the *laissez-faire* allocation.

We abstract from dynamic externalities and endogenous focus in our main analysis for the simple reason that identifying the cumulative nature and scientific content of biotechnological innovations

[26]This requires an additional assumption of substitutability between the two technologies which is familiar from multi-dimensional monotone comparative statics.

is very challenging in our data. We leave both the theory and quantitative substance of these further issues to future work. Our analysis instead focuses on the properties of the observed equilibrium and the average evidence on technological possibilities for crops.

2.5 Mapping to Estimation

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

We allow for multiple crops, indexed by $k \in \{1, \ldots, K\}$, by having a measure K of farms indexed by $i \in [0, K]$, such that farm i grows crop $\lceil i \rceil$.[27] Production has the same form indicated in Equation 2.1. The weather shifter A_i has 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. Note that versions of 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.[28]

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}.[29] We assume that the innovator's cost has an isoelastic form, or $C(x) = \frac{x^{1+\eta}}{1+\eta}$ for some $\eta \geq 0$. And we assume that the inverse demand curve is isoelastic, or $P_k(x) \equiv p_{0,k} x^{-\varepsilon}$ for some $\varepsilon \geq 0$ and for each crop k. Together, these functional forms describe the key trade-offs in the general model and generate tractable equilibrium predictions.

The following two equations characterize innovation and local agricultural rents, up to a suitable approximation described in Appendix A.6. First, if $A_k := \int A \, \mathrm{d}F_k(A)$ is the average climatic productivity shock for a crop k, innovation for a crop k is (log)-linear in this average shock:

$$\log \theta_k = \log \theta_{0,k} + \delta \cdot (\overline{A} - A_k) \tag{2.6}$$

where the constant depends on scaling terms that capture market size. Our results about whether innovation increases or decreases in response to the productivity shock translate to this equation as

[27] That is, crop k is grown on farms $i \in [k-1, k)$.

[28] We will return in Section 6.3, in the context of our quantitative counterfactuals, to discussing the content of these separability assumptions and what happens when they are relaxed.

[29] Technically, the form captured here is in log and not level terms. Up to suitable approximation, however, we show that the notions are interchangeable.

the cases $\delta > 0$ and $\delta < 0$, respectively.

Second, the rents or profits in location i depend on the interaction of local shocks and the aggregate shocks that determine prices and innovation:

$$\log \Pi_i = \log \Pi_{0,i} + \beta \cdot (\overline{A} - A_i) + \gamma \cdot (\overline{A} - A_{k(i)}) + \phi(\overline{A} - A_i)(\overline{A} - A_{k(i)}) \tag{2.7}$$

where $k(i) = \lceil i \rceil$ is the locally grown crop. The final term isolates how the national exposure to the shock, which controls induced innovation, affects climate resilience. Our results about whether innovation increases or decreases resilience translate to the cases $\phi > 0$ and $\phi < 0$, respectively.

This version of the model allows for all three possible cases outlined in Table 1, and also directly generates the estimable equations (2.6) and (2.7). Our subsequent empirical analysis and quantification will follow this structure.

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

Geography of production. To measure the geography of US crop production, we use the US Census of Agriculture. Using the 1959 round, we compute the share of each crop's total production located in each county in the US. That is, for each county we know the land area devoted to each crop and compute that county's contribution to the total US land area devoted to each crop during the period preceding our analysis.[30] We repeat the same data construction process using the 2012 round of the Census of Agriculture, for robustness checks and our analysis of production reallocation.

Temperature. To measure the temperature in each US county for each month since 1960, we use grid-cell level (2.5 mile $\times$ 2.5 mile) temperature data from the PRISM ("Parameter-elevation Regressions on Independent Slopes Model") Climate Group. In particular, we use the format of these data that is available on Wolfram Schlenker's website.[31] Daily data will be important in light of evidence that crop productivity responds to changes in the number of days of extreme weather, discussed in greater detail below (e.g., Hodges, 1990; Grierson, 2001; Schlenker and Roberts, 2009).

For robustness checks that rely on average temperatures, we use US National Oceanic and Atmospheric Administration's New Divisional Data Set (NOAA nCLIMDIV). These are interpolated from weather station data and available as average temperatures by month and year since 1950.

[30] 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.

[31] See http://www.columbia.edu/~ws2162/links.html, accessible as of March 10, 2021.

Crop-specific temperature sensitivity. We compile estimates of crop-specific sensitivity to changes in temperature from the EcoCrop Database, published by the United Nations Food and Agriculture Organization (FAO). The EcoCrop Database provides information about crop-specific growing conditions for over 2,500 plant species and was compiled from expert surveys conducted during the early 1990s; it is frequently used outside of economics in recent analyses at the intersection of agronomics and climate change to estimate crop-specific climate tolerance.[32] The list of crops included in the analysis, and corresponding species names, are reported in Table B1.

For each crop species, the EcoCrop Database reports a set of upper and lower temperature cut-offs, beyond which crop productivity declines.[33] This information makes it possible to account for the fact that crops have different temperatures beyond which productivity declines, as documented empirically for a small set of staple crops by Schlenker and Roberts (2009). This crop-level variation means that changes in the incidence of extreme heat in a particular location could affect two crops very differently depending on their crop-specific temperature sensitivity.

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 (2019b), is a list of all released crop varieties known to the USDA since the start of our sample period.[34] 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.[35] This data set has several key features. First, it tracks new seeds and plant varieties overtime which, both anecdotally and for agronomic reasons, were and remain the primary technology used to adapt agricultural production to extreme temperature. 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).[36] 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,

[32] See, for instance, Hijmans et al. (2001), Ramirez-Villegas, Jarvis and Läderach (2013), and Kim et al. (2018).

[33] While the estimates we derive from the EcoCrop database are fixed at the crop-level, meaning their direct effect is absorbed by crop fixed effects in our empirical analysis, the database was nevertheless compiled during our sample period. To investigate the importance of this, we re-produce all our estimates throughout the paper using the 1980s as the starting decade and without exception our findings remain similar. Moreover, variation across crops in temperature cut-offs is extreme, often representing differences of multiple degrees, and therefore could not conceivably be the outcome of differences in technology.

[34] The List is structured as a series of PDF files with separate columns for the crop name (e.g., alfalfa, sorghum), variety name (e.g., 13R Supreme, Robinson H-400 B), and the year when the variety was released. While sometimes a the day and month are listed, in most cases during the sample period, only the year is included.

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

[36] Matching the *Variety Name List* to the US Census of Agriculture is the rate-limiting step for determining the crops that enter our analysis. Our main analysis has 69 crops. These cover all the main grains, oilseeds, and feed crops as well as a large portion of vegetables grown in the US. Missing from our analysis are a number of fruits and tubers, which are not covered in the *Variety Name List*.

making direct measurement from patent data impossible.[37]

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.[38] 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. 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 keywords lists. 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.

Downstream outcomes. Finally, we combine and harmonize all rounds of the US Census of Agriculture from 1959-2017 to measure local agricultural income. 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.[39,40]

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 that modern agronomic studies show that crop productivity responds in a non-linear fashion to temperature exposure. In particular, 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

[37] See Moscona (2019b) for a discussion of changes in intellectual property law and enforcement for plant varieties, as well as the strengths of the *Variety Name List* as a measure of technology development in agricultural biotechnology during this time period. 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).

[38] 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.

[39] There is some debate in the literature (e.g., Deschênes and Greenstone, 2007; Fisher et al., 2012) about what is the most appropriate outcome measure to use. We discuss this in much greater detail in Section 5.2.

[40] 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).

estimates of these temperature cut-offs and the non-linear response of productivity, however, only exist for a small set of staple crops.[41]

To extrapolate this approach to our larger panel of crops, we leverage the EcoCrop database's reported "maximum optimal temperature" for growing a specific crop, which we denote T_k^{Max}. For each US county, using the temperature realizations in the PRISM data, we can calculate realized degree days in excess of a temperature threshold T over a given time span t as $\text{DegreeDays}_i(T)$; Appendix D fills in the details of this calculation. We then define extreme temperature exposure in location i for crop k in decade t as:

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

or degree-days in location i that are in excess of the *crop-specific threshold*. Our underlying variation in this measure therefore comes from two sources. The first is the spatial pattern of climate change (and, in particular, increased incidence of extreme high temperatures) across the United States. The second is the variation in crop geography 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, defined as degree days in excess of 33 degrees Celsius. But even within Dunklin County, the same weather patterns induce different extreme exposure for soybeans (degree days above 33 degrees Celsius) and cotton (degree days above 36 degrees Celsius), since the latter is biologically more heat tolerant.

We also implement an alternative strategy based on changes in average temperatures, described in Appendix E. This strategy takes into account the fact that average changes in temperature in a location i might be either beneficial or harmful to a given crop k depending on that crop's optimal temperature as defined by EcoCrop. The secondary approach based on temperature averages has the advantage of relying on temperature data which are available over longer periods of the sample and require less extrapolation. While recent work has documented the importance of extreme heat exposure, it is also possible that changes in average temperature have important and potentially independent impacts on crop productivity and incentives to innovate. All of our main results are be robust to using this measure, as we demonstrate throughout the paper.

4. Results: Climate Change and Induced Innovation

We now empirically study how exposure to damaging climate change affects innovation. We find, across a variety of empirical specifications, that increasing exposure to extreme temperatures induces a positive response in biotechnology development. We then explore in greater detail the timing of this innovative response, its relationship with geographic reallocation of production, and its differential

[41] For instance Schlenker and Roberts (2009) estimates such cut-offs only for corn, soybeans, and cotton. Reassuringly, for these crops, the cut-off temperatures we implement from EcoCrop are quite similar to the previous authors'.

effects across different classes of technology.

4.1 Empirical Model

We estimate an empirical model that tests, in the spirit of Propositions 1 and 2, whether new biotechnology development responds positively or negatively to national climate distress. We first need a crop-level exposure to extreme heat in the entire US market. To do this, 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:

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

where $\text{Area}_{i,k}^{\text{Pre}}$ is the area devoted to crop k in county i prior to our sample period, in 1959.[42] As foreshadowed earlier, the ExtremeExposure measure varies across crops in a given decade, owing to variation in both growing locations and the crop-specific temperature cutoffs.[43] The change 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 B1; the sample is composed of all crops included in both the US Census of Agriculture and the *Variety Name List*.

Our 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.[44] y_k is the number of novel seed varieties developed for crop k during the period 1960-2016 and ExtremeExposure_k is a crop-level measure of extreme heat exposure. 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, the level of pre-period innovation, and pre-period climate measures. The former two controls are natural to hold fixed initial market size, as suggested by (2.6). The last ameliorates concerns that we are fitting "mean reversion" in climate that has more to do with latent correlation with levels than true changes.

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

[42] 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.

[43] Table A6 documents that our measure of extreme exposure incorporating crop-level variation in temperature cut-offs is a more robust predictor of innovation than simply measuring crop-level exposure to GDDs in excess of 30°C. In fact, conditional on our measure, GDDs in excess of 30°C has no effect on technology development

[44] For consistency with the literature in innovation economics (which follows Hausman, Hall and Griliches, 1984), we use a Poisson pseudo maximum likelihood estimator. We also also report in Table A1 ordinary least squares (OLS) estimates $\log(y_k)$ as the outcome variable, and all results are robust.

Table 2: **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
Cuf-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 vairable is the number of crop-specific varieties released and the sample period for each specification is listed at the top of each column. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, %, and 1% levels.

has been directed away from crops that have been more exposed to extreme temperature. Through the lens of our model, the sign of δ is theoretically ambiguous. Using the language of Table 1, which translates the content of Proposition 2, the first case corresponds to inventions' being climate substitutes (case (a)) or inventions' being climate complements *and* strong price effects (case (c)); the second case correspond to inventions' being climate complements and weak price effects (case (b)).

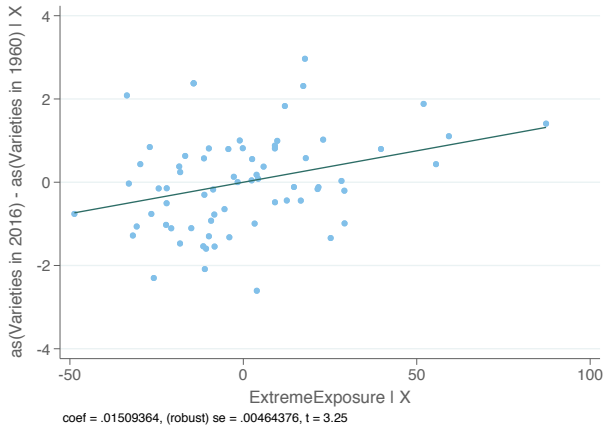
4.2 Results: Temperature Distress and Variety Development

Table 2 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. In the model, this sign-test supports case (a) or (c) described above. The point estimate implies that a one standard deviation in climate distress led to an about 0.2 standard deviation increase in new varieties.

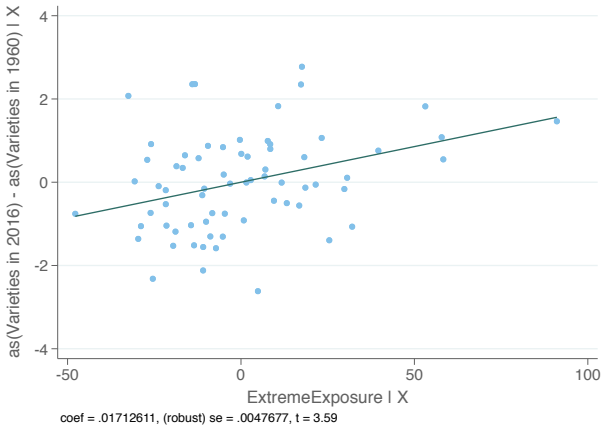
The remaining columns explore the sensitivity of the estimates. In column 2, we control for the average temperature and average precipitation on land devoted to each crop during the pre-period and in column 3, we add the number of varieties released for each crop from 1900-1960; the coefficient of interest 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 (or correlates thereof), which could affect trends in technology development. 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 day exposure we weight by county-level average

Figure 1: **Extreme Exposure and Variety Development: Partial Correlation Plot (OLS)**

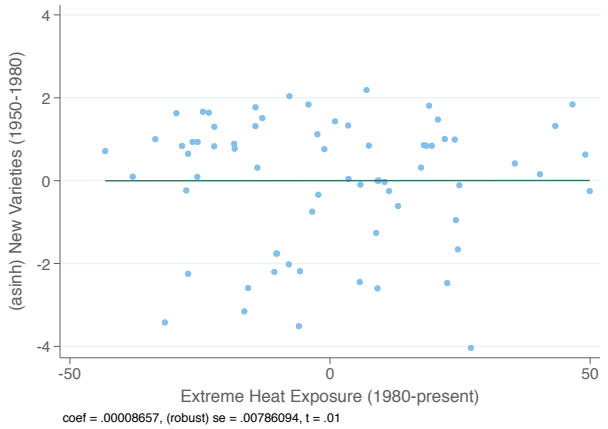
(a) Partial Correlation Plot: Unweighted (t = 3.25)



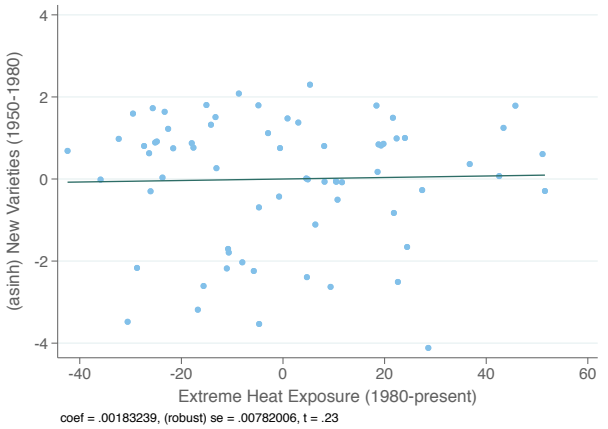
(b) Partial Correlation Plot: Weighted (t = 3.59)



(c) Placebo Partial Correlation Plot: Unweighted (t = 0.01)



(d) Placebo Partial Correlation Plot: Weighted (t = 0.23)



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.

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.

While Table 2 reports Poisson estimates, the results are very similar using ordinary least squares (OLS) and either the raw count of new varieties or the inverse hyperbolic sine transformation of new varieties as the outcome variable (Table A1). The partial correlation plot from the OLS estimates is reported in Figures 1a and 1b, from an un-weighted regression specification and a specification weighted by (log of) pre-period harvested area respectively. The latter estimate ensures the result is

not driven by economically "small" crops. Both estimates are positive and significant, and do not appear driven by outliers.

