Environmental Catastrophe and the Direction of Invention: Evidence from the American Dust Bowl*

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Abstract

This paper investigates how innovation responded to and shaped the economic impact of the American Dust Bowl, an environmental catastrophe that led to widespread soil erosion on the US Plains during the 1930s. Combining data on county-level erosion, the historical geography of crop production, and crop-specific innovation, I document that in the wake of the environmental crisis, agricultural technology development was strongly redirected toward more Dust Bowl-exposed crops and, within crops, toward bio-chemical and planting technologies that could directly mitigate economic losses from environmental distress. County-level exposure to Dust Bowl-induced innovation significantly dampened the effect of land erosion on agricultural land values and revenue. These results highlight the role of crises in shaping the direction of innovation and the importance of endogenous technological progress as an adaptive force in the face of disasters.

Keywords: Climate adaptation, innovation, agriculture, Dust Bowl

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1 Introduction

How does innovation react to catastrophe? Developing new technologies to meet the demands of environmental, public health, or geopolitical crises is likely an important component of an economy's adaptive response. The history of economic growth is rife with examples of technological progress rising to meet the demands of emergent threats, ranging from massive scientific investment during the Second World War to the global redirection of biotechnology research in response to the coronavirus pandemic (e.g. Rosen, 1994; Ruttan, 2006; Woolliscroft, 2020). The view that "necessity is the mother of invention" implies that moments of catastrophe could be key for understanding the direction of technological progress. Moreover, when crises devastate particular regions, sectors, or groups of people, the extent to which new technology dampens or exacerbates the impact of the original shock could play an important role shaping its economic consequences.

This paper investigates how innovation reacts to crises and shapes their economic impact by homing in on the most extreme environmental crisis in US history: the American Dust Bowl, a catastrophe that led to widespread erosion and topsoil damage on the US Plains during the 1930s.[1] Anecdotally, the development and adoption of new technologies helped the agricultural economy adapt. Breeding and chemical companies actively invested in innovation that would meet the high demand for technologies to restore productivity on dry and eroded land (e.g. Crabb, 1947; May, 1949). Indeed, it has been a long-standing hypothesis that the early take-off of US agricultural biotechnology grew from the need to stave off production losses from extreme climatic events, the Dust Bowl chief among them (Crow, 1998). However, there is little empirical evidence documenting how innovation reacts to or shapes the economic consequences of environmental change.

The first goal of this paper is to estimate the response of technology development to the American Dust Bowl and investigate its underlying mechanisms. During and after the Dust Bowl, was innovation systematically re-directed toward more damage-exposed crops and toward technologies that would restore crop productivity? The second goal

[1] Over 400,000 square kilometers of land in the US Plains fell victim to significant drought and erosion (Hakim, 2012). The analogy with COVID-19 is not merely circumstantial – Thomas (2020) argues that "COVID-19's best analog is the 1930s Dust Bowl," in terms of the severity of the crisis and response to it.

is to investigate whether innovation mitigated the Dust Bowl's economic damage. Were places that benefitted from the re-direction of innovation more economically resilient in response to environmental distress?

Economic theory provides relatively limited guidance about how technological progress should be *expected* to react to environmental disaster. Adapting a standard model of directed technological change to the present context, I first show that agricultural innovation could *either increase or decrease* in response to the Dust Bowl depending on a set of competing forces.[2] In a first case, if new technology *substitutes* for favorable land and soil conditions on average, technology development *increases* in response to the Dust Bowl. This formalizes the idea, prevalent in historical accounts, that new biotechnology was directed sharply toward bolstering production on damaged land, where demand for new adaptive technology was high. The extreme climate of the 1930s, according to this narrative, led to an "explosion of demand" for modern seeds, generating large profits for breeding companies that, in turn, invested heavily in innovation (Sutch, 2011, p. 219).

In a second case, however, if technology *complements* favorable climatic conditions on average, innovators flee damaged crops and producers, preferring to direct innovation toward crops that were unscathed by the Dust Bowl and toward increasing productivity on healthy land. This narrative is consistent with the common economic intuition that innovation concentrates in the largest, most productive markets (e.g. Acemoglu, 2002). In this second case of the model, innovators leave faltering producers behind, exacerbating the distributional consequences of environmental distress.

It is essential, therefore, to turn to data in order to investigate how technology development reacted to the Dust Bowl and shaped its economic consequences. The first part of the empirical analysis compares technology development before and after the Dust Bowl across crops that were differentially exposed to its environmental harm. I directly measure the extent to which each crop's land area was eroded during the Dust Bowl by combining land erosion maps digitized by Hornbeck (2012a) with information on the geography of production for each crop immediately prior to the Dust Bowl from the 1930 US Census of Agriculture. I use the share of the national land area devoted to each crop that experienced high levels of erosion, according to the land survey map, as my main

[2]The model builds on the theory of equilibrium technological change developed in Acemoglu (2010), and especially its more recent application in Moscona and Sastry (2021).

measure of crop-specific Dust Bowl exposure.[3]

Next, I use several complementary strategies to measure crop-specific innovation. As the main measure of technology development, I compile a data set of new biotechnology (i.e. crop variety) releases from the United States Department of Agriculture's (USDA) *Variety Name List*, which was obtained via Freedom of Information Act (FOIA) Request. This *List*, which has been compiled by the USDA since the late 19th century, is maintained in order to prevent fraud in the seed market and its goal is to be a comprehensive database of US seed and variety development and release.This data set makes it possible to track the development of new crop varieties, which historical accounts suggest were the primary technology used to adapt production to the changing environment, during a period without systematic patent or intellectual property protection for biotechnology.[4]

I supplement the *Variety Name List* with three additional measures of technology development and innovation. To investigate the re-direction of innovation across different types of technology, which might be an important part of the overall shift in research focus, I compile data on all patent grants related to crop agriculture, and use text analysis to link all patents to individual crops in the production data.[5] The additional detail provided by patent records makes it possible to compare the response of innovation across different types of technology and different types of inventors; moreover, the stricter inclusion criteria in the patent data as well as the ability to proxy the importance of each technology using citation information make the patent data useful for probing the robustness of the baseline finding. I also compile data on all experiments conducted at US agricultural research stations (see Kantor and Whalley, 2019), in order to directly investigate the role of government sponsored innovation. Finally, I collect all research publications related to the agricultural sciences from the *Web of Science* publication database, in order to study the response of science (and not only technology development) to environmental change.

The first main result is that new biotechnology development for crops that were more exposed to the Dust Bowl—which shows no differential trend from that of less damaged

[3]This measure treats the initial crop allocation as fixed; however, in Section 3 and Appendix D, I investigate the potential importance of crop switching. The main conclusion is that planting patterns across crops were remarkably persistent throughout the sample period, so treating the initial land allocation as fixed does not appear to be a strong assumption.

[4]See, for example, Crow (1998), Olmstead and Rhode (2008), Sutch (2011) on the paramount importance of biological technology for adaptation; this history is discussed in more detail in Section 2.1.

[5]In particular, I assign all patents in Cooperative Patent Classification classes related to crop agriculture to a crop if the crop name appears in the patent tile, abstract, or keyword list.

crops prior to the onset of disaster—sharply increased after the crisis began. The baseline estimates suggest that a one standard deviation increase in Dust Bowl exposure led to a 0.18-0.32 standard deviation increase in new crop variety releases. The positive effect of Dust Bowl exposure on innovation persisted long after the worst years of the Dust Bowl were over, suggesting that the crisis led to a long-run shift in the direction of innovation and focus of technology development.

The results are robust to a range of stress tests and alternative specifications. I document that the estimates are similar after controlling flexibly for trends in pre-period research activity, New Deal policy, and a range of other time varying controls; the results are also similar after restricting the sample by excluding crops either at the top or bottom of the market size distribution, suggesting they are not driven by only "large" or "small" crops. I also conduct a series of placebo exercises and show that technology development did *not* respond to crop-level exposure to *low* levels of Plains erosion or to exposure to *ex ante* eroded land *outside* the Plains region. Finally, I show that the estimates are similar using exogenous extreme weather patterns from the 1930s to construct instruments for the extent of crop-specific Dust Bowl erosion, indicating that the findings are not driven by any impact of local human behavior on the extent of Dust Bowl damage.

The next section probes the mechanisms that drive the baseline finding. First, I investigate the types of technologies and innovators that drive the main result. I show that the relationship between Dust Bowl exposure and innovation was strongest for crops for which hybrid varieties could be developed, consistent with historical accounts that hybrids were particularly effective on distressed land. I then document, using the patent data, that the re-direction of technology toward Dust Bowl-exposed crops was driven by biological, chemical and planting technologies; if anything, mechanical and post-harvest processing technologies that do not directly interact with the environment were directed away from damaged crops.[6] This pattern was driven predominately by private sector firms and individual breeders; I find weaker effects for public-sector patenting and corroborate this limited response of government research using independently collected data on all crop experiments at US experiment stations. Interpreted via the model, these re-

[6]While biotechnology development is the focus of most historical accounts, drought and topsoil damage, as well as pest outbreaks that resulted, also increased demand for fertilizer and chemical technology that would make continued production possible (Schlebecker, 1953; Baveye et al., 2011, see Section 2.1) Mechanical technology, as opposed to biotechnology, has long been considered less relevant for relieving environmental and land supply constraints (Hayami et al., 1971; Ruttan and Hayami, 1984).

sults suggest that the main finding is driven by increased demand for technologies that could directly combat environmental distress, and not overall terms of trade effects or an independent public sector push.

Second, I investigate sources of persistence in the re-direction of technology. I compare the effect of crop-specific damage on technology development across crops with different levels of pre-period technology development, and find that while the short-run effect of Dust Bowl exposure on innovation is similar for both sets of crops, the long-run effect is driven by crops with more limited pre-existing breeding infrastructure. This finding, along with qualitative historical evidence, is consistent with heightened technology demand from the Dust Bowl leading to fixed cost breeding investment that sustained innovation even after the worst years of the Dust Bowl were over (Crow, 1998; Sutch, 2011). Finally, using data on scientific research articles during the sample period from the *Web of Science* citation database, I show that scientific publishing was also re-directed toward crops that were more damaged by the Dust Bowl, indicating that the focus of science (and not just technology development) reacted to environmental distress. These changes in "upstream" scientific research could also contribute to the persistent effect of the Dust Bowl on the direction of innovation.

