Climate Change, Invention, and Adaptation: Evidence from US Agriculture

Jacob Moscona† and Karthik Sastry‡

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Abstract

Does innovation (i) react to productivity damage from climate change in agriculture and (ii) mitigate its economic consequences? Using a model in which innovation is directed toward specific applications by profit opportunities, we show the prediction on both fronts is \textit{ex ante} ambiguous, but can be tested using data on agricultural output, innovation, and climate-induced productivity changes. We implement this strategy in the US by combining comprehensive data on the geography of agricultural production, changing temperature realization patterns across space, and agricultural technology development since 1950, along with agronomic models of crop-specific temperature sensitivity. New technology, and particularly novel plant varieties, has been systematically re-directed toward crops that have been exposed to greater temperature distress in historical production locations. Moreover, the national climate distress of a given US county’s crops, which determines the extent to which that location was positioned to benefit from new innovation, significantly dampens the economic effects of local climate distress. Marginal climate damages to agricultural land values increase 75% from the 5th to the 95th cross-sectional percentile in availability of innovation, as we measure it. Taken together, these results suggest that the re-direction of innovation is an important component of adaptation to climate change and mediator of its economic consequences.

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†Department of Economics, M.I.T., 50 Memorial Drive, Cambridge, M.A. 02142, U.S.A. (email: moscona@mit.edu; website: http://economics.mit.edu/grad/moscona)

‡Department of Economics, M.I.T., 50 Memorial Drive, Cambridge, M.A. 02142, U.S.A. (email: ksastry@mit.edu; website: http://economics.mit.edu/grad/ksastry)
1. Introduction

Climate change will have large effects on agriculture in the coming decades. Leading models quantify this damage by extrapolating from historical patterns and, implicitly, assuming that production technology will remain fixed (Zhao et al., 2017). But there is a large scope for human adaptation by inventing new production technologies, like new hybrid seeds better adapted to extreme heat and dryness. To what extent will humankind fight back against Nature with innovations that restore productivity and combat climate damage? How will economic incentives guide this process? And what will be the distributional impact in terms of mitigating—or exacerbating—the harms of climate damage for certain crops in certain places?

This paper provides direct empirical evidence on the redirection of technology in response to climate distress and its impact on economic outcomes in US agriculture since 1950. We compile comprehensive data over this sample period on the (i) geography of crop production, (ii) changing temperature realization patterns across space, (iii) local economic outcomes for farmers, and (iv) new agricultural technology development. We use agronomic estimates of crop-specific temperature sensitivity to translate the first two ingredients into measures of crop-specific “temperature distress” at the local and national levels. With these data, we quantify both the innovative response to climate-induced productivity shocks and the extent to which these innovations have mediated the relationship between temperature change and economic outcomes in recent history.

We document three main findings. First, implementing our novel strategy to estimate the extent to which each crop has been damaged by temperature change since 1950, we show that technology has broadly redirected toward more climate-distressed crops. Moreover, the innovative response has focused disproportionally on seeds and other “biological” technologies that may on average be most useful for adaptation to environmental change.

Second, we document that the re-direction of innovation toward climate-distressed crops has had a large effect on the economic incidence of temperature change across US counties. Our strategy is to compare marginal climate damage in counties that would have access to different levels of climate-mitigating innovations, as predicted (according to the first part of the analysis) by the climate damage experienced on average in the US by the locally grown crops. We find that this heterogeneity is quantitatively large—between the 5th and 95th percentile of the “innovation availability” distribution, marginal climate damages (in units of percentage changes in local land values) decrease by ~ 75%.

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1The meta-analysis by Zhao et al. (2017), as one illustrative case, attempts to quantify climate impacts on the world’s four largest staple crops (wheat, rice, maize, and soybeans) using four state-of-the-art methods: process-based crop models that simulate growth based on scientific principles, at either the global (i) or site-level (ii) scale; regression-based extrapolation from the historical relationship between output and temperature (iii); and artificial warming of test plots (iv). All four, in different ways, extrapolate based on known production technology—the first two through their calibration to match observed growth patterns, the second through its statistical extrapolation, and the last through its reliance on existing varieties to test.

2See, for instance, the aforementioned Olmstead and Rhode (2008) on the broad historical context in the US; Sutch (2011) for a case-study of drought-resistant corn in US history; and Gibbon (2011) for a policy brief that emphasizes the value of biotechnology to help farmers’ adaptation.
Finally, we show that the availability of new innovation, measured in the same way, dampens the extent of switching away from damaged crops and adoption of irrigation. This suggests that adaptation mechanisms interact with each other in quantitatively very important ways.

Taken together, our findings suggest that technological progress in US agriculture has responded dynamically and along multiple margins to temperature change. Innovation has played a major role mediating the economic consequences of climate change in the United States. Looking forward, the interaction between environmental stress and the innovative sector may be crucial for mapping the future of climate impacts and optimal corrective policy.

Context, model, and measurement. Two centuries of history in agricultural science suggests that innovation can rise to meet emergent environmental challenges (Olmstead and Rhode, 2008). But the clearest theory for whether it naturally does in the present context, a model of directed technical change in which profit opportunities guide the research frontier, has no specific prediction. On the one hand, climate distress in a given sector could provide a unique opportunity for developing the damage mitigating technology that farmers desperately need. However, it may just as well provide a clear signal to “jump ship” and shift innovative effort toward markets that are doing relatively better.

We formalize these trade-offs, and potentially ambiguous predictions, in a model that combines a realistic production sector for agriculture, with geography, crop choice, and multiple technologies, with an “idea-production” sector like in Romer (1990) and its multi-sector extensions by Acemoglu (1998, 2002). Climate change functions as a crop and location specific productivity shock. Farmers in a given place can “adapt” to new conditions by changing their investment in different technological inputs, like state-of-the-art hybrid varieties, irrigation systems, or combine harvesters. But, crucially and realistically, the innovation of new varieties of such technologies is carried out by national-scale innovators looking for the best aggregate profit opportunities (e.g., Syngenta, Dow AgroSciences, or John Deere, marketing toward the whole US). These innovators optimize over both the type of technology, distinguished by its role in the production function and relationship with climate damage, and the crop to which the technology applies (e.g. corn seed vs. sorghum harvester).

In the model, we investigate the impact of climate change-induced productivity shocks on innovative activity. An immediately ambiguous, partial equilibrium force is the effect of climate change on the marginal product of, and hence demand for, different technologies. This depends loosely on the “substitutability” of good climate and good technology. On this point, there is anecdotal evidence that certain inputs, including high-yielding and hybrid seed varieties, may be particularly useful in times of environmental stress (i.e., that they partially substitute for a favorable environment)—while, to the same point, new harvesting or post-processing technologies may not. This is discussed in the references of Footnote 2. Farmers’ testimony also echoes the same main points. For example, National Public Radio interviewed Charles Hildenbrand during the 2012 drought; NPR reports: “[H]e says even though this year’s drought is the worst he’s ever seen, today’s hybrid corn is surviving better than the corn he and his father planted ever could. ‘If this would’ve been open-pollinated, it would have been all brown, probably. And there probably wouldn’t be any kernels on these ears,’ he says.” See the full article here: https://www.npr.org/2012/08/04/158119458/soaked-in-drought-lessons-from-the-dustbowl.
rium impacts on the marginal product of different technologies may be amplified or attenuated by general equilibrium effects including changes in aggregate market shares and output prices for specific crops. The overall response of innovation to climate change depends on the relative importance of these competing channels.

We next map the relevant model objects to measurable quantities. Our first goal is to construct a national-level measure of climate distress for all crops cultivated in the US. We do this by combining data on (i) the geography of production from the US Census of Agriculture; (ii) county-level temperature as compiled by the National Oceanic and Atmospheric Administration; (iii) daily temperature at the $2.5 \times 2.5$-mile grid-cell-level from PRISM; and (iv) crop-specific agronomic information on optimal growing temperatures from the UN Food and Agriculture Organization’s (FAO) EcoCrop database.

Our use of the EcoCrop Database draws inspiration from existing work in crop science and biological systems analysis (e.g., Hijmans et al., 2001) and, to our knowledge, has not been used in empirical work in economics. EcoCrop reports optimal and upper-bound temperatures for individual crops based on expert survey and relevant agricultural literature, which allows us to extrapolate, across a much larger set of crops, the empirical insights of numerous recent studies on the effects of heat stress on staple crops (e.g., Ritchie and Nesmith, 1991; Schlenker and Roberts, 2009). Using this information, for each crop we compute two measures of climate distress: (i) the long-run change in each crop’s average distance from its optimal growing temperature and (ii) the long-run change in each crop’s exposure to days of extreme heat or cold, taking into account the differential sensitivity of each crop to temperature extremes.

For technological outcomes, we collect (i) a comprehensive dataset of all for-sale plant varieties and their time of introduction from the USDA’s “Variety Names List,” obtained via a Freedom of Information Act (FOIA) request as discussed in Moscona (2019b); and (ii) crop-specific patents in a number of relevant technology classes over time. Finally, to measure outcomes in the agricultural economy, we compile data from the 1959-2012 rounds of the US Censuses of Agriculture on the county-level value of agricultural land.

Distress and directed innovation. Our first main result is that, across crops, higher climate distress predicts higher rates of new seed introduction since 1960. This result is robust to controlling directly for crop-level proxies for market size, pre-trends in innovative activity, and pre-period climatic characteristics. In a panel data specification, the result is driven almost entirely by effects within the same decade and not lagged response to previous climate conditions or anticipation. Overall, we find that a one standard deviation increase in our crop-level climate distress level led to a 0.2 standard deviation increase in variety development.

Agricultural biotechnology companies also note the fact that demand has grown for climate-resilient seeds relative to existing varieties because of how essential they are when the environment is unfavorable. According to CNN Money (2017), “As the Midwest’s climate grows hotter, Monsanto notes there’s demand for seeds that can thrive in warmer and more extreme environments.”

Other relevant applications in former two contexts include Jarvis et al. (2012), Ramirez-Villegas, Jarvis and Läderach (2013), Kim et al. (2018), and Hummel et al. (2018).
We use two strategies to further hone in on the correct channel. First, we show that, within crops, innovation is disproportionately directed toward biological and chemical technologies (including the aforementioned seeds, as well as patents for fertilizers and biocides) compared to non-biological, non-chemical technologies (including harvesters, mowers, and processing tools). The direct effect for the latter category is an imprecise zero. Since we include crop fixed effects, we absorb the role of crop-level changes in prices; thus, the estimates from this specification only capture changes in the marginal product of particular technologies. Thus, technology-specific redirection of innovation is suggestive, via the model, of strong partial-equilibrium effects relative to the general-equilibrium effects, the latter of which should be shared for all technologies that are used to cultivate same crop.

Second, we investigate the potential role of market size directly. We show that directly controlling for changes in total planted area has a small effect on our results. Thus, the baseline effect does not capture a "market size effect" of more distressed crops. That said, it might be the case that the market size effect matters independently and captures a conceptually different, but still climate-related, channel of directed technological change. Temperature change might have “phased in” certain crops and “phased out” certain crops from production in the US, thereby affecting aggregate crop-level market size and hence innovative activity.

To investigate this possibility, we use our county-by-crop measures of temperature distress to predict aggregate “temperature induced” changes in the total planted area for each crop. We do indeed find temperature-induced market expansion predicts innovation but that crop-level market expansion is uncorrelated with crop-level temperature distress; hence, it represents an empirically distinct channel through which temperature change has shaped agricultural innovation. Moreover, market expansion does not lead to the preferential development of biological technology, which is consistent with the theory.

**Downstream consequences of induced innovation.** We have established so far that there was a redirection of technology in response to temperature change, but not that this re-direction mattered for economic outcomes. To address this second question we turn to panel data on county-level agricultural outcomes from the US Census of Agriculture. As a first step, we verify that our notion of "distress" has bite at the county level. County-level climate distress, appropriately aggregated from county-by-crop measures that combine local temperature changes and crop-level sensitivities, predicts a reduction of local land values.⁵ That is, our climate distress measure indeed captures temperature’s negative effect on agricultural production.

Previous studies have proposed teasing apart direct versus "adaptive" effects of climate change by comparing short and long-run responses.⁶ Our model and previous results suggest this is not

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⁵Our specification is related to influential analysis by Deschénes and Greenstone (2007) and Fisher et al. (2012), but also takes into account the different climate sensitivity (sign and magnitude) for different crops in a warming climate. The main specifications of each of these 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.

⁶This is discussed, for instance, in Dell, Jones and Olken (2012) and Burke and Emerick (2016). We provide more examples in Section 2, the literature review.
so simple. First, it is not clear what is a "short-enough" or "long-enough" run to isolate channels of adaptation—our own results show that innovation responds primarily within the decade. And second, there could be hugely heterogeneous adaptation effects across areas growing different crops if the relevant margin of interest is the national re-allocation of scientific focus across crops and technologies.

For these reasons, we propose a different strategy suggested by the model: to directly measure heterogeneity in the county-level response of climate distress based on aggregate damage to counties’ crop mixes. Aggregate damage is a shifter of innovation which, based on our first set of results, should have larger positive effects on local production when climate damage is high. Thus, a given temperature distress shock should have a more muted economic impact in a county whose crops were damaged by temperature change in the aggregate market and hence the recipient of new climate-mitigating innovation. Empirically, we find this effect is quite large. The range of marginal climate damage effects spanned by exposure to aggregate damage is approximately the same size as the median effect, though it does not flip signs. Thus, endogenous technological change has played a major role mediating the economic impact of temperature change. Places well positioned to benefit from new technologies have experienced much more muted declines in land value resulting from temperature change.

We present a series of additional results to probe the robustness of the baseline estimates and hone in on technology development as the relevant causal pathway. First, we show all results are similar after including state-by-census round fixed effects, directly controlling for changes in output prices, and restricting the sample to include only highly agricultural counties. Second, we conduct a heterogeneity analysis and find that the results are strongest in (i) counties that cultivate crops with larger national market size and (ii) counties that devote a larger share of their cropland to crops for which hybrid varieties can easily be developed.⁷ In the crop-level innovation analysis, we find that technology development was directed particularly strongly toward distressed crops with a large national market size. Moreover, both anecdotally and for agronomic reasons, hybrid varieties are particularly useful at mitigating productivity loss from changing and extreme climate (e.g. Sutch, 2011). Thus, both sets of heterogeneous effects are consistent with technology development driving the impact of our “innovation exposure” measure on land values. Last, we document very similar results using physical agricultural output rather than land values, which suggests that new technology is directly increasing crop productivity (or limiting productivity decline) rather than only reducing input cost.

Finally, we explore how technological change interacts with other margins of adaptation to temperature distress. We find broad evidence that new technology is a substitute for other approaches. We first investigate investment in irrigation, which agronomic research suggests may significantly mitigate the impact of temperature distress on productivity by limiting the impact of heat-induced

⁷We discuss in detail the determinants and measurement of ease of hybrid development in Section 6.5 and in Moscona (2019b).
evapotranspiration (Lobell et al., 2013; Tack, Barkley and Hendricks, 2017; Zaveri and Lobell, 2019).
We find that distress to a county’s crops predicts more local irrigation, but national distress to the
same crop mix reduces the extent of irrigation adoption. Thus, exposure to new innovation by our
measure crowds out investment in irrigation. Second, we investigate crop switching. We find that
our crop-by-county measure of temperature distress predicts local declines in crop harvested area,
although these effects are quantitatively small. Moreover, national distress and hence the availability
of new innovation dampens the aforementioned effect. This set of results suggests that the interactions
between different strategies farmers use to respond to temperature distress are important. Moreover,
studying a given margin of adaptation isolation misses quantitatively important heterogeneity.

**Main conclusions.** Our theoretical and empirical analysis, together, suggests that the market *does*
provide incentives for innovation that mitigates climate distress; innovation, particularly in biological
technology, has been systematically re-directed toward more temperature distressed crops. This
process has already produced winners and losers: Places that are individually harmed when the
rest of the market is not are in the precarious position of needing to adapt, but having less available
technology with which to do so.

The rest of the paper is organized as follows. Section 2 reviews related literature. Section 3
describes a theoretical model that guides measurement and interpretation of results. Section 4
describes data and measurement. Sections 5 and 6 present our main results on directed innovation
and downstream impact, respectively. Section 7 discusses the interaction of directed innovation with
other margins of adaptation. Section 8 provides out-of-sample estimates of innovation and damage
mitigation in future climate scenarios. Section 9 concludes and discusses our results in the context of
contemporary discussions of climate impact and policy.

## 2. Relation to the Literature

**Innovation in agriculture.** A large, classic literature (e.g., Griliches, 1957; Hayami and Ruttan, 1970;
Olmstead and Rhode, 1993) studies directed technical change in agriculture. We extend this literature
to study the response of agricultural innovation to modern climate change.

Case studies for particular crops, such as the study by Roberts and Schlenker (2010) (corn and
soybeans) Roberts and Schlenker (2011) (corn), Tack et al. (2016) (wheat), and Burke and Emerick
(2016) (corn and soybeans), investigate parameter instability in the relationship between extreme heat
and yields for evidence of technological adaptation in response to modern climate change.⁸ These
studies’ general conclusion is that such relationships are quite stable since the mid 20th century,
suggesting a limited role for innovation. Auffhammer and Schlenker (2014) reviews the related
literature on this topic for agriculture. Our paper has a different conclusion, placing innovation front-
and-center in the adaptation process. Relative to earlier studies, it offers a (i) much broader, *cross-crop*

⁸Tack et al. (2016) go one step further and also look at variance in the heat tolerance of new wheat varieties which have
not yet been adopted, and find their empirical heat tolerance does not exceed existing varieties’.
comparison that can spot technological reallocation that single-crop case studies would miss and (ii) direct measurement of new technology development (Section 5).⁹

This paper also relates to one author’s previous work on quantifying the response of new variety development to intellectual property expansion (Moscona, 2019b) and the technological response to the American Dust Bowl (Moscona, 2019a). The latter finds, analogously to this paper but in a different context, that innovation has been directed toward more “environmentally distressed” crops.

**Climate impacts in agriculture.** Mendelsohn, Nordhaus and Shaw (1994), Schlenker, Hanemann and Fisher (2005), Schlenker, Hanemann and Fisher (2006), Deschénes 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 three staple crops in the US (corn, soybeans, and cotton), has pinpointed the increased incidence of extremely hot days as an important mechanism for effects on production and yields.¹⁰

A contribution of our paper is to propose a novel measurement strategy to extrapolate these findings of climate-induced damage to a larger panel of crops (Section 4). This allows a more precise, crop-specific quantification of local damages in value terms, as well as a quantitative decomposition of direct effects and effects mediated by innovation (Section 6).

**Adaptation to climate change.** A broader literature in environmental economics, not limited to agriculture, has investigated the extent of adaptation to climate change by comparing short-run and long-run effects of shocks.¹¹ Our paper has a more targeted approach, focusing on measuring and quantifying a specific channel of adaptation (and not relying on timing assumptions).

By providing evidence on adaptation in a key sector, our findings may help inform a large literature trying to develop quantitative models that model re-allocation and adaptation in response to climate change (e.g., Nordhaus, 2010; Desmet and Rossi-Hansberg, 2015; Hsiang et al., 2017). Our empirical results could aid in realistic calibration for the role of innovation in climate-mitigating technologies.

Other existing work on directed technological change and the environment is predominately theoretical and focuses on developing clean energy or emission-mitigating technology.¹² Our application to technology that dampens climate change’s effects is quite different, and in fact might shed new light on the economic forces that reduce incentives to develop clean technology ex ante.

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⁹A different, more narrative 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.

¹⁰A follow-up literature that extends the previous agronomic work and combines it with novel scientific modeling (e.g., Lobell et al., 2013; Schauburger et al., 2017) corroborates this story.