The remainder of Figure 1 presents a falsification exercise that uses *future* extreme temperature exposure to predict *past* technology development; if the baseline estimates capture the causal effect of extreme heat on variety development, we expect future extreme temperature exposure to have little predictive power. Figures 1c and 1d document the relationship between $\Delta\text{ExtremeExposure}_k$ from 1980-present and new variety releases from 1950-1980, again from both un-weighted and pre-period area weighted specifications. Our estimates are very close to zero and far from statistical significance for both placebo estimates, consistent with a causal interpretation of our baseline finding.[45]

A series of additional sensitivity checks are reported in the Appendix, including estimates excluding the highest and lowest values of the independent variable (Table A2); estimates that extend the pre- and post-period (Table A3); and estimates using alternative parameterizations of the crop-specific temperature shock (see Tables A4 and A5; Section E describes the analysis.) We also show in Table A6 that the results are qualitatively similar measuring using GDDs in excess of 30°C as the key independent variable (Panel A), but that our baseline measure of ΔExtremeExposure is a more robust predictor of technology development and when the two are included in the same regression, the coefficient on the former is small and insignificant (Panel B). This finding suggest that our new strategy for incorporating crop-level differences in temperature sensitivity is important for precisely measuring the crop-level productivity shock.

Finally, Table A7 replicates our baseline results using new seed development measured from the Plant Variety Protection certificates; the specifications are identical to columns 1-5 of Table 2, 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. Again, on this separate and independently constructed data set with more stringent inclusion criteria, we find that the impact of extreme temperature exposure on biotechnology development is positive and significant.

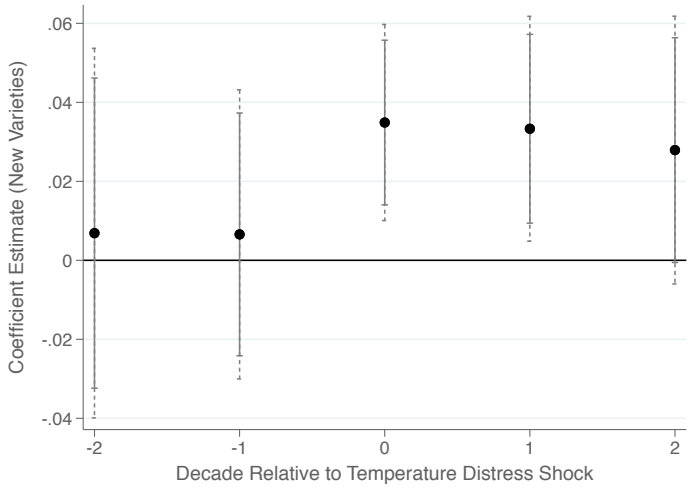
4.2.1 Dynamic Responses of Technology

To this point, we have focused on long difference specifications. This is natural since both temperature change and innovation are long run processes, and our model accordingly abstracted from dynamics. However, it is important in practice to know how quickly innovation responds to changes in temperature and whether innovative activity anticipates future changes.

To investigate these questions, we estimate a modified version of Equation (4.5) in which the unit

[45]For comparison, Figure A2 reports the relationship between $\Delta\text{ExtremeExposure}_k$ from 1980-present and new variety releases from 1980-present and, as expected, we estimate a positive and significant effect ($\delta = 0.011$, $t = 2.77$)

Figure 2: **ExtremeExposure$_{k,t}$ 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 respectively; standard errors are clustered by crop.

of observation is a crop-decade pair. In particular, we estimate the following 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 on the right hand side. The set of leading or lagged values of extreme exposure is denoted by T. Figure 2 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. Although the limited number of decades in our sample means the estimates are necessarily imprecise, the graph shows no evidence of an anticipation effect; variety development increases only during the decade of the temperature shock and persists during the decade that follows.[46]

Using the structure of the panel data, we next test whether the results are driven by temporary or persistent changes in climate. In particular, we estimate:

$$y_{kt} = \exp\left\{\delta_1 \cdot \text{EE}_{k,t} + \delta_2 \cdot \text{EE}_{k,t-1} + \delta_3 \cdot (\text{EE}_{k,t} \times \text{EE}_{k,t-1}) + \Gamma X'_{kt} + \alpha_k + \omega_t + \varepsilon_{kt}\right\} \tag{4.4}$$

where $\text{EE}_{k,t}$ is shorthand for $\text{ExtremeExposure}_{k,t}$. If the baseline findings are driven by persistent changes in climate, we would expect that $\delta_3 > 0$. This would imply that the previous decades impact of extreme heat on innovation is amplified if extreme heat is also high in the current decade. Our

[46]Table A8 reports additional estimates of (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.

estimate of Equation 4.4 is reported in Table A9. We do find that $\delta_3 > 0$, suggesting that inventors are particularly responsive to lasting changes in climate and persistent trends in extreme heat exposure.

Finally, the panel data model also makes it possible to include crop-specific linear trends. We use post double LASSO to determine which crop-specific trends to include and re-estimate the specification with all selected controls using OLS. Even in this demanding specification, we estimate a positive effect of extreme temperature on variety development, whether the dependent variable is the raw variety count (δ = 2.603 (0.811)) or the inverse hyperbolic sine (δ = 0.0058 (0.0033)).

4.2.2 Crop Switching

While our model can accommodate land reallocation, or a number of other production decisions, our empirical strategy uses pre-period planting locations to construct an instrument for the crop-specific productivity shock. By limiting attention to these historical planting locations, we ignore the effects of crop switching and may be shutting down an interesting, independent channel of interaction between climate change and agricultural innovation.

We first attempt to quantify this channel and check whether it is empirically independent from our main channel. In Appendix F.1, we introduce an empirical model of changing crop choice in response to climate change and propose a new empirical strategy to identify the extent of crop switching in response to extreme heat in the historical sample. There are four key conclusions. First, we do find that the expected sign exists in the data—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 is quantitatively small—a one-standard deviation relative increase in crop-by-county extreme temperature exposure reduces planted area by only 0.018 standard deviations. 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 temperature exposure and technology development is unchanged. These results are presented in Table A10. Thus, endogenous planting reallocation does not bias or mediate our baseline estimates of the relationship between climate change and technology development. Fourth, and consistent with previous work on the relationship between market size and innovation (e.g., Acemoglu and Linn, 2004), we find an independent positive correlation between heat-induced changes in market size and biotechnology development (Table A10, columns 1-4).

A second, related question is whether our our findings about temperature change and induced innovation rely on the impracticality of crop switching—in other words, is it the case that climate change induces technology development only when crop switching is limited or costly? In Appendix B.3, we show via a simple extension of our model that this may not be the right theoretical intuition: switching can make input demand more or less sensitive to underlying climate shocks. Nonetheless, we check empirically whether crops that are more prone to switching show more or less response of innovation to climate distress. To proxy ease of crop switching, we compute the average share of

county cropland devoted to each crop among counties where it is cultivated. Higher values of this measure implies that the crop is more constrained in terms of where it can be planted and requires more unique planting conditions. Table A11 documents that we find no evidence of heterogeneous effects along this margin, as we have measured it. Together, these results suggest that crop switching to date (or the lack thereof) is not an important mediating factor in our analysis.

Finally, we investigate whether our baseline effects are heterogeneous based on baseline crop-level market size. Table A12 reports estimates from an augmented version of (4.2) in which we include an interaction term between ExtremeExposure_k and an indicator that equals one if a crop's planted area is above the median value. The interaction term is large in magnitude and highly significant, suggesting that the response of technology to temperature distress is most pronounced in crops with a large (historical) market size. This *does* appear to be an important intermediating mechanism, and we will verify that it also predicts more downstream effects of induced innovation (Section 5.3.2).

4.2.3 Effects on Different Types of Technology

Next, we investigate the impact of climate damage on a broader range of technology classes. The theoretical analysis highlighted that the impact of climate distress on technology development depends on characteristics of the technology in question and, in particular, whether its marginal product increases or decreases in response to climate distress (i.e. whether the technology is a climate substitute or climate complement). While biotechnology has been the focus of most writing on technological responses to climate change, other forms of innovation, including fertilizer, planting, and soil modification technology may also become more crucial in the face of environmental stress.[47] At the same time, mechanical harvesting technologies have a more limited interaction with the climate or may even complement a favorable climate, to the extent that harvesters are finely tuned to particular climates and soil conditions.[48] Finally, we would expect that post-harvest and processing technology—which is not involved in production and is largely unaffected or unrelated to weather patterns—is not affected by climate change *except* through price effects.

Table A13 reports the direct effect of $\Delta\text{ExtremeExposure}_k$ on technology development in a series of technology classes using the estimation framework from (4.2). In column 1, we replicate our baseline results using crop varieties as the dependent variable. In columns 2-4, the dependent variable is a series of technology classes related to planting and soil working; these are planting, sowing, and fertilizing patents (column 2), soil working patents (column 3), and the sum of the two (column 4). In all columns, the coefficient of interest is positive and large in magnitude, and in column 2 and 4 it is statistically significant. In column 5, the dependent variable is harvester and mower patents, and the coefficient of interest is close to zero and statistically insignificant; intuitively, harvester development

[47] See Baveye et al. (2011) on the history of advances in soil science and their relationship to drought and extreme heat.

[48] See Morgan et al. (2014) for a discussion of this idea in orange harvesting. Hayami and Ruttan (1971) and Ruttan and Hayami (1984), moreover, argue that mechanical technology is less important than biological technology for alleviating land-related and ecological constraints in agriculture.

Table 3: **Temperature Distress and Innovation Across Technology Classes**

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable is New Innovations:				
	Varieties vs. All Crop-Specific Patents	Varieties vs. Harvester Patents	Fert. Patents vs. Harvester Patents	Varieties Fert., Soil Tech. vs. Harvesters, Post-Harvest	Fert., Soil Tech vs. Harvesters, Post-Harvest
Δ ExtremeExposure x $\mathbb{1}^{\text{Subst}}$	0.0130***	0.0121*	0.00802*	0.0161***	0.0116***
	(0.00349)	(0.00627)	(0.00438)	(0.00598)	(0.00328)
Tech. Class Fixed Effects	Yes	Yes	Yes	Yes	Yes
Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	138	138	138	345	276

Notes: The unit of observation is a crop-by-technology class pair. The included technology classes are listed at the top of each column. All specifications include crop and technology class fixed effects. Standard errors, clustered by crop, are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

did not increase in response to extreme temperature, but we also find no evidence that it declined. Finally, we find no effect on post-harvest and processing technology (column 6). These findings are a first indication that innovation was directed toward technologies that would directly restore land productivity in the face of extreme temperature; the null effect on certain technology classes furthermore indicates a limited role for price effects, which would increase incentives for innovation in damaged crops across technologies.

We next document that these differences across technology classes are statistically significant. We directly compare the effect of climate damage on different technology classes using the following *triple difference* specification:

$$y_{kx} = \exp\{\xi \cdot \Delta\text{ExtremeExposure}_k \cdot \mathbb{I}_x^{\text{Subst}} + \alpha_k + \omega_x + \varepsilon_{cx}\} \tag{4.5}$$

where x indexes technology classes; α_k and ω_x are crop and technology fixed effects respectively.[49] y_{kx} is the number of new innovations—either seeds or crop-specific patents—for crop k in technology class x. Finally, $\mathbb{I}_x^{\text{Subst}}$ is an indicator that equals one if technology class x more likely to be "climate substituting" in the given comparison. We explore specifications with different sets of technology classes and versions of $\mathbb{I}_x^{\text{Subst}}$ in order to investigate the robustness of ξ.

Table 3 reports our estimates of the re-direction of innovation across technology classes. We find, for all plausible comparisons of more and less biochemical research, that innovation redirected especially toward "climate substituting" categories and that the difference is statistically significant.

[49] Since we focus on a long difference specification, α_k and ω_x absorb crop-by-time trends and technology-by-time trends.

The result holds comparing biological to non-biological technology or comparing fertilizing and soil-working technology to mechanical technology using only the patent data.

Together, these results document that technological progress was disproportionately directed toward climate distressed crops in technology classes that might directly mitigate productivity losses from climate change. Moreover, the magnitude of the effect in columns 1-2 of Table 3 is similar to those in Table 2, despite the inclusion of crop fixed effects which fully absorb trends in all crop-specific characteristics, including output prices. This suggests that the main mechanism underpinning our baseline results is unlikely to be general equilibrium price effects (Proposition 2). In the language of Table 1, we are in model case (a) in which marginal product effects drive innovation, instead of case (c), in which increasing prices compensate for declining marginal physical products. This is also a first indication that we will observe a positive correlation between exposure to innovation and resilience to climate damage, as described in Corollary 1.

5. Results: Induced Innovation and Damage Mitigation

The previous section's results demonstrated that technology development has strongly re-directed toward crops more exposed to extreme heat since 1960. In this section, we investigate the impact of this induced innovation on agricultural outcomes downstream and the extent to which it 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 climate damage and demonstrate the robustness of this finding across a number of variant model specifications.

5.1 Measurement

5.1.1 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:

$$\text{LocalExtremeExposure}_{i,t} = \sum_{k} \left[\frac{\text{Area}_{i,k}^{\text{Pre}}}{\sum_{k'} \text{Area}_{i,k'}^{\text{Pre}}} \cdot \text{ExtremeExposure}_{i,k,t} \right] \tag{5.1}$$

$\text{Area}_{i,k}^{\text{Pre}}$ is the land area devoted to crop k in county i in 1959 and $\text{ExtremeExposure}_{i,k,t}$ is the previously defined extreme degree-day exposure for each crop in the county. This measure thus incorporates crop-specific variation in heat sensitivity, departing from previous work on county-level climate damages that treat all counties the same and estimate the effect of different temperature realizations

across space (e.g., Schlenker, Hanemann and Fisher, 2006, and follow-up literature). In the model, the measure $\overline{A} - A_i$ sufficed to measure local climate distress for the single grown crop; since US counties grow many crops, our empirical analogue is simply the weighted average across crops. Figure A4a displays the the change in $\text{LocalExtremeExposure}_{i,t}$ 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 $\text{LocalEE}_{i,t}$ from 1950-2010 and the change in log of agricultural land values over the same period. This estimate is reported in column 1 of Table A14; it is negative and highly significant, consistent with $\text{LocalEE}_{i,t}$ capturing damage from climate change that translates into lower rents. In columns 2 and 3 we present the relationship between the change in $\text{LocalEE}_{i,t}$ 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.[50]

5.1.2 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:

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

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 it predicts access to innovation, based on the first part of our empirical investigation. This 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. Figure A4b displays the change in $\text{InnovationExposure}_{i,t}$ from the 1950s to the 2010s across US counties.

5.2 Empirical Model

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 year t in location i.[51] The agricultural land price captures the net present value of profits from

[50] Unlike prior work, our county-level measure of exposure to climate change incorporates crop-level variation in temperature sensitivity. This measure has a more precise negative effect on agricultural land values when compared to using growing degree days (GDDs) over 30°C for all counties (t = 4.2 vs. 3.9. Moreover, our measure is much more finely targeted toward damage to crop production. While there is no relationship between our measure and non-crop revenue (β = 0.0634), there is a large, negative correlation between GDDs over 30°C and non-crop revenue (β = −83.24).

[51] 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).

agricultural production and has the benefit of capturing both the benefits of new technology alongside its potentially higher cost.[52] To investigate the role of innovation in mitigating economic damages from temperature change, we estimate versions of the following equation:

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

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 (with no controls) is the empirical analogue to Equation 2.7, derived from our model as discussed in Section 2.5.[53]

We estimate Equation 5.3 with two main specifications: a two-period "long difference" panel, with $t \in \{1959, 2017\}$, and a decadal panel. We focus on theoretically testing the hypothesis that $\phi > 0$. Through the lens of the simple model taxonomy in Table 1, combined with our previous finding that climate distress induced positive innovation, this hypothesis compares case (a) in which mitigation (driven by the marginal product force) corresponds with increased resilience against case (c) in which mitigation (driven by price effects) corresponds with decreased resilience. More heuristically, the prediction tests whether the "best" or "worst" context in which to get hit by climate distress is the one in which other producers of the same crops are also negatively affected.

5.3 Results: Local Adaptation and Resilience

Estimates of Equation 5.3 are reported in Table 4. Columns 1-5 report long difference estimates while columns 6-7 report results form panel estimates with one observation every 10 years. Across specifications, we find that $\phi > 0$ and that this relationship is highly statistically significant.[54] Building on the discussion immediately above, this "sign test" combined with our earlier results on directed

[52] There are two reasons why common criticisms of land value as an outcome are less relevant for our study. First, our more precise, crop-specific measurement of climate distress defeats some of the concerns raised in the literature about conflating the agricultural productivity effects of climate change with its amenity value effects (Fisher et al., 2012). Second, we directly control for changes in temperature—a "conservative control" that leaves usable variation spanned by crop composition and variable sensitivity of each crop to a given change in temperature. Nevertheless, we replicate our key results using in-sample revenue and profits as outcome variables in Table A16 and find broadly similar results.

[53] All results are very similar if instead we use the "inner" interaction to capture the interaction between local extreme exposure and innovation exposure. That is, the results are similar if instead of ($\text{LocalExtremeExposure}_{i,t} \times \text{InnovationExposure}_{i,t}$) we include the following term in the regression:

$$\sum_k \left[\left(\frac{\text{Area}^{\text{Pre}}_{i,k}}{\sum_{k'} \text{Area}^{\text{Pre}}_{i,k'}} \cdot \text{ExtremeExposure}_{i,k,t} \right) \times \left(\frac{\text{Area}^{\text{Pre}}_{i,k}}{\sum_{k'} \text{Area}^{\text{Pre}}_{i,k'}} \cdot \sum_{j \neq i} \left[\frac{\text{Area}^{\text{Pre}}_{j,k}}{\sum_{j \neq i} \text{Area}^{\text{Pre}}_{j,k}} \cdot \text{ExtremeExposure}_{j,k,t} \right] \right) \right]$$

[54] The significance level of our estimates is very similar under a range of strategies for accounting for spatial correlation. In particular, we estimate Hsiang (2010)'s implementation of Conley (1999) standard errors, for several possible choices of the kernel cut-off distance, and the results are very similar. They are also similar if standard errors are simply clustered by state. These estimates are reported in Table A15.