The second part of the paper investigates the extent to which this re-direction of innovation shaped the Dust Bowl's economic impact by turning to county-level data on the agricultural sector. Prior work has proposed identifying adaptation to environmental stress by comparing the short and long run impact of environmental shocks (e.g. Hornbeck, 2012a; Dell et al., 2012). However, this strategy does not make it possible to identify the role of technology apart from other production adjustments. Moreover, my first set of findings suggests that technology development reacted within a decade of the start of the Dust Bowl and that the adaptive role of technology should be highly heterogeneous across producers of differentially exposed crops.

Therefore, I propose an alternative empirical strategy to identify the adaptive role of technology development. Since innovation responded to aggregate crop-level distress, counties that grew crops that were more damaged across all other Plains counties were best positioned to adopt new Dust Bowl-induced technologies. Motivated by this logic, I proxy each county's *innovation exposure* as the level of Dust Bowl exposure of the crops that the county cultivates, averaged across all other Plains counties. Then, I test whether counties that were more exposed to induced innovation were more resilient to the Dust

Bowl shock by estimating the heterogeneous effect of Dust Bowl erosion on agricultural land value across counties with different levels of innovation exposure.

Innovation exposure substantially reduced the negative effects of the Dust Bowl on agricultural land values. The difference in the marginal impact of land erosion on agricultural land value between counties in the 90th and the 10th percentile of the innovation exposure distribution is 120% of the median effect, and counties with the highest in-sample innovation exposure experienced virtually no long run decline in land value as a result of the Dust Bowl. The results are very similar using in-sample revenue and productivity, rather than land values, as the dependent variable, and are also virtually unchanged after controlling directly for crop prices, which could have also responded to aggregate crop-level distress. The effect of innovation exposure is more pronounced in counties with larger farms, which may have been better positioned to access and adopt new inputs. Together, the findings indicate that the re-direction of innovation substantially reduced the economic harm of the Dust Bowl.

To this point, the results have highlighted the role of technology that would to adapt production in counties affected by the Dust Bowl. New technology, however, might have also increased the productivity of more-exposed crops elsewhere in the country, or allowed for production of more-exposed crops to take place outside the Plains region on *ex ante* less productive land. However, I find no evidence of national adaptation through these channels. Innovation exposure is not positively correlated with changes in agricultural land values outside the Plains region, suggesting that Dust Bowl induced technology did not increase crop productivity across the the board. Counties outside the Dust Bowl also did not disproportionately expand cultivation of Dust Bowl-exposed crops, suggesting a limited role for crop switching as a form of production adjustment. Dovetailing with findings from the first part of the paper, these results are consistent with a focus on technology development that increased resilience on distressed land. This narrative accords with the first case of the model, in which technology substitutes for favorable environmental conditions and environmental crisis incentivizes the development of new technology to promote climate resistance.

This paper builds on several bodies of work. It extends research investigating the direction of technological change by documenting how technology development reacted to environmental catastrophe (Hicks, 1963; Habakkuk, 1962; Acemoglu, 2002, 2010, provide the theoretical foundation). There has been a longstanding focus on the extent to which technological progress is driven by moments of crisis—often focused on warfare—and how invention reacts at moments of major necessity (Rosen, 1994; Keller et al., 2003; Ruttan, 2006; Hanlon, 2015; Gross and Sampat, 2020). Little is known, however, about how technology reacts to and shapes the economic impacts of environmental change.[7]

This study also extends research on the economic impact of the climate by investigating the role of innovation as a source of adaptation.[8] There is a growing body of work investigating the extent to which humans are able to adapt to climate change and environmental crises (e.g. Hornbeck, 2012a,b; Olmstead and Rhode, 2011; Moore and Lobell, 2014; Hsiang and Jina, 2014; Burke and Emerick, 2016; Costinot et al., 2016). This paper builds most directly on Hornbeck (2012a), who investigates the short and long run impact of the Dust Bowl on Plains counties, and extends a broader set of studies on the economic impacts of the American Dust Bowl, a uniquely devastating crisis in US history (see McLeman et al., 2014, for a review). A central challenge in studies of environmental adaptation is identifying and quantifying the role of technological progress (Rodima-Taylor et al., 2012; Zilberman et al., 2018), even though it has often been hypothesized that new technology is a key potential source of climate resilience.

Finally, this study draws on a range of work investigating how innovation has shaped US agricultural production. The early 20th century represented a major turning point in US agricultural innovation and productivity growth (e.g. Griliches, 1957; Olmstead and Rhode, 2008). It has been argued that the rise of US agricultural biotechnology during the 20th century originated in part as an effort to adapt to environmental extremes during the 1930s (e.g. Crabb, 1947; May, 1949; Crow, 1998; Fitzgerald, 1990; Sutch, 2008, 2011).[9] The findings in this paper support the hypothesis that innovators reacted dramatically to environmental stress, and that early 20th century climate extremes had persistent effects on US agricultural innovation.

[7] Prior work on endogenous technological change and the environment is predominantly theoretical and focuses on the development of emission-mitigating technology rather than adaptation technology (e.g. Newell et al., 1999; Popp, 2002, 2004; Acemoglu et al., 2012; Aghion et al., 2016). This paper, in contrast, investigates the development of adaptation technology and its impact on economic resilience. Relatedly, Moscona and Sastry (2021) study the relationship between modern temperature change and the direction of agricultural technology development and Miao and Popp (2014) investigate the relationship between natural disasters and patenting across countries.

[8] Several studies investigate the direct effect of the climate on US agriculture, including Mendelsohn et al. (1994); Schlenker et al. (2006); Deschênes and Greenstone (2007); and Burke and Emerick (2016).

[9] Consistent with this hypothesis, and motivated by Sutch (2011)'s analysis, Roberts and Schlenker (2011) find that crop yields became less sensitive to extreme heat during the 1930s.

The next section discusses the history of technology development in response to the Dust Bowl (Section 2.1) and introduces a theoretical framework for analyzing how technological progress reacts to environmental crises (Section 2.2). Section 3 introduces the data used in the empirical analysis. Section 4 presents results on the impact of the Dust Bowl on innovation and Section 5 turns to the role of innovation in shaping the economic consequences of the Dust Bowl. Section 6 concludes.

2 Innovation and the Dust Bowl

2.1 Historical Evidence

The Dust Bowl was a period of severe drought followed by dust storms that devastated large swaths of the US Plains during the 1930s. While the most severe droughts were in 1934 and 1936, leading to widespread crop failure, at least part of the Plains region experienced severe weather in each year from 1930-1939. Over 400,000 square kilometers of land were exposed to drought and water or wind erosion (Hakim, 2012).

Qualitative accounts suggest that new technology was a key source of adaptation to the Dust Bowl. While the main focus of case study evidence is innovation in biotechnology, fertilizers and chemicals were also important anecdotally. Private breeding and chemical companies were active in this wave of technological progress, marking a shift from a research sector that had been dominated by universities and the government.

Individual breeders and breeding companies reacted dramatically to the Dust Bowl's environmental distress, developing and marketing technologies that would remain productive even on damaged land. According to Crow (1998), the Dust Bowl was "possibly the most important" reason for the rapid increase in development and spread of hybrid seeds during the 1930s. Frontier breeding technology had particularly high returns relative to old technology in times of environmental distress; new hybrid varieties, for example, were "strikingly more resistant to drought than the open pollinated varieties then in use." Farmers noted this difference, and demanded new and more resilient seed varieties.

Sutch (2011) argues that drought and the vulnerability of existing crop varieties to climatic fluctuations drastically increased demand for new varieties, particularly hybrid strains, and breeders rose to meet these demands (see also May, 1949; Culver and Hyde, 2001; Pruitt, 2016). Breeding companies quickly noted the profitability of developing crop varieties that would be productive in areas affected by environmental distress: "The explosion of demand for hybrid corn generated large profits for the major hybrid seed companies: Pioneer, Funk, and DeKalb. [C]ompanies invested heavily in research with new hybrid strains," with a focus on "perfecting drought resistance" (Sutch, 2011, p. 219).

According to Crabb (1947, p. 165-166), who recounts the growth of Pioneer's breeding program, early breeding research reacted directly to the dust storms of 1934 and 1936; in 1937, "farmers in Iowa and elsewhere" bought all the new Pioneer seed, to the point where "the Wallace organization [Pioneer] was serving [farmers] the full length and breadth of the corn belt." The historical narrative does not focus only on corn; Baumhardt (2003) describes the development of wheat varieties during the 1930s, as well as new crop rotation and planting practices, that would make production less sensitive to dry land in Dust Bowl-affected regions.

Pest outbreaks, including widespread grasshopper attacks, also increased as a result of drought and soil erosion.In 1936, grasshopper damage to crop production in the most affected states amounted to over \$106 million in farm income losses (Parker, 1939). New pesticides, insecticides, and agricultural chemicals—like new seed varieties—were developed in response to the unprecedented pest outbreaks and to help "in the war against the grasshopper" (Schlebecker, 1953, p. 91). Soil science research, including the development of fertilizers to bolster damaged topsoil, also grew during the Dust Bowl period; in 1936 the Soil Science Society of America formed in direct response to drought and erosion in the Plains (Baveye et al., 2011).

While much of the historical narrative focuses on private sector breeding and technology development, the public sector represented a large share of agricultural innovation during the sample period and may have also reacted to farmer distress. Government innovation policy did not shift in response to the Dust Bowl, and the mandate of US agricultural experiment stations remained to focus on basic scientific advances, rather than applied technology, during the sample period (Nevins, 1962). Nevertheless, there are some examples of varieties developed on US experiment stations helping distressed farmers. The Oklahoma Agricultural Experiment Station released the cotton variety Oklahoma Triumph 44, which proved more resistant to drought and pest outbreaks (Green, 1990), and the Woodward Field Experiment Station identified sorghum varieties that would be less sensitive to wind damage and soil blowing (Stephens, 1937).

According to these accounts, agricultural research and development reacted quickly to environmental distress and the adoption of new technologies was an important source of adaptation to environmental change. A key empirical question is whether these anecdotes represent unique cases or whether innovative activity systematically shifted in response to the Dust Bowl and helped mitigate its economic fallout. The empirical analysis below estimates the average relationship between environmental distress and technology development, across all crops and technologies, and investigates whether its underlying mechanisms are consistent with this historical narrative.