¹²See, for instance, Newell, Jaffe and Stavins (1999); Popp (2002, 2004); Acemoglu et al. (2012, 2016); Aghion et al. (2016).
3. Model

In this section, we build a model of the relationship between climate change and technological change in agriculture, with three main goals. First, we highlight the multiple channels through which climate change affects incentives for innovation and show that the expected relationship between climate distress and innovation is ambiguous \textit{ex ante}. Second, using the model we explain how each channel can be measured and estimated empirically. Third, we show that a standard model of directed innovation \textit{across crops} delivers predictions about the potential benefits from innovation \textit{across places}. This last point will motivate our strategy to quantify adaptation through innovation.

3.1 Primitives

There are two periods, \( t \in \{0, 1\} \). The first period represents a “long-run steady state” in which variety development and production are perfectly adapted to a status quo “climate,” or distribution of agricultural productivity parameters across crops and space.\(^{13}\) At the start of the second period, there is an unanticipated change in the climate and innovation and production re-adjust.

The present model abstracts from growth and expectations formation (learning). Both topics surely matter in real life, but will not be directly addressed with evidence in our empirical investigation.\(^{14}\)

3.1.1 Demand

There is a representative household that in each period has quasi-linear preferences over \( K \) agricultural commodities, consumed in quantities \((C_{k,t})_{k=1}^K\) and a numeraire “money” good \( M_t \). The former is produced by farms, which will be described shortly, and the latter is available in an endowment. The numeraire can be thought of as a “reduced form” for an unmodeled, non-agricultural sector.

The household’s within-period utility function \( U_t \) is defined up to some concave functions \((u_k(\cdot))_{k=1}^K\) as:

\[
U_t = \sum_{k=1}^{K} u_k(C_{k,t}) + M_t, \quad \text{for } t \in \{0, 1\} \tag{3.1}
\]

The household has total income \( Y_t \) and faces agricultural prices \((p_{k,t})_{k=1}^K\), both of which are in money terms. Between periods 0 and 1, the household has linear preferences with discount rate \( \beta \) (i.e., \( U = U_0 + \beta U_1 \)) and can save at interest rate \( r \).

3.1.2 Production

There is a continuum of locations \( i \in [0, 1] \), each of which operates a small farm with fixed land area \( L_i > 0 \). The farmer has access to \( K \) different production technologies, one for each possible crop.

\(^{13}\)Formally, the model could be derived in a fully dynamic setting, and the exercise we consider would be a transition between two dynamic steady states.

\(^{14}\)To the latter point, we will later show empirical evidence that, at least over the current sample period, “myopic but reactive” behavior by innovators is not unreasonable (Section 5.1).
Production of a given crop requires three main inputs: land \( L_i \), crop-specific biological intermediate inputs or "seeds" \( S_{i,k,t} \), and crop-specific mechanical intermediate inputs or "harvesters" \( H_{i,k,t} \). The production frontier is also shifted by \( A_{i,k,t} \), a climate-induced productivity shifter for growing crop \( k \) in location \( i \) at time \( t \).

Production represented by a crop-specific production function

\[
F_k(L_i, S_{i,k,t}, H_{i,k,t}; A_{i,k,t})
\]

which we assume to be constant-returns-to-scale in its first three arguments for every value of \( A_{i,k,t} \), and to increase in \( A_{i,k,t} \) for all values of the first three inputs. The latter is a normalization, so \( A_{i,k,t} \) measures "favorable climate."

The two technological inputs, seeds and harvesters, are aggregates of a continuum of imperfectly substitutable intermediate inputs, as in Romer (1990). Let \( (N_{k,S,t}, N_{k,H,t}) \) be the number of varieties for these inputs available at any point in time, \( (x_{i,S,k,t}(\cdot), x_{i,H,k,t}(\cdot)) \) denote the mappings from each frontier of intermediates to farm \( i \)-level demands, and \( (S_{i,k,t}(\cdot), H_{i,k,t}(\cdot)) \) denote the (crop-specific) constant-returns-to-scale aggregator of these intermediates. We specialize to the standard case where the last objects have a constant elasticity of substitution \( \varepsilon \):

\[
S_{i,k,t} := \left( \int_0^{N_{k,S,t}} x_{i,S,k,t}(v)^{1-\frac{1}{\varepsilon}} \, dv \right)^{\frac{1}{1-\varepsilon}} \quad H_{i,k,t} := \left( \int_0^{N_{k,H,t}} x_{i,H,k,t}(v)^{1-\frac{1}{\varepsilon}} \, dv \right)^{\frac{1}{1-\varepsilon}} \quad (3.2)
\]

This last assumption (which embeds also constant substitutability across crops and technology types) is for convenience, as it allows simple expressions for each farm’s demand function for intermediates.

Farmers, who own the land, choose what crop to grow in each period by picking the choice that maximizes \( R_{i,k,t} \), the local land rent when crop \( k \) is grown in location \( i \). Let \( k^*_{it} = \arg\max_k \{ R_{i,k,t} \}_{k=1}^K \) denote the optimal crop choice and \( R_{it} \) denote the corresponding maximum value rent.

The crop-specific rents are defined as the solution to the following profit maximization problem

\[
R_{i,k,t} := \max_{x_{i,S,t}(\cdot), x_{i,H,t}(\cdot)} p_{k,t} F_k(L_i, S_{i,k,t}, H_{i,k,t}; A_{i,k,t}) \\
- \int_0^{N_{k,S,t}} q_{k,S,t}(v) x_{i,S,t}(v) \, dv \\
- \int_0^{N_{k,H,t}} q_{k,H,t}(v) x_{i,H,t}(v) \, dv
\]

where \( (q_{k,S,t}(\cdot), q_{k,H,t}(\cdot)) \) give the prices of the intermediate goods.

Note at this point the following interpretation of input choice as “adaptation.” The consumed quantities of each variety of seed or harvester will generically respond or “adapt” to the climate shock \( A_{i,k,t} \), as will the crop choice \( k^*_{it} \). But farmers take as given, and cannot directly control, the research frontiers \( N_{k,S,t} \) and \( N_{k,H,t} \). It is a separate innovative sector, which we will outline next, that determines how much adaptation is actually possible at any point in time.
3.1.3 Intermediates Production and Innovation

In each period, each intermediate good is produced by a monopolist with constant marginal cost $\psi_{k,z}$ in terms of the numeraire good. These monopolists set the price $q_{k,z,t}$ to maximize their total profits from selling to all farmers. Denote the profits of a new variety $\Pi_{k,z,t}$, which solves the following problem:

\[
\Pi_{k,z,t} := \max_{q_{k,z,t}} \left( q_{k,z,t} - \psi_{k,z} \right) \cdot \int_0^1 x_{i,k^*_{t,z,t}} \cdot \mathbb{1}_{\{k^*_{t,z,t} = k\}} \, di 
\]  

(3.3)

where the first term is the mark-up; $\mathbb{1}_{\{k^*_{t,z,t} = k\}}$ indicates whether the crop is grown. Hence the integral term is the economy-wide (“national”) input demand. Because these demands are always isoelastic for each individual farm, the optimal price is always a constant mark-up over the marginal cost, $q_{k,z,t} \equiv \psi_{k,z} / (\varepsilon_{k,z} - 1)$. For simplicity we use the normalization $\psi_{k,z} = \varepsilon_{k,z} - 1$ so the optimal price is $q_{k,z,t} \equiv 1$ for all crops $k$, technology classes $z$, and time periods $t$.

At the beginning of the period, a continuum of innovators can turn the numeraire good into a new innovation. The innovators can do this for any pair of crop $k \in \{1, \ldots, K\}$ and technology type $z \in \{S, H\}$. We assume that investing $1/\eta$ units of the numeraire into this activity, for some $\eta > 0$, yields a single new variety which the innovator can monopolistically produce. The innovations fully depreciate between periods, so the process is independent at $t = 0$ and $t = 1$. Thus an innovation in period $t$ has a benefit given exactly by the profits in equation (3.3), and a cost given by the research investment $1/\eta$.

New innovators can freely enter, so it must be that in equilibrium all technology categories (i.e., $k$ and $z \in \{S, H\}$ combinations) that receive any research have a zero return to that research. Letting $X_{k,z,t}$ denote total research spending in a particular $(k, z)$ category, this condition can be written in complementary slackness form as the following:

\[
\eta \Pi_{k,z,t} \leq 1 \quad \text{AND} \quad X_{k,z,t} \geq 0, \forall (k, z, t) 
\]  

(3.4)

with at least one equation, per $(k, z, t)$ tuple, holding at equality.

3.1.4 Equilibrium and Interpretation of Climate Change

An equilibrium of the model allows for optimization of consumers and firms, competitive free entry for new innovators, and market clearing for all agricultural commodities. This is more precisely defined in Appendix A.

We model climate change as an unanticipated shock to the vector of place and crop-specific productivities from an initial level $A_{i,k,0}$ to new levels $A_{i,k,1}$. In a fully dynamic re-interpretation of

\footnote{These need not be indexed by the "cardinal number" of the innovation, $v \in [0, N_{k,z,t}]$, because all such innovations within a particular category are symmetric for the farmers who buy them.}

\footnote{This assumption is different than the standard one in dynamic models of directed innovation, but here allows much simpler comparative statics that involve no asymmetry between varieties being created or destroyed between the two periods.}
the model (i.e., with intermediate time-increments and transitional dynamics), one would interpret the same exercise as a comparison of long-run steady states. As stated earlier, our interpretation abstracts from these dynamics as well as from learning about new productivity parameters to put the focus squarely on the market incentives to innovate.

The questions of interest, within the model, are (i) how the variety frontiers $N_{k,z}$, across crops and technology classes, change from period 0 to period 1 as a function of the aggregate climate shock and (ii) how local agricultural rents $R_{i,t}$ change from period 0 to period 1 as a function of both local and aggregate climate shocks.

### 3.2 Directed Innovation: Isolating Channels

We now focus on the different forces that would shift demand for intermediates. An increase in aggregate demand for a given intermediate would perturb the left expression in (3.4), and require an increase in research expenditure (and hence the production of new innovations) in order to restore equilibrium.

For now, assume that the “climate shock” reduces the productivity of a single “damaged crop” indexed by $k$. Assume further that the productivity of growing this crop in each place is constant in both periods. In math, $A_{i,k,0} \equiv A_{k,0} > A_{k,1} \equiv A_{i,k,1}$, for all $i \in [0,1]$.

In such a homogenous case, one can leverage the iso-elastic form of input demand and the “identical up to scale” nature of the farms to express the profit of producing an input any input (here, seeds) for crop $k$ as the following product of three terms:

$$
\Pi_{k,z,t} = \left( \frac{\partial F_k}{\partial S_{k,t}} \right)^\varepsilon \times \left( L_{k,t} \cdot \hat{s}(A_{k,t}) \right) \times \frac{p_{k,t}^\varepsilon}{\varepsilon} 
$$

The first term is the (constant across farms) marginal product of new seeds; the second term, in parenthesis, is the product of the total land on which the crop is planted, or $L_k := \int L_i \cdot I\{k_j = k\} \, di$, and constant which scales the level of seed demand per unit of land area; and the third term scales with the price of the crop. The first and third terms include an $\varepsilon$ power, encoding the fact that intermediate demand is more sensitive to local profit opportunities when intermediate goods are more substitutable or $\varepsilon$ is high.

We now consider how each of the key forces embodied in (3.5) shift with the climate shock.

#### 3.2.1 Marginal Products

Without a further restriction on the production function, the marginal product of the input bundle could increase or decrease in response to the negative climate shock.

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Formally, assume that $A_{i,k,0} = A_{i,k,1}$ for all $k \neq k_d$ and $i \in [0,1]$; and $A_{i,k,0} > A_{i,k,1}$ for all $i \in [0,1]$, or the crop of interest is uniformly negatively affected.
Consider first a specification of the production function that is consistent with the narrative evidence provided by Olmstead and Rhode (2008) and Sutch (2011) on the role of biotechnology in directly mitigating the impact of environmental change and distress, or an intuition that biotechnology is a “defensive expenditure” (in the terminology of Bartik, 1988, among others) that can fight negative environmental effects:

**Example 1 (Climate damage increases marginal products)** Let the production function have the representation $F_k(L, S, H; A) = G(L, S + AH)$ for some constant-returns-to-scale and concave $G(\cdot)$. This encodes the possibility that seeds are harvesters are perfect substitutes with one another, and additionally that “seeds and good climate” are perfect substitutes. In this case, the sensitivity of the marginal product of seeds to the climate shock is $\partial_{SA} F = \partial_{22} G \cdot H$. Given the concavity condition $\partial_{22} G < 0$, this implies that a negative climate shock increases the marginal product of seeds.

In the model, what is happening is that (i) new seeds can directly substitute for the benefits of a more favorable climate and (ii) concave production makes the marginal benefits of new seeds larger when production is lower.

Consider next the opposite storyline in which new seeds have no “defensive” role and instead become marginally less useful in a less appropriate climate:\(^8\)

**Example 2 (Climate damage decreases marginal products)** Let the production function have the representation $F_k(L, S, H; A) = L + H + AS$. In this case, good climate and new seeds are complements with one another ($\partial_{AS} G = 1 > 0$) and there are no diminishing returns to new technologies. The sensitivity of the marginal product of seeds to the climate shock is $\partial_{SA} F = A > 0$. Consequently, a negative climate shock decreases the marginal product of new seeds.

In the model, we have flipped both of the intuitions of the other example: (i) new seeds are complements, not substitutes, with a favorable climate and (ii) there is no concavity in the aggregate production function, preventing low production from increasing the marginal product of technology.

### 3.2.2 Market size

Consider next the middle term of (3.5). This has two sub-parts, each of which encode a type of “size effect” in the market for intermediates.

The first is scale “across farms.” All else equal, an innovator would like to serve as many farms as possible (in area terms) with their new invention. In the model, which has each area plant only one crop, this shift is necessarily on the extensive (crop-switching) margin. This underscores the importance of jointly modeling both local production and local crop choice to capture the full spectrum of effects for directed innovation.

\(^8\)To continue the previous analogy with “defensive expenditures,” seeds are now a “complementary expenditure” to environmental conditions. Hence these expenditures would be lower, all else equal, when environmental conditions deteriorate.
The second is scale “within farms,” measured by the usage of seeds per unit area. This, holding marginal products fixed, increases the amount of seeds that innovators can sell to a given farm at a fixed price, and also incentivizes more innovation.

3.2.3 Prices

Consider finally the role of equilibrium prices, which comprise term 3 of (3.5). Prices, along the demand curve, are the following negative function of equilibrium quantities produced: \( p_{k,t} = u'_k(Y_{k,t}) \).\(^{19} \) If a crop’s demand is very price-sensitive relative to the rest of the economy embedded in the numeraire good, or the elasticity of demand \( |u''_k \cdot Y_{k,t}/p_{k,t}| \) is sufficiently high, then a negative shock to the production of crop \( k \) will lead to a large price increase. This can make production of crop \( k \) equally or more profitable, and likewise for production of \( k \)-specific inputs.

If a particular crop is particularly "essential" with respect to the numeraire of non-agricultural commodities, lower production can always phase in innovation in general equilibrium. Succinctly, GE forces may more powerfully induce innovation to save corn because it is a necessity in the consumption basket; but the same force may not provide incentives to innovate in kale, because there exist readier substitutes.

The standard theory of directed technological change, outlined in Acemoglu (2002), focuses entirely on the “market size” and “price” effects codified here in terms 2 and 3. In that model, specific assumptions on the relationship between the exogenous shifter of research incentives (in that model, the supply of a relevant factor of production instead of a productivity shock) and intermediate goods in the production function prevent marginal products and total production from moving in different directions. Thus an additional theoretical contribution of our model is to highlight an additional channel, the direct and asymmetric effect of exogenous shocks on the marginal product of particular types of innovation. This seems a priori relevant in the agricultural context, and broadly speaking any other context in which a “shock-mitigating” (or “shock-amplifying”) class of technology is well-defined.

3.3 First-order Approximation and Regression Equations

In Appendix A, we show how to derive an exact “model-derived regression equation” linking new variety innovations to an appropriate definition of aggregate climate distress. We formally consider the case of small climate shocks from period 0 to period 1 and express results as log deviations from the period 0 steady state. The upshot of this calculation is summarized in the following three results, all of which are shown in Appendix A.

First, the “correct” measure of national climate distress weights individual locations growing...
a given crop by their contribution to national demand for the relevant input. In the case with homogenous period 0 productivities and constant returns to scale, it turns out to be equivalent to weight by any other pre-period input, including land area. This version of the result is formalized below:

**Proposition 1 (Area weighting)** All aggregate quantities for crop $k$, including total production, prices, and the number of varieties of seeds and harvesters, can be written in log-deviations as linear in the following land-weighted aggregate productivity shock:

$$
\hat{A}_k := \int_0^1 \frac{L_i}{L_k} \cdot \hat{A}_{ik} \cdot \mathbb{I}\{k_{i,0}^* = k\} \, di
$$

where $L_i$ is the pre-period area of a given location; $L_k$ is the total pre-period land devoted to a given crop; $\mathbb{I}\{k_{i,0}^* = k\}$ is an indicator function for a location growing crop $k$ in the pre-period; and $\hat{A}_{ik}$ is the period 1 productivity shock for crop $k$ in log deviations from the period 0 productivity.

We closely follow this template in constructing our empirical specification in Section 4—in part for model consistency, and in part for practical reasons with the data (see Section 4.2.1).

Second, variety development in a specific input category is linear in the aforementioned national distress with an ambiguously-signed coefficient:

**Proposition 2 (Ambiguous sign)** The aggregate percentage change in varieties for crop $k$ for technology type $z \in \{S, H\}$ can be written as

$$\hat{N}_{k,z} = \beta_{k,z} \cdot \hat{A}_k
$$

for some $\beta_{k,z} \geq 0$.

The different sign cases correspond to the relative strength of the three channels outlined in the previous subsection, excluding the crop-switching margin which would not show up to the first order. The heterogeneity of $\beta_{k,z}$ across crops is natural given no restrictions on crop-specific production and demand functions. What is important for identification, or getting a reasonable average estimate of $\beta_{k,z}$ in a cross-crop regression context, is that the previously mentioned heterogeneity is orthogonal to the level of our measured climate shifters $\hat{A}_k$. Finally the heterogeneity of $\beta_{k,z}$ across technology classes reflects the different roles of each input in the production function, and the relationship between each input’s marginal product and climate damage.

Building on this last point, the model suggests how we can compare across technology classes to isolate channels. If we assume symmetry in the local behavior of the production function for seeds and harvesters, then the relative growth rate of seeds and harvesters technology reveals the relative sign of the “marginal product” effect:

**Proposition 3 (Within-crop comparison)** The relative growth in varieties for seeds and harvesters for a fixed crop $k$ can be written as

$$\hat{N}_{k,S} - \hat{N}_{k,H} = \tau_k \cdot \hat{A}_k
$$
Assuming that there are sufficiently decreasing returns to scale in innovation (a necessary condition for “stable” transition behavior), then $\tau_k < 0$ if and only if the (positive) climate shock decreases the marginal product of seeds more than it decreases the marginal product of harvesters.

While the production function homogeneity assumptions required to formalize this result are quite strong, and ultimately very difficult to test in this context, the main idea is intuitive. If innovation disproportionately flows toward seeds, rather than harvesters, it suggests that the shock particularly affected demand for seeds (by shifting the marginal product thereof) and thus was not entirely related to general equilibrium trends like price increases or market size expansions.\(^{20}\)

In Section 4 we will describe a method to check both of these hypotheses in the data, and in Section 5 we will present the results. This will constitute our primary empirical strategy for measuring the response of innovation to the climate change shock.