Table 4: **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*	
LocalEE	-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)
LocalEE x InnovationExposure	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)
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 are double clustered at the county and state-by-decade levels and *, **, and *** indicate significance at the 10%, %, and 1% levels.

innovation identifies a case of the model in which technological progress is directed toward damaged crops and leads to increased resilience.

To provide a quantitative benchmark for this resilience, we calculate the marginal effects of a unit increase in Extreme Exposure on land values as a function of Innovation Exposure:

$$\frac{\text{Percentage Points of Land Value}}{\text{DD of LocalExtremeExposure}} = 100 \cdot (\beta + \phi \cdot \text{InnovationExposure}) \tag{5.4}$$

In the panel specification (column 6), the marginal effect evaluated at the median level of innovation exposure in the 2010s is a -0.01 percentage point change in land value per acre per exposed extreme degree day. Evaluated at the in-sample-median of Local Extreme Exposure, this corresponds with a 11 percentage point loss from extreme temperatures. The difference in marginal effects between the 75th and 25th percentile is 115% of the median effect, and the difference from the 90th and 10th percentiles is 230% of the median effect. For the baseline long-difference specification, the same two ratios are 65% and 130%, respectively.

5.3.1 Alternative Model Specifications

We include all US counties in the regression sample, which necessarily means that the sample includes counties that are largely non-agricultural. However, the estimates are similar and if anything larger in magnitude after weighting the regression by pre-period county-level agricultural land area (columns 2 and 7). One potential concern with our approach is that our innovation exposure measure might

be correlated with national variation in crop prices and that prices have non-log-linear effects on agricultural land values.[55] 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:[56]

$$\text{Output Price}_{it} = \sum_k \frac{\text{Area}_{i,k}^{\text{Pre}}}{\sum_{k'} \text{Area}_{i,k'}^{\text{Pre}}} \cdot \log(\text{Producer Price}_{k,t}) \tag{5.5}$$

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 reports estimates of Equation 5.3 in which we control for both this county-level output price measure, as well as the county-level output price measure interacted with $\text{LocalEE}_{i,t}$. Estimates of our coefficient of interest are virtually unchanged.

Another potential concern is that 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 crop biology, in column 4 we control directly for county-level temperature (in degrees Celsius), counties' crop mix exposure to average temperature changes, and the interaction of the two. Again, our results remain very similar after controlling directly for these proxies for the amenity value of changing temperature. In column 5 we include both the full set of price controls and the full set of temperature controls and the results are again very similar.

The results are also very similar using in-sample agricultural revenues and profits as the dependent variable rather than land values. Table A16 repeats the specifications from columns 1-2 of Table 4, using revenue from crop production per acre, total agricultural profits, and agricultural profits per acre as the dependent variables. In all cases, we find again that $\beta < 0$ and that $\phi > 0$.[57] Even during the historical sample period, technology development mediated the relationship between temperature distress and agricultural revenue and profits.

In Appendix G, we describe a series of additional sensitivity checks of our baseline findings. These include replicating all estimates using decade fixed effects in place of state-by-decade fixed effects (Table A17); controlling directly for non-linear effects of extreme heat exposure (Table A18); replicating our results after dropping counties West of the 100th meridien (Table A19); removing the effect of local spillovers by estimating a version of innovation exposure that excludes any variation in

[55] In the model of Section 2.5, prices have only a log-linear impact on land values because of the Cobb Douglas structure. Thus 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.

[56] 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.

[57] Our revenue measure only takes into account agricultural revenue from crop production. Since we are not able to fully measure expenditure by end use, our measure of profits incorporates both crop and non-crop agricultural production. This likely explains the fact that the results using profits per acre as the outcome are more noisy; indeed, in Table A14 we showed that our measure of temperature distress has no impact on revenues from non-crop production.

crop distress that occurs in other counties in the same state (Table A20); replicating the findings using our alternative measures of climate distress and innovation exposure (Table A21); and replicating our findings using 2-decade averages to estimate our measure of climate distress at each end of the long difference (Table A22). Across all specification checks, our results remain very similar.

5.3.2 Market Size and Innovation

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 A12). If innovation were the mechanism driving the county-level estimates, we would expect the results in Table 4 to be driven by *counties that cultivate crops with a larger national pre-period market size.* To measure the average market size of the crops grown in each county we compute the following measure of "market-size exposure" averaged over crops grown in a location i:

$$\text{CropMixMS}_i = \sum_k \frac{\text{Area}_{i,k}^{\text{Pre}}}{\sum_{k'} \text{Area}_{i,k'}^{\text{Pre}}} \cdot \log\left(\text{National Area Harvested}_k^{\text{pre}}\right) \tag{5.6}$$

We then estimate an augmented version of Equation (5.3) that includes a triple interaction between (i) $\text{LocalEE}_{i,t}$, (ii) $\text{CropMixEE}_{i,t}$, and (iii) CropMixMS_i. If the adaptive role of innovation were driving the results, we would expect the coefficient on the triple interaction to be positive.

Table A23 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 on the marginal impact of temperature distress.

6. Counterfactual Analysis: Aggregate Damage Mitigation

In this section, we synthesize our empirical estimates and theoretical framework to quantify the aggregate causal effect of innovation on climate damage mitigation. We study this question in-sample, based on realized changes in temperature distributions, and out-of-sample, based on the best existing projections for future temperature distributions.

6.1 Methods

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. By altering the climate inputs in the model, we estimate counterfactual scenarios (i) in a world without climate change and (ii) in a world with climate change but without directed innovation. Letting t_0 and t_1 represent our pre-period and post-period respectively, we define the two scenarios below:

Definition 2. *The following are counterfactual scenarios for local land prices at time t_1:*

1. *No Climate Change. $LocalExtremeExposure_{i,t}$ and $InnovationExposure_{i,t}$ are fixed at their t_0 values, or*

$$\log AgrLandPrice^{NCC}_{i,t_1} = \hat{\delta}_i + \hat{\alpha}_{s(i),t_1} + \hat{\beta} \cdot LocalExtremeExposure_{i,t_0} + \hat{\gamma} \cdot InnovationExposure_{i,t_0} + \hat{\phi} \cdot \left(LocalExtremeExposure_{i,t_0} \times InnovationExposure_{i,t_0} \right)$$

2. *Climate change but No Innovation. Innovation exposure is based on the t_0 climate, or*

$$\log AgrLandPrice^{NI}_{i,t_1} = \hat{\delta}_i + \hat{\alpha}_{s(i),t_1} + \hat{\beta} \cdot LocalExtremeExposure_{i,t_1} + \hat{\gamma} \cdot InnovationExposure_{i,t_1} + \hat{\phi} \cdot \left(LocalExtremeExposure_{i,t_1} \times InnovationExposure_{i,t_0} \right)$$

Heuristically, the counterfactual without directed innovation halts the process by which the damage-temperature relationship changes as a function of national incentives for innovation.

We aggregate the local predictions from Definition 2 to a national total value of agricultural land value, in (contemporaneous) dollars, using the pre-determined agricultural land areas in each US county.[58] 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 percentage damage due to climate change in scenarios with and without innovation:

$$\text{PercentDamage}^{\text{I}} := 100 \cdot \frac{\text{AgVal}_{t_1} - \text{AgVal}^{\text{NCC}}_{t_1}}{\text{AgVal}^{\text{NCC}}_{t_1}} \qquad \text{PercentDamage}^{\text{NI}} := 100 \cdot \frac{\text{AgVal}_{t_1} - \text{AgVal}^{\text{NI}}_{t_1}}{\text{AgVal}^{\text{NCC}}_{t_1}}$$

These are both in units of percentage change relative to the no-climate-change benchmark. The third is the damage abated by directed technology, or

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

This captures in percentage units the extent to which directed innovation has mitigated climate damages relative to a counterfactual world lacking directed innovation.

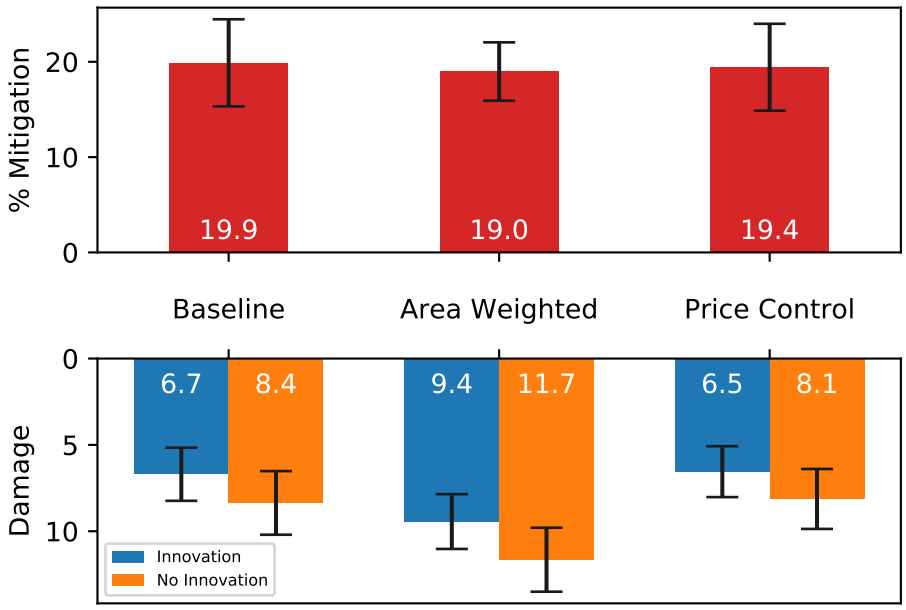
We can use the model of Section 2.5 to clarify the conditions under which this strategy delivers correct counterfactual predictions:[59]

Corollary 2. *Consider the model from Section 2.5, mapping local profits $\log \Pi_i$ to the fixed-factor price $\log AgrLandPrice_i$, and climate shock $\overline{A} - A_i$ to our empirical measure $ExtremeExposure_i$. The counterfactuals*

[58] In particular, we use total harvested cropland areas measured in the 1959 census.

[59] A formal derivation is given in Appendix A.7.

Figure 3: **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.

of Definition 2 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* $ExtremeExposure_i = 0$*.*

These assumptions allow us to proceed in a relatively simple and transparent way. The first assumption is to set the price response across counterfactuals to zero, since we lack tools to separately identify it from other forces. We are reassured by our findings above suggesting that price effects have not been an important mechanism driving technology development (Section 4.2.3) and that they play little role in our county-level estimates, even when included as an endogenous control (Table 4). The second is to assume that climate-induced technology has zero effect on land values when the county experiences zero climate distress. Given our previous findings that innovation exposure increases resilience to climate change (i.e., $\hat{\phi} > 0$), this is a normalization for how "climate-specific" these innovations are and, if anything, likely biases our estimates toward zero.

6.2 Results: Historical Damage Mitigation

Figure 3 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 4. We show error bars corresponding to 95% confidence intervals from a bootstrap procedure.[60] 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. To put this number in perspective, the value of all US farm output in 2017, including both crop and non-crop production, was $133 billion.

The second column reports the same results if instead we use our coefficient estimates from the area-weighted specification in Table 4. These findings suggest larger damages (9.4% in the observed scenario with innovation) but very comparable percent mitigation (19.0%). The last column uses the version of the model that controls directly for prices and thus allows us to more directly implement our assumption of rigid prices in the counterfactual.[61] Reassuringly, this scenario implies almost identical damage and mitigation to the baseline (6.6% and 19.4%, respectively).

6.3 Extensions

6.3.1 Alternative Counterfactual Trends for Innovation

An assumption in our model from Section 2, and the special case used to justify our counterfactuals in Corollary 2, is that there is no aggregate *resource constraint* for research across sectors of biotechnology. This is tantamount to saying that the "substitute" research for the agricultural science our model describes are other, *non*-agricultural research activities; firms are not forced to reduce investment in innovation in crop k when they want to increase investment in crop k'. There are two reasons why this assumption is not extreme within the studied sample. First, agricultural R&D investment, and investment in biotechnology in particular, experienced unprecedented growth during our sample period (Kloppenburg, 2005). From 1960 to 2000, private sector R&D investment in crop breeding increase nearly 1500% (Figure A3). Second, much of the historical increase in agricultural biotechnology research indeed came from firms that began with a different focus. Monsanto, now a ubiquitous player in seed development, started as a non-agricultural chemical company specializing in food additives, cleaning products, and pharmaceuticals; it is currently a subsidiary of Bayer, which is also primarily known for its non-agricultural (pharmaceutical) research. The companies that would become Syngenta began with a focus on pharmaceutical research and chemical production.

[60] 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 3.

[61] We do this, in a very slight alteration of the formulae in Definition 2, by holding prices fixed at their observed values.

Nevertheless, we investigate the extent to which our baseline estimate is sensitive to relaxing this assumption. In Appendix B.4, we explore a tractable variant of our baseline 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 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 A5 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. Figure A5 is reassuring because it suggests that our main estimates are not sensitive to rather extreme relaxations of the key modeling assumption about aggregate trends in innovation (sometimes referred to as the "intercept problem").

6.3.2 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 4.2.2 and Appendix F.1. We found in the data that an *ex ante* proxy for "switchability" had limited bite for predicting innovation (Table A11) 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 F.2, 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%).

6.4 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.

6.4.1 Methods

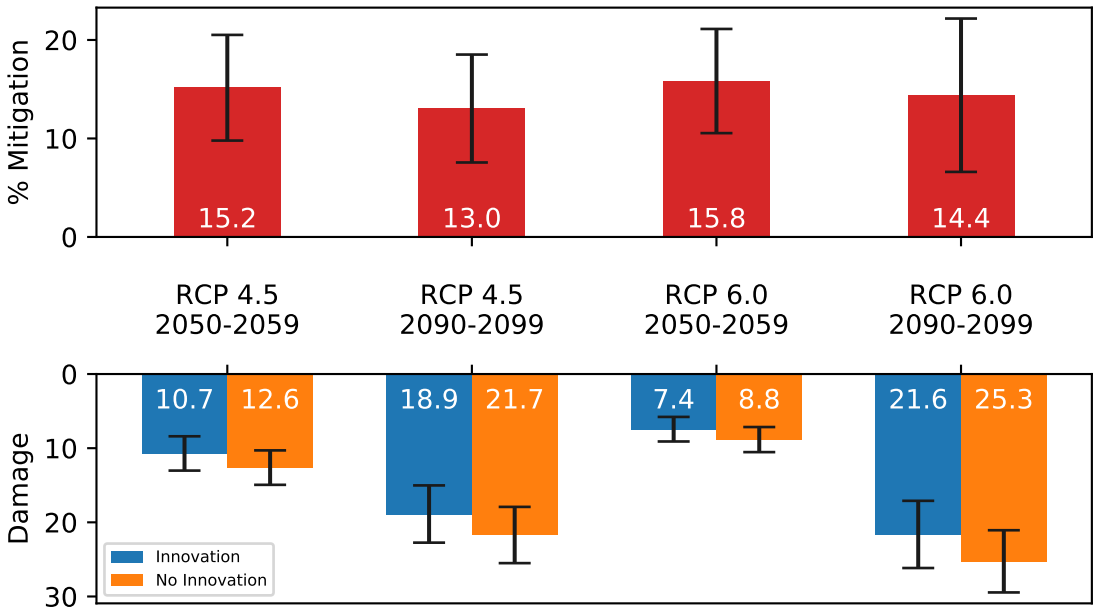
This analysis maintains the assumption that, while the relationship between climate distress and local outcomes can change over time as a function of innovation, both the speed of technology's response to climate change and the effectiveness of that technology remain constant. This assumption becomes more tenuous as we extend our predictions further into the future. On the one hand, ecological damage may pass critical thresholds beyond which innovation cannot help within biological constraints. On the other hand, innovation itself may experience a *paradigm shift* that changes the rate of invention for and/or effectiveness of new technology. The development of direct gene editing with CRISPR-Cas9 technology may very well be such a paradigm shift unfolding before our eyes. Our (unavoidable) assumption is that these and other forces offset one another to keep our estimated effects stable over time.

We use projections for daily temperature realizations from a surrogate/model mixed ensemble method developed by Rasmussen, Meinshausen and Kopp (2016) and applied in the state-of-the-art regional climate projections of Hsiang et al. (2017).[62] 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).[63] Finally, we use crop-level planted areas from the 2012 Census of Agriculture to estimate county-level temperature damage and

[62] We thank James Rising for invaluable advice on how to use these data, which are available at https://zenodo.org/record/582327. The code used to generate the data can be found at https://github.com/dmr2/acp_physical. We defer to Rasmussen, Meinshausen and Kopp (2016) and its accompanying documentation for details on data construction, but two points are worth highlighting. First, each model has independent prediction for regional as well as aggregate climate trends. Second, the forecasts use existing relationships between long-run mean temperatures and daily realizations to impute forecasts for daily temperatures. Thus the projections account for broad climatic trends, but do not incorporate the additional possibility of weather extremes becoming more (or less) likely conditional on the same mean temperatures.