2.2 Theoretical Framework

Before turning to the empirical analysis, I formalize the relationship between Dust Bowl exposure and innovation in a model of directed technological change. The model builds on the theory of equilibrium technological change developed in Acemoglu (2010), and especially its more recent application in Moscona and Sastry (2021). The goal of the model is to convey that the predicted response of innovation to the Dust Bowl is ambiguous *ex ante* and to articulate the conditions under which technology development could increase, or decrease, in response to Dust Bowl damage. This theoretical ambiguity makes empirical analysis all the more crucial.

2.2.1 Set-Up

Consider an economy in which a continuum of farmers $i \in [0, 1]$ produce a single crop. The productivity of the local environment at each location is $A_i \in [A', A'']$ with cumulative distribution $F(.)$ across locations. There is a crop-specific technological input and each farmer uses T_i of this input. The productivity of this input in location i depends on the national technological frontier—parameterized by θ—and productivity A_i. In particular, the production function of farm i is:

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

where Y_i is total output, $\alpha^{-\alpha}(1-\alpha)^{-1}$ is a normalization added only to simplify the analysis, and $\alpha \in [0, 1]$ captures the relative importance of technology in the production function. Assume that $G(.)$ is concave and twice continuously differentiable, and that $G_1 \geq 0$ and $G_2 \geq 0$ so that, naturally, output is increasing in the technological level of the economy and local productivity. Each farmer maximizes profits taking output price p and input cost q as given.

This simple production technology makes it possible to home in on the economic mechanisms of interest that drive the relationship between environmental distress and innovation. Taking the first order condition of the farmer's maximization problem, it is possible to show that $T_i = \alpha^{-1} p^{\frac{1}{\alpha}} q^{\frac{-1}{\alpha}} G(A_i, \theta)$ Thus, use of the technological input is directly increasing in $G(A_i, \theta)$.

The Dust Bowl reduces land productivity differentially across locations. I consider the crop *damaged by the Dust Bowl* if the Dust Bowl shifted the productivity distribution from $F(.)$ to $F^{DB}(.)$, where the former first order stochastic dominates the latter. That is, the Dust Bowl reduced land productivity across crop planting locations to the point of lowering aggregate production.[10]

There is a representative innovator that determines both the price of T_i and the the aggregate level of technological progress (θ) in order to maximize profits, and faces a marginal cost of technology development $1 - \alpha$ and a convex cost $C(\theta)$ of expanding the technological frontier.[11] Substituting for technology input use from the farmer's maximization problem, the innovator's problem becomes:

$$\max_{q,\theta} (q - (1 - \alpha)) \alpha^{-1} p^{\frac{1}{\alpha}} q^{\frac{-1}{\alpha}} \int G(A_i, \theta) dF(A) - C(\theta) \tag{2.2}$$

The first order condition for q is satisfied for any θ if $q^{-\frac{1}{\alpha}} - (q - (1 - \alpha)) \frac{1}{\alpha} q^{-\frac{1}{\alpha} - 1} = 0$; thus, the profit maximizing technology price is $q = 1$. Plugging this into the original maximand, the innovator's problem simplifies to one-dimensional optimization over the technology level θ:

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

Finally, assume that the price of the crop is determined by an inverse demand function

[10] Since we assume $G_1 > 0$, this definition is indeed sufficient for Dust Bowl damage to reduce total production holding fixed crop planting locations and technology.

[11] Focusing on a profit-maximizing innovator builds on existing models of directed technological change; however, it may fail to capture the motivation behind all sources of innovation, most notably government-sponsored research. In Section 4.3.3, I investigate the role of public vs. private sector research and find that the results do not seem to be driven by government-sponsored innovation, suggesting that this simplification is consistent with the present context. Moreover, government innovation policy and the mandate of the experiment stations did not change in response to the Dust Bowl (see Nevins, 1962, and Section 4.3.3).

$p = D(Y)$, where D is continuous and non-increasing and Y is total output in the economy: $Y = \int Y_i(A_i)dF(A)$. An equilibrium is defined as price p, output Y, and technology level θ such that both farmers and innovators maximize profits and the crop price is on the demand curve.

The theoretical results in the next section examine the relationship between environmental damage from the Dust Bowl and technological progress (θ), and identify the economic conditions that determine technology's response to environmental distress.

2.3 Theoretical Results

Before presenting the main results, I define two key cases for the role of technology in the farmer's production function; the impact of Dust Bowl damage on technological progress hinges crucially on the relationship between technology and land productivity damage:

Definition 1 *Technological progress is a topsoil substitute if* $G_{12} \leq 0$ *and a topsoil complement if* $G_{12} \geq 0$.

New technology is a *topsoil substitute* if it reduces the marginal impact of the Dust Bowl's damage to agricultural land on output. This would be the case if technological progress makes production less sensitive to soil erosion and drought, which seems consistent with the ways in which new seed varieties—and hybrids in particular—were anecdotally more resilient in the face of environmental hardship (Section 2.1).

New technology is a *topsoil complement* if it increases the marginal impact of the Dust Bowl's damage to agricultural land on output. Recent evidence on crop resilience to climate change, for example, suggests that breeding can increase crop yields *at the expense of* resilience to drought, in part because seed varieties can be finely tuned to specific environmental characteristics and, as a result, are more sensitive to fluctuations (Lobell et al., 2014). Moreover, mechanical technologies like harvesters may be designed for particular ecological conditions and their marginal impact on output could decline when the environment changes.

The impact of the Dust Bowl on the direction of innovation depends on this feature of technological progress:

Proposition 1 *Assume that output prices are fixed. If the Dust Bowl damages cropland, θ weakly increases if technology is a topsoil substitute and θ weakly decreases if technology is a topsoil complement.*

Proof. See Appendix B.1.

In words, technology development increases in response to Dust Bowl damage if new innovation is most productive in the face of ecological constraints, and declines if it becomes less productive in the face of environmental distress. The former case is consistent with the narrative that variety development increased in response to the Dust Bowl, and the fact that there was a focus on the development of crop varieties that would be productive damaged land (e.g. Crow, 1998; Sutch, 2011). The latter case, however, rings truer with the conventional wisdom that innovation is "pulled forward" when downstream industries thrive and "pushed back" when they falter (Acemoglu, 2002).

Allowing for price adjustment increases the return to technology development in damaged crops for *all* types of technology. Exposure to the Dust Bowl reduces crop output, thereby increasing crop scarcity and output prices; this force is analogous to the *price effect* in the parlance of Acemoglu (2002). It reinforces the re-direction of technology toward more damaged crops in the *topsoil substitute* case, and fights against the re-direction of technology away from more damaged crops in the *topsoil complements* case, making the overall effect of the Dust Bowl on technology ambiguous. Since, as discussed below, I do not find strong evidence of price effects driving the technological response to the Dust Bowl, I only mention them briefly here.[12]

While the model focuses on a single crop in order to home in on the key theoretical tension, in the empirical analysis I exploit the fact that crops were *differentially exposed* to the Dust Bowl and investigate whether technological progress was directed toward or away from more exposed crops, the relevant notion of sectors in the studied context. First, I document the sign of the relationship between Dust Bowl exposure and crop variety development. Next, I explore several strategies to examine heterogeneity across crops and technologies that are more (or less) plausibly topsoil-substituting; this makes it possible

[12]See Moscona and Sastry (2021) for an in-depth discussion and proof of the role of price effects in a related context. With price adjustment, if the Dust Bowl damages cropland, θ weakly increases if technology is a topsoil substitute and θ either increases or decreases if technology is a topsoil complement.

to investigate the key mechanism and distinguish between the "marginal product" effects outlined in Proposition 1 and general equilibrium price effects.

3 Measurement

3.1 Data Sources

County Erosion I measure county-level exposure to the Dust Bowl using maps digitized by Hornbeck (2012a) on cumulative county-level erosion measured during the mid-1930s, and focus on the sample of counties identified in that study as those that comprise the contiguous and ecologically similar Plains region (see United States Department of Agriculture, 1924.). The original maps were compiled from reconnaissance surveys and divide US land into one of three categories: low erosion (less than 25% topsoil lost), medium erosion (25-75% topsoil lost), and high erosion (greater than 75% topsoil lost). The sample of counties and erosion distribution are displayed in Figure A1. The main shortcoming of these data, discussed in Hornbeck (2012a), is that they do not measure erosion due to the Dust Bowl but rather cumulative erosion prior to 1935. Throughout the paper, I return to tests of potential bias due to this data feature.

Technology Development I use several complementary sources of data to measure crop-specific innovation. First, in order to measure biotechnology development, I compile data on the release of novel crop varieties from the United States Department of Agriculture (USDA) *Variety Name List*; this is the main measure of crop-level technology development in the empirical analysis. The *List*, which was obtained through a Freedom of Information Act (FOIA) request and discussed at greater length in Moscona (2021), is a list of all released crop varieties known to the USDA and the year in which each was released. It is designed to be comprehensive and uses a broad range of sources in order to identify crop varieties, including "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, particularly during the period under investigation when seeds were not patentable subject matter.[13] The key advantage of this data source is that it is possible to track innovation in biotechnology, which is anecdotally the most relevant technology for adapting to environmental change but cannot be measured with intellectual property data during the sample period. Moreover, it is straightforward to link technologies in the *List* set to individual crops, the units of observation in the empirical analysis (e.g. a corn seed is a corn technology).

I supplement the *Variety Name List* with several additional measures of innovation.

First, I compile data on crop-specific patenting in order to measure crop-level technology development across *multiple technology classes*. Using the database *PatSnap*, I compute 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, I search for the name of each crop in the *Variety Name List* in all patent titles, abstracts, and keywords lists. The key advantage of this data set is that, by measuring innovation in multiple technology classes, it is possible to investigate the re-direction of invention across technologies (see Section 4.3.2). The patent data are also useful for corroborating a version of the baseline results with an independent data set with more restrictive inclusion criteria.

Second, I use data on crop-specific experiments from US federal experiment stations (1910-1945), compiled and discussed in detail in Kantor and Whalley (2019). Experiment-level information, including the crop of focus, were collected from individual reports published by each station during the sample period. This data set makes it possible to investigate the extent to which US government research contributes to the main finding.