### 3.4 Measuring the Adaptive Role of Innovation

Finally, we highlight here a cross-sectional prediction that was implicit in the previous discussion of marginal product effects. For this discussion, we will assume that one of the technological inputs is “defensive” in the sense outlined in Section 3.2.1: the marginal product of this intermediate is higher precisely when local climate conditions are poor for a given crop. We will suggest, via our empirical results, that on average new seed varieties in the data have this property.

The model suggests that the national availability of new seed varieties, or the extent of the variety frontier $N_{k,N}$ for crop $k$, should have two effects. First, it should increase the level of production, all else equal, for farms growing crop $k$. But second, it should do so especially much in a particular location in severe climate distress (i.e., with low $A_{i,k}$). The latter force reflects seeds’ particular marginal effectiveness in a harsh climate.

The model also suggests that national climate distress is the unique shifter of national changes in the variety frontier to the first order (Proposition 2). Moreover, for a “defensive technology,” it is unambiguous up to approximation that national climate distress (a negative productivity shock on average) increases the availability of this technology.

The following example formalizes a simple example in which such a force—shifting marginal products of technology—produces a sharp prediction that the interaction of local and aggregate climate distress positively predicts local rents, conditional on the level of each term:

**Example 3 (Measuring adaptation)** Specialize to a production function of the following form for all crops:

\[
Y_{i,k} = L^\alpha X_k (S_k, H_k; A_i)^{1-\alpha}
\]  

\(^{20}\)A separate identification threat, which is not encapsulated in the model we wrote down, is that seeds have a greater external return to research (“idea production externality”) and/or generically higher profit sensitivity for research redirection. While we have no direct evidence on either of these points, we can reject the more extreme version of the hypothesis that certain types of innovation are totally unresponsive to incentives.

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where composite input $X_k$ is defined as

$$X_k(S_k, H_k; A_i) := \left((S_k)^{1-\frac{1}{\sigma}} + (A_i H_k)^{1-\frac{1}{\sigma}}\right)^{\frac{1}{\sigma-1}}$$

Total profits equal the return to the fixed factor land, which after some manipulation can be written up to scale as

$$\Pi_i^f = \alpha p_k Y_{i,k} \propto L_i \cdot p_k^{1+\frac{1}{\sigma}} \cdot p_{X,k}^{-\frac{1}{\sigma}} \tag{3.10}$$

where $p_{X,k}$ is the price of the composite input, given by

$$p_{X,k} := \left(N_{S,k}^{(1-\varepsilon S_k)(1-\sigma)} + A_{i,k}^{\sigma-1} N_{H,k}^{(1-\varepsilon H_k)(1-\sigma)}\right)^{\frac{1}{\sigma-1}} \tag{3.11}$$

after substituting in the unit price of intermediate goods.

Consider now an approximation of (3.10), in logarithms, that is second-order in $(p_k, N_{S,k}, N_{H,k}, A_{i,k})$, and approximates the aggregate variables $(p_k, N_{S,k}, N_{H,k})$ to the first-order. Such an approximation has the form

$$\hat{\Pi}_i^f = \beta \cdot \hat{A}_{i,k} + \gamma \cdot \hat{A}_k + \phi \cdot (\hat{A}_{i,k} \cdot \hat{A}_k) + \zeta_0 \cdot \hat{A}_{i,k}^2 + \zeta_1 \cdot \hat{A}_k^2 \tag{3.12}$$

in which the term $\phi \cdot (\hat{A}_{i,k} \cdot \hat{A}_k)$ exists if and only if (3.11) is not log-linear, or the log marginal product of new technology shifts as a function of local climate damage.

The previous example highlights some limitations of the proposed approach of using the response of local outcomes to the interaction of local and aggregate climate distress to quantify the effects of directed innovation. First, the exercise necessarily mixes the positive adaptive value of certain innovations with the negative adaptive value of others (since, in equilibrium, both “seed” and “harvester” innovation responds to incentives). Second, the strategy is immune from mixing in the effects of price changes and/or input mix changes under strong (and, ultimately, difficult to test) assumptions on the structure of the production function (here, the outer Cobb-Douglas form). In Section 6, we will propose empirical robustness exercises that try to deal with such issues.

Nonetheless, an appealing feature of this approach is that it requires no assumption about the timing of adaptation in production (e.g., whether adaptation occurred in the “short run” or “long run”) or independent data on input use and local production decisions (e.g., whether new seeds are being used locally, which is difficult to measure at the relevant scale).

4. Data and Measurement

4.1 Data Sources

The goal of our empirical analysis is to estimate the relationship between temperature changes, innovative activity, and downstream agricultural production. To do this, we need measures of: (i) the
geography of crop production, (ii) the US climate since 1950, (iii) how changes in temperature translate into changes in crop productivity, (iv) crop-specific innovation, and (v) place-specific estimates of agricultural profitability. We combine several sources of data to estimate each ingredient (i) - (v).

**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.

**Temperature.** To measure the temperature in each US county for each month since 1960, we use the 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. We complement this with grid-cell level (2.5 mile × 2.5 mile) temperature data from the PRISM (“Parameter-elevation Regressions on Independent Slopes Model”) Climate Group.21 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).

**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 a sweeping set of agronomist and expert surveys conducted during the early 1990s; it is frequently used in recent analyses at the intersection of agronomics and climate change to estimate crop-specific climate tolerance (e.g. Hijmans et al., 2001; Jarvis et al., 2012; Ramirez-Villegas, Jarvis and Läderach, 2013; Kim et al., 2018; Hummel et al., 2018). In particular, for each crop species, the EcoCrop Database reports a set of upper and lower temperature cut-offs, beyond which crop productivity declines. This information makes it possible to account for the fact that: (i) crops are differentially sensitive a given change in temperature, (ii) crops have different optimal growing conditions, which means that a given change in temperature might increase the productivity of one crop and decrease the productivity of another, and (iii) crops have different temperatures beyond which productivity declines markedly, as documented empirically for a small set of staple crops by Schlenker and Roberts (2009).

**Innovation.** We use two complementary measures of crop-specific innovation. The first is the United States Department of Agriculture (USDA) *Variety Name List*. The *Variety Name List*, obtained through a Freedom of Information Act (FOIA) request and discussed at length in Moscona (2019b), is a list of all released crop varieties known to the USDA since the start of our sample period.22 The *Variety Name

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21We use the format of these data that is available on Wolfram Schlenker’s website: [http://www.columbia.edu/~ws2162/links.html](http://www.columbia.edu/~ws2162/links.html).

22Seed and variety innovation is not possible to measure during this period from patent data because patent protection for seeds was not introduced until 1985 following the *Ex Parte Hibberd* ruling; even after 1985, identifying seed patents from
List is designed to be comprehensive; 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.” Breeders have an incentive to report new varieties to the USDA for inclusion in the list because farmers checked the List to make sure that varieties they purchase were cleared. New seeds and plant varieties, both anecdotally and for agronomic reasons, were and remain the primary technology used to adapt agricultural production to environmental stress and changing climate. Moreover, it is straightforward to link new seeds and varieties to crops (i.e. a corn seed is a corn innovation, a wheat seed is a wheat innovation, etc.)

The second measures of crop-specific innovation is compiled from US patent data; this makes it possible to investigate not just changes in variety innovation, but also compare the impact of temperature change across different technology classes. 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.

Downstream outcomes. Finally, we combine all rounds of the US Census of Agriculture from 1959-2012. The key outcome of interest is the value of agricultural land per acre, which our model says should summarize the local return to landowners net of costs. A dynamic extension thereof would also have the appealing feature of allowing land values to capture (independently interesting) expected future.

4.2 Measuring Crop-Level Distress

Our first task to estimate an empirical analogue of “climate distress for crop k in location i,” or the negative productivity parameter $\hat{\mathcal{A}}_{i,k}$ in the model. We will want also to construct the national level of distress, or $\hat{\mathcal{A}}_k$ as defined in Proposition 1, by taking a weighted average of the county-by-crop measures of temperature distress. Our method combines data on the geography of crop production and temperature with the EcoCrop Database.

We implement two different measures of distress, each of which has an independent agronomic motivation. We now describe each in more detail.

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23 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 the day and month are listed, in most cases during the sample period, only the year is included.

24 See Sutch (2011) and Olmstead and Rhode (2008)

25 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 6.1.
4.2.1 Strategy #1: Change in Temperature Averages

Our first 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 $T_{i}^{\text{Pre}}$.

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 $T_{i}^{\text{Post}}$. 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 $T_{k}^{\text{Opt}}$, $T_{k}^{\text{Max}}$, and $T_{k}^{\text{Min}}$ respectively.

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

$$F(T_{i}^{\text{Pre}}, T_{i}^{\text{Post}}; k) = 100 \cdot \frac{|T_{i}^{\text{Post}} - T_{k}^{\text{Opt}}| - |T_{i}^{\text{Pre}} - T_{k}^{\text{Opt}}|}{T_{k}^{\text{Max}} - T_{k}^{\text{Min}}}$$

(4.1)

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.

Next, we sum these crop-by-county distress measures over all counties, weighting each county by $\text{Share}_{i,k}^{\text{Pre}}$, the share of total land devoted to $k$ located in $i$

$$\Delta\text{Distress}_{k} = \sum_{i} \text{Share}_{i,k}^{\text{Pre}} \cdot F(T_{i}^{\text{Pre}}, T_{i}^{\text{Post}}, k)$$

(4.2)

This is the crop-level measure of temperature distress that results from our first measurement strategy.

There are two reasons we favor weighting by area over using any other input or output measure. First, output is likely to be less stable than harvested areas over time (because of high-frequency fluctuations in weather), so an output-weighted average might be noisier in the data. Second, output data are missing in the early Census of Agriculture for a large portion of our studied crops (including $\text{Share}_{i,k}^{\text{Pre}}$). 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.

The optimal temperature $T_{k}^{\text{Opt}}$ 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.

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almost all vegetables). Finally, as discussed in Proposition 1, there is a model interpretation for area-weighting being exact as long as output and area scale linearly in one another.\textsuperscript{28}

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

$$\text{TempChange}_k = \sum_i \text{Share}_{i,k} \cdot (T_{i,\text{Pre}} - T_{i,\text{Post}})$$

(4.3)

This resembles more closely a "crop-level shift-share" of the sort of empirical design that has been widely used to study the effects of temperature changes on economic outcomes (e.g., Dell, Jones and Olken, 2012; Burke, Hsiang and Miguel, 2015).\textsuperscript{29} In the model, it would involve treating temperature changes as a uniform (i.e., in sign and magnitude) instrument for the productivity changes for growing any crop in location \(i\).

Figure 1 plots a comparison between this simple measure TempChange\(_k\) and the agronomically-motivated measure Distress\(_k\). A rough "<" ("sideways V") pattern is visible—as temperatures increase, some crops with Distress\(_k > 0\) move further from their theoretical optimum \(T_{k,\text{Opt}}\) calculated from EcoCrop. These are the crops above the horizontal dotted line in the figure. Other crops—those with Distress\(_k < 0\) that are below the horizontal dotted line in the figure—move closer. It is worth pointing out that a majority of crops are in the latter category, offering a preliminary evidence to the previously (if not unambiguously) claimed result in the literature that realized changes in US climate in recent

\textsuperscript{28}In practice, in the data, 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.

\textsuperscript{29}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).
history have been a net good for the agricultural sector.

4.2.2 Strategy #2: Change in Temperature Extremes

To capture the role of temperature extremes, our second strategy is to estimate the change crop-specific exposure to days of extreme weather. Crop productivity responds in a non-linear fashion to exposure to days of extreme temperature. It has well documented that exposure to extreme heat has a quantitatively large impact on crop productivity (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); however, empirical estimates of these temperature cut-offs and the non-linear response of productivity only exist for a small set of large crops (Schlenker and Roberts, 2009). To extrapolate this approach to our larger panel of crops, we leverage the EcoCrop database’s reported “maximum optimal temperature” for individual crops.

For each crop-by-county pair, we define a day as “extremely hot” if its average temperature is above $T_{Max}^k$ and refer to a day as “extremely cold” if its average temperature is below $T_{Min}^k$. To measure the crop-by-county change in the number of extremely hot days, we estimate:

$$\text{Extreme Hot Days}_{ik} = \text{InRange}_{i}(T_{Max}^k, \infty, \text{Post}) - \text{InRange}_{i}(T_{Max}^k, \infty, \text{Pre})$$  \hspace{1cm} (4.4)

In words, $\text{InRange}_{i}(T_{Max}^k, \infty, \text{Post})$ captures the number of days per month during the summer growing seasons (April to October) from 2010-2017 in county $i$ that would be considered extremely hot for the production of crop $k$. $\text{InRange}_{i}(T_{Max}^k, \infty, \text{Pre})$ is the analogous measure for the period 1950-1959. Thus, Extreme Hot Days$_{ik}$ is the change in the number of extremely hot days in county $i$ from the perspective of crop $k$. We compute analogous crop-by-county measures for extremely cold days and days that fall within the crop’s optimal growing range.

To build a crop-level measure of exposure to extreme temperature days, we sum these crop-by-county estimates across counties, again weighting each county by $\text{Share}^\text{Pre}_{i,k}$:

$$\text{Distress Days}_{k}^{\text{Hot}} = \sum_i \text{Share}^\text{Pre}_{i,k} \cdot \text{Extreme Hot Days}_{i,k}$$
$$\text{Distress Days}_{k}^{\text{Cold}} = \sum_i \text{Share}^\text{Pre}_{i,k} \cdot \text{Extreme Cold Days}_{i,k}$$  \hspace{1cm} (4.5)

To compute the change in exposure to extreme weather, we compute the difference between each measure computed using daily data from growing season months during the 2010s and each measure using daily data from growing season months during the 1950s. Thus, $\Delta \text{Distress Days}^\text{Hot}_k$ and $\Delta \text{Distress Days}^\text{Cold}_k$ are our estimates of crop-level changes in climate distress computed from temperature extremes. The distribution of $\Delta \text{Distress Days}^\text{Hot}_k$ across crops is reported in Appendix Figure A1. A majority of crops have experienced increased exposure to extreme hot days since 1960, consistent with anthropogenic climate change temperature variability and periods of extreme heat.
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 quite highly correlated (Appendix Figure A2). Thus, even though our two strategies are conceptually distinct and computed from different sources and temporal aggregations of US temperature data, they are very related in the data.

4.3 Measuring County-Level Distress

We apply a related logic and empirical strategy to measure county-level “distress” to agricultural production. County level distress is high when its temperature change since the 1950s—or its change in daily temperature distribution—has caused distress to the county’s crop composition. In particular, we compute the area-weighted average of crop-by-location distress:

$$\text{County Distress}_{i,t} = \sum_k \left[ \frac{\text{Area}_{i,k}^{\text{Pre}}}{\sum_k \text{Area}_{i,k}^{\text{Pre}}} \cdot F(T^i_{t,k}) \right]$$  \hspace{1cm} (4.6)

Here, $F(T^i_{t,k})$ is crop $k$’s distance from its optimal temperature in year $t$ when the temperature in county $i$ is $T^i_t$; $\text{Area}_{i,k}^{\text{Pre}}$ is the land area devoted to crop $k$ in county $i$ in 1959. Thus, the county-level distress measure is the weighted sum of temperature distress to all crops that the county cultivates.

Note that in the model, as written, there is no equivalent object because each location $i$ grows only one crop. If instead we considered a multi-crop extension, or assumed counties to comprise finite-measure “sub-intervals” of the model’s geography, then (4.6) would be an accurate weighting of local distress under an assumption analogous to the one underlying Proposition 1: homogeneity in initial land value across different crops.\footnote{Of course such a condition is also a natural equilibrium condition for indifference between planting these crops.}

Next, for each county $i$ we also compute a measure of the damage to $i$’s crop composition in all other counties. This measure allows us to investigate the role of endogenous technological progress in mediating the direct effect of climate distress on US counties, as discussed in Subsection 3.4. If the crops that county $i$ cultivates are also damaged by temperature change in other counties, innovation will endogenously increase for those crops and hence temperature distress in county $i$ will be limited by the availability of new technologies. We compute the damage to county $i$’s crop composition as:

$$\text{Crop Composition Distress}_{i,t} = \sum_k \left[ \frac{\text{Area}_{i,k}^{\text{Pre}}}{\sum_k \text{Area}_{i,k}^{\text{Pre}}} \cdot \sum_{j \neq i} \text{ShareOfUSA}_{j,k} \cdot F(T^j_{t,k}) \right]$$  \hspace{1cm} (4.7)

This is the same expression as Equation 4.6, except that rather than weight the share of county $i$’s land devoted to crop $k$ by temperature distress to crop $k$ in county $i$, it is weighted by temperature distress to crop $k$ in all US counties excluding county $i$.\footnote{Of course such a condition is also a natural equilibrium condition for indifference between planting these crops.}
The change in County Distress, from 1959 to 2012 for each county in the US is displayed in Figure 2a; the change in Crop Composition Distress, is displayed in 2b. The logic behind the county-level analysis below can be seen in these maps. Consider counties in the Southeast of the US, shaded in dark blue in Figure 2a but (relatively) whiter in Figure 2b; these counties were relatively damaged by temperature change, but grow crops that have not been. In contrast, California’s Central Valley is darkly shaded in both maps. The identifying variation in our study of “adaptation effects,” as highlighted in Section 3.4, comes exactly from this contrast between areas that are “mis-aligned” or “aligned” with the national-level distress. We will investigate this formally in Section 6.

5. CLIMATE-INDUCED INNOVATION

5.1 Temperature Distress and Variety Development

To examine the relationship between crop-level distress and innovation, we first estimate a version of the regression suggested by Proposition 2 that relates new variety innovation with national climate
where $k$ continues to index crops. New Seeds$_k$ is the number of novel seeds developed for crop $k$ during the period 1960-2012 and Distress$_k$ is a crop-level measure of climate distress discussed in Section 4.2. $X'_k$ is a series of crop-level controls, including total land under cultivation, the level of pre-period innovation, and pre-period climate estimates. The former two controls are natural to control for initial market size. 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.

$\beta > 0$ implies that variety innovation has been directed toward crops that have been more distressed by temperature changes; $\beta < 0$ implies that variety innovation has been directed away from crops that have been more distressed by temperature changes. As explored in Section 3, the relationship between temperature distress and innovation is theoretically ambiguous.

**Innovation redirects to distressed crops.** Table 1 presents estimates of Equation 5.1. In the first column, only Distress$_k$ and the log of total area harvested, our proxy for crop-level market size, are included on the right hand side. We find that $\beta > 0$; innovation in variety development was directed toward crops that were more damaged by temperature change. The coefficient estimate is also quantitatively meaningful and 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 robustness of the results. In column 2, we control for the average temperature and average precipitation on land devoted to each crop during the pre-period; the coefficient of interest remains similar. A potential concern is that the estimate is driven by pre-existing trends in crop-level innovation. To address this, in column 3 we control for (inverse hyperbolic sine of) the number of varieties released from 1900-1960. Again, the coefficient estimate is similar. Moreover, we find no evidence of a relationship between crop-level climate distress and variety development before 1960 (see Figure A3). Since crop-level variation in optimal temperature was used to construct our measure of temperature distress, one could be concerned that the innovation response we estimate is driven by variation across crops in optimal temperature and not changing temperature realizations associated with climate change. Therefore, in column 4 we control directly for each crop’s optimal temperature and optimal temperature squared—if anything, the coefficient of interest increases in magnitude. Finally, column 5 documents that the result is very similar if we instead restrict the sample period to years since 1980.

Incentives to develop new varieties may be particularly strong for crops with a large market size. Columns 6-7 document that this was the case; the impact of climate distress on innovation is

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31For consistency with the literature in innovation economics (which follows Hausman et al., 1984), we adopt here a Poisson specification. For all outcomes we report specifications that control directly for log of pre-period innovation, thus closely approximating the specification in Proposition 2. We also also report in Table A3 ordinary least squares (OLS) estimates of our fully controlled specification, using growth rate changes in innovations as the outcome variable (thus, exactly replicating Proposition 2), and all results are robust.
significantly larger for crop with above-median harvested area during the pre-period. The baseline results are not driven by “small” crops but instead by crops that occupy a large share of US agricultural production.