[63] 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.

Figure 4: **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.

construct our aggregate damage measures, so that our future exposure measures are more precisely estimated.

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.[64]

6.4.2 Results: Directed Technology and Future Climate Damage

Figure 4 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, which is slightly less than it does in 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

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

Table 5: **The Benefits of Reducing Greenhouse Gasses vs. Improving Technology**

	(1)	(2)	(3)	(4)
	Damage Relative to Best Scenario (Percent)			
	Mid-Century (2050-59):		Late Century (2090-99):	
Scenario	*Without Innovation*	*With Innovation*	*Without Innovation*	*With Innovation*
RCP 4.5	0.958	0.965	1	1
RCP 6.0	1	1	0.955	0.966
RCP 8.5	0.887	0.906	0.521	0.748

Notes: Each number is the value of agricultural land relative to the best case RCP in the given decade and counterfactual scenario. In 2050-2059, the best case RCP is 6.0 and in 2090-2099, the best case RCP is 4.5. Values for non-best case RCPs are reported as fractions of the best case scenario.

projected RCP 4.5 scenario, directed innovation recovers 1.9% and 2.8% of all agricultural land value in the US respectively by mid-century and the end of the century. This translates in present-value terms, if we assume 3% inflation, to $218 billion and $1.05 trillion. Table A24 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").[65] Finally, analogously to Section 6.3.2, 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 A25 and are very similar to our baseline projections.

6.4.3 The Value of Curbing Climate Change

Among the two intermediate scenarios, RCP 4.5 implies higher climate damage in the early part of the 21st century and RCP 6.0 implies higher damages in the second half. This comparison across models begs the question of how the effects of technological progress *within* a given climate scenario compare with the effects of moving between the climate scenarios themselves (e.g., via reducing emissions). This may be a more interpretable counterfactual than freezing the climate in place, given the existing accumulation of greenhouse gasses in the atmosphere.

Table 5 reports percent differences in total agricultural land value from moving to an alternative climate scenario relative to the best scenario in the time period (RCP 6.0 for the near term, columns 1-2 and RCP 4.5 for the long term, columns 3-4). We report these estimates for our projections both without directed innovation (columns 1 and 3) and with directed innovation (columns 2 and 4). The

[65]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 far 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.

units are total land value relative to the best case RCP scenario in the decade. For example, column 1 can be interpreted as showing that in the counterfactual without innovation, by 2050-2059, the value of US agricultural land in the world resembling RCP 4.5 is 95.8% the value of US agricultural land in the world resembling RCP 6.0; the value of US agricultural land in the world resembling RCP 8.5 is 88.7% the value of US agricultural land in the world resembling RCP 6.0.

Across all columns, avoiding a more damaging climate scenario has substantial benefits and these benefits are larger than the benefits from directed innovation *within* a given concentration scenario. For example, in the 2050s the world resembling RCP 8.5 has 9.4% more damage than the best case scenario (RCP 6.0); however, within RCP 6.0, removing endogenous technology increases damages by just 1.4%. In the world resembling RCP 8.5, removing endogenous technology increases damages by 1.9%. This brings into sharp relief our broad conclusion that while enabling technological progress can certainly help mitigate climate damage, far greater benefits come from limiting climate change in the first place—though of course in this analysis we can only speculate about the costs and requirements of changing the trajectory of greenhouse gas concentrations.

Moreover, damage mitigation technology may itself hinder emissions reductions by shaping incentives to develop emissions reducing technology and hence the path of greenhouse gas concentrations. At both mid-century and late-century, aggregate damages in the counterfactual where technology is frozen at its current level is larger than damages when we account for continued innovation. As a result, however, the *ex ante* incentive to curb emissions may be dampened by the potential for technology to undo a considerable fraction of future climate damage. By lowering expected damages from any given climate scenario, the expected (private and social) usefulness of technologies that reduce emissions declines.[66] We leave a full model of the endogenous development of both emission-reduction and damage-mitigation technologies, each of which likely has uninternalized social benefits in isolation but also negative externalities on incentives for the other, to future research.

7. Conclusion

Are some sectors doomed to be ill-fated victims 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 the development of new biotechnology has been directed toward more distressed crops. We next find that counties

[66] These economic issues may be thrown into even sharper relief when combined with time inconsistent preferences for a given country's policymaker's, as explored by Harstad (2020) and Acemoglu and Rafey (2018) and/or the reality that emissions reductions require international consensus, as explored by Harstad (2012). In the first case, it may be optimal for government policy to *disincentivizes* research into climate abatement to simulate infeasible commitment to more severe carbon taxes; in the latter, government policy may want to *incentivize* the same research to improve their bargaining power in an international agreement.

exposed to new damage-mitigating technology 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 half century. This is economically significant but not a panacea. Even in the US, a country that has a comparatively large and wealthy agricultural sector and is the global leader in agricultural R&D, 80% of climate damage as we measure it has been unchecked by technological progress.

References

Acemoglu, Daron (2002) "Directed Technical Change," *The Review of Economic Studies*, 69 (4), 781–809, 10.1111/1467-937X.00226.

——— (2007) "Equilibrium bias of technology," *Econometrica*, 75 (5), 1371–1409.

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

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

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

Acemoglu, Daron and Joshua Linn (2004) "Market size in innovation: theory and evidence from the pharmaceutical industry," *The Quarterly journal of economics*, 119 (3), 1049–1090.

Acemoglu, Daron and Will Rafey (2018) "Mirage on the Horizon: Geoengineering and Carbon Taxation Without Commitment,"Technical report, National Bureau of Economic Research.

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

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

Auffhammer, Maximilian (2018) "Climate adaptive response estimation: Short and long run impacts of climate change on residential electricity and natural gas consumption using big data,"Technical report, National Bureau of Economic Research.

Auffhammer, Maximilian and Wolfram Schlenker (2014) "Empirical studies on agricultural impacts and adaptation," *Energy Economics*, 46, 555 – 561, https://doi.org/10.1016/j.eneco.2014.09.010.

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S Shapiro (2016) "Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century," *Journal of Political Economy*, 124 (1), 105–159.

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

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

Burke, Marshall, Solomon M Hsiang, and Edward Miguel (2015) "Global non-linear effect of temperature on economic production," *Nature*, 527 (7577), 235.

Carleton, Tamma, Michael Delgado, Michael Greenstone et al. (2018) "Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits," *Working Paper*.

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

Conte, Bruno, Klaus Desmet, Dávid Krisztián Nagy, and Esteban Rossi-Hansberg (2020) "Local sectoral specialization in a warming world," *NBER Working Paper* (w28163).

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

Crabb, Alexander Richard (1947) *The Hybrid-Corn Makers. Prophets of Plenty.*: Rutgers University Press, New Brunswick.

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

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

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

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

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

Donaldson, Dave and Richard Hornbeck (2016) " Railroads and American Economic Growth: A "Market Access" Approach *," *The Quarterly Journal of Economics*, 131 (2), 799–858, 10.1093/qje/qjw002.

Fernandez-Cornejo, Jorge (2004) *The seed industry in US agriculture: An exploration of data and information on crop seed markets, regulation, industry structure, and research and development* (786): US Department of Agriculture, Economic Research Service.

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

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

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

Griliches, Zvi (1957) "Hybrid Corn: An Exploration in the Economics of Technological Change," *Econometrica*, 25 (4), 501–522, http://www.jstor.org/stable/1905380.

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

Gustin, Georgina (2019) "Industrial Agriculture, an Extraction Industry Like Fossil Fuels, a Growing Driver of Climate Change," *Inside Climatte News*, https://insideclimatenews.org/news/25012019/climate-change-agriculture-farming-consolidation-corn-soybeans-meat-crop-subsidies/.

Harstad, Bård (2012) "Climate contracts: A game of emissions, investments, negotiations, and renegotiations," *Review of Economic Studies*, 79 (4), 1527–1557.

——— (2020) "Technology and time inconsistency," *Journal of Political Economy*, 128 (7), 2653–2689.

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

Hayami, Yujiro and V. W. Ruttan (1970) "Factor Prices and Technical Change in Agricultural Development: The United States and Japan, 1880-1960," *Journal of Political Economy*, 78 (5), 1115–1141, 10.1086/259694.

Hayami, Yujiro and Vernon W Ruttan (1971) *Agricultural development: an international perspective.*: Baltimore, Md/London: The Johns Hopkins Press.

Heutel, Garth, Nolan H Miller, and David Molitor (2017) "Adaptation and the mortality effects of temperature across US climate regions,"Technical report, National Bureau of Economic Research.

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

Hodges, Tom (1990) *Predicting crop phenology*: Crc Press.

Hornbeck, Richard (2012) "The enduring impact of the American Dust Bowl: Short-and long-run adjustments to environmental catastrophe," *American Economic Review*, 102 (4), 1477–1507.

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

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

Keane, Michael and Timothy Neal (2020) "Climate change and U.S. agriculture: Accounting for multidimensional slope heterogeneity in panel data," *Quantitative Economics*, 11 (4), 1391–1429, https://doi.org/10.3982/QE1319.

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

Kloppenburg, Jack Ralph (2005) *First the seed: The political economy of plant biotechnology*: Univ of Wisconsin Press.

Klotz, Cassandra, Keith Fuglie, and Carl Pray (1995) "Private-Sector Agricultural Research Expenditures in the United States, 1960-92.,"Technical report.

Lemoine, Derek (2018) "Estimating the Consequences of Climate Change from Variation in Weather," Working Paper 25008, National Bureau of Economic Research, 10.3386/w25008.

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

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

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

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

May, Edward (1949) "The development of hybrid corn in Iowa," *Iowa] Agricultural Experiment Station Research Bulletin*, 371 (1), 512–516.

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

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

Moore, Frances C and David B Lobell (2014) "Adaptation potential of European agriculture in response to climate change," *Nature Climate Change*, 4 (7), 610.

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

Moscona, Jacob (2019a) "Environmental Catastrophe and the Direction of Invention: Evidence from the American Dust Bowl," Working paper.

——— (2019b) "Flowers of Invention: Patent Protection and Productivity Growth in US Agriculture," Working paper.

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

Nordhaus, William D (2010) "Economic aspects of global warming in a post-Copenhagen environment," *Proceedings of the National Academy of Sciences*, 107 (26), 11721–11726.

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

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

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

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

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

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

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

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

Ritchie, Joe T and D Scott Nesmith (1991) "Temperature and crop development," *Modeling plant and soil systems* (modelingplantan), 5–29.

Roberts, Michael J and Wolfram Schlenker (2010) "Is Agricultural Production Becoming More or Less Sensitive to Extreme Heat? Evidence from U.S. Corn and Soybean Yields," Working Paper 16308, National Bureau of Economic Research, 10.3386/w16308.

Roberts, Michael J. and Wolfram Schlenker (2011) *The Evolution of Heat Tolerance of Corn: Implications for Climate Change*, 225–251: University of Chicago Press, 10.7208/chicago/9780226479903.001.0001.

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

Romer, Paul M (1990) "Endogenous technological change," *Journal of political Economy*, 98 (5, Part 2), S71–S102.

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

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

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

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

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

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

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

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

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

Sutch, Richard C (2008) "Henry Agard Wallace, the Iowa corn yield tests, and the adoption of hybrid corn,"Technical report, National bureau of economic research.

Tack, Jesse, Andrew Barkley, and Nathan Hendricks (2017) "Irrigation offsets wheat yield reductions from warming temperatures," *Environmental Research Letters*, 12 (11), 114027.

Tack, Jesse, Andrew Barkley, Trevor W. Rife, Jesse A. Poland, and Lawton Lanier Nalley (2016) "Quantifying variety-specific heat resistance and the potential for adaptation to climate change," *Global Change Biology*, 22 (8), 2904–2912, 10.1111/gcb.13163.

Zaveri, Esha and David B Lobell (2019) "The role of irrigation in changing wheat yields and heat sensitivity in India," *Nature communications*, 10 (1), 1–7.

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

Appendix

Supplementary Tables and Figures

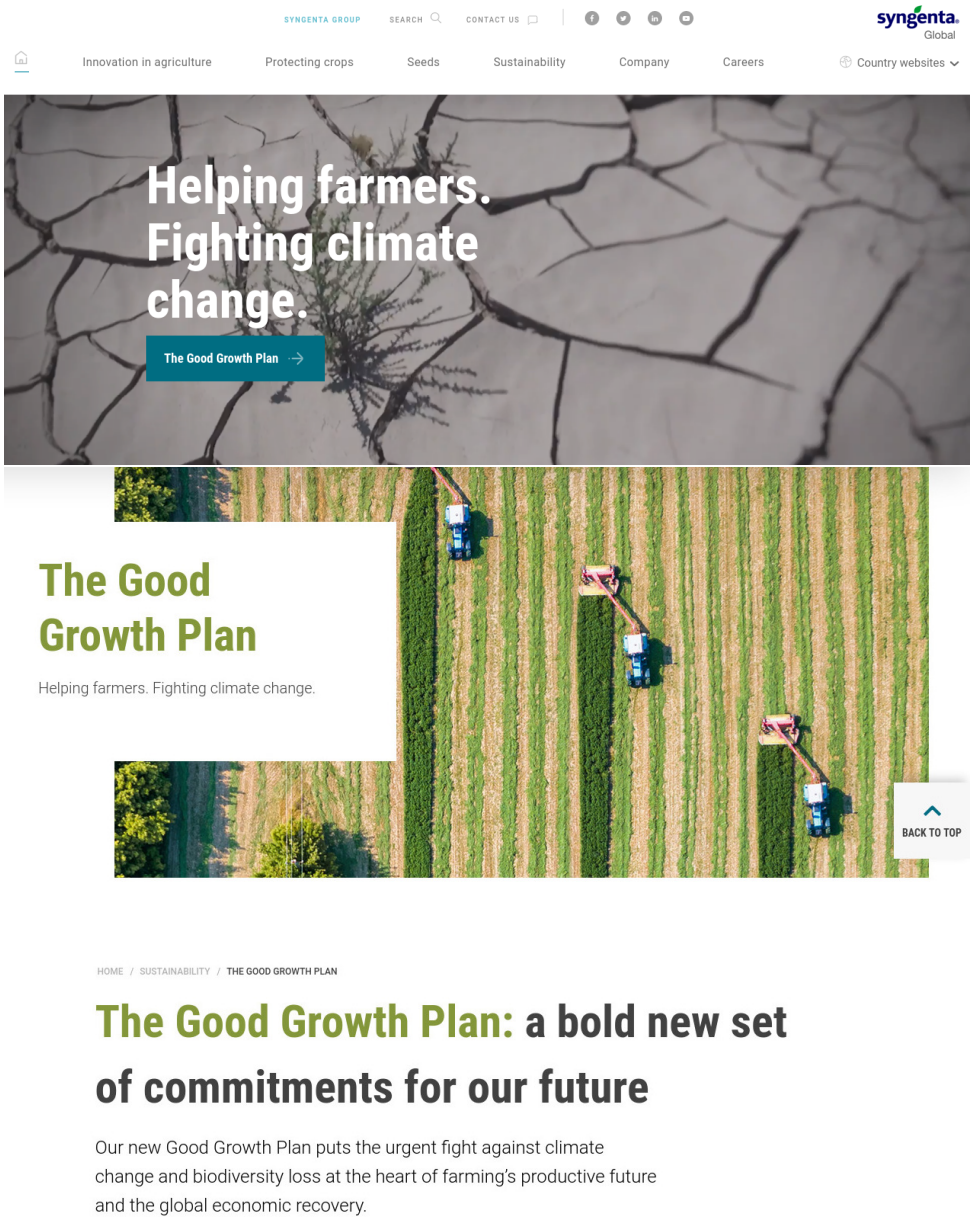


Figure A1: The Syngenta homepage (top) and landing page for the Good Growth Plan (bottom), accessed on January 19, 2021.

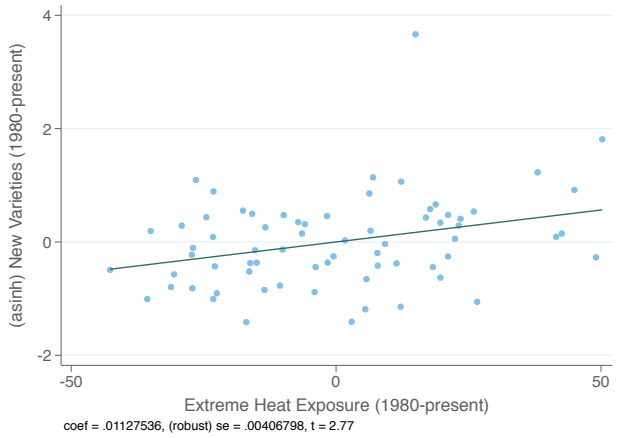


Figure A2: **Extreme Exposure and Variety Development: 1980 to Present.** This figure displays the partial correlation plot between crop-level extreme temperature exposure and new variety releases, both measured since 1980. Controls included are: log of pre-period area, pre-period temperature, pre-period precipitation, and (asinh of) pre-period variety releases. The coefficient estimate, (robust) standard error, and t-statistic are reported at the bottom of each graph.