Third, I compile data on all research articles in the agricultural sciences from the Institute for Scientific Information's (ISI) *Web of Science* database. The *Web of Science* combines article and citation information from 12,000 high-impact journals and 160,000 conference proceedings; I link all articles within the agricultural sciences section to crops by searching for the name of each crop in article titles.

Agricultural Production Data on county-level outcomes are from the 1910-1959 rounds of the US Census of Agriculture. Variables constructed from the Census of Agriculture

[13]The 1930 Plant Patent Law introduced limited IP protection for vegetatively generated varieties, but most crops, including all seed crops, had no form of protection until 1970 (Kloppenburg, 2005).

include the value of land, agricultural revenue, farm size, and measures of land use.[14] I also use the 1930 and 1959 Censuses of Agriculture to measure the land area devoted to each crop in each county immediately prior to and after the Dust Bowl period.

3.2 Measuring Dust Bowl Exposure

I estimate the Dust Bowl exposure of all crops listed in the 1930 Census of Agriculture with at least one variety release during the period under investigation; in total, this sample consists of 43 crops. The exposure measure, capturing aggregate crop-level damage from the Dust Bowl, is the share of land on which a crop was grown prior to 1930 that was eroded during the Dust Bowl. Since the erosion data measure cumulative erosion and not erosion due to the Dust Bowl, the crop-level measure captures the share of land on which each crop was grown that was both (i) in the Plains region, as defined in Section 3.1 and (ii) eroded by the time of the erosion survey. Crop-level Dust Bowl exposure is:

$$\text{Exposure}_c = \sum_i \frac{L_{ic}}{\sum_{i'} L_{i'c}} \cdot \mathbb{I}\{\text{Plains}_i\} \cdot \text{High Erosion}_i \tag{3.1}$$

where i indexes counties and c indexes crops; L_{ic} is the land devoted to crop c in county i, as measured in the 1930 Census of Agriculture; and $\mathbb{I}\{\text{Plains}_i\}$ as an indicator that equals one if a county is in the Plains region. High Erosion$_i$ is the share of land in county i that had experienced high erosion (over 75% topsoil eroded).

Exposure$_c$ is the main independent variable in the first part of the empirical analysis and captures the extent to which each crop's land area was damaged by Dust Bowl erosion. Appendix C discusses the underlying data used for this measure in more detail, alongside summary statistics, and documents that more- and less-erosion exposed crops are balanced across a range of crop-level characteristics that affect crop breeding.

This measurement strategy uses crop planting patterns measured just prior to 1930 to estimate crop-specific Dust Bowl exposure. The advantage to this strategy is that these planting patterns were pre-determined with respect to the environmental shock. The potential disadvantage is that, if crop planting patterns shifted in a major way in response to the Dust Bowl, or for any other reason during the subsequent decades, crop-specific Dust Bowl exposure could be mis-measured during the later part of the sample period.

[14] The data were cleaned and harmonized following Hornbeck (2012a).

However, crop allocations were remarkably persistent throughout the sample period (see Appendix D); the correlation between crop-by-county planted area in 1930 and 1960 is very close to one and the relationship is not mediated by county-level erosion or crop-level aggregate Dust Bowl exposure. This is consistent with narrative accounts of strong inter-generational persistence in crop specialization on the Plains, as well as the substantial importance of crop-specific human capital (e.g. Schaper, 2012; Huffman, 2001).

4 The Direction of Innovation

4.1 Estimation Framework

This section estimates the impact of the Dust Bowl on the direction of innovation. The main estimating equation is:

$$y_{ct} = \alpha_c + \gamma_t + \beta \cdot \text{Exposure}_c \cdot \mathbb{I}_t^{\text{Post 1930}} + \Gamma X'_{ct} + \epsilon_{it} \tag{4.1}$$

where c indexes crops and t indexes years. The independent variable of interest is an interaction term between crop-level exposure to the Dust Bowl (Exposure_c), and an indicator that equals one in all years after the start of the Dust Bowl in 1930 ($\mathbb{I}_t^{\text{Post 1930}}$). All specifications also include crop and year fixed effects, α_c and γ_t, and I test the sensitivity of the results to the inclusion of a vector of time-varying controls, X'_{ct}. The outcome variable is the number of new crop variety releases for crop c in year t.

The coefficient of interest is β. $\beta > 0$ implies that variety innovation was directed toward crops that were more damaged by the Dust Bowl, whereas $\beta < 0$ implies that variety innovation was directed away from crops that were more damaged by the Dust Bowl. Section 2.2 articulates why either sign is theoretically possible.

In order to investigate the dynamic relationship between Dust Bowl Exposure and innovation, as well as explore pre-existing trends in technology development, I also present results from the following estimating equation:

$$y_{ct} = \alpha_c + \delta_t + \sum_{\tau \in \mathcal{T}^{pre}} \beta_\tau \cdot \text{Exposure}_c \cdot \delta_\tau + \sum_{\tau \in \mathcal{T}^{post}} \beta_\tau \cdot \text{Exposure}_c \cdot \delta_\tau + \epsilon_{ct} \tag{4.2}$$

If differentially exposed crops are on similar trends prior to the Dust Bowl, then when

Table 1: Dust Bowl Exposure and New Crop Varieties

	(1)	(2)	(3)	(4)
Dependent Variable:	New Varieties (asinh)		New Varieties (count)	
Specification:	OLS	OLS	Poisson	Neg. Bin.
$\text{Exposure}_c \times \mathbb{1}_t^{\text{Post 1930}}$	0.0694***	0.114***	0.0750***	0.0529**
	(0.0244)	(0.0278)	(0.0283)	(0.0230)
Crop Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Weighting	None	Initial Area	None	None
Crops	43	43	43	43
Observations	1,720	1,720	1,720	1,720
R-squared	0.663	0.828		

Notes: The unit of observation is a crop-year. All specifications include crop and year fixed effects. In columns 1-2 the outcome variable is the inverse hyperbolic sine of the number of new varieties in each crop-year and in columns 3-4 it is the number of new varieties. Columns 1-2 report OLS estimates and columns 3-4 report Poisson and negative binomial estimates respectively. Standard errors, double clustered by crop and year in columns 1-3 and clustered by crop in column 4, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

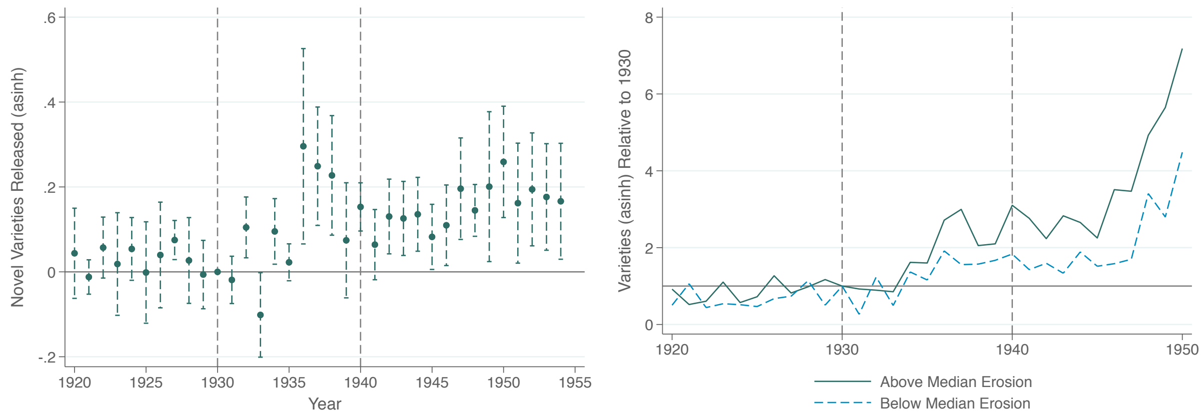
$\tau \in \mathcal{T}^{pre}$, β_τ should not be statistically distinguishable from zero. When $\tau \in \mathcal{T}^{post}$, the β_τ identify the effect of Dust Bowl exposure on innovation in year τ.

4.2 Main Results

Estimates of Equation 4.1 are presented in Table 1. Columns 1-2 report OLS estimates and the outcome variable is the (inverse hyperbolic since of the) number of new agricultural varieties released for each crop in each year.[15] In column 1, the regression is unweighted, and in column 2, the regression is weighted by the total area on which each crop was planted in 1929 in order to make sure that the finding in column 1 is not driven by crops that are a small share of national agricultural production.[16] Since the dependent variable

[15]I use the inverse hyperbolic sine transformation of the outcome instead of the log transformation because there are several zeroes. The results are very similar if instead I parameterize the outcome as log(1+x).

[16]The results are also not driven only by "large" crops (that is, crops with a large market size). In Table A4, I repeat the baseline specification after excluding in the top 25% or crops in the top 50% of the pre-period area distribution, and find very similar estimates. These findings indicate that the baseline result is



(a) Event Study

(b) Raw Data Trend

Figure 1: Figure 1a reports coefficient estimates from 4.2, and 95% confidence intervals are displayed. The dotted gray lines mark the decade during which the Dust Bowl took place. Standard errors are double-clustered by crop and year. Figure 1b displays new varieties (asinh) released, relative to 1930, for crops with above median (solid line) and below median (dotted line) Dust Bowl exposure.

is a count variable, columns 3-4 report estimates using Poisson and negative binomial regression models respectively.[17] Across columns, the coefficient of interest is positive and statistically signifiant, suggesting that the development of new plant varieties was directed *toward* crops most affected by the Dust Bowl. Estimates from columns 1 and 2 imply that a one standard deviation increase in Dust Bowl exposure led to a 0.18 and 0.32 standard deviation increase in new varieties respectively.

Figure 1a displays coefficient estimates from Equation 4.2. Prior to 1930, more- and less-exposed crops were on very similar trends—the coefficient estimates are all similar and close to zero. During the mid-1930s, the coefficient estimates become positive and significant. Figure 1b reports the same pattern in the raw data; it displays the number of new crop varieties released in each year (relative to 1930), plotted separately for crops with above and below median Dust Bowl exposure. During the worst years of the Dust Bowl, innovation in more vs. less exposed crops sharply diverged, and the shift in the direction of technology development persisted even after the worst years of the Dust

not driven by just a handful of large crops.