Next, we turn to estimates of the impact of our second climate distress measure – the change in the number of extreme days. Estimates of 5.1 in which crop-level distress is measured using the change in the number of extreme days are reported in Table 2. In the first column, we include the number of extreme hot days on the right hand side; the coefficient estimate is positive and significant, suggesting that an increase in the crop-level number of extremely hot days led to variety development. In column 2, we include the full set of controls from Table 1, and the coefficient estimate is similar.

In column 3, the independent variable of interest is the change in the number of days within each crop’s optimal growing range. Intuitively, the coefficient estimate is negative; increasing the number of optimal days reduced incentives for variety development. Column 4 documents the relationship between changes in the number of extreme cold days and variety development; the coefficient estimate is not significantly different from zero. Moreover, when both the change in extreme hot days and the change in extreme cold days are included on the right hand side, we find that extreme hot days continue to predict variety development while extreme cold days have no effect. This is consistent with the asymmetric impact of temperature change on productivity and the particularly harmful impact of hot days (Schlenker and Roberts, 2009).32

Finally, column 5 returns to heterogeneity based on initial market size. Again, we find that the effect of extreme hot days on innovation is driven by crops with a large market size (i.e. with large

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32In a more literal model interpretation, it suggests that DistressDays\textsuperscript{HOT} is a better proxy for the negative productivity shock $-\tilde{A}_k$ than DistressDays\textsuperscript{COLD} is.
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<tr>
<td>Δ Distress Days\textsuperscript{HOT}</td>
<td>0.0329**</td>
<td>0.0382**</td>
<td>-0.0114</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(0.0167)</td>
<td>(0.0173)</td>
<td>(0.0197)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ Days in Optimal Range</td>
<td></td>
<td></td>
<td>-0.0342*</td>
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<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.0196)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ Distress Days\textsuperscript{COLD}</td>
<td></td>
<td>0.00879</td>
<td>0.0260</td>
<td>-0.0230</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0302)</td>
<td>(0.0317)</td>
<td>(0.0343)</td>
<td></td>
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<tr>
<td>Δ Distress Days\textsuperscript{HOT} x Above Median Area</td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.0627)</td>
<td></td>
</tr>
<tr>
<td>Δ Distress Days\textsuperscript{COLD} x Above Median Area</td>
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<td></td>
<td></td>
<td>0.108</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.0693)</td>
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</table>

Log area harvested: Yes Yes Yes Yes Yes
Pre-period climate controls: Yes Yes Yes Yes Yes
Pre-period varieties (asinh): Yes Yes Yes Yes Yes
Observations: 69 69 69 69 69

Notes: The unit of observation is a crop. The outcome variable is the number of crop-specific varieties released. Pre-period climate controls include growing season temperature and rainfall during the 1950s and pre-period varieties is the number of varieties released prior to 1960. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

In Table A2, we show results from an alternative specification that calculates damage in units of degree days instead of day counts.\textsuperscript{33} This secondary approach is common in the agronomic literature and also explored by Schlenker and Roberts (2009). Our results with this measure are extremely similar to those in Table 2.

**Innovation redirects quickly.** 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 5.3 in which the unit of observation is a crop-decade pair. In particular, we estimate:

\textsuperscript{33}For example, if a crop’s maximum temperature is 30°C then one additional day at 33°C would add one day of extreme temperature based on our measure in Table 2 but would add three “growing degree days.”
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. We include both the lagged and leading value of temperature distress, along with the contemporaneous value, on the right hand side.

Estimates of Equation 5.2 are reported in Table A4. Climate distress in the contemporaneous decade is positively correlated with variety development; both the leading and lagged values are small in magnitude, inconsistent in sign, and statistically indistinguishable from zero. There are two key takeaways. First, innovative activity responds quickly: new varieties are developed for crops that experience climate distress within the same decade. Second, we find no evidence that during our sample period innovators are either backward or forward looking. Within-decade temperature distress is what matters.

### 5.2 Heterogeneity by type of innovation

As discussed in the model, not all technologies necessarily respond in the same way to temperature distress. In particular, we have conjectured that certain crop-specific technologies (e.g. new seeds) may be particularly useful to mitigate productivity loss from environmental change; other technologies, we hypothesize, might experience no change or even a decline in marginal product under climate distress (e.g. harvesters).

Proposition 3 showed how this would translate into a “triple difference” regression specification: climate distress should predict relatively more innovation in such mitigating technologies (the model’s “seeds”) relative to others (the model’s “harvesters”) for a fixed crop. This specification has the added benefit of, to first approximation, canceling out general equilibrium mechanisms like price changes (explicitly modeled) or consumer demand changes (which could be added in a simple way) because we are able to include crop fixed effects. Thus, any potentially omitted variables in our estimates of Equation 5.1 are fully absorbed.

To implement these ideas, we estimate:

$$\text{New Innovations}_{kt} = \exp\left\{ \sum_{\tau=-1}^{1} \beta_{t+\tau} \cdot \text{Distress}_{k,t+\tau} + \Gamma X' + \alpha_k + \omega_t + \epsilon_{kt} \right\} \quad (5.2)$$

where $x$ indexes technology classes; $\alpha_k$ and $\omega_x$ are crop and technology fixed effects respectively.

New Innovations$_{kt}$ is the number of new “innovations”—either seeds of crop-specific patents—for crop $k$ in technology class $x$. Finally, $\Gamma_{x}^{\text{BioChem}}$ is an indicator that equals one if technology class $x$ is “biological/chemical” and might be useful for adaptation in the event of environmental stress (e.g. seeds, fertilizers, soil modification, etc.). We explore specifications with several different sets of technology classes and versions of $\Gamma_{x}^{\text{BioChem}}$ in order to investigate the robustness of $\xi$.

---

34 This idea builds on scholarship investigating induced innovation in US agriculture, and the idea that particularly “biological” and “chemical” technologies are useful for increasing land productivity (e.g. Hayami and Ruttan, 1970).
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. In Panel A, the independent variable of interest is our baseline crop-level distress measure while in Panel B it is the change in the number of extremely hot days. Standard errors, clustered by crop, are reported in parentheses and *, **, and *** indicate significance at the 10%, %, and 1% levels.

Climate distress particularly promotes biological and chemical innovation. We first estimate a version of Equation 5.3 in which \( x \in \{\text{Varieties, Harvesters}\} \) and \( \tau^\text{BioChem}_x = 1 \) if \( x = \text{Varieties} \). We continue to measure varieties using the Variety Name List; harvester innovations consist of all crop-specific patents in CPC class A01D. We estimate that \( \xi > 0 \); the result is similar measuring climate distress as either changes in average growing season temperature (Panel A) or changes in the number of extremely hot days (Panel B). In words, among climate distressed crops, innovation was disproportionately directed toward crop-specific varieties over crop-specific harvesters. This is consistent with certain technologies being particularly useful in times of environmental stress—and hence profitable for inventors to develop. Moreover, this suggests that general equilibrium price effects are not the only channel driving the results in Tables 1 and 2.

A potential downside to the specification in column 1 is that it compares innovation measures in two separate data sets – the varieties list and the patent data – and differences in inclusion standards and reporting strategies in the two data sets might affect the results. Therefore, in columns 2 and 3, we report estimates that only rely on the patent data. Instead of using plant varieties as the “biological” technology class, we instead use patents for fertilizers (column 2) and patents for all soil and soil modification technologies (column 3). In both cases, we again find that innovative output was disproportionately directed toward the biological technology class.
The remaining columns probe extend the specifications from columns 1-3 to many technology classes. In column 4, we include five technology classes of which three are “biological” (varieties, fertilizers, non-fertilizer soil technology) and three are not biological (harvesters, post-harvest processing technology). Our results are similar in this more general specification. Finally, column 5 repeats the specification from column 4 except varieties are excluded as a technology class in order to only compare measures of innovation computed from the patent data. The results are again similar in magnitude and, if anything, more precise.

**Non-biological innovation responds very little.** Are these results driven by an absolute increase, in biological/chemical patenting, and absolute decline in mechanical patenting, or both? Estimates of the relationship between crop-level temperature distress and patenting activity in each technology class separately are reported in Table A4. We find no significant relationship between temperature distress and patenting in harvester/mower technologies (column 1). However, we find a positive relationship between temperature distress and patenting across the biological/chemical technology classes, including fertilizers (column 2), all soil modification technology (column 3), and biocides and plant growth regulators (column 4).

The positive impact of temperature distress on biological/chemical patenting is also a validation of our baseline crop-level results using varieties as the outcome variable; moreover, the fact that we find similar results in the patent data, which has higher barriers to entry than the varieties data and is therefore less likely to include marginal or non-novel technologies, suggests that the re-direction of technology in response to temperature distress is not restricted to insubstantial technologies.

Taken together, these results suggest that the results in Table 3 are driven by a large, positive impact of temperature distress on innovative output in biological and chemical technology and a limited impact on mechanical technology. In the model, this could reflect the fact that partial and general equilibrium channels amplify one another for biological technology, while they fight one another for mechanical technology.

### 5.3 Second Order Effects: Crop Switching and Market Size

We have so far analyzed 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—while the impact of these changes are strictly second order in the model, they may be quantitatively important in practice. Moreover, the presence of systematic re-allocation of land toward certain crops opens a second potential channel through which temperature change might affect innovation.

The model predicts that innovation would be directed toward crops that experienced a temperature-induced increase in market size (Section 3.2.2). But by construction, since these land use changes occur at the extensive margin (i.e., location \(i\) switches entirely from crop \(k\) to crop \(k'\)), they would not necessarily increase the marginal product of and/or relative demand for particular inputs. Thus the model
asks for production re-allocation to predict more innovation in every technology type, but does not require a bias toward a certain technology class even in light of the previous subsection’s results.

In this section we (i) empirically document that this re-allocation has occurred but that re-allocation has been small in magnitude and (ii) 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, the pre-period, and let $\text{Area}_{k,i}^{2012}$ be the same in 2012, the post-period. We measure both for all counties and crops for which data are available in the 1959 and 2012 rounds of the Census of Agriculture. For all county-by-crop observations, and subsetting to counties above median area planted, we estimate the following specification:

$$
\log(1 + \text{Area}_{k,i}^{2012}) = \alpha_k + \delta_i + \psi \cdot \log(1 + \text{Area}_{k,i}^{1959}) + \pi \cdot \Delta \text{County-by-Crop Distress}_{k,i} + \varepsilon_{k,i}
$$

(5.4)

where $\alpha_k$ are crop fixed effects (which can be replaced with crop-by-state fixed effects) and $\delta_i$ are location fixed effects. The coefficient $\pi$ measures the extent to which local damage—our EcoCrop-derived estimate of climate distress to crop $k$ in location $i$—induces switching away from a particular crop. Note that, because of the fixed effects, this is a comparison within crops and, in the second specification, within crops in the same state. The inclusion of county fixed effects also absorbs the fact that certain countries have become more or less agricultural overall since 1960. Thus, the specification allows us to home in on the effect of crop-by-county specific climate distress on production allocation.

If we are measuring climate distress appropriately and 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 in crop-by-county pairs where temperature change has made cultivation less productive and that production has increased in crop-by-county pairs where temperature change has made cultivation more productive. Estimates of Equation 5.4 are reported in columns 1-2 of Table 8 since we will return to them below. We indeed find that $\pi < 0$; additional climate damage does predict switching away from an additional crop. However, the effect is small in magnitude: a one standard deviation increase in crop-by-county level distress led to an under 0.05 standard deviation reduction in the log of the land area devoted to the crop in the county. While temperature distress indeed predicts crop allocation choices, crop switching to date has been relatively limited.

**New Markets Induce Innovation.** For each county in the sample, we use the estimation of (5.4) to predict an area planted for each crop in each county in 2012: $\widehat{\text{Area}_{k,i}^{2012}}$. We then aggregate these

---

30The 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).
estimate to compute a measure of “predicted national area” for each crop in 2012:

\[
\text{Predicted Area}_{2012}^k := \sum_i \text{Area}_{k,i}^{2012}
\]  

(5.5)

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. Figure A4 displays the correlation between the predicted area expansion measure and our baseline measure of crop-level temperature distress from the previous section. While this need not have been the case \textit{ex ante}, we find no evidence of a correlation between crop-level market expansion and crop-level distress, which indicates that our baseline results were not biased by temperature-induced crop switching.

Next, we estimate a version of Equation (5.1)

\[
\text{New Seeds}_k = \exp \left\{ \beta_{\text{MS}} \cdot \log \left( \text{Predicted Area}_{2012}^k \right) + \Gamma X_k' + \varepsilon_k \right\}
\]  

(5.6)

The coefficient of interest is \( \beta_{\text{MS}} \), which 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 \( \beta_{\text{MS}} \) measures the effect of expanded market size holding fixed initial market size.

The results, reported in Table 4, show that the predicted area variable significantly predicts a greater rate of variety arrival (columns 1-2). This is consistent with the market size effects suggested

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Table 4: Land Reallocation, Market Size, and Innovation

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<tr>
<td>Dependent Variable</td>
<td>New Crop Varieties</td>
<td>New Crop Varieties</td>
<td>New Crop Varieties</td>
<td>New Crop Varieties</td>
</tr>
<tr>
<td>Log Predicted Area (2012)</td>
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<td>0.885***</td>
<td>0.767***</td>
<td>0.842***</td>
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<td></td>
<td>(0.310)</td>
<td>(0.270)</td>
<td>(0.268)</td>
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<tr>
<td>Δ Temp. Distress</td>
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<tr>
<td></td>
<td>(0.0672)</td>
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<td>Log area harvested (1959)</td>
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<tr>
<td>Pre-period climate controls</td>
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<td>Yes</td>
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<tr>
<td>Observations</td>
<td>55</td>
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Notes: The unit of observation is a crop. The outcome variable is the number of crop-specific varieties released. Log predicted area (2012) is the crop-level area harvested in 2012 as predicted by estimates of Equation 5.1 and the aggregation procedure in 5.2. All specifications control for the log of the area on which each crop was harvested in 1959. Pre-period climate controls include growing season temperature and rainfall during the 1950s. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
by the model. In addition, this coefficient remains essentially the same size after adding controls for the two measures of climate damage identified in the previous section, both of which remain independently positive and statistically significant. This suggests that two independently important margins of climate-induced directed technological change matter in this context.

Finally, we find no evidence that innovation driven by market size expansions are concentrated in biological and chemical technologies; these results are presented in Table A5. This confirms the model-informed prior that new land expansions did not involve input demand that was particularly biased toward biological and chemical innovation (“seeds”). Instead, temperature-induced market expansions led to similar increases in innovative output across technology classes. One interpretation of this result given by the model is that market expansions did not differentially increase the marginal product of different technologies, while temperature distress did.

6. Downstream Consequences of Induced Innovation

We have established so far that national climate distress predicts an innovative response. In this section, we measure the extent to which this affects downstream outcomes. Our finding is that the interaction of local climate distress and the national climate distress of the same crop mix is a significant mediator of the former’s direct effect. We argue, through the lens of the model, that this is highly suggestive of a significant role for innovation in mediating the local impacts of climate distress shocks.

6.1 Estimation Framework

Let AgrLandPrice$_{i,t}$ be the agricultural land price per acre of cultivated land, measured from the Census of Agriculture in year $t$ in location $i$. This price includes the price of the land itself plus buildings and improvements. We favor the land price metric over others in the Census of Agriculture because it is a more forward-looking and more temporally stable measure of the theoretical object of interest, the return to landholding, than yearly profits or revenues.

Let County Distress$_{i,t}$ and Crop Composition Distress$_{i,t}$ be the county-level measures defined in Section 4.3. We estimate variations on the following equation:

$$\log \text{AgrLandPrice}_{i,t} = \delta_i + \alpha_{s(i),t} + \beta \cdot \text{County Distress}_{i,t} + \gamma \cdot \text{Crop Comp. Distress}_{i,t} + \phi \cdot \left( \text{County Distress}_{i,t} \times \text{Crop Comp. Distress}_{i,t} \right) + \Gamma X'_{it} + \varepsilon_{i,t}$$

where $\alpha_{s(i),t}$ is a state-by-time fixed effect. Of particular interest are the coefficients $\beta$ and $\phi$, which trace out the heterogeneous impacts of own climate impact depending on the value of crop composition distress.

The qualitative prediction of our model, in the case when the marginal product of new seeds increases in the extent of climate damage and others’ damage predicts innovation, is that $\phi > 0$. This
prediction is exact in the version of the model studied in Example 1, modulo the inclusion of other second-order terms.\footnote{\textsuperscript{36}}

For our main specifications, we estimate the previous using a two-period panel with $t \in \{1959, 2012\}$. We can also replicate the main results in a panel that "stacks" multiple Censuses within the same decade, for which we measure the same damage regressors.

**Choosing the outcome variable.** Intuitively, we think our more precise, crop-specific measurement of climate distress (as described in Section 3) defeat 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). For one, we can 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. This addresses the potential concern that temperature change affect not only land productivity but also other characteristics of a place that might make it more or less appealing to live (see Table A6). Second, we also include state-by-time fixed effects which soak up any variation in building and improvement prices that is varies at the state level (as assumed, for instance, by Donaldson and Hornbeck, 2016).
Table 5: Innovation and Land Values

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
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<td>-1.735***</td>
<td>-1.517***</td>
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<td>-0.571**</td>
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<td>(0.349)</td>
<td>(0.258)</td>
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<td>County Distress</td>
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</tr>
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<td>County Distress x Crop Composition Distress (Φ)</td>
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<td>0.623**</td>
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<td>3,030</td>
<td>15,162</td>
<td>15,162</td>
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<td>R-squared</td>
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<tr>
<td>Full Sample</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Above Median Cropland</td>
<td>-0.506*</td>
<td>-0.571**</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>(0.258)</td>
<td>(0.256)</td>
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</tr>
</tbody>
</table>

Notes: The unit of observation is a county-year. Columns 1 and 4 include county and decade fixed effects, while columns 2-3 and 5-6 include county and state-by-decade fixed effects. Columns 1-3 report long difference estimates (1960-2012) while columns 4-6 report panel estimates. In columns 3 and 6, the sample is restricted to counties with above median cropland. The coefficient of interest is the interaction between a county’s temperature distress and the aggregate damage to a county’s crop composition. Standard errors are double clustered at the county and state-by-decade levels and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

6.2 The Direct Effect of Climate Distress

As a first exercise, to again verify whether our climate distress measure has "bite" for the outcomes of interest, we estimate (6.1) with just the regressor for own damage (i.e., imposing $\gamma = \phi = 0$). Figure 3 shows the partial correlation plot for this regression, with the coefficient, standard error, and t-statistic printed at the bottom. Our robust negative relationship is a sharp contrast with part of the literature (Deschênes and Greenstone, 2007; Fisher et al., 2012), which tends to find generally ambiguous and imprecise effects of raw temperature changes on outcomes. Our argument is that this is because temperature changes, or even a GDD analysis in which all crops are treated equally, are not the right measure of—and not even positively correlated with—the impact of temperature on agricultural productivity. Thus, our findings—although not our methods—are in fact more closely aligned with a slightly earlier generation of analysis (e.g. Schlenker, Hanemann and Fisher, 2006).