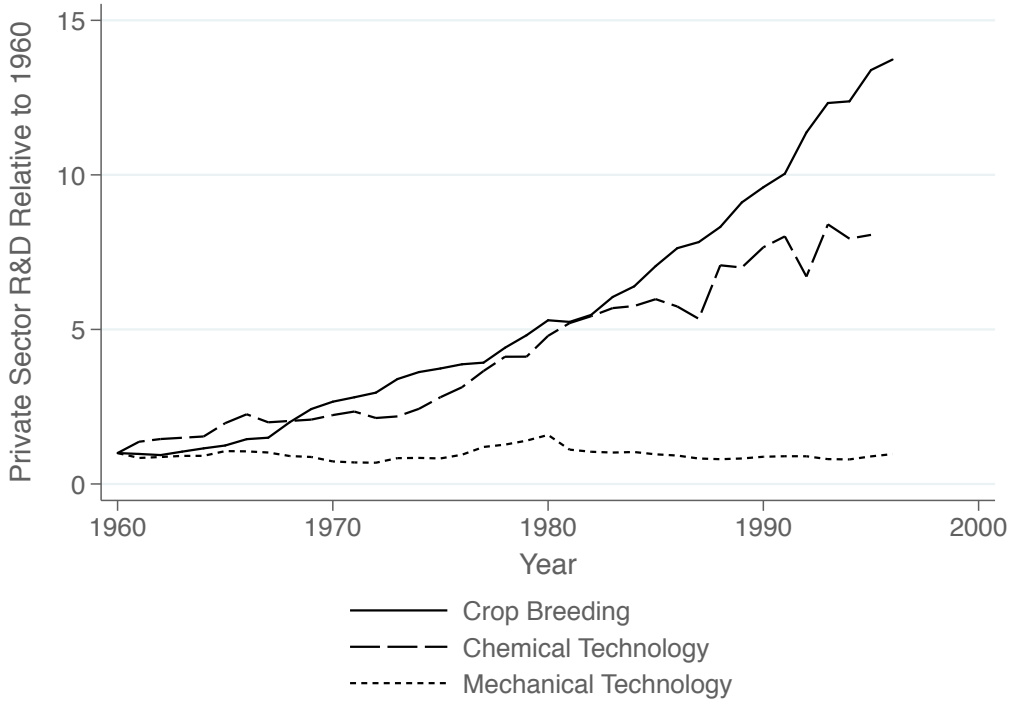
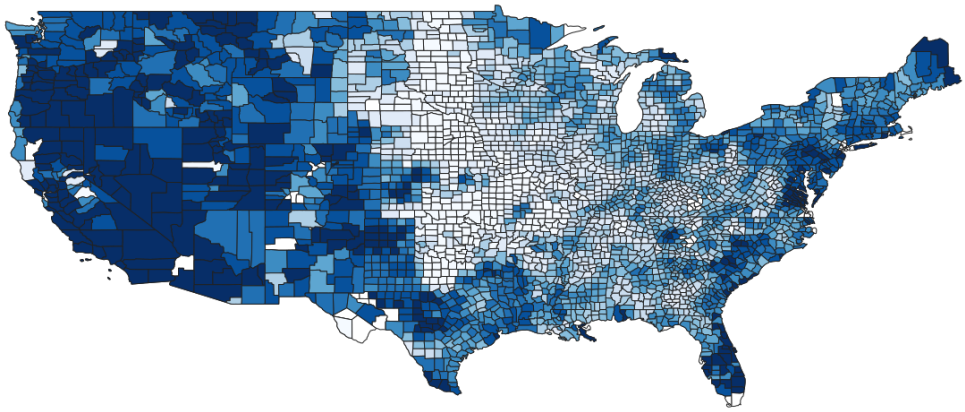
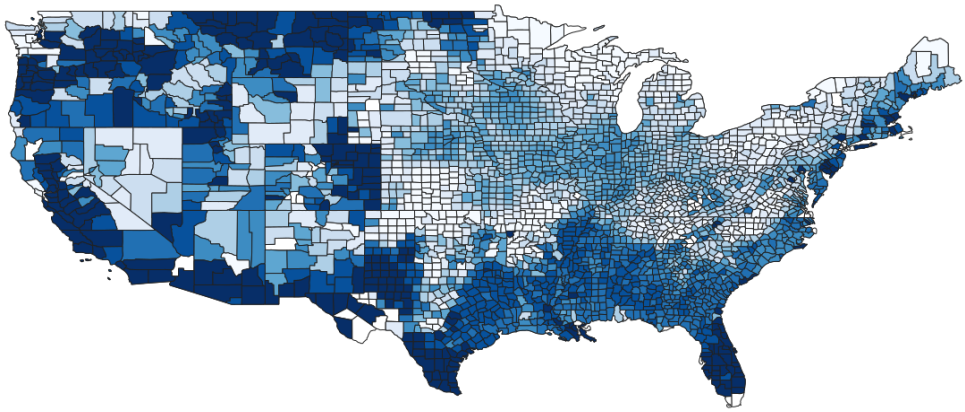


Figure A3: Trends in private sector R&D investment, relative to 1960, all estimated in 1996 USD. Data were compiled from Klotz, Fuglie and Pray (1995) and Fernandez-Cornejo (2004).



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



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

Figure A4: **Distribution of Extreme Heat Exposure and Innovation Exposure Across Counties.** In Figure A4a we report the distribution of local extreme exposure across counties and in Figure A4b we report the distribution of innovation exposure across counties. In both cases, counties are color coded by decile with darker colors indicating higher deciles.

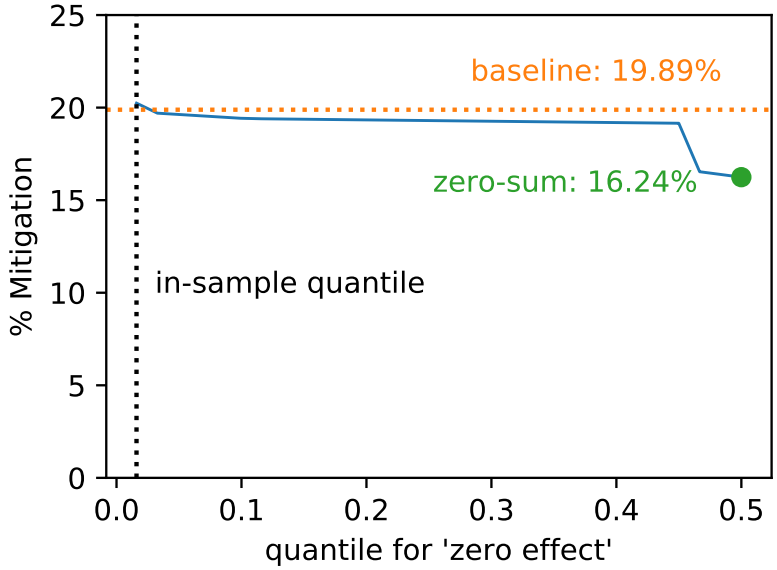


Figure A5: Historical Damage Mitigation as a Function of "Zero Choice"

Table A1: Temperature Distress and Crop Varieties: OLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable:					
	New Crop Varieites			Change in (asinh) Crop Varieites		
Δ ExtremeExposure	9.150***	8.386***	11.03**	0.0135**	0.0151***	0.0199***
	(3.256)	(2.758)	(4.410)	(0.00535)	(0.00464)	(0.00621)
Log area harvested	Yes	Yes	Yes	Yes	Yes	Yes
Pre-period climate controls	Yes	Yes	Yes	Yes	Yes	Yes
Pre-period varieties	No	Yes	Yes	No	Yes	Yes
Cuf-off temp. and cut-off temp sq.	No	No	Yes	No	No	Yes
Observations	69	69	69	69	69	69
R-squared	0.387	0.481	0.496	0.128	0.306	0.328

Notes : The unit of observation is a crop and all columns report OLS estimates. The dependent variable for each specification is listed at the top of each column. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, %, and 1% levels.

Table A2: Temperature Distress and Crop Varieties: Excluding Extreme Values

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable is New Crop Varieties					
	Excluding Bottom 10% ΔExtremeDD			Excluding Top 10% ΔExtremeDD		
Δ ExtremeExposure	0.0166***	0.0133***	0.0172***	0.0222***	0.0190***	0.0228**
	(0.00453)	(0.00358)	(0.00560)	(0.00779)	(0.00720)	(0.00922)
Log area harvested	Yes	Yes	Yes	Yes	Yes	Yes
Pre-period climate controls	Yes	Yes	Yes	Yes	Yes	Yes
Pre-period varieties	No	Yes	Yes	No	Yes	Yes
Optimal temp. and optimal temp sq.	No	No	Yes	No	No	Yes
Observations	63	63	63	63	63	63

Notes : The unit of observation is a crop. The sample restriction is listed at the top of each column. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A3: Temperature Distress and Crop Varieties: 2-Decade Average Endpoint Temperatures

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable is New Crop Varieties				
Sample Period	1950-2016				
Δ ExtremeExposure, Averaged Endpoints	0.0186***	0.0200***	0.0160***	0.0226***	0.0272***
	(0.00302)	(0.00395)	(0.00350)	(0.00522)	(0.00657)
Log area harvested	Yes	Yes	Yes	Yes	Yes
Pre-period climate controls	No	Yes	Yes	Yes	Yes
Pre-period varieties	No	No	Yes	Yes	Yes
Cuf-off temp. and cut-off temp sq.	No	No	No	Yes	Yes
Average Temperature Change	No	No	No	No	Yes
Observations	69	69	69	69	69

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

Table A4: Temperature Distress and Crop Varieties: Raw Extreme Day Count

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable is New Crop Varieties					
Sample Period	1950-2016					1980-2016
Δ ExtremeDays (Raw)	0.0579***	0.0644***	0.0418**	0.0886***	0.0967**	0.133***
	(0.0209)	(0.0243)	(0.0205)	(0.0297)	(0.0398)	(0.0392)
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
Cuf-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 vairable is the number of crop-specific varieties released and the sample period for each specification is listed at the top of each column. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, %, and 1% levels.

Table A5: Temperature Distress and Crop Varieties: Average Temperature Changes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable is New Crop Varieties							
Sample Period	1950-2016						1980-2016	
Δ DistFromOpt	0.185***	0.197***	0.141***	0.312***	0.322***	0.229***	0.336***	0.159*
	(0.0630)	(0.0596)	(0.0502)	(0.0856)	(0.0806)	(0.0886)	(0.102)	(0.0939)
Δ ExtremeExposure						0.0117**		0.0287***
						(0.00551)		(0.00803)
Log area harvested	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-period climate controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-period varieties	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Optimal temp. and optimal temp sq.	No	No	No	Yes	Yes	Yes	Yes	Yes
Average Temperature Change	No	No	No	No	Yes	No	No	No
Observations	69	69	69	69	69	69	69	69

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

Table A6: Temperature Distress and Crop Varieties: GDDs in Excess of 30° C

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

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

Table A7: Temperature Distress and Crop Varieties: Plant Variety Protection Certificates

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

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

Table A8: Temperature Distress and Crop Varieties: Panel Estimates

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

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

Table A9: Temperature Distress and Crop Varieties: Persistent vs. Transitory Shocks

	(1)	(2)
	Dependent Variable is New Crop Varieties	
EE, *current decade*	0.00349***	-0.000136
	(0.00127)	(0.00190)
EE, *first lag*		0.000963
		(0.00206)
(EE, *current decade*) x (EE, *first lag*)		2.88e-06*
		(1.63e-06)
Crop & Year Fixed Effects	Yes	Yes
log Area Harvested x Year Fixed Effects	Yes	Yes
Pre-Period Varieties x Year Fixed Effects	Yes	Yes
Observations	483	414

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

Table A10: Temperature Distress and Crop Varieties: Accounting for Market Size Changes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable is New Crop Varieties							
Δ ExtremeExposure	0.0174***	0.0133***	0.0193***	0.0178**	0.0135***	0.0103***	0.0114***	0.0105**
	(0.00496)	(0.00377)	(0.00620)	(0.00710)	(0.00381)	(0.00342)	(0.00402)	(0.00433)
log Δ EE-Predicted Natl. Area	0.545**	0.306	0.371*	0.387*				
	(0.276)	(0.248)	(0.225)	(0.226)				
log Natl. Area *(endogenous control)*					0.269***	0.286***	0.275***	0.278***
					(0.0413)	(0.0540)	(0.0572)	(0.0595)
Log 1959 area harvested	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-period climate controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Pre-period varieties	No	No	Yes	Yes	No	No	Yes	Yes
Optimal temp. and optimal temp sq.	No	No	No	Yes	No	No	No	Yes
Observations	55	55	55	55	55	55	55	55

Notes: The unit of observation is a crop. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A11: Temperature Distress and Crop Varieties: "Switchability" Heterogeneity

	(1)	(2)
	Dependent Variable is New Crop Varieties	
Δ ExtremeExposure	0.0212***	0.0215**
	(0.00728)	(0.00854)
Δ ExtremeExposure x Above Med Switchability	-3.24e-05	0.000111
	(0.000945)	(0.000900)
Log area harvested	Yes	Yes
Pre-period climate controls	No	Yes
Pre-period varieties	No	Yes
Optimal temp. and optimal temp sq.	No	Yes
Observations	69	69

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

Table A12: Temperature Distress and Crop Varieties: Market Size Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable is New Crop Varieties					
Sample Period	1950-2016					1980-2016
Δ ExtremeExposure	0.00212	0.000178	-6.66e-05	0.00438	0.00721	0.0155**
	(0.00406)	(0.00405)	(0.00397)	(0.00510)	(0.00652)	(0.00778)
Δ ExtremeExposure x Above Med. Area	0.0256***	0.0334***	0.0263***	0.0258***	0.0248***	0.0277***
	(0.00541)	(0.00827)	(0.00828)	(0.00741)	(0.00760)	(0.00905)
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
Optimal temp. and optimal 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 vairable is the number of crop-specific varieties released and the sample period for each specification is listed at the top of each column. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, %, and 1% levels.

Table A13: Temperature Distress and Patenting: Direct Effects

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

Notes: The unit of observation is a crop. The dependent variable in each specification is noted at the top of each column; in each case, it is a different technology type, either seed varieties (column 1) or paten grants from a particular patent class, with the CPC class ntoed in the technology description (columns 2-6). All baseline controls are included in each specification, noted at the bottom of each column. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A14: County-Level Estimates: Direct Effect of Temperature Distress

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

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

Table A15: County-Level Estimates: Alternative Standard Error Clusters

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

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

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

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable is:					
	log Crop Revenue per Acre		Total Agricultural Profits		Agricultural Profits per Acre	
LocalEE	-0.829**	-2.029***	-1,278**	-4,143***	-8.451*	-4.457*
	(0.358)	(0.411)	(498.4)	(1,449)	(5.045)	(2.678)
LocalEE x InnovationExposure	0.234**	0.570***	339.7***	1,252***	2.687	0.923
	(0.114)	(0.113)	(128.6)	(450.4)	(1.694)	(0.783)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State x Decade Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Weighted by Agricultural Land Area	No	Yes	No	Yes	No	Yes
Observations	5,880	5,880	5,986	5,986	5,982	5,982
R-squared	0.979	0.985	0.727	0.814	0.698	0.886

Notes: The unit of observation is a county-year. All columns report long difference estimates. Standard errors are double clustered at the county and state-by-decade levels and *, **, and *** indicate significance at the 10%, %, and 1% levels.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is log Land Value per Acre						
	Long Difference Estimates (1950s-2010s)					*Panel Estimates*	
LocalEE	-0.768***	-1.756***	-0.690***	-1.023***	-0.797***	-0.200	-0.330**
	(0.199)	(0.347)	(0.198)	(0.195)	(0.206)	(0.127)	(0.162)
LocalEE x InnovationExposure	0.306***	0.643***	0.251***	0.319***	0.270***	0.0925**	0.136***
	(0.0858)	(0.124)	(0.0674)	(0.0788)	(0.0675)	(0.0371)	(0.0439)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Decade Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weighted by Agricultural Land Area	No	Yes	No	No	No	No	Yes
Output Prices and Interactions	No	No	Yes	No	Yes	No	No
Avg. Temp. (°C) and Interactions	No	No	No	Yes	Yes	No	No
Observations	6,000	6,000	5,990	6,000	5,990	20,931	20,931
R-squared	0.986	0.987	0.986	0.986	0.986	0.968	0.972