[17]Whenever Poisson estimates are reported, I use pseudo-maximum likelihood estimators in order to ensure appropriate standard error coverage; see Wooldridge (1999).

Bowl were over. The following subsections investigate the robustness of this baseline finding, before turning to a detailed analysis of underlying mechanisms.

Falsification Tests This section presents two falsification exercises designed to validate the measure of Dust Bowl exposure and causal interpretation of the results. First, I compute a crop-level measure of erosion exposure *outside* of the Plains region:

$$\text{Exposure Outside Plains}_c = \sum_i \frac{L_{ic}}{\sum_{i'} L_{i'c}} \cdot \mathbb{I}\{\text{Not Plains}_i\} \cdot \text{High Erosion}_i \tag{4.3}$$

If the baseline findings are driven the onset of the Dust Bowl, cumulative erosion *outside* the Plains region, which was not as closely associated with extreme weather from the 1930s, should have no effect on technology development. In column 1 of Table A3, I control directly for this placebo measure in the baseline specification; the placebo coefficient is close to zero, while the coefficient of interest remains positive and significant. The baseline estimates do not capture the effect of cumulative erosion or poor land management.

Next, I compute a second placebo measure that weights crop land area in each Plains county by the share of each Plains county that had *low* levels of erosion:

$$\text{Low Exposure}_c = \sum_i \frac{L_{ic}}{\sum_{i'} L_{i'c}} \cdot \mathbb{I}\{\text{Plains}_i\} \cdot \text{Low Erosion}_i \tag{4.4}$$

In column 2 of Table A3, I control directly for this second placebo measure, and again the coefficient on the placebo measure is close to zero. This finding indicates that the main results do not capture a re-direction of technology toward Plains crops *in general*, but rather towards the specific crops that were more damaged by the environmental distress.

Last, I compare the estimated effect of crop-level exposure to *high* levels of erosion to the effect of crop-level exposure to *medium* levels of erosion; this is the crop-level analog of the triple-difference identification strategy in Hornbeck (2012a). Crop-level exposure to medium levels of erosion is estimated as in (4.4), except low erosion is replaced with medium erosion. Table A9 documents that, while the impact of medium erosion exposure is positive, the estimated impact of high erosion exposure is larger in magnitude and the difference is statistically significant. These findings further support the argument that environmental damage was the cause of technology development.

Controlling for Observables I next investigate the robustness of the baseline finding to controlling for a series of potential confounders; these results are presented in columns 4-8 of Table A3. First, I control for "crop-specific trends" in pre-period biotechnology releases, meaning that I include pre-period biotechnology releases at the crop-level interacted with a full set of year fixed effects on the right-hand-side of the regression. This set of controls is designed to flexibly account for potential underlying dynamic effects of the level of innovation (column 4). Next, I investigate the role of New Deal policy. The only program that had a crop-specific component was the 1933 Agricultural Adjustment Act (AAA), which paid farmers to not plant certain crops; the program was initiated prior to the worst years of the Dust Bowl and before the extent and distribution of its damage was known. Nevertheless, in column 5 I control for crop-specific trends in an AAA inclusion indicator. The sample period also intersects with the Great Depression and World War II; while it is hard to imagine why this effect would differ *across crops*, in column 6 I control for Dust Bowl exposure interacted with an indicator that equals one during the years of the Depression (1929-1939) and an indicator that equals one during the years of US involvement in World War II (1941-1945).

A remaining potential confound is the growth in development of hybrid crop varieties during the early 20th century. This is only an empirical concern if the *ex ante* ease of hybrid development were correlated with Dust Bowl exposure. While hybrid seed development is endogenous, following Moscona (2021) I identify crops for which hybrid development would have been feasible based on features of plant flower structure that facilitate hybrid development.[18] I then control directly for this hybrid indicator interacted with a full set of year fixed effects (column 7). In column 8, I include all controls mentioned thus far on the right hand side. Despite the stringency of the specification with the inclusion of 176 controls, the result remains similar.

Finally, if certain crops are disproportionately grown in certain states, and those states are on separate trends, it may also bias the results. To address this, in Table A2, I control directly for the share of each crop's planted area located in each of a series of states. The

[18]In particular, if a crop has "perfect flowers"—both the male and female parts of the plant are in the center of the same flower—it is painstakingly difficult or impossible to generate new hybrids by combining genetic material from multiple plants. This is not the case if a crop has "imperfect flowers"—when male and female reproductive material are on different parts of the plant (e.g. Wright, 1980; Butler and Marion, 1985). In Moscona (2021), I collect data on the flower structure of each crop and use this information to construct the hybrid control variable here.

coefficient of interest is very similar across specifications.

Instrumental Variables Estimates Next, I show that the results are also very similar using exogenous weather shocks from the 1930s to construct instruments for Dust Bowl exposure. This strategy isolates the variation in cumulative erosion measured in the reconnaissance surveys that took place during the 1930s, thereby circumventing the issue that any finding is driven by pre-existing patterns of topsoil damage or topsoil damage due to human behavior. I construct crop-level measures of weather severity from the 1930s by aggregating county-level weather data from Vose et al. (2014) using Equation 3.1. As measures of local weather severity, I use the standard deviation of local temperature, the Palmer drought index, and indicators for extreme quantiles of the Palmer drought index. I then use these measures of crop-level severity as instruments for topsoil erosion, and generate 2SLS estimates of the impact of erosion on innovation.

2SLS estimates of Equation 4.1 are very similar in magnitude to the baseline difference-in-differences estimates (albeit somewhat less precise); they are reported in columns 1-3 of Table A8. In column 1, the instruments are the number of months of extreme and severe drought per acre interacted with post-period indicators. In column 2, they are the average Palmer drought index and temperature standard deviation interacted with post-period indicators. In column 3, all four extreme weather estimates are included in the instrument set. As in the baseline results, estimates from specifications weighted by pre-period area are also reported; these are larger in magnitude and more precisely estimated.

4.3 Mechanisms

4.3.1 The Role of Hybrids

Qualitative evidence suggests that the innovative response to the Dust Bowl was driven especially by the development of hybrid crop varieties, and particularly those for corn, which were more resilient in the face of extreme drought and erosion (e.g. Sutch, 2008; Meyers and Rhode, 2020, also see Section 2.1). Hybrid development began with corn during the 1920s, but was extended to several other crops in subsequent years; however, the heterogeneity in hybrid penetration was substantial, with certain major crops, like wheat, experiencing virtually no hybrid development. While I am unaware of data on the development of hybrid varieties compared to non-hybrid varieties during the sample period, it is possible to test whether the results are more pronounced for crops from which it was easier to generate hybrids. I again identify all crops that have "imperfect flowers," which makes the development of hybrids substantially easier, as a fixed crop-level proxy for the feasibility of hybrid development (e.g. Wright, 1980; Butler and Marion, 1985). Interpreted through the lens of the model, these are the crops for which new technology is most strongly a substitute for distressed land (i.e. $G_{12} < 0$), since hybrids were, anecdotally, "strikingly more resistant" in the face of drought and environmental degradation (Crow, 1998). I then estimate an augmented version of (4.1) in which I interact the treatment variable with an imperfect flower indicator.

Table A5 reports estimates from this specification. While a positive and significant effect remains for "hybrid-incompatible" crops, suggesting that the baseline results are not solely driven by hybrid development, the response was significantly larger for hybrid compatible crops (column 1). The result is similar after adding the full set of baseline controls (column 2). These findings suggest that hybrid variety development played a particularly important role in the innovative response, and are consistent with the re-direction of technology being driven by growing demand for topsoil-substituting technologies (see Proposition 1), rather than general equilibrium effects, which do not likely differ *ex ante* across crops that are and are not amenable to hybrid development.

4.3.2 Effects by Technology Class

In addition to shifting focus across crops, technology development may have also redirected toward technologies that are most useful for adapting to environmental change. The theory predicts that while "topsoil substituting" technology should increase following the Dust Bowl—and the first set of findings document this pattern in the case of biotechnology—the effect could differ drastically across technology classes, and even reverse sign for technology classes that are, on average, "topsoil complementing."

While variety development is the focus of most analyses of adaptation to the Dust Bowl (e.g. Crabb, 1947; Crow, 1998), damage to soil nutrition and the pest outbreaks that resulted from drought made chemical, planting, and soil conservation technology potentially more valuable as well (e.g. Schlebecker, 1953; Baveye et al., 2011). Most harvest and post-harvest machines, however, do not interact as clearly with the climate or land directly, and likely played a more limited role in bolstering production resilience. Innovators may have directed attention *away* from developing technologies that did not directly compensate for lost topsoil and worsening land conditions.[19]

To investigate the effect of the Dust Bowl on innovation across different types of technology, I turn to the patent data. I use the cooperative patent classification (CPC) of each patent to determine which relate to biochemical and planting technologies—those that are most plausibly "topsoil substituting"—and which relate to mechanical harvesting and post-harvest technology—those that are least likely to interact with the environment.[20]

I then compare the impact of the Dust Bowl on technology development across different technology classes using the following specification:

$$y_{xct} = \alpha_{cx} + \delta_{tx} + \gamma_{ct} + \psi \cdot \text{Exposure}_c \cdot \mathbb{I}_t^{\text{Post 1930}} \cdot \mathbb{I}_x^{\text{S}} + \epsilon_{kct} \tag{4.5}$$

where x indexes technology classes, c indexes crops, and t indexes years. The independent variable of interest is a triple interaction between (a) crop-specific Dust Bowl exposure, (b) an indicator that equals one in all years after 1930, and (c) and indicator that equals one if a technology class is in the more topsoil-substituting category. The coefficient of interest is ψ. If $\psi > 0$, crops that were more damaged by the Dust Bowl experienced a disproportionate increase in the more plausibly topsoil-substituting technology class. All specifications include the full set of possible two-way fixed effects, including crop-by-year fixed effects which capture any crop-level dynamics (e.g. price changes).

Table 2 reports estimates of Equation 4.5 for a series of potential cross-technology comparisons. Column 1 compares variety development to all patented technologies, which does not include any biotechnology during the sample period, and column 2 compares variety development directly to harvesting and post-harvest mechanical patents. In both

[19] This is true in the version of the model with fixed prices; if prices are allowed to adjust, then the effect of topsoil damage on *topsoil complementing* technology is ambiguous.