6.3 The Role of Innovation

Our method for discerning the role of innovation from production data is to consider the possibility that the interaction between local damage and aggregate damage to the same crops ameliorates the marginal effect of local damage ($\phi > 0$ in Equation 6.1). Estimates of Equation 6.1 are reported in Table 6. Columns 1-3 report long difference estimates (1959-2012) while columns 4-6 report results form

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30We show the robustness of our main finding in such a case in Table A9.
panel estimates with one observation every 10 years. Across specifications, we find that $\phi > 0$ and that this relationship is statistically significant. The result holds when we include state-by-year fixed effects (columns 2 and 5) and, if anything, increases in magnitude and statistical precision when we restrict the sample to counties that are more agricultural (columns 3 and 6). While we, intuitively, find that the estimated magnitudes are larger in the long difference specifications (columns 1-3), we still estimate significant effects in the panel specification; this is consistent with our finding that innovative activity responds quickly to temperature distress (but nevertheless accumulates over time).

The intuitive interpretation of these results, as mentioned in Section 4.3, is that ”best” context in which to get hit by climate distress is the one in which other producers of the same crops are also negatively affected. Concretely, based on the distribution of distress variables (Figures 2a and 2b), this suggests ameliorated effects for agricultural counties in California and the Great Plains, but larger effects in the US Southeast and the Pacific Northwest.

**Quantifying the heterogeneous effects.** How much of a difference does crop composition distress make to the marginal effect of climate change? Figure 4 plots these effects (from regression column 1) in percentage units as a function of others’ damage:

$$100 \cdot (\beta + \phi \cdot \text{Crop Composition Distress})$$

for several percentiles of the distribution for Crop Composition Distress as measured across counties in 2012. The difference in marginal effects between the 99th and 1st percentiles is exactly 97.1% of the median (50% percentile) effect. The standard error on this “relative heterogeneity” estimate is 14.2%—meaning that a 95% confidence interval would cover between 69.3% and 125.0%.

Interpreted through the lens of the model, this implies that innovative activity plays a quantitatively large role in mediating the direct impact of temperature distress on land values.

### 6.4 Robustness

**Controlling for changes in average temperature.** While we show a robust negative correlation between our measure of county-level distress and land prices, consistent with heat stress reducing agricultural productivity, changes in temperature also might affect the amenity value of a location which can directly impact land prices. Since our distress measure captures not only the distribution of temperature changes but also the distribution of crop production and differential sensitivity of different crops to a given change in temperature, in Table A6 we reproduce the baseline county-level results controlling directly for county-level average temperature, as well as the “crop composition” exposure measure computed using aggregate changes in average temperature, as well as the interaction between the two. If the baseline results were driven by a relationship between temperature changes and county amenities, we would expect the coefficients of interest to be attenuated in Table A6. However, our estimates remain very similar across specification after flexibly controlling for tem-
Temperature changes, suggesting our baseline results capture the impact of heat exposure on productivity and not amenity value.

**Controlling for output price changes.** One possible confounder of the previous argument is that prices are also set nationally and may have non-log-linear effects on the outcome variable of interest. Recall that in the model of Example 1, prices have only a log-linear impact on land values and so the relationship between output prices and land values do not bias our estimates of $\phi$. Nevertheless, in practice, the relationship between prices and land values might be more complicated because input shares are not fixed.

To ameliorate these concerns, we directly measure the change in output prices of the crops produced in each county and control directly for counties’ “price change exposure.” We also control directly for the interaction between county-level “price change exposure” and county-level temperature distress and crop composition damage in order to flexibly account for potential non-linear impacts of price changes.

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:\footnote{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.}

\[
\text{Output Price Aggregate}_{it} = \sum_k \frac{\text{Area}_{ik}}{\text{Area}_i} \cdot \log(\text{Producer Price}_{kt})
\]

where Producer Price$_{kt}$ is the national producer price for crop $k$ in year $t$ as recorded by the USDA. Table A7 reports estimates of Equation 6.1 in which we control for both this county-level output price...
measure, as well as the county-level output price measure interacted with counties’ “crop composition distress.” Reassuringly, estimates of our coefficient of interest remain very similar after controlling for the potential impact of producer price changes.

**Controlling for nonlinear terms.** Another potential concern is that estimates of $\phi$ 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 $\phi$ might be picking up the fact that the functional form of the relationship between distress and land values is quadratic. Moreover, the model of Example 1 demanded these terms. To address this issue, we control directly for both the square of county-level distress and the square of the crop composition distress measure. This version of the results is reported in Table A9. 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. If our baseline results were driven by the western United States, therefore, it would be puzzling. Table A9 reproduces the baseline county-level estimates from Table 6 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 intuitively larger in magnitude (although we are underpowered to conclude the estimates are statistically different on the restricted sample).

**Excluding within-state distress from crop composition distress measure.** The goal of our “crop composition distress” measure is to capture each county’s crops’ national exposure to temperature distress and hence the extent to which new technologies are endogenously developed. 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, “crop composition distress” 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.\(^38\)

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 A10. Reassuringly, all estimates are very similar in magnitude and remain highly precise.

**Measuring county-level distress using temperature extremes.** While Table 6 reports estimates in which county-level “distress” is computed from crop-level distress measures incorporating changes in average growing season temperatures (i.e. our Strategy #1), the results are very similar if we compute

\(^{38}\text{We thank Wolfram Schlenker for a helpful discussion on this point.}\)
analogous measures using instead variation in changing exposure to extreme heat. These estimates are presented in Table A11; if anything, estimates from Table A11 are more precisely estimated than estimates from Table 6. The results are very similar restricting the sample to counties with above-median farmland (column 2); controlling flexibly for county-level output prices (column 3); restricting the sample to counties east of the 100th Meridian (column 4); and controlling flexibly for changes in county-level average temperatures (column 5). These results are consistent with the finding that innovative activity itself is responsive to crop-level exposure to extreme heat.

6.5 Additional Evidence of the Innovation Mechanism

Here, we present additional evidence consistent with the interpretation of our results as evidence of adaptation-through-innovation. Both strategies share the common feature of intersecting the previous discussion of “local and aggregate interaction” with an additional shifter that predicts more variety development.

First, recall that we found that the impact of temperature distress on innovative output was stronger for crops with a larger pre-period market size. If innovation were the mechanism driving the results in Table 6, we would expect the results in Table 6 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:

\[
\text{Crop Composition Market Size}_i = \sum_k \frac{\text{Area}_{i,k}}{\text{Area}_i} \cdot \log\left(\frac{\text{National Area Harvested}_{k}^{1959}}{\text{Area}_{i,k}}\right)
\]

We then estimate an augmented version of Equation 6.1 that includes a triple interaction between (i) County Distress$_{i,t}$, (ii) Crop Composition Distress$_{i,t}$, and (iii) Crop Composition Market Size$_i$. If the adaptive role of innovation were driving the results, we would expect the coefficient on the triple interaction to be positive.

Panel A of Table 6 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 in Tables 1 and 2 are also the crops driving the mitigating impact of “crop composition distress” on land value decline. This is consistent with our estimates of $\phi$ in Table 6 capturing the effect of innovation on the marginal impact of temperature distress.

Second, we document that the county-level results are also driven by counties growing crops for which adaptive innovation were likely to be particularly useful. Hybrid seeds, both anecdotally and for agronomic reasons, have particularly high potential for dampening the impact of extreme weather on crop productivity (e.g. Sutch, 2011). According to a National Public Radio report on the 2012-2013 episode of extreme heat and drought on the US Plains, one farmer Charles Hildenbrand said that:

”Even though this year’s drought is the worst he’s ever seen, today’s hybrid corn is surviving better than the corn he and his father planted ever could. ‘If this could have
been open-pollinated [i.e. not hybrid], it would have been all brown, probably, And there probably wouldn’t be any kernels on these ears.

To investigate whether our county-level results are strongest in places with hybridization technology, we borrow the insight from Moscona (2019b) that developing hybrid seeds for certain crops—those with “imperfect flowers”—is relatively straightforward, while developing hybrid seeds for other crops—those with “perfect flowers”—is often technologically infeasible or prohibitively expensive. Moscona (2019b) also collects data on the flower structure of each crop produced in the U.S., making it possible to determine the “hybrid compatibility” of each crop and—using the crop composition of each county—the share of each county’s cropland devoted to crops that are “hybrid compatible.” In particular, using the crop-level data on hybrid compatibility, we estimate for each county:

Table 6: Evidence of the Innovation Mechanism

<table>
<thead>
<tr>
<th>(1)</th>
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<th>(4)</th>
<th>(5)</th>
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<td>Dependent Variable is log Land Value per Acre</td>
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<td>Long Difference Estimates</td>
<td>Panel Estimates</td>
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</tr>
<tr>
<td>Full Sample</td>
<td>Above</td>
<td>Median Cropland</td>
<td>Full Sample</td>
<td>Above</td>
<td>Median Cropland</td>
</tr>
<tr>
<td>Panel A: Heterogeneity by National Market Size</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>County Distress x Crop Composition Distress (Φ)</td>
<td>-19.49***</td>
<td>-11.67***</td>
<td>-8.477**</td>
<td>-15.33***</td>
<td>-7.844**</td>
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<tr>
<td>(4.517)</td>
<td>(4.264)</td>
<td>(3.831)</td>
<td>(3.967)</td>
<td>(3.442)</td>
<td>(3.084)</td>
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<td>&quot; x Crop Composition Market Size</td>
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<tr>
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<td>R-squared</td>
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<td>0.990</td>
<td>0.962</td>
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<td>Panel B: Heterogeneity by Hybrid Compatible Share</td>
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<tr>
<td>County Distress x Crop Composition Distress (Φ)</td>
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<td>(0.226)</td>
<td>(0.169)</td>
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<td>&quot; x Share &quot;Hybrid Compatible&quot;</td>
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<tr>
<td>3.985***</td>
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<td>Yes</td>
<td>Yes</td>
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<td>-</td>
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<td>3,030</td>
<td>15,162</td>
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Notes: The unit of observation is a county-year. Columns 1 and 4 include county and decade fixed effects, while columns 2-3 and 5-6 include county and state-by-decade fixed effects. Columns 1-3 report long difference estimates (1960-2012) while columns 4-6 report panel estimates. The coefficients of interest are (i) the interaction between a county’s temperature distress and the aggregate damage to a county’s crop composition and (ii) the triple interaction between a county’s temperature distress, the aggregate damage to a county’s crop composition, and the average national market size of a county’s crop composition (in Panel A) or the share of a county’s cropland devoted to ‘hybrid compatible’ crops (Panel B). Standard errors are double clustered at the county and state-by-decade levels and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
Share Hybrid Compatible \(_i\) = \(\sum_k \frac{\text{Area}_{ik}}{\text{Area}_i} \cdot \mathbb{1}[^{\{\text{Hybrid Compatible}\}_k}]\)

This measure captures each county’s exposure to potential innovation in hybrid seed technology; we would expect the re-direction of innovation to be particularly useful in counties that devote a large share of their cropland to hybrid compatible crops.

Next, we estimate an augmented version of Equation 6.1 that includes the triple interaction between (i) County Distress \(_{i,t}\), (ii) Crop Composition Distress \(_{i,t}\), and (iii) Share Hybrid Compatible \(_i\). If the county-level results are driven by adaptive innovation, we would expect the coefficient on the triple interaction to be positive. Results from this specification are reported in Panel B of Table 6. Across all specifications, we find that the coefficient on the triple interaction is positive and statistically significant (although it is only marginally significant in column 2). We interpret this finding as further evidence that the endogenous response of innovation to temperature distress is driving the heterogeneous county-level effects documented in this section.

### 6.6 Innovation and the Impact of Temperature Distress on Physical Productivity

To this point, we have focused on land values as the key downstream economic outcome of interest. Other studies of the impact of temperature change on US agriculture have focused on a small set of staple crops and used measure of physical productivity as the outcome (i.e. output and yield measured in quantities). There are several downsides to using these physical productivity measures in our empirical and theoretical context.

First, measures of physical productivity do not account for the fact that in response to temperature distress, farmers may increase input spending and total costs may go up as a result. If this is the case, one impact of new innovation could be to reduce the cost of climate-mitigating input investment. While changing input use and the impact of innovation on input cost are both captured in a county’s land value—and thus our model suggests that land values are an appropriate statistic to measure the impact of innovation downstream—neither is captured in measures of physical productivity alone (see Fisher et al., 2012, for a discussion). Indeed, our model has no prediction for the impact of temperature distress or innovation exposure on physical yields.

Second, there is likely substantial measurement error in census data on production for individual crops in individual counties; land values, on the other hand, are slower moving and incorporate consensus and expert opinion about the production possibilities of a given county. This is relevant for our paper, and less important for earlier work, since our identification strategy and analysis exploit variation across crops in their “exposure” to innovation; hence we need to combine data for many crops across different rounds of the US Census of Agriculture. This is not a concern if one is interested in, for example, estimating the impact of temperature on the yield of a small set of staple crops on

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39See, for example, Schlenker and Roberts (2009); Burke and Emerick (2016); etc.
which substantial data exist (Schlenker and Roberts, 2009; Burke and Emerick, 2016).

Nevertheless, we investigate the impact of our measure of temperature distress and endogenous innovation on physical productivity by estimating the following regression specification:

$$\Delta \log(\text{Productivity}_{k,i}) = \delta_i + \alpha_{k,i(i)} + \beta \cdot \Delta \text{Distress}_{k,i} + \gamma \cdot \Delta \text{Aggregate Crop Distress}_{k,i} + \phi \cdot \Delta (\text{Distress}_{k,i} \times \text{Aggregate Crop Distress}_{k,i}) + \varepsilon_{k,i}$$  \hspace{1cm} (6.3)

where the outcome variable is the change in log output or yield for crop $k$ in county $i$ from 1959 to 2012. This estimating equation is conceptually equivalent to Equation 6.1, except here we have also added a crop dimension to the data. $\Delta \text{Distress}_{k,i}$ is the change from 1959 to 2012 to crop-by-county temperature distress; note that we can compute a measure of temperature distress in county $i$ for crop $k$ even if the $k$ is not grown in $i$ in 1959. Finally, $\text{Aggregate Crop Distress}_{k,i}$ is the national temperature damage to crop $k$ (i.e. innovation “exposure”); for a given crop, it only varies across counties because we use a “leave one out” estimate excluding the county in question.

If we abstract from the issues noted above related to input adjustment, we would expect that $\beta < 0$ and $\phi > 0$; that is, temperature distress reduces output and yield, but we hypothesize that this effect would be muted for crop-county pairs that are most “exposed” to new innovation. Although some estimates are imprecise, this is broadly what we find. Across specifications the estimates document (i) a negative impact of crop distress on output and yield for crop-by-county pairs that are unexposed to innovation and (ii) that the negative effect is declining in innovation exposure (i.e. $\phi > 0$). These results are reported in Table A12.40

In terms of the mechanism underpinning the baseline results, this finding suggests that at least part of the impact of innovation is not just to affect input costs, but also to increase or maintain physical productivity in the face of environmental distress. Moreover, since we measure physical productivity rather than revenue productivity in estimates of Equation 6.3, the results from this specification also reduce concerns that the baseline results are driven by variation in output prices: temperature distress and innovation exposure affect output measured in terms of physical quantities purged of prices. However, price changes might affect input adjustment and crop choice and thus may indirectly

40One pattern in the results are that the estimates when (log of) total output is the outcome, the estimates are larger in magnitude are more precise than when (log of) yields (i.e. output/area) is the outcome. There are several possible explanations for this. First, as noted above there is no reason from the perspective of the model to expect either temperature distress or innovation exposure to affect measured yields. Temperature distress might (and indeed did) lead farmers to reduce area allocated to given crops thereby moving production away from more marginal lands; in this case, we could observe no relationship between temperature distress and yield. Temperature distress reduces productivity everywhere but crops are being re-allocated away from ex ante less productive land.

A second reason for the limited impact on yield might have to do with the fact that out crop-by-county measure of the area devoted to each crop captures harvested rather than area planted. One impact of temperature distress could be that farmers actually harvest a smaller share of the cropland that they plant because, for example, some of what they planted is destroyed. However, by our measure this would actually show up in part as an increase in yield because it would reduce the denominator (i.e. area harvested) in addition to the numerator (i.e. total output). The combination of these effect—both the conceptual shortcomings of yield as an outcome variable and the issues related to measurement—could explain the imprecise estimates on yield.
shape measures of physical output; thus, this interpretation of the result should be considered with caution.

7. OTHER MARGINS OF ADAPTATION

So far, we have been relatively silent on adaptation mechanisms other than adopting new seeds. However, other margins of adjustment are available to farmers; in particular, farmers could either invest in irrigation or switch crop allocations (or both) in response to temperature change. This section investigates two related questions. First, do farmers adapt along these other margins? Second, does innovation “crowd out” other margins of adjustment?

7.1 Irrigation

Existing work has documented that irrigation may play an important role in mitigating the impact of temperature distress on crop productivity, especially by limiting the impact of heat-induced evapotranspiration (Lobell et al., 2013; Tack, Barkley and Hendricks, 2017; Zaveri and Lobell, 2019). However, we are unaware of existing, national-level evidence that farmers expand irrigation in response to changes in temperature distress.

To investigate this question, and its interaction with new seed development, we estimate a version of Equation 6.1 with the share of each county’s cropland that is irrigated as the outcome variable:

\[
\text{Share Irrigated}_{i,t} = \delta_i + \alpha_{s(i),t} + \beta \cdot \text{County Distress}_{i,t} + \gamma \cdot \text{Crop Comp. Distress}_{i,t} + \phi \cdot (\text{County Distress}_{i,t} \times \text{Crop Comp. Distress}_{i,t}) + \Gamma X'_{it} + \varepsilon_{i,t}
\]  

(7.1)

If investment in irrigation is an adaptive response to temperature distress, we would expect to find that \(\beta > 0\). Furthermore, if the availability of adaptive innovation “crowds out” irrigation investment, using the same logic as the previous section, we would expect to find that \(\phi < 0\).

Estimates of Equation 7.1 are reported in Table 7. In Panel A, we report estimates from the full sample of mainland US counties. Recall, however, that west of the 100th Meridian irrigation is highly subsidized and has been since before the start of our sample period; therefore, we would expect most variation in irrigation adoption during our sample period to take place east of the 100th Meridian. Panel B reports estimate from the same set of specifications after restricting the sample to counties east of the 100th Meridian. Across specifications, we find that \(\beta > 0\) and \(\phi < 0\); intuitively, the results are particularly strong and precise east of 100th Meridian (Panel B).