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

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is log Land Value per Acre						
	Long Difference Estimates (1950s-2010s)					*Panel Estimates*	
LocalEE	-1.066***	-1.574***	-1.011***	-1.103***	-0.986***	-0.264**	-0.359***
	(0.208)	(0.262)	(0.203)	(0.239)	(0.225)	(0.109)	(0.129)
LocalEE x InnovationExposure	0.181**	0.389***	0.154**	0.173**	0.148**	0.0771**	0.145***
	(0.0765)	(0.0793)	(0.0668)	(0.0743)	(0.0684)	(0.0356)	(0.0371)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Decade Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountyEDD Squared	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weighted by Agricultural Land Area	No	Yes	No	No	No	No	Yes
Output Prices and Interactions	No	No	Yes	No	Yes	No	No
Avg. Temp. (°C) and Interactions	No	No	No	Yes	Yes	No	No
Observations	6,000	6,000	5,990	6,000	5,990	20,931	20,931
R-squared	0.989	0.991	0.989	0.989	0.989	0.979	0.984

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

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is log Land Value per Acre						
	Sample is Restricted to Counties East of the 100th Meridian						
	Long Difference Estimates (1950s-2010s)					*Panel Estimates*	
LocalEE	-0.880***	-1.229***	-0.751***	-0.845***	-0.656**	-0.210*	-0.260**
	(0.263)	(0.278)	(0.233)	(0.290)	(0.272)	(0.121)	(0.129)
LocalEE x InnovationExposure	0.311***	0.408***	0.269***	0.295***	0.245**	0.0960**	0.127***
	(0.103)	(0.0990)	(0.0934)	(0.106)	(0.0972)	(0.0373)	(0.0381)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Decade Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weighted by Agricultural Land Area	No	Yes	No	No	No	No	Yes
Output Prices and Interactions	No	No	Yes	No	Yes	No	No
Avg. Temp. (°C) and Interactions	No	No	No	Yes	Yes	No	No
Observations	4,852	4,852	4,842	4,852	4,842	16,956	16,956
R-squared	0.991	0.993	0.991	0.991	0.991	0.981	0.987

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

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is log Land Value per Acre						
	CropMixEE is Computed Excluding the State in which the County is Located						
	Long Difference Estimates (1950s-2010s)					*Panel Estimates*	
LocalEE	-0.707***	-1.293***	-0.693***	-0.699***	-0.651***	-0.204*	-0.368***
	(0.208)	(0.220)	(0.194)	(0.226)	(0.214)	(0.109)	(0.140)
LocalEE x InnovationExposure	0.192**	0.339***	0.187**	0.188**	0.181**	0.0830**	0.121***
	(0.0770)	(0.0752)	(0.0719)	(0.0772)	(0.0735)	(0.0322)	(0.0333)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Decade Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weighted by Agricultural Land Area	No	Yes	No	No	No	No	Yes
Output Prices and Interactions	No	No	Yes	No	Yes	No	No
Avg. Temp. (°C) and Interactions	No	No	No	Yes	Yes	No	No
Observations	6,000	6,000	5,990	6,000	5,990	20,966	20,966
R-squared	0.989	0.991	0.989	0.989	0.989	0.979	0.984

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

Table A21: County-Level Estimates: Exploiting Changes in Average Temperatures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is log Land Value per Acre						
	Long Difference Estimates (1950s-2010s)				Panel Estimates		
LocalDFO	-0.821**	-1.107***	-0.928**	-0.693**	-0.153	-0.473**	-0.245
	(0.325)	(0.313)	(0.440)	(0.348)	(0.171)	(0.187)	(0.194)
LocalEE x InnovationExposure (DFO)	0.722***	0.972***	1.007***	0.568**	0.195**	0.412***	0.215**
	(0.223)	(0.250)	(0.262)	(0.256)	(0.0953)	(0.120)	(0.109)
LocalEE				-0.756***			-0.249**
				(0.199)			(0.111)
LocalEE x InnovationExposure				0.217***			0.0968***
				(0.0731)			(0.0363)
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	Yes	No
Output Prices and Interactions	No	No	Yes	No	Yes	No	No
Avg. Temp. (°C) and Interactions	No	No	Yes	No	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 are double clustered at the county and state-by-decade levels and *, **, and *** indicate significance at the 10%, %, and 1% levels.

Table A22: County-Level Estimates: 2-Decade Average Endpoint Temperatures

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable is log Land Value per Acre				
	Long Difference Estimates				
LocalEE	-0.799***	-1.434***	-0.805***	-0.760***	-0.730***
	(0.225)	(0.312)	(0.224)	(0.265)	(0.259)
LocalEE x InnovationExposure	0.205**	0.398***	0.214**	0.200**	0.197**
	(0.0841)	(0.0941)	(0.0840)	(0.0897)	(0.0885)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
State x Decade Fixed Effects	Yes	Yes	Yes	Yes	Yes
Weighted by Agricultural Land Area	No	Yes	No	No	No
Output Prices and Interactions	No	No	Yes	No	Yes
Avg. Temp. (°C) and Interactions	No	No	No	Yes	Yes
Observations	6,000	6,000	5,990	6,000	5,990
R-squared	0.989	0.991	0.989	0.989	0.989

Notes: The unit of observation is a county-year. Pre-period extreme exposure is the average from 1950-1969 and post-period extreme exposure is the average from 2000-present. Standard errors are double clustered at the county and state-by-decade levels and *, **, and *** indicate significance at the 10%, %, and 1% levels.

Table A23: County-Level Estimates: Heterogeneity by Crop Mix Market Size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is log Land Value per Acre						
	Long Difference Estimates (1950s-2010s)					*Panel Estimates*	
(LocalEE) x (InnovationExposure) x (CropMixMarketSize)	0.178***	0.140*	0.192***	0.179***	0.190***	0.0800***	0.104***
	(0.0490)	(0.0838)	(0.0509)	(0.0479)	(0.0507)	(0.0268)	(0.0325)
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 are double clustered at the county and state-by-decade levels and *, **, and *** indicate significance at the 10%, %, and 1% levels.

Table A24: Climate Change Damage, With and Without Innovation: All Projection Estimates

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

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

Table A25: Climate Change Damage, With and Without Innovation: All Projection Estimates with Predicted Future Areas

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

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

Table B1: List of Crops in Main Sample and Summary Statistics

Crop Name	*Species Name*	*Δ Extreme Exposure (1950s-2010s)*	*Δ Extreme Exposure (1980s-2010s)*	*log Planted Area*
alfalfa and alfalfa mixtures	Medicago sativa	-7.67	-5.63	17.12
alsike clover seed	Trifolium hybridum	32.57	16.65	9.89
asparagus	Asparagus officinalis	5.64	2.72	11.97
barley	Hordeum vulgare	10.21	4.44	16.47
beets	Beta vulgaris	19.69	30.65	9.74
bentgrass seed	Agrostis stolonifera	31.83	31.08	10.01
birdsfood trefoil seed	Lotus corniculatus	-0.17	10.60	8.92
bluegrass (junegrass) seed	Poa pratensis	-21.40	-10.97	10.84
broccoli	Brassica oleracea var. italica	29.46	15.92	10.26
bromegrass seed	Bromus inermis	-33.73	-25.15	10.36
buckwheat	Fagopyrum esculentum	-3.74	0.60	10.81
cabbage	Brassica oleracea var. capitata	39.32	45.62	11.59
carrots	Daucus carota	66.33	77.90	11.25
cauliflower	Brassica oleracea var. botrytis	18.53	12.51	10.03
celery	Apium graveolens var. dulce	52.75	37.30	10.34
chewings fescue seed	Festuca rubra var. commutata	56.53	55.05	10.10
coastal bermuda grass	Cynodon dactylon	-2.19	-2.54	11.68
common ryegrass seed	Lolium multiflorum	4.66	3.61	11.72
corn	Zea mays	-3.37	-2.48	18.30
cotton	Gossypium hirsutum	0.47	2.18	16.50
cowpeas	Vigna unguiculata	-1.42	3.04	11.25
crimson clover seed	Trifolium incarnatum	5.26	38.95	10.93
dry field and seed peas	Vigna unguiculata	0.42	0.39	12.73
dry onions	Allium cepa	30.43	44.63	11.51
durum wheat	Triticum durum	-14.96	-31.24	13.92
eggplant	Solanum melongena	-0.16	-0.11	8.24
emmer and spelt	Triticum spelta	-0.02	-19.11	10.89
escarole endive and chicory	Cichorium endivia	111.22	81.41	9.29
flaxseed	Linum usitatissimum	-20.34	-35.11	14.85
green lima beans	Phaseolus lunatus	5.11	5.83	11.35
green onions and shallots	Allium fistulosum	69.59	75.03	7.66
green peas	Pisum sativum	-0.97	-0.85	9.70
hairy vetch seed	Vicia villosa sp. varia	21.24	19.11	10.22
kale	Brassica oleracea var. acephala	65.70	65.34	6.37
ladino clover seed	Trifolium repens	46.27	54.08	9.74
lentils	Lens culinaris	7.91	8.32	10.60
lespedeza	Lespedeza cuneata	-14.39	6.71	14.95
lettuce and romaine	Lactuca sativa var. capitata	83.11	76.86	12.19
lupine seed	Lupinus angustifolius	30.07	75.78	9.27
mung beans	Vigna radiata	-4.50	-1.47	9.47
muskmelons	Cucumis melo	12.91	26.12	11.77
oats	Avena sativa	-12.11	-3.31	17.13
okra	Hibiscus sabdariffa	-3.31	3.48	9.83
orchardgrass seed	Dactylis glomerata	-9.14	3.97	10.89
other vetch seed	Astragalus cicer	18.00	16.32	8.78
peanuts	Arachis hypogaea	-7.29	8.96	12.99
perennial ryegrass seed	Lolium perenne	22.63	23.03	10.69
popcorn	Sapium sebiferum	-14.51	-5.89	11.74
pumpkins	Cucurbita maxima	-5.51	-3.90	8.91
radishes	Raphanus sativus var. radicula	80.03	52.53	10.02
redtop seed	Panicum virgatum	-8.94	-5.90	11.05
rice	Oryza sativa	-3.21	7.57	14.29
rye	Secale cereale	-4.85	8.34	14.14
sorghum	Sorghum bicolor	0.84	2.80	16.49
soybeans	Glycine max	-3.49	-2.81	16.93
spinach	Spinacia oleracea	41.36	50.34	10.56
squash	Cucurbita mixta	12.08	17.87	10.59
sudangrass seed	Sorghum x drummondii	2.36	8.21	10.40
sugar beets	Beta vulgaris var. saccharifera	17.15	16.97	13.59
sunflower seed	Helianthus annuus	-0.63	-1.00	9.52
sweetclover seed	Melilotus albus	-15.51	-3.92	11.59
tall fescue seed	Festuca arundinacea	-3.61	35.28	11.82
tobacco	Nicotiana tabacum	-5.70	-1.08	13.92
turnips	Brassica campestris	-3.62	9.24	9.00
vetch seed	Vicia sativa ssp. nigra	18.72	55.48	11.34
watermelons	Citrullus lanatus	0.09	2.32	12.49
wheat	Triticum aestivum	-12.43	20.95	17.28
white clover seed	Trifolium repens	25.27	39.03	10.11

Notes: This table reports the crop name; species name (from EcoCrop); change in extreme exposure from the 1950s-2010s and 1980s-2010s; and log of total planted area in 1959, for all crops in the baseline analysis.

A. Omitted Proofs and Derivations

A.1 Derivation of the Farm's Technology Demand

Here, we derive (2.2) starting with the farm's profit maximization problem:

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

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

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

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

A.2 Derivation of Firm's Optimal Pricing

Here we derive (2.3) by first solving for the technology firm's optimal price. The first-order condition for q is

$$\max_{q} \left(q^{-\frac{1}{\alpha}} - \frac{1}{\alpha} q^{-\frac{1}{\alpha}-1} (q - (1-\alpha)) \right) \alpha^{-1} \, p^{\frac{1}{\alpha}} \int G(A, \theta) \, \mathrm{d}F(A) = 0 \tag{A.3}$$

This is satisfied for any θ_k if $q_k^{-\frac{1}{\alpha}} - \frac{1}{\alpha} q_k^{-\frac{1}{\alpha}-1}(q_k - (1-\alpha)) = 0$ or $q_k = 1$. Plugging this back into the outer profit maximization problem and simplifying yields

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

as desired.

A.3 Proof of Proposition 1

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

$$\theta \in \operatorname{argmax} \; \overline{p}^{\frac{1}{\alpha}} \int G(A, \theta) \, \mathrm{d}F(A) - C(\theta) \tag{A.4}$$

Because $G(\cdot)$ is concave and twice continuously differentiable in θ and $C(\cdot)$ is convex and differentiable in θ, a necessary and sufficient condition is the first-order condition

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

and similarly, for the second equilibrium,

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

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

$$\int G_2(A, \theta) \, \mathrm{d}F(A) \leq \int G_2(A, \theta) \, \mathrm{d}F'(A) \tag{A.7}$$

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

$$\int G_2(A, \theta) \, \mathrm{d}F'(A) \leq \int G_2(A, \theta') \, \mathrm{d}F'(A) \tag{A.8}$$

Combined with the previous expressions, this implies,

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

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

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

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

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

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

Combined with the previous expressions, this implies,

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

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

A.4 Proof of Proposition 2

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

$$p^{\frac{1}{\alpha}} \int G_2(A, \theta) \, \mathrm{d}F(A) = \frac{\mathrm{d}}{\mathrm{d}\theta} C(\theta) \tag{A.11}$$

and similarly, for the second equilibrium,

$$p'^{\frac{1}{\alpha}} \int G_2(A, \theta') \, \mathrm{d}F'(A) = \frac{\mathrm{d}}{\mathrm{d}\theta} C(\theta') \tag{A.12}$$

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

$$p = P\left(\alpha^{-1}(1-\alpha)^{-1} p^{\frac{1}{\alpha}-1} \int G(A, \theta) \, \mathrm{d}F(A)\right) \tag{A.13}$$

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

Let us argue first that $p^*(\cdot)$ is weakly decreasing in θ and $F(\cdot)$, the latter via the FOSD order. See that, for any fixed (A, θ), the right-hand-side of (A.13) is a continuous, non-increasing function on the range $[0, \infty]$. The left-hand-side is a continuous function that increase without bound from 0. Thus the fixed point solution exists and is unique. Moreover, increasing θ or $F(\cdot)$ increases the term $\int G(A, \theta) \, \mathrm{d}F(A)$ under the global assumptions that $G_1 \geq 0$ and $G_2 \geq 0$, which decreases for every p the value of the right-hand-side of (A.13). Thus the unique solution is non-increasing in these arguments.

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

$$\int G_2(A, \theta) \, \mathrm{d}F(A) \leq \int G_2(A, \theta) \, \mathrm{d}F'(A) \tag{A.14}$$

Observe in this case that

$$\frac{\mathrm{d}}{\mathrm{d}\theta} C(\theta) = p^{\frac{1}{\alpha}} \int G_2(A, \theta) \, \mathrm{d}F(A) \leq p'^{\frac{1}{\alpha}} \int G_2(A, \theta) \, \mathrm{d}F'(A) \tag{A.15}$$

by combining (A.14) with the previous claim.

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

$$p'^{\frac{1}{\alpha}} \int G_2(A, \theta) \, \mathrm{d}F'(A) \leq p'^{\frac{1}{\alpha}} \int G_2(A, \theta') \, \mathrm{d}F'(A) \tag{A.16}$$

by weak concavity of $G(\cdot)$. Combining this with (A.15) implies that $\frac{\mathrm{d}}{\mathrm{d}\theta} C(\theta) \leq \frac{\mathrm{d}}{\mathrm{d}\theta} C(\theta')$. But the conjecture $\theta > \theta'$ and the strict convexity of $C(\cdot)$ implies $\frac{\mathrm{d}}{\mathrm{d}\theta} C(\theta) < \frac{\mathrm{d}}{\mathrm{d}\theta} C(\theta')$. This is a contradiction. Therefore, $\theta' \geq \theta$ as desired.

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

$$\beta p^{\frac{1}{\alpha}} A \theta^{\beta - 1} = 1 \tag{A.17}$$

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

$$\theta = M_1 \cdot A^{\frac{\alpha(1-\varepsilon)}{\alpha(1-\beta)+\varepsilon(1-\alpha(1-\beta))}} \tag{A.18}$$

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

A.5 Proof of Corollary 1

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

$$\begin{aligned} \Delta\text{Resilience}(A, p) &= M_0 p^{\frac{1}{\alpha}} \cdot (G_1(A, \theta) - G_1(A, \theta')) \\ &= -M_0 p^{\frac{1}{\alpha}} \int_{\theta}^{\theta'} G_{12}(A, z) \, \mathrm{d}z \end{aligned} \tag{A.19}$$

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

Consider next case 2. Proposition 2 tells us that we could have either $\theta' \geq \theta$ or the opposite. If $\theta' \geq \theta$, $\Delta\text{Resilience}(A, p) \leq 0$ by following the argument above and noting that $G_{12} \geq 0$. If $\theta' \leq \theta$,

then we revise the first argument to integrate from the lower to the higher technology level

$$\Delta\text{Resilience}_i = M_0 p^{\frac{1}{\alpha}} \int_{\theta'}^{\theta} G_{12}(A, z)\, \mathrm{d}z \tag{A.20}$$

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

A.6 Mapping Model to Estimation: Derivations

Here, we derive expressions (2.6) and (2.7) from Section 2.5.