[20] I identify patents in CPC classes A01H and A01N as biochemical technologies. A01H and A01N include technologies corresponding to: new plants or processes for obtaining them, and plant reproduction by tissue culture techniques; and biocides e.g. as disinfectants, as pesticides, as pest repellant or attractants, plant growth regulators. I identify patents in CPC classes A01D, A01F, and A01G as mechanical harvest and post-harvest technologies. A01D, A01F, and A01G include technologies corresponding to: harvesting and mowing; processing of harvested produce, hay or straw presses, devices for storing agricultural or horticultural produce; horticulture, cultivation of vegetables, flowers, rice, fruit, hops, or seaweed, forestry, watering. Finally, I identify planting patents as those belonging to A01B and A01C. A01B and A01C include technologies corresponding to: soil working in agriculture or forestry and parts, details, or accessories of agricultural machines or implements; fertilizing, planting, and sowing.

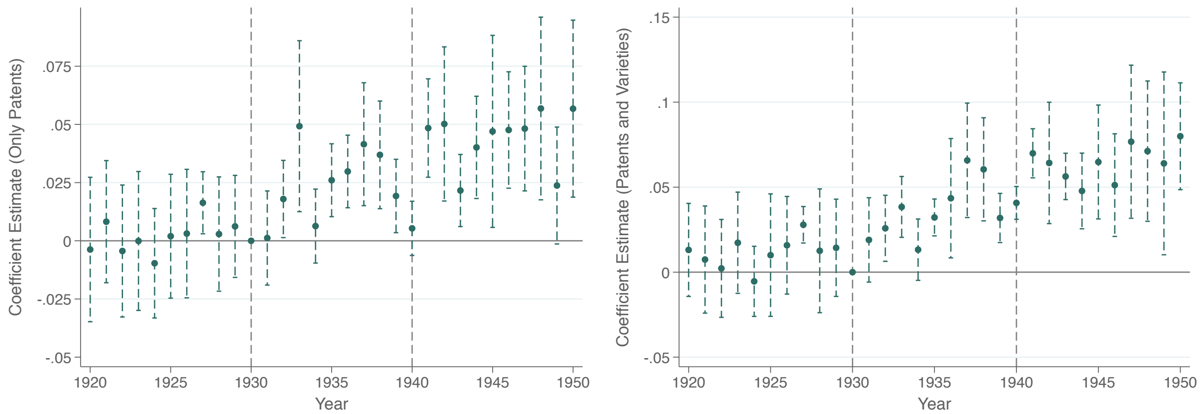
Table 2: Dust Bowl Exposure and Innovation Across Crops and Technology Classes

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable is the Number of Innovations in the Crop-Year-Class Bin (asinh)					
More topsoil-*substituting* class(es)	Varieties	Varieties	Bio-Chemical + Planting Patents	Bio-Chemical Patents	Bio-Chemical + Planting Patents + Varieties	Bio-Chemical Patents + Varieties
More topsoil-*complementing* class(es)	All Patent Classes	Mechanical Harvest + Post-Harvest Patents	Mechanical Harvest + Post-Harvest Patents	Mechanical Harvest + Post-Harvest Patents	Mechanical Harvest + Post-Harvest Patents	Mechanical Harvest + Post-Harvest Patents
$\text{Exposure}_c \times \mathbb{1}_t^{\text{Post 1930}} \times \mathbb{1}_k^S$	0.0733***	0.0823***	0.0187***	0.0389**	0.0314***	0.0534**
	(0.0264)	(0.0283)	(0.00673)	(0.0183)	(0.0105)	(0.0210)
Initial area weighted estimates:						
$\text{Exposure}_c \times \mathbb{1}_t^{\text{Post 1930}} \times \mathbb{1}_k^S$	0.138***	0.148***	0.0283***	0.0830***	0.0523***	0.105***
	(0.0342)	(0.0359)	(0.00848)	(0.0259)	(0.0133)	(0.0284)
Crop x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Crop x Technology Class Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year x Technology Class Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Crops	43	43	43	43	43	43
Observations	15,867	7,052	12,341	8,815	14,104	10,578
R-squared	0.725	0.785	0.682	0.719	0.726	0.752

Notes: The unit of observation is a crop-year-technology class. All specifications include crop-by-year fixed effects, crop-by-technology class fixed effects, and year-by-technology class fixed effects. The outcome variable is the inverse hyperbolic sine of the number of new innovations, either patents or new varieties, in a crop-year-class bin. Estimates of the coefficient of interest from analogous specifications in which the regression is weighted by each crop's initial area are also reported. Standard errors, double clustered by crop and year, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

cases, technology development in more Dust Bowl-exposed crops is directed disproportionately toward crop varieties ($\psi > 0$). Columns 3 and 4 focus on the patent data alone, and compare biochemical and planting patents to harvesting and post-harvest mechanical patents (column 3) or biochemical patents alone to harvesting and post-harvest mechanical patents (column 4). Again, technology development is directed disproportionately toward the technologies that more plausibly interact with the environment and could increase resilience. Columns 5-6 are identical to columns 3-4, except new varieties are included among the topsoil-substituting technologies; the estimates are similar.

These triple-difference results are driven by *both* an absolute increase in biochemical and planting patenting in crops more-exposed to the Dust Bowl, and an absolute decline in mechanical harvest and post-harvest patenting in crops more-exposed to the Dust Bowl



(a) BioChem & Planting vs. Mech. Patents

(b) BioChem & Planting & Varieties vs. Mech. Patents

Figure 2: **Dust Bowl Exposure and Innovation Across Technologies.** The outcome variable is the inverse hyperbolic sine of the number of patents or unique crop varieties in a crop-by-technology class bin. Standard errors are double-clustered by crop and year. The dashed lines are 95% confidence intervals.

(Table A7). Analogous to the baseline findings, Table A8 shows that the cross-technology results are similar if crop-level Dust Bowl exposure is instrumented using contemporaneous weather shocks. Finally, all estimates using the patent data are also similar using citation-weighted patenting as the dependent variable, indicating that the findings are not driven by insubstantial discoveries (Table A10).

Figure 2 presents the results graphically over time, using a dynamic triple-differences specification; the two figures correspond to the specifications from columns 4 and 6 of Table 2 respectively. Prior to 1930 there is differences in innovation trends across crop-by-technology bins. A stark difference emerges only at the height of the Dust Bowl, when technological progress in more damaged crops shifted toward biochemical and planting technologies. Mirroring the baseline results, the effect persists over time, further indicating that the Dust Bowl precipitated a long-run shift in the focus of innovation.

There are two key conclusions from this set of results. First, methodologically, the significant findings after the inclusion of crop-by-time fixed effects in all estimates of Equation 4.5 further suggests that the baseline results were not driven by any crop-level unobservable characteristics. Second, more conceptually and dovetailing with the findings in Section 4.3.1, these estimates are consistent with a narrative in which the re-direction of innovation was driven by demand for technology that would directly increase production resilience. The positive response of innovation is concentrated in technologies that could have directly bolstered production on damaged land, and innovation shifted away from technologies that do not interact directly with the environment. A major role for general equilibrium effects is inconsistent with the distinct effects across technology classes, and especially the absolute decline in mechanical innovation related to crops exposed to the Dust Bowl, which also would have been subject to positive price incentives.

4.3.3 Sources of Re-Direction of Innovation

This section investigates the source of the re-direction of innovation in response to the Dust Bowl. While the public sector played—and continues to play—an important role in US agricultural research, the 1930s have been identified as a turning point when private sector firms also began to play an active role. These emergent firms and private breeders feature prominently in historical accounts of Dust Bowl induced innovation (see Section 2.1). The *Variety Name List* does not contain information on the entity that released each variety, so I turn to the additional data sets to identify the source of new innovation.

The patent data from the sample period contained assignee information that makes it possible to identify where each technology comes from. I first classify each patent as belonging to a private sector firm if the assignee name contained any one of a series of words or word fragments associated with private sector firms.[21] Columns 1-2 of Table A11 report estimates of Equation 4.5 that include only patents assigned to private sector firms. The coefficient estimate is positive and significant (column 1), somewhat larger in magnitude when weighted by initial land area (column 2), and similar in magnitude to the analogous estimate using the full sample of patents (column 3 of Table 2).

In columns 3-4, I report analogous specifications except the the dependent variable is patents assigned to colleges, universities, and government institutions.[22] While the coefficient estimates are both positive, they are smaller in magnitude than the previous estimates and indistinguishable from zero. This indicates that the main findings do not

[21] The words are: company, corporation, LTD, INC, CO., industries, limited, CORP., PLC, and LLC. This procedure identifies 33% of the patents in the sample; while this likely does not capture *all* firms, it seems unlikely that this procedure would falsely identify a patent as belonging to a private firm and thus findings estimated on this sample of patents should still be an indication of private sector innovative activity.

[22] Again, I identify these patents using a keyword search of the patent assignees. The words are: university, college, institute, government, state, federal, research station, experiment station, usda.

seem to be driven by public sector patenting. Finally, many patents were not linked to either private sector firms of the public sector using the text analysis strategy; these patents are predominately assigned to individual breeders or have missing assignee information in the patent record. When the dependent variable is constructed from these patents, I estimate $\psi = 0.29$ $(p < 0.1)$, suggesting that individual breeders also played a role.

In order to analyze government research in greater detail, I turn to independently collected data on experiments conducted on US federal experiment stations during the sample period, originally compiled by Kantor and Whalley (2019), and identify the crop that was the focus of each experiment. Panel A of Table A12 reports estimates of Equation 4.1 in which the dependent variable captures the number of experiments related to each crop. In column 1-2 of Panel A, the outcome is the (inverse hyperbolic sine of the) number of unique experiments, and in columns 3-4 it is an indicator that equals one if there was at least one experiment. Panel B is identical to Panel A, except that the outcome variables measure experiments only in stations located in Dust Bowl states (Figure A1), which might be more likely to shift focus in response to the Dust Bowl. The coefficients of interest are all small and statistically indistinguishable from zero, further indicating that the baseline result is not driven by government research.