These estimates suggest that farmers indeed invest in irrigation in response to temperature distress. However, the counties that we identify as the beneficiaries of new technologies are significantly less likely to invest in irrigation in response to increase temperature distress.
Table 7: Temperature Distress and Irrigation Investment

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
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<tbody>
<tr>
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<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>County</td>
<td>0.0649</td>
<td>0.122</td>
<td>0.145</td>
<td>0.0530</td>
<td>0.0951*</td>
<td>0.145</td>
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<tr>
<td></td>
<td>(0.0748)</td>
<td>(0.0828)</td>
<td>(0.118)</td>
<td>(0.0454)</td>
<td>(0.0547)</td>
<td>(0.0646)</td>
</tr>
<tr>
<td>County Distress x Crop Composition Distress (Φ)</td>
<td>-0.0414</td>
<td>-0.113*</td>
<td>-0.0842</td>
<td>-0.0242</td>
<td>-0.0696*</td>
<td>-0.0629*</td>
</tr>
<tr>
<td></td>
<td>(0.0320)</td>
<td>(0.0625)</td>
<td>(0.0662)</td>
<td>(0.0212)</td>
<td>(0.0363)</td>
<td>(0.0363)</td>
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<td>County Fixed Effects</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Decade Fixed Effects</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
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<td>Yes</td>
<td>Yes</td>
<td>-</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>5,574</td>
<td>5,574</td>
<td>2,826</td>
<td>14,087</td>
<td>14,087</td>
<td>7,175</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.851</td>
<td>0.892</td>
<td>0.926</td>
<td>0.902</td>
<td>0.924</td>
<td>0.947</td>
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Panel A: Baseline Sample (All Counties)

<table>
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<th>Panel Estimates</th>
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<td>County Distress</td>
<td>0.238**</td>
<td>0.378***</td>
<td>0.693***</td>
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<tr>
<td></td>
<td>(0.107)</td>
<td>(0.130)</td>
<td>(0.175)</td>
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<tr>
<td>County Distress x Crop Composition Distress (Φ)</td>
<td>-0.103*</td>
<td>-0.283**</td>
<td>-0.436***</td>
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<td>(0.0536)</td>
<td>(0.110)</td>
<td>(0.108)</td>
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<td>Yes</td>
<td>Yes</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>State x Decade Fixed Effects</td>
<td>-</td>
<td>Yes</td>
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<tr>
<td>Observations</td>
<td>4,450</td>
<td>4,450</td>
<td>2,160</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.762</td>
<td>0.837</td>
<td>0.900</td>
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</table>

Panel B: Sample East of 100th Meridian

Notes: The unit of observation is a county-year. The unit of observation is a county-year. Columns 1 and 4 include county and decade fixed effects, while columns 2-3 and 5-6 include county and state-by-decade fixed effects. Columns 1-3 report long difference estimates (1960-2012) while columns 4-6 report panel estimates. In columns 3 and 6, the sample is restricted to counties with above median cropland. The dependent variable is the share of county cropland that is irrigated. Standard errors are double clustered at the county and state-by-decade levels and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

7.2 Crop Switching

Our model (Section 3) suggested that crop switching was an additional margin of local adaptation that would not show up in “first-order” analysis of small climate shocks. We already documented in Section 5.3 that this channel is active in the data. And finally, we have also documented that innovation has been directed toward crops whose total market size has been expanded by temperature changes.

Here, we return to estimates of crop switching and investigate whether access to innovation reduced farmers’ tendency to switch crop allocation decisions.
Table 8: Climate Distress and Crop Switching

<table>
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<th>(2)</th>
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</thead>
<tbody>
<tr>
<td>Dependent Variable</td>
<td>( \log \text{Area Harvested in 2012} )</td>
<td>( \log \text{Area Harvested in 2012} )</td>
<td>( \log \text{Area Harvested in 2012} )</td>
<td>( \log \text{Area Harvested in 2012} )</td>
</tr>
<tr>
<td>( \log \text{Area Harvested in 1959} )</td>
<td>0.374***</td>
<td>0.358***</td>
<td>0.373***</td>
<td>0.358***</td>
</tr>
<tr>
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<td>(0.00392)</td>
<td>(0.00610)</td>
<td>(0.00392)</td>
<td>(0.00610)</td>
</tr>
<tr>
<td>County Distress ((\pi))</td>
<td>-0.905***</td>
<td>-0.538***</td>
<td>-0.946***</td>
<td>-0.542***</td>
</tr>
<tr>
<td></td>
<td>(0.173)</td>
<td>(0.209)</td>
<td>(0.174)</td>
<td>(0.208)</td>
</tr>
<tr>
<td>County Distress x Crop Compositioon Distress ((\Phi))</td>
<td>32.92***</td>
<td>24.24***</td>
<td>(2.775)</td>
<td>(5.295)</td>
</tr>
</tbody>
</table>

Notes: The unit of observation is a county-crop pair. Odd numbered columns include county and crop fixed effects and even numbered include county and state-by-crop fixed effects. Log area harvested is the area of the crop-county pair in 1959. Standard errors, clustered by county are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Recall the estimating equation used to estimate crop switching:

\[
\log \left( 1 + \text{Area}_{k,i}^{2012} \right) = \alpha_k + \delta_i + \psi \cdot \log \left( 1 + \text{Area}_{k,i}^{1959} \right) + \pi \cdot \Delta \text{County-by-Crop Distress}_{k,i} + \epsilon_{k,i} \tag{7.2}
\]

To investigate whether innovation “crowds out” crop switching, we estimate an augmented version of this crop-by-county level regression, including an interaction term between the crop-by-county measure of temperature distress and the crop-level measure of temperature distress:

\[
\log \left( 1 + \text{Area}_{k,i}^{2012} \right) = \alpha_k + \delta_i + \psi \cdot \log \left( 1 + \text{Area}_{k,i}^{1959} \right) + \pi \cdot \Delta \text{County-by-Crop Distress}_{k,i} + \phi \cdot \left( \Delta \text{County-by-Crop Distress}_{k,i} \times \Delta \text{Crop Temp. Distress}_k \right) + \epsilon_{k,i} \tag{7.3}
\]

If farmers adapt by optimally re-allocated crops toward less-distressed crops, we would expect to find \( \pi < 0 \). Moreover, if the availability of new technologies reduces the extent to which farmers undergo costly production reallocation, we would expect to find \( \phi > 0 \). Estimates of Equation 7.3 are reported in Table 8. Columns 1-2 document that \( \pi < 0 \). Farmers do adjust crop choices in response to our measure of crop-by-county temperature distress by re-allocating land toward relatively less distressed crops. Moreover, columns 3-4 document that \( \phi > 0 \): the impact of temperature distress on crop switching is muted in counties that benefit most from technology development.

Taken together, this section showed that innovation was not the only driver of adaptation to climate change. We find evidence that farmers invested in expanding irrigation and altering planting decisions in response to temperature distress. These margins of adjustment, however, interact with the
availability of new technologies. The counties that were best positioned to benefit from new adaptive technologies were less likely adapt along other margins. Analysis of local forms of adaptation that ignore the changes in the national direction of technological process miss an important part of the story.

8. INNOVATION AND IMPACT OVER THE NEXT 60 YEARS

What is the impact of endogenous technological change on the projected damages from future climate scenarios? We use our estimates of how technology development has reacted to temperature distress since 1960—and how this channel has shaped the economic outcomes of temperature distress—to investigate how innovation might shape the consequences of future temperature change. Our goal is to estimate the extent to which the projected economic damage of future temperature change differs once the role of innovation is taken into account.

There are several caveats for this exercise. There is no reason to necessarily believe, for example, that innovation will respond in the same way to future temperature change as it has to temperature change since 1960. This could be because there is a crop-specific temperature distress point beyond which new varieties can do little to restore productivity. Alternatively innovation policy might change or some paradigm-shifting invention may alter the whole biotechnology innovation production function. The cutting edge “genetic revolution” of direct gene editing (for instance, with the CRISPR-Cas9 technology) may very well be such a paradigm shift unfolding before our eyes.

With these and all other caveats in mind, however, we proceed using our estimates from historical data to investigate the role innovation might play in shaping the impact of projected temperature change.

Methodology. Following other state-of-the-art climate impact analysis within the US (e.g., Hsiang et al., 2017), we use the methodology outlined of Rasmussen, Meinshausen and Kopp (2016) to estimate county-level temperature projections for Representative Concentration Pathways (RCPs) 4.5 and 8.5. These roughly scale in the “intensity” of predicted future warming, across all models. Like in our main specifications, we use a “60-year long-difference average”: in this context, comparing the average climate of the decade 2071-2080 with the decade 2011-2020, in analogy to our comparison of 2011-2020 with 1951-60. Appendix C describes in more detail our methodology for constructing the temperature projections.

Using these projections and our method for computing crop-level temperature distress in Section 4.2, we estimate projected change crop-specific temperature distress from 2010-2070. Using these estimates, we construct county-level measures of both crop distress and “crop composition distress.” Finally, we use our coefficient estimates from Section 6 to estimate the impact of future temperature change on US land value, in both the presence and absence of directed technological change.
8.1 Future innovation

We first re-do our construction of crop-level temperature damage using the projected climate changes over the next 60 years. We do this with model-ensemble averages under each of the three climate scenarios previously described.

Figure 6 summarizes our findings for the future damage measure. Perhaps surprisingly, and for reasons that are not required by our data construction, we find a strong positive correlation between future damage and past damage. The more intense emissions scenarios tend to exacerbate both the gains and the losses for different crops, though in general they also make losses more likely than they were in the past. Under our model, if the relationship between distress and innovation remains stable over time (obviously subject to the aforementioned caveats), this suggests that directed technical change will be much more “extreme” in the future—the difference in innovative resources put toward the most and least distressed crops in the US will increase considerably.

8.2 Future mitigation

We next collapse the crop-level analysis back to the county-level in the manner suggested by Section 4.3 and implemented in Section 6. Using the reduced-form estimates of estimating equation (6.1), along with projected future values for the distress measures, we can estimate the cross-sectional distribution of future climate impacts in the future. We emphasize here that we cannot credibly, in the present
specification, comment on the level of average damage—or, more specifically, the behavior of the "time-intercept" term \( \alpha_{s(i),t} \)—because we have not been able to credibly identify the time trend across all crops in either total innovation or total climate-induced damage to land values. Instead, what we can do, is to focus on the same cross-sectional statistic reported in Figure 4: the cross-sectional distribution of marginal effects of climate damage. Through the lens of our model, this captures the power of innovation to locally mitigate the effects of climate damage.

We can also calculate, in both the past and future scenarios, the following “comparison point” for a world without innovation: the same marginal damages, but with all counties’ crop-composition damage evaluated at the national median for that statistic. This number summarizes one possible counterfactual for what would happen in a world that shut off directed innovation across crops and the climate-mitigating role thereof—but maintained any direct “level effects” that new innovations had on productivity (i.e., those that would enter in the composition distress term of (6.1) and not the level term).

Figure 6 plots the cross-sectional distribution of marginal damages in the sample and the two studied climate scenarios, where the solid lines denote the distribution with innovation (the interactive term “turned on”) and the dotted lines the aforementioned “no innovation comparison points.” The green line in this Figure corresponds with the point estimates from Figure 4, evaluated at more quantiles (and without error bars).

The overall conclusion is that innovation has a large role to play in mitigating damage in all
scenarios; but overall that marginal damages will be higher across the board in the future scenarios. Knowing that crop distress is higher overall in both scenarios from Figure 6, the latter result owes to the fact that directed innovation (here, proxied by high composition distress) is moving relatively to crops that are less planted and/or already, in levels, less distressed to begin with. Though this exercise cannot speak to corrective policy and/or counterfactual innovation scenarios, this exercise suggests that directed innovation as it has occurred in the past may not target the most “socially valuable” spectrum of crops to assist in the future climate scenarios.

9. Discussion

Climate change is one of the greatest existential threats to humankind and its quest to improve quality of life. Yet there is remarkably little existing work on the race between environmental change and people’s ability to “innovate around” the challenges it presents. This paper offers a theoretical framework and empirical analysis suited to understanding these forces in a specific, but important, sector: agriculture.

We document using comprehensive data in the US that innovation has dramatically shifted both toward crops that have been more negatively affected by temperature change and toward crops whose market size has expanded because their production has been “phased in” by temperature change. Intuitively, this re-direction of innovation has been concentrated in the development of novel plant varieties and other technologies most useful in the adaptation process.

Next, we show that the endogenous response of technology to temperature change has shaped climate change’s economic consequences. US counties that were best positioned to benefit from new damage-mitigating technologies experienced far more muted changes in land value as a result of temperature change. Our framework identifies which regions are likely to be “saved” and which are likely to be “left behind” in the process of free market innovation.

These findings have major implications for policy design—both on the research and production sides of the economy—and for our understanding of feedback loops between different climate adaptation and mitigation strategies. On these issues our paper only scratched the surface of a much deeper issue. This final section discusses, along several different dimensions, how this paper’s results may help guide such conversations in the future.

The innovation landscape. This paper has offered empirical evidence of the "macro footprint" of innovation directed toward climate damaged crops. But what does the ground reality of new agricultural technology look like?

According to reports in the popular press, agricultural biotechnology companies are presently “racing to develop products” that address the problem of “rising temperatures and changing rainfall patterns.”⁴¹ According to CNN Money (2017),

⁴¹See here: https://www.motherjones.com/environment/2015/12/climate-change-business-opportunities/
Monsanto poured more than $1.5 billion into research and development efforts last year to design better quality corn seeds and products. ‘In our breeding efforts and biotech efforts, we’re making sure our products can withstand that extreme weather,’ explains Pam Strier, Monsanto’s sustainability chief.

The public sector is also involved in this innovative push. Researchers at the University of California, Davis 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 (see Figure 1).

These are modern examples. But our analysis clarifies that the same pattern of directed innovation might pre-date the present era’s awareness of climate change and its consequences. Our model clarified how "anonymous" profit incentives, even absent a detailed awareness of climate science or very long-run trends, could have induced these innovations.

To both points, consider the modern “mega-drought” of 2012-2013 in the US Plains. Within 2 years, Monsanto released the corn variety Genuity DroughtGard Hybrids and DuPont released Optimum AQUAMax, both of which were designed to remain productive in drought-like conditions. In the words of Connie Davis, corn systems technology development manager for Monsanto, the timing was partially fortuitous and partially intentional:

“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...

As our empirical results make clear, this pattern is not restricted to corn or staple crops. In another part of the country—California—farmer demand is highest for climate-resilient vegetable varieties. 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.”

This is directed innovation in practice. But of course the existing stock of accumulated technology also played a mitigating role. 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.

Interestingly, the Central Valley of California is one of the regions that is shaded dark in both maps in Figure 2. Thus, the region’s crop production has been negatively affected by climate change but we would also expect there to be a large response in innovation and the development of adaptive technologies for the crops grown in the Central Valley. Anecdotally, this seems to have been the case.


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Our framework unifies both forces—past and present innovation—under a common umbrella of technological change responding to profit incentives. This crucially offers some hope in predicting where directed innovation may flow in the future (and perhaps more importantly, where directed innovation is unlikely to flow on its own). This could be of great interest to policymakers who contemplate research subsidies, or "directed" research subsidies that focus on particularly affected and/or essential crops.

**Innovation and other adaptation.** It is understood anecdotally that climate change in the 20th century has moved the geography of crop production in the US. The Bismarck, North Dakota, Tribune wrote in March 2016 about how the "Changing Climate Means Changing Crops" in the region:

Slight increases in temperature in North Dakota have offered some dividends to agriculture, allowing some crops, such as corn, to creep northward. In the 1970s, drivers along Interstate 94 in North Dakota might have seen some corn growing in fields. But such sights wouldn’t have been likely had they headed very far north. State climatologist Adnan Akyuz said corn growth in North Dakota has undergone major changes in the intervening decades. Now, corn grows in the counties that border Canada — something that certainly wasn’t happening 40 years ago.

This paper quantified this pattern of reallocation systematically, for all crops and regions of the US, (Section 5.3). It then subsequently showed that these dynamics also predict new innovations (Section 5.3), in line with the model prediction of a pure "market size effect," and necessarily feeding back into the first effect. Our model and empirical evidence suggests a positive feedback loop between land re-allocation and the innovation of new biological technology that makes that re-allocation more profitable.

The last point is subtle and worth exploring further. If innovation is an important enabler of geographic redistribution, the absence of sufficiently large research sectors in other parts of the world could be (for better or worse) a major impediment to this type of transformation. This topic certainly merits further research, especially in light of evidence that global adaptation to climate change in the agricultural sector may hinge on the re-allocation of crop production across space (Costinot, Donaldson and Smith, 2016).

**The “invisible hand” and redistribution.** Since innovation responds to national incentives when the free market guides adaptation, the local areas whose crop or industry mix most closely match crops or industries exposed to national climate distress will be best positioned to benefit from new technologies. This implies it is precisely the areas that are negatively affected by climate change but whose crop or

---

⁴⁴Indeed, 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.” 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.
industry composition is relatively unscathed at the national level that will be most damaged absent government intervention. This distinction between regions that—by virtue of their crop or industry mix and its alignment with aggregate damage—will be “saved” by innovation compared to regions that will be “left behind” by innovation is potentially even more extreme internationally. It could even be, for example, that the most distressed crops in certain countries (e.g. low income countries) do not benefit from directed innovation if the incentives faced by inventors are insufficient.⁴⁵

By making it possible to predict how local regions will be best able to adapt to climate change, our results shed light on which policies might be most effective for a given region. For example, agricultural input subsidies, which have become increasingly popular and common in low and middle income countries, would be unlikely to be effective in regions that we identify are being “left behind” by innovation. Those regions fail to adapt not because they are unable to afford inputs; they fail to adapt because the necessary inputs that might allow them to adapt do not exist. Some places might struggle because of a failure to acquire or adopt essential inputs; other places might struggle because those inputs do not exist in the first place. Distinguishing between these two situations is crucial and our framework makes it possible to do so.

A caveat is worth noting. While we have identified major innovative responses to climate distress since 1960, and shown that technological progress has mediated the impact of climate distress to date, there is no way of knowing if this will continue to be the case going forward as the climate becomes more extreme. That is, while it might be possible to retain agricultural productivity as the temperature and number of days of extreme heat begin to increase, it is unknown if this process could continue indefinitely or if there is some point beyond which biotechnological development becomes less effective. There may be certain problems that innovation cannot solve, even if our model suggests incentives exist to do so; in these cases, other margins of adjustment, including re-allocating production, will be brought to the fore. While this paper zeroed in on a single adaptation mechanism—innovation—understanding the full set of adaptation strategies, as well as their interactions, is an exciting and essential area for future work.

⁴⁵For a discussion of sources of adaptation in low-income countries, see Auffhammer and Kahn (2018)
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Figure A1: Crop-Level Correlation Between Distress$_k$ and Distress Days$_k$
Figure A2: Crop-Level Correlation Between Distress$_k$ and Distress Days$_k$

Figure A3: Temperature Distress and pre-1960 Variety Development
Figure A4: Temperature Distress and Temperature-Induced Market Expansions

Table A1: Climate Distress and Crop Varieties: Panel Estimates

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<td>0.0964**</td>
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Notes: The unit of observation is a crop-decade pair. The outcome variable is the number of crop-specific varieties released in the crop-decade and the sample period for each specification is listed at the top of each column. Pre-period varieties is the number of varieties released prior to 1960. Average temperature dynamics include crop level temperature in degrees, as well as the lagged and leading values. Standard errors, clustered by crop, are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
Table A2: Temperature Distress and Crop Varieties: Alternative Estimates of Crop-Level Distress

<table>
<thead>
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<th>(1)</th>
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<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Δ Temperature Distress</td>
<td>-0.0342*</td>
<td>-0.00756</td>
<td>0.00476</td>
<td>0.0581**</td>
<td>-0.00577</td>
<td>-0.0224</td>
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<tr>
<td></td>
<td></td>
<td>(0.0196)</td>
<td>(0.0162)</td>
<td>(0.0268)</td>
<td>(0.0286)</td>
<td>(0.0241)</td>
<td>(0.0213)</td>
<td>(0.0284)</td>
</tr>
<tr>
<td></td>
<td>Δ Temperature Distress x Above Median Area</td>
<td>0.0415**</td>
<td>-0.147**</td>
<td>0.127**</td>
<td>-0.136*</td>
<td>0.0560**</td>
<td>0.0311</td>
<td>(0.107)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0469)</td>
<td>(0.0745)</td>
<td>(0.0623)</td>
<td>(0.0730)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Log area harvested</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Pre-period climate controls</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<td>Pre-period varieties</td>
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<td>Yes</td>
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<td>69</td>
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</tbody>
</table>

Notes: The unit of observation is a crop. The outcome variable is the number of crop-specific varieties released. Pre-period climate controls include growing season temperature and rainfall during the 1950s and pre-period varieties is the number of varieties released prior to 1960. 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: OLS Estimates

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<th>(6)</th>
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<tbody>
<tr>
<td></td>
<td>Δ Temp. Distress</td>
<td>0.223**</td>
<td>0.166*</td>
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<td></td>
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</tr>
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<td></td>
<td></td>
<td>(0.107)</td>
<td>(0.0869)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Δ Temp. Distress x Above Median Area</td>
<td>0.310**</td>
<td>0.0560**</td>
<td>0.0311</td>
<td>0.0401</td>
<td>0.0213</td>
</tr>
<tr>
<td></td>
<td>Δ Distress Days&lt;sup&gt;HOT&lt;/sup&gt;</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Δ Distress Days&lt;sup&gt;COLD&lt;/sup&gt;</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>Δ Distress Days&lt;sup&gt;HOT&lt;/sup&gt; x Above Median Area</td>
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<tr>
<td></td>
<td>Δ Distress Days&lt;sup&gt;COLD&lt;/sup&gt; x Above Median Area</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>Δ Days in Optimal Range</td>
<td>-0.0949*</td>
<td>-0.0513**</td>
<td>-0.0311</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0562)</td>
<td>(0.0240)</td>
<td>(0.0276)</td>
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<td></td>
<td>Δ Days in Optimal Range x Above Median Area</td>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Pre-period climate controls</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
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<td>Yes</td>
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<tr>
<td></td>
<td>Optimal temp. and optimal temp sq.</td>
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<td>Yes</td>
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<td>R-squared</td>
<td>0.167</td>
<td>0.240</td>
<td>0.145</td>
<td>0.258</td>
<td>0.144</td>
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</table>

Notes: The unit of observation is a crop. The outcome variable is change in the log number of varieties for each crop, 1960-present. Pre-period climate controls include growing season temperature and rainfall during the 1950s and pre-period varieties is the number of varieties released prior to 1960. All columns report OLS estimates. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
### Table A4: Temperature Distress and Patenting: Direct Effects

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<th>Dependent Variable:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δ Temp. Distress</td>
<td>0.0259</td>
<td>0.151***</td>
<td>0.137**</td>
<td>0.0949*</td>
</tr>
<tr>
<td></td>
<td>(0.0651)</td>
<td>(0.0518)</td>
<td>(0.0554)</td>
<td>(0.0490)</td>
</tr>
<tr>
<td>Δ Distress Days&lt;sup&gt;HOT&lt;/sup&gt;</td>
<td>0.0153</td>
<td>0.0458**</td>
<td>0.0417**</td>
<td>0.0160</td>
</tr>
<tr>
<td></td>
<td>(0.0222)</td>
<td>(0.0200)</td>
<td>(0.0201)</td>
<td>(0.0197)</td>
</tr>
<tr>
<td>Log Area Harvested</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<td>Observations</td>
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</tbody>
</table>

**Panel A: Baseline Distress Measure**

**Panel B: Extreme Hot Days**

**Notes:** The unit of observation is a crop. The outcome variable is the number of crop-specific patents in the noted technology class listed at the top of each column. In Panel A, temperature distress is computed using Strategy #1 and in Panel B, temperature distress is computed using Strategy #2. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, %, and 1% levels.