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

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

We approximate this around the point at which $A_i = \tilde{A}$, $\theta_k = \tilde{\theta}_k$, and $G(A_i, \theta_k) = \tilde{G}_k := G(\tilde{A}, \tilde{\theta}_k)$ for each crop. In this approximation, provided that $\tilde{g} = g_{20} + g_{21}(\overline{A} - \tilde{A}) \neq 0$,

$$\frac{\partial}{\partial \theta} G(A_i, \theta_k) \approx \frac{\tilde{G}_k \tilde{g}}{\tilde{\theta}_k} \cdot \frac{g_{20}}{\tilde{g}} + \frac{g_{21}}{\tilde{g}} (\overline{A} - A_i) \tag{A.22}$$

The first-order condition for the innovator's choice of θ_k is, in logs and applying the previous approximation,

$$\eta \log \theta_k = \frac{1}{\alpha} \log p_k + \log \left[\frac{\tilde{G}_k \tilde{g}}{\tilde{\theta}_k} \right] + \log \int \left(\frac{g_{20}}{\tilde{g}} + \frac{g_{21}}{\tilde{g}} (\overline{A} - A) \right) \mathrm{d}F_k(A) \tag{A.23}$$

Under the assumption that $x(z) \approx 1$, we can approximate $\log \int x(z)\, \mathrm{d}F(z) \approx \int (x(z) - 1)\, \mathrm{d}F(z)$ which translates in our context into

$$\eta \log \theta_k = T_k + \frac{1}{\alpha} \log p_k + \frac{g_{21}}{\tilde{g}} (\overline{A} - A_k) \tag{A.24}$$

in which we define the crop-level shock

$$A_k := \int A\, \mathrm{d}F_k(A) \tag{A.25}$$

and the crop-level constant

$$T_k := \log \left[\frac{\tilde{G}_k \tilde{g}}{\tilde{\theta}_k} \right] + \left(\frac{g_{20}}{\tilde{g}} - 1 \right) \tag{A.26}$$

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

$$\log p_k = \log p_{0,k} - \varepsilon \log Y_k \tag{A.27}$$

Using an expression for $\log Y_k$, which itself depends on prices via input choices, this expression becomes

$$\log p_k = \log p_{0,k} - \varepsilon \left(\frac{1}{\alpha} - 1\right) \log p_k + \varepsilon \log(\alpha(1-\alpha)) - \varepsilon \log \int G(A, \theta_k)\, \mathrm{d}F_k(A) \tag{A.28}$$

We again apply an approximation around the $\tilde{G}_k$ points. We first take out the constant in the integral to get

$$\log p_k = \log p_{0,k} - \varepsilon \left(\frac{1}{\alpha} - 1\right) \log p_k + \varepsilon \log\left(\alpha(1-\alpha)\tilde{G}_k\right) - \varepsilon \log \int \frac{G(A, \theta_k)}{\tilde{G}_k}\, \mathrm{d}F_k(A) \tag{A.29}$$

and then approximate the integral as

$$\begin{aligned} \log p_k = \log p_{0,k} - \varepsilon \left(\frac{1}{\alpha} - 1\right) \log p_k + \varepsilon \log\left(\alpha(1-\alpha)\tilde{G}_k\right) - \varepsilon \left(g_1((\overline{A} - A_k) - (\overline{A} - \tilde{A}))\right) \\ - \varepsilon \left((g_{20} + g_{21}(\overline{A} - A_k)) \log \theta - (g_{20} + g_{21}(\overline{A} - \tilde{A})) \log \tilde{\theta}_k\right) \end{aligned} \tag{A.30}$$

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

$$(\overline{A} - A_i) \log \theta \approx (\overline{A} - \tilde{A}) \log \theta \tag{A.31}$$

This is required to obtain a closed-form solution for prices. We then write, with this substitution,

$$\log p_k = \log \tilde{p}_{0,k} - \varepsilon \left(\frac{1}{\alpha} - 1\right) \log p_k - \varepsilon g_1(\overline{A} - A_k) - \varepsilon \left(g_{20} + g_{21}(\overline{A} - \tilde{A})\right) \log \theta_k \tag{A.32}$$

or, solving for p_k,

$$\log p_k = \frac{\left(\log \tilde{p}_{0,k} - \varepsilon g_1(\overline{A} - A_k) - \varepsilon \left(g_{20} + g_1(\overline{A} - \tilde{A})\right) \log \theta_k\right)}{1 + \varepsilon(\alpha^{-1} - 1)} \tag{A.33}$$

where the constant is

$$\log \tilde{p}_{0,k} := \log p_{0,k} + \varepsilon \log\left(\alpha(1-\alpha)\tilde{G}_k\right) + \varepsilon(g_{20} + g_{21}(\overline{A} - \tilde{A})) \log \tilde{\theta}_k + \varepsilon g_1(\overline{A} - \tilde{A}) \tag{A.34}$$

We now solve for the equilibrium level of technology by combining (A.24) and (A.33). Direct substitution gives

$$\eta \log \theta_k = \frac{\left(\tilde{p}_{0,k} - \varepsilon g_1(\overline{A} - A_k) - \varepsilon \left(g_{20} + g_{21}(\overline{A} - \tilde{A})\right) \log \theta_k\right)}{\alpha + \varepsilon(1-\alpha)} + T_k + \frac{g_{21}}{\tilde{g}}(\overline{A} - A_k) \tag{A.35}$$

which simplifies to

$$\log \theta_k = \log \theta_{0,k} + \delta(\overline{A} - A_k) \tag{A.36}$$

with slope

$$\delta := \frac{\frac{g_{21}}{\tilde{g}} - \frac{\varepsilon g_1}{\alpha+\varepsilon(1-\alpha)}}{\eta + \frac{\varepsilon \tilde{g}}{\alpha+\varepsilon(1-\alpha)}} \tag{A.37}$$

and constant

$$\log \theta_{0,k} := \frac{T + \frac{\tilde{p}_{0,k}}{\alpha+\varepsilon(1-\alpha)}}{\eta + \frac{\varepsilon \tilde{g}}{\alpha+\varepsilon(1-\alpha)}} \tag{A.38}$$

See that in the fixed-price variant with $\varepsilon = 0$, we have $\text{sign}[\delta] = \text{sign}[g_{21}]$ which isolates the intuition about climate complements and substitutes.

We finally consider equilibrium rents. Log rents for farm i, growing crop $k = k(i) = \lceil i \rceil$, are

$$\log \Pi_i = -\log(1-\alpha) + \frac{1}{\alpha} \log p_{k(i)} + \log G(A_i, \theta_{k(i)}) \tag{A.39}$$

Using the assumed form of $\log G$ from (2.5), p from (A.33), and θ from (A.36),

$$\begin{aligned} \log \Pi_i = &-\log(1-\alpha) + \frac{1}{\alpha} \frac{\left(\tilde{p}_{0,k(i)} - \varepsilon g_1(\overline{A} - A_{k(i)}) - \varepsilon \left(g_{20} + g_{21}(\overline{A} - \tilde{A})\right)(\log \theta_{0,k(i)} + \delta(\overline{A} - A_{k(i)}))\right)}{1 + \varepsilon(\alpha^{-1} - 1)} \\ &+ g_0 + g_1(\overline{A} - A_i) + (g_{20} + g_{21}(\overline{A} - A_i))(\log \theta_0 + \delta(\overline{A} - A_{k(i)})) \end{aligned} \tag{A.40}$$

which simplifies, as desired, to

$$\log \Pi_i = \log \Pi_{0,i} + \beta \cdot (\overline{A} - A_i) + \gamma \cdot (\overline{A} - A_{k(i)}) + \phi(\overline{A} - A_i)(\overline{A} - A_{k(i)}) \tag{A.41}$$

with coefficients

$$\begin{aligned} \beta &= g_1 \\ \gamma &= -\varepsilon\beta \frac{g_1 + \tilde{g}\delta}{\alpha + \varepsilon(1-\alpha)} + g_{20}\delta \\ \phi &= g_{21}\delta \end{aligned} \tag{A.42}$$

and constant

$$\log \Pi_{0,i} = -\log(1-\alpha) + \frac{\left(\tilde{p}_{0,k(i)} - \varepsilon \tilde{g} \log \theta_{0,k(i)}\right)}{\alpha + \varepsilon(1-\alpha)} + g_0 + g_{20} \log \theta_{0,k(i)} \tag{A.43}$$

A.7 Proof of Corollary 2

The stated assumptions translate to $g_{20} = 0$ and $\varepsilon = 0$. See, under these conditions, that the regression coefficients in representation (A.42), from the derivation in Appendix A.6, are $\beta = g_1$, $\gamma = 0$, and $\phi = g_{21}\delta$.

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

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

we want to show that $\log \Pi_i''$ corresponds with each of the expressions in Definition 2 under the assumed conditions.

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

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

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

In the counterfactual without innovation, technology is held counterfactually at $\theta_k'' = \theta_k$ while the climate satisfies $A_{i,k}'' = A_{i,k}'$ and $A_k'' = A_k'$ for all locations and crops. Using (A.40) from the derivation in Appendix A.6, and substituting in $\varepsilon = 0$ and $g_{20} = 0$, we have

$$\log \Pi_i'' = -\log(1-\alpha) + \frac{\tilde{p}_{0,k(i)}}{\alpha} + g_0 + g_1(\overline{A} - A_i') + (g_{20} + g_{21}(\overline{A} - A_i'))(\theta_0 + \delta(\overline{A} - A_{k(i)})) \tag{A.44}$$

See that this corresponds with

$$\log \Pi_i'' = \log \Pi_{0,i} + \beta \cdot (\overline{A} - A_i') + \gamma \cdot (\overline{A} - A_{k(i)}) + \phi \cdot (\overline{A} - A_i')(\overline{A} - A_{k(i)}) \tag{A.45}$$

given the expressions for the coefficients outlined above.

B. Model Extensions

B.1 Efficiency

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

B.1.1 Static Baseline

We begin with the main static model introduced in the text. We first fully specify the consumer block of the model. In addition to the agricultural good (the "crop"), there is a second numeraire good which can be interpreted as leisure (i.e., negative labor).[67] The agent has an endowment $\overline{z}$ of this good and consumes at level z. The consumer's problem is

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

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

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

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

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

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

for θ; and

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

for each $T(A)$. See that (B.4) coincides with decentralized technology demand (2.2) and (B.3) corresponds with decentralized quality choice (2.3) if $q = 1-\alpha$, or technology is priced at marginal cost. Thus the singular source of inefficiency in the decentralized allocation is the monopoly power of the technology producer, which could be fixed by leveraging an appropriate subsidy of rate α (i.e., having consumers face price $(1-\alpha)q$). Moreover, the effect of the monopoly power is to unambiguously reduce the amount of technology used by each firm ($T(A)$ for all $A \in [\underline{A}, \overline{A}]$) and the level of technological progress θ. This is clear from the combination of (B.3) and (B.4) which gives the socially

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

optimal level of technological progress:

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

which differs from the equilibrium condition (A.5), in the proof of Proposition 1 in Appendix A.3, by the scaling $(1-\alpha)^{-\frac{1}{\alpha}} > 1$ on the marginal benefit. Under the established conditions that G is concave in θ and C is convex in θ, it is immediate that the socially optimal level of technology exceeds the equilibrium level.

Note finally that, since correcting the externality affects technology demand only up to a scaling factor, the comparative static in Proposition 1 continues to hold as a comparative static for the planner's preferred allocation. This can be verified by going through the steps of the proof in Proposition A.3 under a different definition for $\overline{p}$, which is also a scaling factor. Therefore, the "direction" of technological change is not different in the planner's solution and the equilibrium allocation.

B.1.2 With Dynamic Externalities

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

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

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

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

while the equilibrium in the second period is characterized by

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

Consider now the problem of a social planner who maximizes total utility of agents across periods

with discount factor β.[68] It is straightforward to show, extending the results above, that optimal investment at $t = 0$ and $t = 1$ satisfy the following system of equations:

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

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

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

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

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

B.2 Multiple Types of Technology

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

B.2.1 Equilibrium and Comparative Statics

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

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

in which we assume

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Together, however, these statements imply

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

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

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

B.2.2 Dynamic Externalities and Lock-In

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

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

B.3 Variable Utilization

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

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

where optimal utilization solves

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

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

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

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

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

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

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

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

Consider first the case in which ψ is not too concave or $2\psi' > -\psi''$. Then, endogenous utilization can result in $\frac{\partial^2}{\partial A_i\partial\theta_k}\tilde{G}(A_i,\theta_k)\geq 0$ even when $G_{12}\leq 0$. In this sense, endogenous utilization "fights

against case 1 and fights for case 2," referring to the cases of Proposition 1. This embodies the economic intuition that farmers respond to bad climate shocks by planting less. Even if conditional on "digging in their heels" and planting they demand more technology, lower planting can be the dominant effect when utilization is very sensitive to productivity (high ψ').

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

B.4 Capacity Constraints for Research

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

B.4.1 Model

We now consider an extension of the baseline model in which there are K crops indexed by $k \in \{1, \ldots, K\}$. For each crop, there is a unit measure of locations which produce the crop. We use $(p_k)_{k=1}^K$ to denote each crop's price in terms of the numeraire; $(F_k)_{k=1}^K$ to denote each crop's productivity distribution; and $(\theta_k)_{k=1}^K$ to denote each crop's technology level. The production function for each crop is givenby (2.1).

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

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

It is straightforward to show, as in the baseline model (see Appendix A.1), that the profit-maximzing

price is $q_k \equiv 1$ for all crops and therefore the problem reduces to

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

Let λ denote the Lagrange multiplier on the capacity constraint and

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

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

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

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

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

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

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

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

B.4.2 Tractable Variant

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

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

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

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

which implies

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

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

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

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

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

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

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

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

and

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

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

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

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

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

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

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

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

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

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

C. Climate Change and Innovation: Qualitative Evidence

In this section, we report a range of case-study evidence from recent advances in biotechnology suggesting that inventors have been directing innovation toward crops experiencing temperature distress. The notion that developing technological solutions to temperature distress has only gained prominence in recent years. These anecdotes support a narrative in which, in the long run, technological progress has allowed US agriculture to surmount ecological and climatic challenges (as discussed at length in, e.g., Olmstead and Rhode, 2008, 2011; Sutch, 2011). While recent technological advance has been couched in language related to "climate change," as our model and the discussion below make clear, awareness about the cause of environmental change is not a necessary condition for inventors to pursue the profit opportunities that it presents.

According to myriad news reports, agricultural biotechnology companies are presently "racing to develop products" that address the problem of "rising temperatures."[69] According to *CNN Money* (2017), "Monsanto poured more than $1.5 billion into research and development efforts last year to design better quality corn seeds and products...'In our breeding efforts and biotech efforts, we're making sure our products can withstand that extreme weather,' explains Pam Strier, Mosanto's sustainability chief." In 2019, Syngenta allocagted $2 billion toward developing technologies that will "help farmers prepare for and tackle the increasing threats posed by climate change."[70] Biotechnology

[69] See here: https://www.motherjones.com/environment/2015/12/climate-change-business-opportunities/

[70] See here: https://www.syngenta.com/en/company/media/syngenta-news/year/2019/syngenta-commits-2-

companies also note the fact that demand has grown for climate-resilient seeds—relative to other varieties—because of how essential they are when the environment is unfavorable: "As the Midwest's climate grows hotter, Monsanto notes there's demand for seeds that can thrive in warmer and more extreme environments."

A particularly illustrative case study was the modern "mega-drought" of 2012-2013 in the US Plains. A central way that extreme temperature limits crop productivity is by the reduction in plant moisture through heat-induced evapotranspiration (Lobell et al., 2013; Tack, Barkley and Hendricks, 2017; Zaveri and Lobell, 2019). Varieties that remain productive despite lower levels of moisture are thus a key source of adaptation to increased extreme heat. Within 2 years of the drought, Monsanto released the corn variety Genuity DroughtGard Hybrids and DuPont released Optimum AQUAMax, both of which were designed to remain productive in low-moisture environments. In the words of Connie Davis, corn systems technology development manager for Monsanto:

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

Technology development responded to demand for seeds that remain resilient in extreme climates. Indeed, the implication from our findings that there are potentially large profits to be made from developing climate-mitigating agricultural technologies may explain why agricultural biotechnology firms frequently top lists of companies that financial advisors say investors should own if they want to "invest in climate change."[71]

As our empirical results make clear, this pattern is not restricted to corn or staple crops. In California, for example, farmer demand is anecdotally highest for temperature-resistant vegetable varieties; our own measurement strategy shows that the production of several vegetables in California have been subject to extreme temperature distress. Both Monsanto and Syngenta are investing extensively in the development of more resilient vegetable and fruit varieties, particularly in response to climate stress in California; Monsanto's vegetable development headquarters in Woodland has "22 crops in its portfolio, ranging from sweet corn and cucumbers to peppers, tomatoes and melons."[72]

The public sector is also involved in this innovative push. Researchers at the University of California, Davis, for example, received a $4.5 million grant in 2015 to "support a multidisciplinary research program aimed at leveraging new technologies to sustain the supply of lettuce in spite of changes in climate." Interestingly, lettuce is one of the crops that, according to our measure, has been most negatively affected by temperature change.