One explanation for the limited response of federal research, even though experiment stations were aware of production challenges posed by the Dust Bowl, is that federal researchers focused their attention on documenting the value of production adjustment (Stephens, 1937). Experiment station researchers published on the benefits of shifting land from cropland to pasture, and on the resilience of hay production (compared to wheat) on dry and eroded land (Nelson et al., 1940; Wenger, 1941). However, as documented in Hornbeck (2012a) and Appendix D of the present study, despite their potential benefits, these types of production adjustments were limited in practice, even in the most distressed counties. Experiment stations were also instructed to focus on basic, rather than applied, research and to "not simply focu[s] research on solving local problems" (Nevins, 1962; Kantor and Whalley, 2019). While basic research may underly the development of environmentally resistant technology, and private researchers no doubt built on discoveries first made in experiment stations (Kantor and Whalley, 2019), basic research may be less responsive to shifting technological demand and operate over longer time horizons.

4.3.4 Persistence

While biotechnology development was directed toward Dust Bowl exposed crops starting at the height of the Dust Bowl, the effect persisted after the Dust Bowl ended (Figure 1a). There are several potential explanations for this. First, while the period of extreme weather and dust storms largely concluded in 1939, the effect on land quality persisted, and much of the land never recovered its topsoil (e.g. Worster, 2004, p. 24). Once damaged, topsoil often takes over 100 years to re-generate (United States Department of Agriculture, n.d.). Farming on land exposed to the Dust Bowl thus remained challenging and demand for technologies that increased resilience could have remained high.

Another explanation for the persistent effect, however, is that the growth in demand for crop-specific innovation during the Dust Bowl allowed breeders to invest in the fixed cost of setting up breeding and research programs. Programs that were first financed and set up during the Dust Bowl continued to operate after the 1930s; crops that were not exposed to the Dust Bowl, however, did not experience the same boost. In the words of Sutch (2011), "climate change was a tipping point" and higher sales during the 1930s "financed research at private seed companies that led to new varieties with significantly improved yields in normal years." Moreover, there is growing evidence from other contexts that short-term changes in research investment can have lasting effects on innovation (e.g. Gross and Sampat, 2020, on public investment during WWII).

To investigate this channel, I estimate the short and long run effects of Dust Bowl exposure separately and examine heterogeneity by the amount of pre-period innovation in each crop. If the long run effect of the Dust Bowl on innovation is driven by the payment of breeding fixed costs for crops with limited pre-existing innovative infrastructure, then it should be larger for crops with more limited breeding before 1930. This is exactly what the results presented in Table A6 suggest. During the 1930s the innovative response is, if anything, more pronounced for crops with *more* pre-period innovation; this is intuitive, since these crops have more developed research programs that could respond to the onset of environmental distress. However, during the 1940s and 1950s, the effect of Dust Bowl exposure is weaker for crops with more pre-period innovation. Thus, the long run effect of the Dust Bowl on variety development is driven by crops with limited pre-existing innovative activity, consistent with the idea that the Dust Bowl led to fixed cost breeding investment that had long run consequences for crop-specific variety development.

4.3.5 Direction of Science

To this point, the results have focused on technology development, in the form of new seed varieties and patents. Next, I investigate whether scientific research also shifted in response to the Dust Bowl. A change in the focus of science itself could contribute to the adaptation process, as well as underly the long run shift in the direction of subsequent technology development. To measure crop-specific scientific production, I turn to the Institute for Scientific Information's *Web of Science* research article and citation database. I use all articles published from 1925-1960 in the "Agricultural Sciences" research category and match articles to individual crops by searching for each crop name in all article titles.[23] To investigate the impact of the Dust Bowl on scientific output, I estimate Equation 4.1 with measures of scientific publication as the dependent variables.

In the first column of Table A13, the dependent variable is the (inverse hyperbolic sine transformation of the) number of research articles, and the coefficient of interest is positive and significant. In the second column, the dependent variable is an indicator that equals one if any articles were published related to crop c in year t, and again the coefficient of interest is positive and statistically significant, indicating that the findings are not driven by observations with an extreme number of articles. Finally, in column 3 the dependent variable is the citation-weighted number of articles, and the coefficient estimate is similar to column 1, indicating that the main effect is not driven by low-quality research.

Together, these findings suggest that the Dust Bowl catastrophe shifted not only the development of new technology, but also the focus of knowledge production "upstream" from technology development, indicating that scientists can also be responsive to environmental change and a potentially important part of the adaptation process.

5 Innovation and Adaptation

Did the major shift in the direction of technology in response to the Dust Bowl shape its economic consequences? This section investigates the role of innovation in mitigating the Dust Bowl's economic harm.

[23] Article abstracts are not available for the vast majority of articles during the sample period, and are not available for any articles during the pre-period in the difference-in-differences design.

5.1 Empirical Strategy

Measurement I first construct a measure of the extent to which each county was exposed to Dust Bowl-induced technology development. Counties that cultivated crops more exposed to the Dust Bowl *on average* were the beneficiaries of more induced innovation (Section 4). Therefore, if innovation mitigated the Dust Bowl's economic harm, the direct county-level effect of Dust Bowl exposure should be dampened for counties that grew crops that were more damaged across all other Plains counties, and hence the recipient of more induced innovation.

For example, consider two counties in Colorado that both experienced the same land erosion during the Dust Bowl One of these counties, however, grew predominantly sorghum, which experienced the highest aggregate damage from the Dust Bowl; the other grew soybeans, which was much less exposed to the Dust Bowl. Since innovation responded to national crop-level damage, more sorghum-related innovations than soybean-related innovations were developed in the Dust Bowl's aftermath. If new technology increased resilience to the Dust Bowl, the sorghum growing county should experience a more limited decline in profits following the Dust Bowl than the soybean growing county, even though the direct effect of the Dust Bowl was identical. The reason, put simply, is that a farmer with eroded land who grew sorghum had a lot of new technology to work with; a farmer with eroded land who grew soybeans did not.

Following this logic, I proxy the innovation exposure of county i as:

$$\text{InnovationExposure}_i = \sum_c \left(\frac{L_{ic}}{L_i} \cdot \frac{\sum_{j \neq i} \text{ErodedLand}_{jc}}{\sum_{j \neq i} \text{Area}_{jc}} \right) \tag{5.1}$$

where L_{ic} is the amount of land devoted to crop c in county i in 1929 and ErodedLand_{jc} is defined in Section 3.2. Rather than use the crop-level exposure measure from the previous part of the paper, I compute a "leave-out" measure that excludes the county in question. Thus, the variable $\text{InnovationExposure}_i$ captures the extent to which the crops that county i grows were damaged across all other Plains counties and hence the county's exposure to Dust Bowl-induced technology.

Estimation To investigate the role of induced innovation in mitigating the economic harm of the Dust Bowl, I estimate versions of the following equation:

$$\begin{aligned} y_{it} =& \alpha_i + \delta_{st} + \beta \cdot \left(\text{Erosion}_i \cdot \mathbb{I}_t^{\text{Post 1930}}\right) + \gamma \cdot \left(\text{InnovationExposure}_i \cdot \mathbb{I}_t^{\text{Post 1930}}\right) + \\ & \phi \cdot \left(\text{Erosion}_i \cdot \mathbb{I}_t^{\text{Post 1930}} \cdot \text{InnovationExposure}_i\right) + X_{it}'\Gamma + \epsilon_{it} \end{aligned} \tag{5.2}$$

where i indexes counties, t indexes census rounds, and s indexes states. The primary dependent variable is the agricultural land price per acre, measured from the Census of Agriculture for each county i in year t, which captures the net present value of profits from agricultural production; unlike measures of physical productivity, it incorporates the benefits of new technology alongside its potentially higher cost. All specifications include county and state-by-census round fixed effects (α_i and δ_{st} respectively), and I document the robustness of the estimates to the inclusion of a range of controls, X_{it}'.

The coefficients of interest are β and ϕ. β captures the direct effect of Dust Bowl erosion on county-level land values and other features of production, as documented extensively by Hornbeck (2012a). The clear hypothesis is that $\beta < 0$. ϕ captures the extent to which the economic impact of Dust Bowl erosion is shaped by exposure to Dust Bowl-induced innovation. If innovation mitigated damage from the Dust Bowl, we expect $\phi > 0$. This would imply that the marginal impact of Dust Bowl erosion is dampened in counties that were more exposed to induced innovation.

5.2 Main Results

Table 3 presents long difference estimates of Equation 5.2.[24] In column 1, the outcome variable is (log of) the value of land and buildings per acre. While β is negative and significant, I find that $\phi > 0$, consistent with technology development mitigating the negative effect of the Dust Bowl on the value of land and buildings.[25] The results are

[24] The pre-period and post-period year for the long difference estimates switch slightly due to data availability. In columns 1, 3, and 4, they are 1920 and 1959 respectively and in column 2 they are 1920 and 1940. While the baseline results report long difference estimates since technology development is a long-term process, full panel estimates are qualitatively similar and intuitively smaller in magnitude (Table A16).

[25] I document that the precision of the baseline estimates is very similar after adjusting the standard errors for spatial correlation. Table A14 reports the t-statistic for ϕ using Hsiang (2010)'s implementation of Conley (1999) standard errors for a series of spatial kernel cut-off values, ranging from 200km to 1000km. It also shows that the precision is similar double clustering by state-year and county or clustering by state.