### Table A5: Market Expansion and Innovation Across Technology Classes

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<th>Dependent Variable is New Innovations:</th>
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<th>(3)</th>
<th>(4)</th>
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<tbody>
<tr>
<td>Seeds vs. Harvesters</td>
<td>-0.0780</td>
<td>-0.0870</td>
<td>-0.0589</td>
<td>-0.163</td>
</tr>
<tr>
<td>Fertilizers vs. Harvesters</td>
<td>(0.141)</td>
<td>(0.102)</td>
<td>(0.0800)</td>
<td>(0.117)</td>
</tr>
<tr>
<td>All Soil Tech. vs. Harvesters</td>
<td>-0.149**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Seeds, Fert., Soil Tech. vs. Harvesters, Post-Harvest</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fert., Soil Tech vs. Harvesters, Post-Harvest</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Predicted Area (2012) x Biological</td>
<td>-0.0227</td>
<td>-0.0552</td>
<td>-0.0327</td>
<td>-0.120</td>
</tr>
<tr>
<td></td>
<td>(0.141)</td>
<td>(0.0959)</td>
<td>(0.0720)</td>
<td>(0.114)</td>
</tr>
<tr>
<td>Δ Temp. Distress x Biological</td>
<td>-0.128**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>(0.0951)</td>
<td>(0.0656)</td>
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<td>Tech. Class Fixed Effects</td>
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<td>Yes</td>
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<tr>
<td>Crop Fixed Effects</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<td>Observations</td>
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<td>110</td>
<td>110</td>
<td>275</td>
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</tbody>
</table>

**Panel A: Temperature Induced Market Expansion**

**Panel B: Temperature Induced Market Expansion and Temperature Distress**

**Notes:** The unit of observation is a crop-by-technology class pair. All specifications include crop and technology class fixed effects. The included technology classes are listed at the top of each column. Standard errors, clustered by crop, are reported in parentheses and *, **, and *** indicate significance at the 10%, %, and 1% levels.
Table A6: County-Level Estimates: Direct Effects of Temperature

<table>
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<tr>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full Sample</td>
<td>Above Median Cropland</td>
<td>Full Sample</td>
<td>Above Median Cropland</td>
<td></td>
<td></td>
</tr>
<tr>
<td>County Distress</td>
<td>-1.396***</td>
<td>-1.248***</td>
<td>-1.993***</td>
<td>-1.293***</td>
<td>-0.882***</td>
<td>-0.839***</td>
</tr>
<tr>
<td></td>
<td>(0.461)</td>
<td>(0.390)</td>
<td>(0.389)</td>
<td>(0.344)</td>
<td>(0.251)</td>
<td>(0.241)</td>
</tr>
<tr>
<td>County Distress x Crop Composition Distress (Φ)</td>
<td>1.220***</td>
<td>1.025***</td>
<td>1.380***</td>
<td>1.008***</td>
<td>0.610***</td>
<td>0.545***</td>
</tr>
<tr>
<td></td>
<td>(0.226)</td>
<td>(0.192)</td>
<td>(0.180)</td>
<td>(0.185)</td>
<td>(0.133)</td>
<td>(0.130)</td>
</tr>
<tr>
<td>Average Temperature Controls</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>County Fixed Effects</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Decade Fixed Effects</td>
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<td>-</td>
<td>-</td>
<td>Yes</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>State x Decade Fixed Effects</td>
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<td>Yes</td>
<td>-</td>
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<td>3,030</td>
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<td>15,162</td>
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</tr>
<tr>
<td>R-squared</td>
<td>0.977</td>
<td>0.985</td>
<td>0.990</td>
<td>0.962</td>
<td>0.976</td>
<td>0.982</td>
</tr>
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</table>

Notes: The unit of observation is a county-year. Columns 1-4 include county and decade fixed effects, while columns 2-3 and 5-6 include county and state-by-decade fixed effects. Columns 1-3 report long difference estimates (1960-2012) while columns 4-6 report panel estimates. In columns 3 and 6, the sample is restricted to counties with above median cropland. All columns include average temperature (C), crop composition average temperature exposure, and the interaction of the two on the right hand side of the regression. Standard errors are double clustered at the county and state-by-decade levels and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A7: County-Level Estimates: Addressing Output Price Changes

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<th>(3)</th>
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<th>(6)</th>
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<tr>
<td></td>
<td>Long Difference Estimates</td>
<td>Panel Estimates</td>
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<td></td>
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</tr>
<tr>
<td></td>
<td>Full Sample</td>
<td>Above Median Cropland</td>
<td>Full Sample</td>
<td>Above Median Cropland</td>
<td></td>
<td></td>
</tr>
<tr>
<td>County Distress x Crop Composition Distress (Φ)</td>
<td>0.752***</td>
<td>0.623**</td>
<td>1.075***</td>
<td>0.467***</td>
<td>0.308**</td>
<td>0.310**</td>
</tr>
<tr>
<td></td>
<td>(0.247)</td>
<td>(0.240)</td>
<td>(0.183)</td>
<td>(0.188)</td>
<td>(0.139)</td>
<td>(0.122)</td>
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<tr>
<td>log Output Price Estimate</td>
<td>0.714***</td>
<td>0.717***</td>
<td>0.556***</td>
<td>0.360***</td>
<td>0.378***</td>
<td>0.379***</td>
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<td></td>
<td>(0.117)</td>
<td>(0.152)</td>
<td>(0.144)</td>
<td>(0.0606)</td>
<td>(0.0998)</td>
<td>(0.0998)</td>
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<tr>
<td>County Distress x log Output Price Estimate</td>
<td>-0.00133</td>
<td>0.0694**</td>
<td>(0.0335)</td>
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<td>(0.0331)</td>
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<tr>
<td>County Fixed Effects</td>
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<td>Yes</td>
<td>Yes</td>
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<td>0.986</td>
<td>0.963</td>
<td>0.963</td>
<td>0.977</td>
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Notes: The unit of observation is a county-year. Columns 1-2 and 4-6 include county and decade fixed effects, while columns 3 and 6 include county and state-by-decade fixed effects. Columns 1-3 report long difference estimates (1960-2012) while columns 4-6 report panel estimates. The coefficient of interest is the interaction between a county's temperature distress and the aggregate damage to a county's crop composition. Columns 2-3 and 5-6 include controls for county-level output prices and county-level output prices interacted with county-level temperature distress. Standard errors are double clustered at the county and state-by-decade levels and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
Table A8: County-Level Estimates: Controlling for Higher Order Terms

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<td><strong>Long Difference Estimates</strong></td>
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<td>Full Sample</td>
<td>Above Median Cropland</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Own Incidence x Crop Mates’ Incidence (φ)</td>
<td>1.527***</td>
<td>1.166***</td>
<td>1.538***</td>
<td>0.617**</td>
<td>0.479**</td>
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<td></td>
<td>(0.486)</td>
<td>(0.401)</td>
<td>(0.417)</td>
<td>(0.273)</td>
<td>(0.223)</td>
<td>(0.262)</td>
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<td>-</td>
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<td>-</td>
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<td>Yes</td>
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<td>15,162</td>
<td>7,627</td>
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<td>R-squared</td>
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</tbody>
</table>

**Notes:** The unit of observation is a county-year. Columns 1 and 4 include county and decade fixed effects, while columns 2-3 and 5-6 include county and state-by-decade fixed effects. Columns 1-3 report long difference estimates (1960-2012) while columns 4-6 report panel estimates. The coefficient of interest is the interaction between a county’s temperature distress and the aggregate damage to a county’s crop composition. All specifications include controls for temperature distress squared and crop composition distress squared. Standard errors are double clustered at the county and state-by-decade levels and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A9: County-Level Estimates: Sample East of 100th Meridian

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variable</strong></td>
<td>log Land Value per Acre</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Long Difference Estimates</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Full Sample</td>
<td>Above Median Cropland</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>County Distress</td>
<td>-2.905***</td>
<td>-1.034</td>
<td>-1.878**</td>
<td>-1.929***</td>
<td>-0.690</td>
<td>-0.849</td>
</tr>
<tr>
<td></td>
<td>(0.691)</td>
<td>(0.655)</td>
<td>(0.714)</td>
<td>(0.592)</td>
<td>(0.478)</td>
<td>(0.552)</td>
</tr>
<tr>
<td>County Distress x Crop Composition Distress (φ)</td>
<td>1.006***</td>
<td>0.869**</td>
<td>1.365***</td>
<td>0.676**</td>
<td>0.475*</td>
<td>0.520*</td>
</tr>
<tr>
<td></td>
<td>(0.366)</td>
<td>(0.362)</td>
<td>(0.322)</td>
<td>(0.314)</td>
<td>(0.251)</td>
<td>(0.265)</td>
</tr>
<tr>
<td>County Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Decade Fixed Effects</td>
<td>Yes</td>
<td>-</td>
<td>-</td>
<td>Yes</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>State x Decade Fixed Effects</td>
<td>-</td>
<td>Yes</td>
<td>Yes</td>
<td>-</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>4,890</td>
<td>4,890</td>
<td>2,354</td>
<td>12,245</td>
<td>12,245</td>
<td>5,917</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.977</td>
<td>0.986</td>
<td>0.991</td>
<td>0.957</td>
<td>0.975</td>
<td>0.981</td>
</tr>
</tbody>
</table>

**Notes:** The unit of observation is a county-year. The unit of observation is a county-year. Columns 1 and 4 include county and decade fixed effects, while columns 2-3 and 5-6 include county and state-by-decade fixed effects. Columns 1-3 report long difference estimates (1960-2012) while columns 4-6 report panel estimates. In columns 3 and 6, the sample is restricted to counties with above median cropland. In all columns, the sample is restricted to counties East of the 100th Meridian. Standard errors are double clustered at the county and state-by-decade levels and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
Table A10: County-Level Estimates: “Leave State Out” Estimates

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variable</strong></td>
<td><strong>log Land Value per Acre</strong></td>
<td><strong>Long Difference Estimates</strong></td>
<td><strong>Panel Estimates</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Full Sample</strong></td>
<td><strong>Above Median Cropland</strong></td>
<td><strong>Full Sample</strong></td>
<td><strong>Above Median Cropland</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>County Distress</td>
<td>-2.804***</td>
<td>-1.159***</td>
<td>-1.816***</td>
<td>-1.620***</td>
<td>-0.621**</td>
<td>-0.709***</td>
</tr>
<tr>
<td></td>
<td>(0.445)</td>
<td>(0.404)</td>
<td>(0.358)</td>
<td>(0.347)</td>
<td>(0.267)</td>
<td>(0.267)</td>
</tr>
<tr>
<td>County Distress x Crop Composition Distress (Φ)</td>
<td>0.783***</td>
<td>0.635***</td>
<td>1.016***</td>
<td>0.521***</td>
<td>0.345**</td>
<td>0.358***</td>
</tr>
<tr>
<td></td>
<td>(0.240)</td>
<td>(0.221)</td>
<td>(0.170)</td>
<td>(0.179)</td>
<td>(0.135)</td>
<td>(0.122)</td>
</tr>
<tr>
<td>County Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>State x Decade Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>6,054</td>
<td>6,054</td>
<td>3,030</td>
<td>15,162</td>
<td>15,162</td>
<td>7,627</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.977</td>
<td>0.985</td>
<td>0.990</td>
<td>0.962</td>
<td>0.976</td>
<td>0.982</td>
</tr>
</tbody>
</table>

Notes: The unit of observation is a county-year. Columns 1 and 4 include county and decade fixed effects, while columns 2-3 and 5-6 include county and state-by-decade fixed effects. Columns 1-3 report long difference estimates (1960-2012) while columns 4-6 report panel estimates. In columns 3 and 6, the sample is restricted to counties with above median cropland. The coefficient of interest is the interaction between a county’s temperature distress and the aggregate damage to a county’s crop composition. Crop Composition Distress is computed excluding temperature distress in the state in which the county is located. Standard errors are double clustered at the county and state-by-decade levels and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A11: County-Level Estimates: Extreme Heat Exposure

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variable</strong></td>
<td><strong>log Land Value per Acre</strong></td>
<td><strong>Long Difference Estimates</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Full Sample</strong></td>
<td><strong>Above Median Cropland</strong></td>
<td><strong>Controlling for Output Prices</strong></td>
<td><strong>East of 100th Meridian</strong></td>
<td><strong>Controlling for Average Temperature + Interactions</strong></td>
<td></td>
</tr>
<tr>
<td>County Distress (Extreme Days)</td>
<td>-0.0432***</td>
<td>-0.0560***</td>
<td>-0.0364***</td>
<td>-0.0593***</td>
<td>-0.0325***</td>
</tr>
<tr>
<td></td>
<td>(0.0101)</td>
<td>(0.0108)</td>
<td>(0.0107)</td>
<td>(0.0111)</td>
<td>(0.0100)</td>
</tr>
<tr>
<td>County Distress (Extreme Days) x Crop Composition Distress (Φ)</td>
<td>0.000760**</td>
<td>0.00104***</td>
<td>0.000647**</td>
<td>0.00127***</td>
<td>0.000579**</td>
</tr>
<tr>
<td></td>
<td>(0.000291)</td>
<td>(0.000231)</td>
<td>(0.000274)</td>
<td>(0.000320)</td>
<td>(0.000242)</td>
</tr>
<tr>
<td>County Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>State x Decade Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Output Price Controls</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Average Temperature Controls</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>6,054</td>
<td>3,030</td>
<td>6,042</td>
<td>4,890</td>
<td>6,052</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.986</td>
<td>0.991</td>
<td>0.986</td>
<td>0.986</td>
<td>0.987</td>
</tr>
</tbody>
</table>

Notes: The unit of observation is a county-year. All columns include county and state-by-census round fixed effects. The sample restrictions and controls included in each specification are noted at the top of each column. County-level distress is computed from the crop-level distress measures based on exposure to days of extreme heat. Standard errors are double clustered at the county and state-by-decade levels and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
Table A12: County-By-Crop Estimates: Temperature Distress, Innovation, and Physical Productivity

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δ Distress (β)</td>
<td>-2.429***</td>
<td>-2.208***</td>
<td>-2.607***</td>
<td>-2.466***</td>
<td>0.181</td>
</tr>
<tr>
<td></td>
<td>(0.715)</td>
<td>(0.735)</td>
<td>(0.685)</td>
<td>(0.683)</td>
<td>(0.384)</td>
</tr>
<tr>
<td>Δ (Distress x Aggregate Crop Distress) (Φ)</td>
<td>1.403**</td>
<td>1.336**</td>
<td>1.586***</td>
<td>1.536***</td>
<td>0.310</td>
</tr>
<tr>
<td></td>
<td>(0.576)</td>
<td>(0.587)</td>
<td>(0.529)</td>
<td>(0.530)</td>
<td>(0.283)</td>
</tr>
</tbody>
</table>

Dependent Variable is Change (1959-2012) in:

<table>
<thead>
<tr>
<th>asinh(Production)</th>
<th>log(Production/Area)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full Sample</td>
<td>Observations with positive production in 1959</td>
</tr>
<tr>
<td>Trends in 1959 log Area Harvested</td>
<td>No</td>
</tr>
<tr>
<td>Crop-by-State Fixed Effects</td>
<td>Yes</td>
</tr>
<tr>
<td>County Fixed Effects</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>21,319</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.861</td>
</tr>
</tbody>
</table>

Notes: The unit of observation is a crop-by-county pair. Columns 1, 3, and 5 include county and crop-by-US state fixed effects and columns 2, 4, and 6 also include trends in pre-period log area harvested. The reported coefficients are coefficients on (i) the crop-by-county temperature distress measure and (ii) the interaction term between crop-by-county distress and aggregate crop-level distress. All regression specifications are weighted by 1959 area harvested. Standard errors, clustered by county, are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
Appendix

A. Model and Proofs

This appendix works out the details of our model from Section 3. The proofs of all propositions in the text are given in Subsection A.3, which builds upon the exact calculation of the log-linearized equilibrium in Subsection A.2.

A.1 Equilibrium concept

A competitive equilibrium of the model economy from Section 3 is the following:

Definition 1 A competitive equilibrium of this economy is an allocation of consumer demand

\[
\left( M_t, \left( C_k,t \right)_{k=1}^K \right)_{t \in \{0,1\}}
\]

production

\[
\left( k_{i,t}^*, x_{i,k_{i,t}^*,t}(\cdot), x_{i,k_{i,t}^*,H,t}(\cdot) \right)_{i \in [0,1], t \in \{0,1\}}
\]

innovation investments and variety frontiers

\[
\left( (X_{k,z,t}, N_{k,S,t}, N_{k,H,t})_{k=1}^K \right)_{t \in \{0,1\}}
\]

and prices

\[
\left( r_t, \left( p_{k,t} \right)_{k=1}^K, q_{k,S,t}(\cdot), q_{k,H,t}(\cdot) \right)_{t \in \{0,1\}}
\]

such that

(i) Consumers and firms optimize as described above;

(ii) The free-entry condition (3.4) holds;

(iii) Markets for all final goods clear

A.2 Log-linearized model

We now consider a first-order expansion of the steady-state equilibrium conditions, and treat the shift in productivities as a small deviation. Henceforth let variables with a hat denote log deviations from the original steady state and let variables with a bar equal the values in the initial steady state (e.g., \( \hat{x} = dx/\bar{x} \)). We drop time sub-scripts to ease exposition.
**Input demand.** An individual farmer’s demand for each innovative input has the following isoelastic form in levels:

\[ x_{i,k,z}(v) = z_{i,k} \cdot \left( p_k \cdot \frac{\partial F_k}{\partial z_{i,k}} \right)^{\frac{\epsilon}{\epsilon - 1}} \cdot q_{i,z}^{-\frac{\epsilon}{\epsilon - 1}}, \quad \forall v \in [0, N_k, S], \quad z \in \{S, H\} \tag{A.1} \]

Let \( \partial_z F_k \) denote the marginal product of composite input \( z \in \{S, H\} \) evaluated at the initial steady state for a farm producing crop \( k \). For simplicity, we assume all such farms are ex-ante identical in their productivity and/or input mix. The log-linearization of the demand curve (A.1) is

\[ \hat{x}_{i,k,z} = \hat{z}_i + \epsilon \hat{p}_k + \epsilon (\hat{\partial}_z \hat{F}_{i,k}) - \epsilon \hat{q}_z \tag{A.2} \]

where \( (\hat{\partial}_z \hat{F}_{i,k}) \) is the log deviation in location \( i \)'s marginal product of input \( z \) for producing crop \( k \).