While recent trends in technology development seem driven by an understanding of climate

billion-and-sets-new-targets-innovation

[71]See, for example, here: https://www.cnbc.com/2014/07/28/investing-in-climate-change-a-25-stock-indexenvironmentcommentary.html. Also here: https://www.nytimes.com/2019/04/12/business/climate-change-funds-profit-global-warming.html.

[72]See here: https://www.cnbc.com/2015/06/23/ag-giants-look-to-plant-a-seed-to-fight-the-drought.html

change and the idea that it will be a persistent phenomenon, our theoretical framework makes clear that awareness of the drivers of climate change is not necessary for technology development to react. Inventors react to changing profit opportunities brought about by climate-induced productivity changes; these productivity changes can be observed directly and affect R&D investment. Inventors have been endogenously developing climate-resilient technologies for decades, long before there was a clear sense of the scope and determinants of modern climate change. A CNN report concluded that compared to earlier periods of environmental stress, what farmers "have working in their favor [are] new tools, technologies, and other developments [including] hybrid seeds." This may, at least in part, reflect the directed innovation of the *past* responding to experienced environmental stress. A broad range of observers have argued that directed technology development has been an important source of resilience to environmental change since the mid-20th century (Crabb, 1947; May, 1949; Crow, 1998; Sutch, 2008, 2011; Moscona, 2019a).

D. Detailed Construction of Extreme Days

We follow the procedure outlined in Schlenker and Roberts (2009) to compute daily temperature averages since 1950 from raw data on daily maximum and minimum temperatures. This includes interpolating the portion of a day that is within a particular temperature range and aggregating to US counties using only grid cells that are identified via satellite data to contain crop-land. The last step, in particular, poses a small complication because the identity of this farmland is not measured in the pre-period and could be endogenous to the forces we study, but does dramatically speed up the computational time. We thank Wolfram Schlenker for making these data available on his website at the following link: `http://www.columbia.edu/~ws2162/links.html`.

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

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

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

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

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

Next, within a given county, we aggregate the previous measure across grid cells that have planted

cropland using weights w_g:

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

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

We sum the previous over days in a given period of interest t, a decade (e.g., 1950-59, 1960-69):

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

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

We finally make this measure crop-specific by substituting in the crop-specific maximum optimal temperature from EcoCrop. This step is described in the main text. This discussion connects with the measurement in the main text when we define

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

E. Alternate Strategy for Measuring Climate Distress

Our second approach leverages the substantial heterogeneity in changes in *average* temperatures across different parts of the United States, interacted with heterogeneity in where different crops have historically been grown. The goal is to produce a transformation of this average temperature change that is scaled to the "correct units," in terms of sign and magnitude, to properly reflect the impact of temperature change on a particular crop's productivity.

For each county i, we use the Census of Agriculture to measure the share of the total land area devoted to crop k located in county i in 1959; we refer to this share as $\text{Share}_{i,k}^{\text{Pre}}$. We compute the summer growing season (April to October) average temperature for the pre-period, averaged over all years 1950-1959; we refer to this pre-period temperature measure as T_i^{Pre}.[73] Analogously, we compute the same growing season temperature for the post-period, averaged over all years 2010-2019; we refer to this post-period temperature measure as T_i^{Post}. Finally, from the EcoCrop database, we obtain *crop-specific* estimates of the optimal growing season temperature, as well as the maximum and minimum temperatures at which each crop can theoretically be grown. These numbers are referred to as T_k^{Opt}, T_k^{Max}, and T_k^{Min} respectively.[74]

[73] In our analysis, for all crops, we fix a growing season from April to October. In future drafts we hope to do a more careful analysis that takes into account crop-specific growing seasons.

[74] The optimal temperature T_k^{Opt} is calculated as the average of the two endpoints of an "optimal growing range," which is a strict sub-range of the "max to min range" referenced above.

First, for each crop-by-county pair, we compute the *percent change in distance to the optimal temperature*, $F(.)$:

$$F(T_i^{\text{Pre}}, T_i^{\text{Post}}; k) = 100 \cdot \frac{|T_i^{\text{Post}} - T_k^{\text{Opt}}| - |T_i^{\text{Pre}} - T_k^{\text{Opt}}|}{T_k^{\text{Max}} - T_k^{\text{Min}}} \tag{E.1}$$

In particular, $F(T_i^{\text{Pre}}, T_i^{\text{Post}}; k)$ measures how much closer or farther away each crop k in county i is from its optimal temperature, and scales this distance measure by the crop's total temperature range. This scaling procedure accounts for the fact that crops are differentially sensitive to given temperature degree changes. We then aggregate these crop-by-county pair measures to the crop level by, for each crop, summing over all counties weighing by the share of crop k's total area planted in county i:

$$\text{DistFromOpt}_k = \sum_i \text{Share}_{i,k}^{\text{Pre}} \cdot F(T_i^{\text{Pre}}, T_i^{\text{Post}}; k) \tag{E.2}$$

This yields our second measure of crop specific exposure to a worsening climate.

Comparison with raw temperature change. To help build the intuition behind our distress measure, we calculate also a "raw temperature change" version of the previous formula as follows:

$$\text{TempChange}_k = \sum_i \text{Share}_{i,k}^{\text{Pre}} \cdot (T_i^{\text{Pre}} - T_i^{\text{Post}}) \tag{E.3}$$

This resembles a "crop-level shift-share" of the sort of empirical design that has been used to study the effects of temperature changes on economic outcomes (e.g., Dell, Jones and Olken, 2012; Burke, Hsiang and Miguel, 2015).[75] In the model, it would involve treating temperature changes as a uniform (in sign and magnitude) instrument for the productivity changes for growing any crop in location i.

Figure B1 plots a comparison between this simple measure TempChange_k and the agronomically-motivated measure DistFromOpt_k. A rough "<" (“sideways V”) pattern is visible—as temperatures increase, some crops with $\text{DistFromOpt}_k > 0$ move further from their theoretical optimum T_k^{Opt} calculated from EcoCrop. These are the crops above the horizontal dotted line in the figure. Other crops—those with $\text{DistFromOpt}_k < 0$ that are below the horizontal dotted line in the figure—move closer.

How related are our two measures of crop distress? Conceptually, they could be very different since there is no reason that crops that became more exposed to days of extreme weather also experienced an unfavorable change in average temperature. But in practice they are highly correlated (see Figure B2, which reports the partial correlation plot).

[75] It also, in first differences, would capture any (average-temperature) growing-degree-day (GDD) calculation for a fixed reference temperature (as in Deschênes and Greenstone, 2007; Fisher et al., 2012).

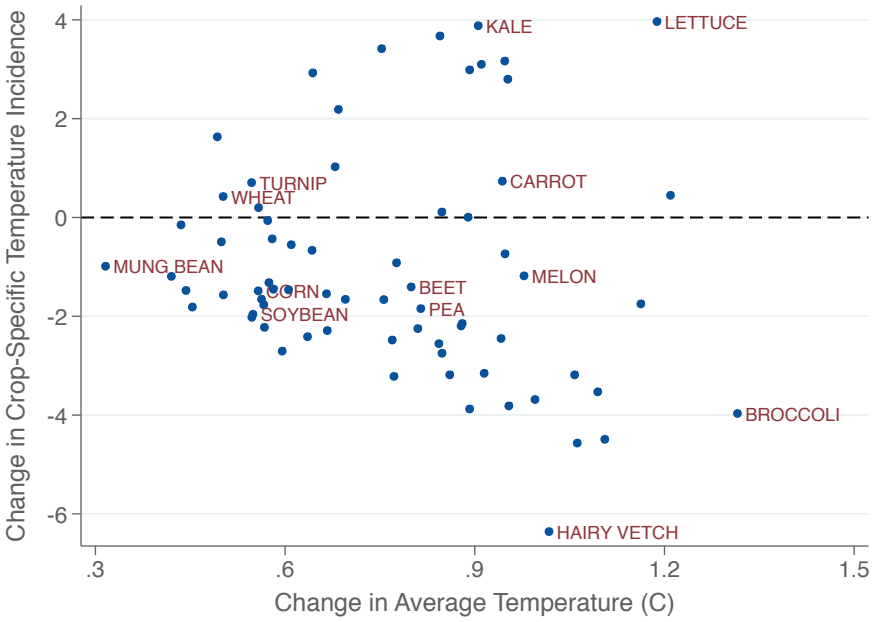


Figure B1: Comparison of TempChange_k, defined in (E.3), and Distress_k, defined in (4.1), with specific crops labeled.

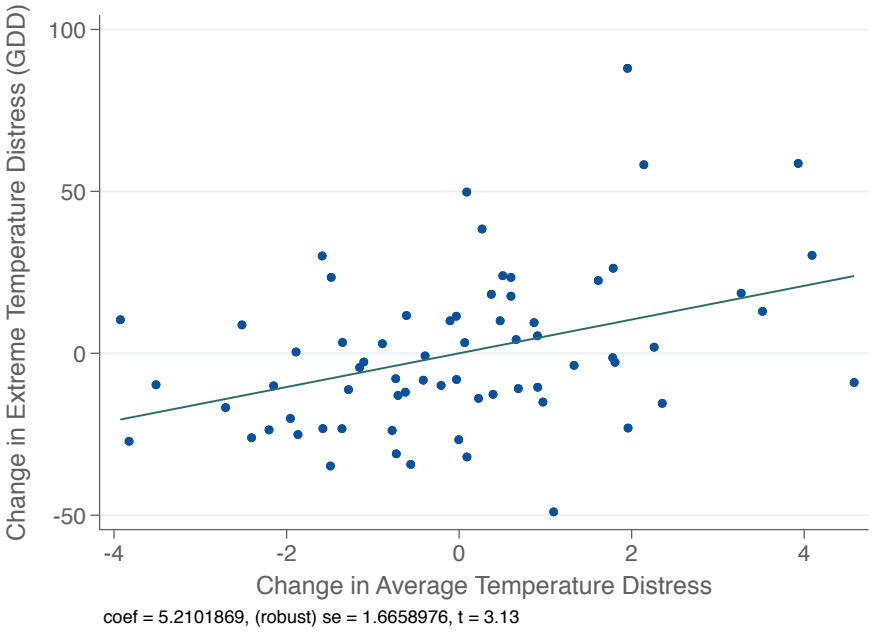


Figure B2: Crop-Level Partial Correlation Between DistFromOpt_k and ExtremeExposure_k. Controls included for (log of) total area, pre-period average temperature, and pre-period average precipitation.

F. Crop Switching

F.1 Second Order Effects: Crop Switching and Market Size

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

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

County-level Reallocation. The first sub-question that needs to be answered is whether climate incidence predicts re-allocation of land in particular areas away from more damaged crops and toward less-damaged crops. Let $\text{Area}_{k,i}^{1959}$ be the area planted for crop k in county i in 1959 and let $\text{Area}_{k,i}^{2012}$ be the same in 2012. For all county-by-crop observations we estimate the following specification:[76]

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

where α_{ks} are crop-by-state fixed effects and δ_i are county fixed effects. The inclusion of county fixed effects absorbs the fact that certain countries have become more or less agricultural overall since 1960. The coefficient π measures the extent to which local temperature distress induces switching away from a particular crop. Crucially, since our measure of $\text{ExtremeExposure}_{k,i}$ relies only on temperature realizations and crop-level physiology, ewe can measure $\text{ExtremeExposure}_{k,i}$ for all county-crop pairs *even if the crop is not grown in the county during the pre period*. Thus, the specification allows us to home in on the effect of crop-by-county specific climate distress on production allocation.

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

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

Table B2: Crop Switching and Technology Development

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable is New Crop Varieties							
Δ ExtremeExposure	0.0174***	0.0133***	0.0193***	0.0178**	0.0135***	0.0103***	0.0114***	0.0105**
	(0.00496)	(0.00377)	(0.00620)	(0.00710)	(0.00381)	(0.00342)	(0.00402)	(0.00433)
log Δ EE-Predicted Natl. Area	0.545**	0.306	0.371*	0.387*				
	(0.276)	(0.248)	(0.225)	(0.226)				
log Natl. Area *(endogenous control)*					0.269***	0.286***	0.275***	0.278***
					(0.0413)	(0.0540)	(0.0572)	(0.0595)
Log 1959 area harvested	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-period climate controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Pre-period varieties	No	No	Yes	Yes	No	No	Yes	Yes
Optimal temp. and optimal temp sq.	No	No	No	Yes	No	No	No	Yes
Observations	55	55	55	55	55	55	55	55

Notes: The unit of observation is a crop. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

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

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

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

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

Our new coefficient of interest β^{MS} captures the impact of temperature-induced expansions in crop market size on innovative output. The control vector X_k' always includes the log of 1959 area planted for each crop. This ensures that the coefficient β^{MS} measures the effect of expanded market size holding fixed initial market size.

Estimates of Equation F.3 are reports in columns 1-4 of Table B2. The first key finding is that controlling for temperature-induced changes in market size have virtually no impact on β, the relationship between temperature distress and variety development. Our baseline estimates are not biased by changes in planted area. The second key finding is that, intuitively, β^{MS} is positive; more-

over, is is statistically distinguishable from zero in three of the four specifications. This suggests that temperature-induced market expansion is an independent and potentially important channel through which climate change affects patterns of innovation.

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

F.2 Modeling Crop Choice in the Counterfactual

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

Using measures of extreme exposure $\Delta\text{ExtremeExposure}_{k,i}(d,r)$ for each decade $d \in \{2050, 2090\}$ and for each RCP $r \in \{4.5, 6.0, 9.5\}$ we estimate $\text{Area}_{k,i}(d,r)$ as:

$$\text{asinh}(\text{Area}_{k,i}(d,r)) = \hat{\alpha}_{ks} + \hat{\delta}_i + \hat{\psi} \cdot \text{asinh}(\text{Area}_{k,i}^{2012}) + \hat{\pi} \cdot \Delta\text{ExtremeExposure}_{k,i}(d,r) + \varepsilon_{k,i} \qquad \text{(F.4)}$$

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

G. Sensitivity Analysis of County-Level Estimates

Before continuing to the main counterfactual exercise, we discuss several additional empirical investigations which are consistent with our main interpretation of the results.

Controlling for Nonlinear Terms. A potential concern is that estimates of ϕ are simply capturing a non-linear effect of climate damage on land values. If county-level distress and our crop-composition distress measures are correlated, then ϕ might be picking up the fact that the functional form of the relationship between distress and land values is quadratic. To address this issue, we control directly for the square of county-level distress. This version of the results is reported in Table A18. If anything, after including these controls the coefficient of interest is larger in magnitude across specifications.

Sample Restrictions. Our baseline estimates include all counties in the mainland United States. However, there are important differences in agricultural production east and west of the 100th Meridian (e.g., Schlenker, Hanemann and Fisher, 2006; Schlenker and Roberts, 2009). In particular, agricultural production west of the 100th Meridian relies extensively on highly subsidized irrigation systems that plausibly mitigate the direct effect of heat stress and the importance of adaptive innovations. Table A19 reproduces the baseline county-level estimates from Table 4 after restricting the sample to counties east of the 100th Meridian. Reassuringly, the results tell the exact same story on this restricted sample and all point estimates are, as expected, larger in magnitude.

Ruling out Local Spillovers. The goal of our CropMixEE measure is to capture each county's crops' national exposure to temperature distress and hence the extent to which new technologies are endogenously developed. This is consistent with our model, in which the relevant general equilibrium effects were price changes and

The cultivation of certain crops (e.g., lettuce), however, is concentrated in a relatively small set of nearly counties within the same state. For this set of crops, CropMixEE might capture not only the re-direction of new technologies but also spillover effects of temperature distress from nearby counties. If this were driving the results, it would be cause for concern.[77] To address this, we compute a version of each county's crop composition distress *after dropping data from all other counties within the same state.* We reproduce the baseline results using this version of the crop composition distress measure in Table A20. Reassuringly, all estimates are very similar in magnitude and remain highly precise.

Measuring Distress Using Changes in Average Temperature. While Table 4 reports estimates in which county-level "distress" is computed from crop-level distress measures incorporating changes in crop-level exposure to extreme GDD, the results are very similar if we compute analogous measures using instead variation in changing temperature averages and their differential effects across crops (see Appendix E). These estimates are presented in Table A21. The results are very similar and in fact seem to operate partially independently from the effect of changes in temperature damage from extreme GDD (columns 4 and 7). This is consistent with our finding that the impact of crop-level distress from changes in average temperature also had an independent impact on crop-level technology development from crop-level exposure to extreme GDD (see Table A5).

Average Endpoint Temperatures. Columns 1-5 of Table 4 report long difference estimates in which temperature distress is first measured in the decade 1950-1960 to capture the pre-period and 2010-present to capture the post period. In order to make sure our results are not driven by these particular decades, in Table A22 we report estimates in which we use a 2-decade period at each endpoint to measure the pre-period and post-period climate. That is, we use temperature data from 1950-1970 to compute pre-period climate distress and 2000-present to compute post-period climate distress. The

[77] We thank Wolfram Schlenker for a helpful discussion on this point.

results are very similar.