We next expand \( \hat{\partial}_z \hat{F}_k \) in the following way as a function of the inputs and productivity shifter

\[
(\hat{\partial}_z \hat{F}_{i,k}) = \frac{\partial_{zz} F_k}{\partial \hat{F}_k} \hat{z}_i + \frac{\partial_{zz} F_k}{\partial \hat{F}_k} \hat{z}_i' + \frac{\partial_{zz} A_k}{\partial \hat{F}_k} \hat{A}_{i,k} \\
=: r_{zz} \hat{z}_i + r_{zz} \hat{z}_i' + r_{zz} \hat{A}_{i,k} \tag{A.3}
\]

where \( z' \) is the other input. Note that \( r_{zz} < 0 \) would be standard for single-input concavity; \( r_{zz} \leq 0 \) depends on local complementarity or substitutability between the inputs; and \( r_{zz} \leq 0 \) depends on a similar property for the productivity shifter relative to the input of interest.

In the production function, demands for all varieties of a given input are the same. Hence we ignore any explicit notation labeling the varieties. The deviation of the aggregate, \( \hat{z}_{i,k} \), is to the first order the sum of the percentage increase in input demand plus the percentage increase in varieties:

\[ \hat{z}_{i,k} = \hat{x}_{i,z} + \hat{N}_{k,z} \tag{A.4} \]

Combining equations (A.2), (A.3), and (A.4) yields the following demand system that maps aggregate prices and variety counts, plus the local productivity shock, to local demands

\[ \hat{x}_{i,k,z} = d_{zp} \hat{p}_k + d_{zn} \hat{N}_{k,z} + d_{zn'} \hat{N}_{k,z'} + d_{ZA} \hat{A}_{i,k} \tag{A.5} \]

The coefficients, in terms of primitives, are given by the following expressions:

\[
\begin{align*}
     d_{zp} &= \left( \frac{1}{\epsilon} - r_{zz} - r_{zz} \frac{k}{z} \left( \frac{1}{\epsilon} - r_{zz} \right) \right)^{-1} \left( 1 + r_{zz} \left( \frac{1}{\epsilon} - r_{zz} \right) \right) \\
     d_{zn} &= \left( \frac{1}{\epsilon} - r_{zz} - r_{zz} \frac{k}{z} \left( \frac{1}{\epsilon} - r_{zz} \right) \right)^{-1} \left( r_{zz} + r_{zz} \frac{k}{z} \left( \frac{1}{\epsilon} - r_{zz} \right) \right) \\
     d_{zn'} &= \left( \frac{1}{\epsilon} - r_{zz} - r_{zz} \frac{k}{z} \left( \frac{1}{\epsilon} - r_{zz} \right) \right)^{-1} \left( r_{zz} + r_{zz} \frac{k}{z} \left( \frac{1}{\epsilon} - r_{zz} \right) \right) \\
     d_{ZA} &= \left( \frac{1}{\epsilon} - r_{zz} - r_{zz} \frac{k}{z} \left( \frac{1}{\epsilon} - r_{zz} \right) \right)^{-1} \left( r_{zz} + r_{zz} \frac{k}{z} \left( \frac{1}{\epsilon} - r_{zz} \right) \right)
\end{align*}
\]
The first term in each expression is a “multiplier” that comes from solving out the effect of input demand on marginal products, which feeds back to input demand. The second part encodes the direct exposure of a given product’s demand to each of the forces, through both own-input second derivatives of the production function and cross-derivatives (i.e., seeds usage goes up, which also affects the marginal product of harvesters).

**Equilibrium prices.** The next step is to solve for equilibrium prices using the aggregate supply and demand schedules. Aggregate demand for each crop is conveniently isolelastic relative to the numeraire. Assume that these elasticities of demand equal \( \eta_k \) for each crop \( k \), so the demand functions all have the form

\[
\hat{p}_k = -\eta_k^{-1}\hat{y}_k \tag{A.7}
\]

One can simulate the case of a small open economy by setting \( \eta \uparrow \infty \). In this case prices are fixed at some global-level despite any of the dynamics within the country.

The farm-level production function is

\[
\hat{y}_{i,k} = s^k_S\hat{s}_i + s^k_H\hat{H}_i + s^k_A\hat{A}_{i,k} \tag{A.8}
\]

where \((s^k_S, s^k_H)\) are the input shares for seeds and harvesters, respectively, for all farms growing crop \( k \); \( s^k_A \) is the first-order impact of the productivity shock; and local crop choice \( k \) is fixed for a local change. After substituting in the definition (A.4) and the input demand (A.5), expression (A.8) turns into

\[
\hat{y}_{i,k} = y^k_p\hat{p}_k + y^k_{N_S}\hat{N}_{k,S} + y^k_{N_H}\hat{N}_{k,H} + y^k_A\hat{A}_{i,k} \tag{A.9}
\]

where the coefficients are

\[
y^k_p = s^k_Hd_{Hp} + s^k_Sd_{Sp} \\
y^k_{N_S} = s^k_S + s^k_Sd_{SN_S} + s^k_{nH}d_{HN_S} \\
y^k_{N_H} = s^k_H + s^k_Hd_{HN_H} + s^k_{nS}d_{SN_H} \\
y^k_A = s^k_A + s^k_Ad_{HA} + s^k_{nH}d_{SA} \tag{A.10}
\]

These come from combining the production function (A.8) with the previous demand for intermediates.

The aggregation of this farm-level supply to the crop-level is

\[
Y_k = \sum_i w_{i,k}\hat{y}_{i,k} \tag{A.11}
\]

where the aggregation weights are relative production shares in the initial steady state, or equivalently any input share including the land share

\[
w_{i,k} = \frac{Y_{i,k}}{Y_k} = \frac{L_{i,k}}{L_k} \tag{A.12}
\]
where $L_{i,k}$ is the steady-state land devoted to crop $k$ in location $i$, and $L_k$ is the total steady-state land devoted to a given crop.

The aggregate supply can be re-written then in terms of the aggregate crop-level productivity shock $\hat{A}_k := \sum_i w_{i,k} \hat{A}_i$ as

$$\hat{Y}_i = y^k_p \hat{p}_k + y^k_{Ns} \hat{N}_{k,S} + y^k_{Nh} \hat{N}_{k,H} + y^k_A \hat{A}_k$$  \hspace{1cm} (A.13)

Combined with the demand curve (A.7), the goods market equilibrium can be solved as

$$\hat{Y}_k = \left(1 + y^k_p \eta^{-1}_k\right) \left(y^k_{Ns} \hat{N}_{k,S} + y^k_{Nh} \hat{N}_{k,H} + y^k_A \hat{A}_k\right)$$

$$\hat{p}_k = p^k_{Ns} \hat{N}_{k,S} + p^k_{Nh} \hat{N}_{k,H} + p^k_A \hat{A}_k$$  \hspace{1cm} (A.14)

where the coefficients $p^k_j$ are defined by $p^k_j = -\eta^{-1}_k y^k_j$ for $j \in \{p, N_S, N_H, A\}$. Note again that all of these go to zero if $\eta \uparrow \infty$, or prices are externally fixed.

**Aggregate profits.** We can now solve for value of each innovation in terms of the TFP shock and the counts of varieties. Note first that the values, for fixed interest rates are directly proportional to profits; and profits, for a fixed optimal price and marginal cost, are proportional to aggregate demand for the input. Thus we write

$$\hat{\Pi}_{k,z} = \sum_i w_{i,k} \hat{x}_{i,k,z}$$  \hspace{1cm} (A.15)

for the value of producing input $z$ for crop $k$.

This is readily calculated in terms of primitives as

$$\hat{\Pi}_{k,z} = \left(d^k_{z N_S} - \eta^{-1}_k d^k_{zp} y^k_{N_S}\right) \hat{N}_{k,z} + \left(d^k_{z N_H} - \eta^{-1}_k d^k_{zp} y^k_{N_H}\right) \hat{N}_{k,z'} + \left(d^k_{z A} - \eta^{-1}_k d^k_{zp} y^k_{A}\right) \hat{A}_k$$  \hspace{1cm} (A.16)

where each term has a “partial equilibrium” (i.e., fixed price) effect and a “general equilibrium” (i.e., adjusting price) term.

Let us define the following “stability condition” for comparing steady-states in the model

**Assumption 1 (Stability)** Assume that, for both each input $z$, that aggregate valuations for producing that input $z$ for crop $k$ decrease in the amount of varieties for $z$ holding fixed aggregate productivity, or

$$\left(d^k_{z N_S} - \eta^{-1}_k d^k_{zp} y^k_{N_S}\right) < 0$$

Additionally these decreasing returns to scale are more severe for the input $z$ than the other input $z'$, or

$$\left(d^k_{z N_S} - \eta^{-1}_k d^k_{zp} y^k_{N_S}\right) < \left(d^k_{z N_H} - \eta^{-1}_k d^k_{zp} y^k_{N_H}\right)$$

The first part ensures that the equilibrium response to a productivity-induced demand shock for a given input results, in equilibrium, in the number of varieties increasing to restore equilibrium. It relates, economically, to their being sufficient decreasing returns to scale in the production function.
and utility function to offset the standard externality of additional variety creation. It is satisfied in standard models of directed technical change (e.g., Acemoglu, 2002) and helps provide intuitive comparative statics—i.e., when a given technology is demanded more, the equilibrium response is to provide more of that technology (until demand is satiated) instead of providing less (to lessen externalities). It also relates, more informally, to stability—it is a sufficient (thought not strictly necessary) condition for the excess demand pressure of moving the variety count slightly away from equilibrium to restore equilibrium, instead of leading to a shooting away (e.g., there is extra demand for corn seeds; more corn seeds create a larger positive externality and even more demand; and this process does not converge upon a finite amount).

The second part allows this equilibration force to be stronger for the perturbed input than the other input. This intuitively suggests that the equilibrium response to a higher productivity for seeds is more biased toward being an expansion of seed varieties and not an expansion of harvester varieties.

**Number of varieties.** The free entry condition remains unchanged by the productivity shock, so we have $\hat{\Pi}_{k,z} = 0$ for each crop $k$ and input type $z \in \{S, H\}$. This is a system of $2K$ equations to solve for the $2K$ unknowns, the number of each type of variety, in terms of the crop-level productivity shocks $\hat{A}_k$.

In particular, because of our simplifying assumptions that the demand system for final agricultural goods had no cross-price elasticities, this can be solved for crop-by-crop (i.e., in pairs of two equations). In closed form, the varieties can be written as

$$\hat{N}_{k,z} = \beta_{k,z} \cdot \hat{A}_k \quad \text{(A.17)}$$

where $\beta_{k,z}$ is defined by

$$\beta_{k,z} := \frac{(d_{zN_z}^k - \eta_k^{-1}d_{zp}^ky_z^k)(d_{zN_z}^k - \eta_k^{-1}d_{zp}^ky_z^k) - (d_{zN_z}^k - \eta_k^{-1}d_{zp}^ky_z^k)(d_{zA} - \eta_k^{-1}d_{zp}^ky_A^k)}{(d_{sN_s}^k - \eta_k^{-1}d_{sp}^ky_s^k)(d_{HN_{H}}^k - \eta_k^{-1}d_{Hp}^ky_{N_{H}}^k) - (d_{sN_s}^k - \eta_k^{-1}d_{sp}^ky_s^k)(d_{HN_s} - \eta_k^{-1}d_{Hp}^ky_{N_{S}}^k)} \quad \text{(A.18)}$$

**A.3 Proofs**

**Proposition 1.** See discussion, in previous Appendix section, of equations (A.11) and (A.12).

**Proposition 2.** To prove this by example, consider a version of the economy with no harvesters. In this case, the regression equation (A.17) reduces to:

$$\hat{N}_{k,S} = \frac{d_{sA}^k - \eta_k^{-1}d_{sp}^ky_s^k}{\eta_k^{-1}d_{sp}^ky_{N_s}^k - d_{sN_s}^k} \hat{A}_n$$

Under the case of Assumption 1, the denominator of this expression is positive and we can focus on the sign of the numerator. Given the statement (about the possibility of either sign for the coefficient), applying Assumption 1 is without loss.
In the numerator, \( d_{SA}^k \) has ambiguous sign for all the reasons discussed about the relative substitutability of seed purchases and good climate. Moreover, \( y_A^k > 0 \) and \( -\eta^{-1} \eta^{-1} y_A^k \) always, or output goes up and prices go down when a crop is produced more and/or productivity is higher. This means that the term \( -\eta^{-1} d_{SA}^k y_A^k \) in the numerator, which encodes the price response and the feedback back to input demand, is always negative.

Thus, in the simple example, a positive response of input demand to favorable climate conditions requires \( d_{SA}^k > 0 \), or input demand to increase in a more favorable climate holding equal GE forces. This is associated most clearly with an increasing marginal product in \( A \), or \( r_{SA}^k > 0 \).

Proposition 3. Assume the production function is symmetric for cross-input terms. Then the condition

\[
\hat{V}_{nS} - \hat{V}_{nH} = 0
\]

can be re-arranged to imply

\[
\tilde{N}_{k,S} - \tilde{N}_{k,H} = \tau_k \cdot \tilde{A}_k
\]

for

\[
\tau_k := \frac{d_{SA}^k - d_{HA}^k}{d_{zNz}^k - d_{zNz}^k}
\]

The denominator is positive as long as new varieties in a given technology category crowd-own more investment than new varieties in the other, from Assumption 1 (adapted to the case with a symmetric production function). In this case, the regression inherits the sign of the relative “partial equilibrium” impacts of changes in \( A \) on demands respectively for \( S \) and \( H \).

B. Detailed Construction of Extreme Days

We follow the procedure outlined in Schlenker and Roberts (2009) to compute daily temperature averages since 1960 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 fraction of a day between two temperature cut-offs in a specific (2.5 mile by 2.5 mile) grid cell:

\[
\text{FrBetween}(t_0, t_1; T_{high,d,g}, T_{low,d,g}) := \text{FrAbove}_{g,d} \left[ t_1; T_{high,d,g}, T_{low,d,g} \right] - \text{FrAbove}_{g,d} \left[ t_0; T_{high,d,g}, T_{low,d,g} \right]
\]

where \((t_0, t_1)\) are the temperatures of interest and \((T_{high,d,g}, T_{low,d,g})\) are the high and low temperatures.
in a given grid cell, from PRISM data. The function FractionAbove encodes a calculation of what fraction of a day was above the specified temperature based on the day's maximum, minimum, and average temperatures. It divides a standard degree days calculation over the "maximum possible degree days" that would could be attributed based on the average temperature. i.e., if $T_{\text{high},d,g} < t$ it returns 0; if $T_{\text{low},d,g} > t$ it returns 1; and in-between it returns $2 \cdot \text{GDD} / (T_{\text{high}} - T_{\text{low}})$.

Note that we can replace $\text{FrAbove}[]$ in the previous calculation with a measure of degree-days to get a degree-days equivalent of the same measure.

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

$$\text{InRange}_i(t_0, t_1; d) := \left[ \sum_{g \in i} w_g \cdot \text{FrBetween}(t_0, t_1; T_{\text{high},d,g}, T_{\text{low},d,g}) \right]$$

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).

Finally we sum the previous over days in a given period of interest $D$ and normalize by the number of months $M(D)$:

$$\text{InRange}_i(t_0, t_1; D) := \frac{1}{M(D)} \sum_{d \in D} \text{InRange}_i(t_0, t_1; d)$$

The units for this measure are “extreme days per month” over the period of interest (e.g., summer months in the 1950s decade).

C. Projecting the Future Climate in US Counties

In this Appendix, we describe in more detail our method for applying the method of Rasmussen, Meinshausen and Kopp (2016) to construct model-ensemble predictions for future temperatures in US counties in summer months. We follow the same template that is used in Hsiang et al. (2017) to aggregate across models

We obtain the relevant data from the following open-access data portal made available by the authors of the aforementioned papers: [https://zenodo.org/record/582327](https://zenodo.org/record/582327). From this page, we can download county-level binned climate forecasts for a number of different models across both the RCP 4.5 and RCP 8.5 scenarios. For the former we have estimates from 43 different models, and for the latter 44. These are “point estimate” forecasts that are themselves the result of within-model Monte Carlo simulations of each model.

The data are provided, for each year by model by county, in the form of day counts (which add up to 365) for average temperatures in 1 degree Celsius bins from -40 to 59 degrees. We assume for all bins, including the endpoints, that an average temperature between $x$ and $x + 1$ corresponds to an
average temperature of \( x + 1/2 \).

For each model \( M \), and for each county in the US, we calculate in each decade the average temperature in the county in that county’s 185 hottest days. This last choice is meant to approximate measuring temperature changes over the summer months. The average temperature measure is

\[
T_{i,t}^M = \frac{1}{185} \sum_{b \in [-40, \ldots, 59]} d_{i,b,t}^M \cdot (b + 1/2)
\]

where \( b \) indexes the bin by its lower endpoint and \( d_{i,b,t} \) is the estimated (integer) number of days in that bin in a given year \( t \).

We next construct decadal averages, model-by-model, for this average temperature. Denote in particular \( T_{i,\text{pre}}^M \) as the model-implied average temperature for 2011-2020 and \( T_{i,\text{post}}^M \) as the model-implied average temperature for 2071-2080. Next, we take the difference \( \Delta T_i^M \) as a measure of county-level warming during the summer months.

Next, we construct a model-ensemble average of these temperature changes

\[
\Delta T_i^e = \sum_{M \in M} w_M \cdot \Delta T_i^M
\]

where the model weights \( w_M \) are provided with the temperature projection replication file. This is a method recommended by the references to average over the possible climate trajectories suggested by each model. An alternative method would have been to do model-averaging for our final estimands of crop-level distress and induced innovation. This method would have allowed us to quantify the model uncertainty in our forward-looking projections—we focus on the point estimate with “internal averaging” merely for simplicity of exposition.

Finally, to construct a model-predicted average temperature in county \( i \) in the post-period, we add this estimate of warming to the realized temperature during summer months in county \( i \) as measured with NOAA data from our main analysis. This removes any model-specific bias in predicting the current weather and focuses only on model-implied changes. With this model-predicted county-level temperature in the future decade, we can calculate all relevant model objects using the methods described in our main analysis.\(^46\)

\(^46\)Throughout the exercise, for consistency with our main estimates, we use the 1959 local areas that are pre-determined for all statistical anlyses in the paper. An alternative strategy would have been to use later (e.g., 2012) planting locations, which should provide more precise future projections. But we focus on the former strategy to make all estimates most directlycomparable to what we show in-sample throughout the paper.