Table 3: Innovation and Adaptation to the Dust Bowl: County-Level Estimates

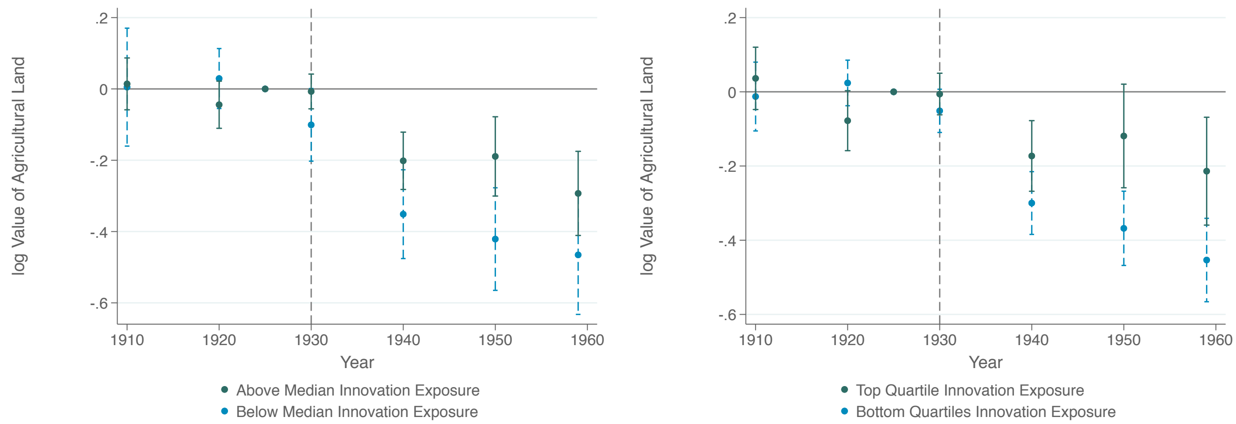
	(1)	(2)	(3)	(4)
Dependent Variable:	log Value of Land and Buildings per Acre	log Value of Land per Acre	log Total Revenue	log Total Revenue per Acre
$\text{Erosion}_i \times \mathbb{1}_t^{\text{Post 1930}}$	-1.416***	-0.964***	-1.660***	-1.265***
	(0.441)	(0.317)	(0.530)	(0.474)
$\text{Erosion}_i \times \mathbb{1}_t^{\text{Post 1930}} \times \text{InnovationExposure}_i$	11.99**	7.931**	15.25**	11.42**
	(5.160)	(3.745)	(6.231)	(5.555)
County Fixed Effects	Yes	Yes	Yes	Yes
Census Round x State Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,592	1,592	1,592	1,592
R-squared	0.949	0.974	0.881	0.922

Notes: The unit of observation is a county-year. All estimates are from long differences specifications; the starting year is either 1920 or 1925 and ending year either 1940 or 1959, depending on data availability. The sample of counties was selected as in Hornbeck (2012). All specifications include county fixed effects and census round-by-state fixed effects. The dependent variable is listed at the top of each column. Standard errors, clustered by county, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

similar in column 2, when the outcome variable is the (log of the) value of land per acre, or when the outcome variable is (log of) in-sample agricultural revenue (column 3) or agricultural revenue per acre (column 4).

Figure 3 displays the dynamic relationship between Dust Bowl exposure and the value of agricultural land, separately for counties with high and low innovation exposure. In Figure 3a, high innovation exposure is defined as counties above the in-sample median and in Figure 3b it is defined as counties in the top quartile. Prior to 1930, in both the high and low innovation-exposed groups, counties that were more exposed to the Dust Bowl are on similar trends to ones less exposed to the Dust Bowl. Land values decline for more Dust Bowl exposed counties in both groups after 1930; however, the decline is significantly dampened in counties with higher levels of innovation exposure. Innovation exposure mitigates Dust Bowl damage starting in 1940—consistent with a strong response of new technology during the 1930s (Figure 1a)—after which land values in more and less innovation exposed counties appear to evolve on parallel trends.

The main threat to the interpretation of estimates of (5.2) is that innovation exposure may be correlated with changes in crop prices. Since all estimates control for the direct



(a) Above vs. Below Median Innovation Exposure (b) Top vs. Bottom Quartiles Innovation Exposure

Figure 3: **Innovation Exposure and Land Values: Dynamic Effects.** Estimates of the relationship between county-level Dust Bowl exposure and log of the value of agricultural land in each decade, separately by innovation exposure. In Figure 3a, the effects are estimated separately for counties above and below median in-sample innovation exposure. In Figure 3b, the effects are estimated separately for counties in the top quartile and counties in the bottom three quartiles of the in-sample innovation exposure distribution. 95% confidence intervals are reported.

effect of innovation exposure (captured by γ), estimates of ϕ are only biased if price effects have a non-log-linear effect on agricultural profits. Stated differently, the empirical model captures the direct effect of innovation exposure on prices and hence the value of land; estimates of ϕ are biased only if price effects have a larger effect on profits in counties that were more exposed to the Dust Bowl. Nevertheless, to ameliorate these concerns, I compile data on crop-specific producer prices from the USDA and estimate the output price bundle in county i in year t:

$$\text{Output Price}_{it} = \sum_{c} \frac{L_{ic}}{L_i} \cdot \log(\text{Producer Price}_{ct})$$

where Producer Price_{ct} is the national producer price for crop c in year t.[26] I then control directly for county-level changes in output prices, as well as the interaction between

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

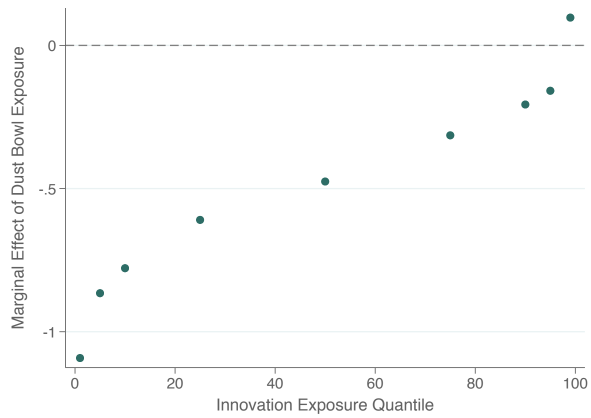


Figure 4: **Quantitative Impact of Directed Technology.** The points display the marginal impact of Dust Bowl exposure (y-axis) by innovation exposure quantile (x-axis).

changes in output prices and Dust Bowl exposure. Estimates with these controls are reported in Table A15 and, if anything, the coefficient estimates are slightly larger than the baseline estimates, making it unlikely that that producer prices drive the relationship between innovation exposure and agricultural production.

In Appendix E, I discuss additional results that further probe the sensitivity and causal interpretation of the county-level estimates. These include replicating the findings using the full panel of census rounds, rather than long difference estimates (Table A16); re-producing all estimates without state-by-time fixed effects (Table A17); controlling directly for county-level government spending, including spending from a series of New Deal programs (Table A18); and purging the effect of local spillovers by estimating a version of innovation exposure that excludes any variation in crop distress that occurs in other counties in the same state (Table A19). I also document that the results hold comparing the marginal effect of exposure to medium and high levels of erosion and the corresponding measures for innovation exposure (Table A20). Dovetailing with the analogous crop-level estimates, this is consistent with a causal effect of innovation exposure on adaptation. Finally, I show that the results are driven by counties with larger farms on average which, as discussed in Appendix E, further rules out out the possibility that the baseline estimates are driven by producer price changes (Table A21).

Figure 4 illustrates the magnitude of the innovation effect, using the specification from column 1 of Table 3. On the vertical axis is the marginal impact of county-level Dust Bowl erosion on agricultural land values, and on the horizontal axis is the county's position in the innovation exposure distribution.[27] The marginal impact of land erosion for a county with median innovation exposure is under half that of a county at the bottom of the innovation exposure distribution. Counties at the highest part of the innovation exposure distribution experienced no discernible long run decline in land value as a result of the Dust Bowl (top right). The difference in marginal effect between the 90th and 10th percentile of the innovation exposure distribution is 120% of the median effect.

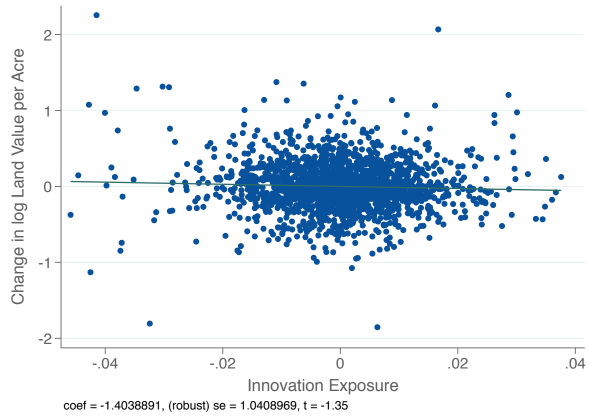
Taken together, these findings demonstrate that innovation had a major impact on the distributional and long run economic impact of the American Dust Bowl. Even decades after the Dust Bowl was over, eroded counties that were positioned to benefit from new technology had far higher land values and agricultural revenues than those that were not.

5.3 Mechanism: Resilience on Damaged Land

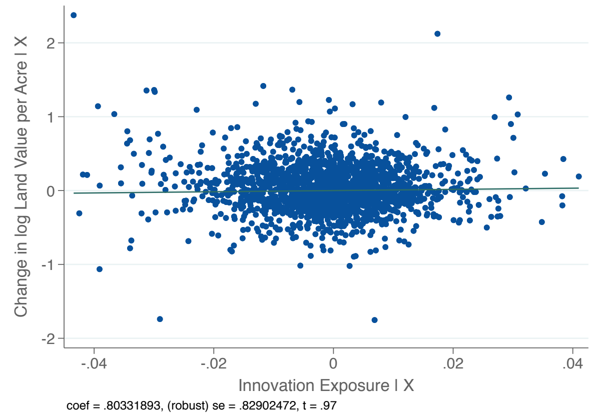
To this point, the results have focused on the impact of the development of new technology that directly affected productivity in counties hit by the Dust Bowl. Historical evidence suggests that the main benefit of new technology was that it increased resilience on damaged land (Section 2.1). The fact that technology development was focused on hybrids (Section 4.3.1), and was directed *away* from harvesting technologies and *toward* biological, chemical, and planting technologies for more damaged crops (Section 4.3.2), further indicates that innovators' focus was not to increase productivity across the board. Instead, these findings are consistent with technology development targeting producers affected by environmental change, where demand for new technology was high.

This mechanism can also be documented using data on production. If price effects, rather than "marginal product" effects, were an important mechanism, then innovation exposure would be expected to increase productivity in *all* counties and not only increase resilience in counties that directly experienced the Dust Bowl. To investigate this possibility, Figure 5 reports a partial correlation plot between county-level innovation exposure and county-level changes in land value in *non-Plains* counties. In Figure 5a, the estimate is un-weighted, and in Figure 5b, the estimate is weighted by initial farm area in order to make sure the finding is not driven by non-agricultural counties. In both cases,

[27] In particular, Figure 4 plots the function $g(q) = 100 \cdot (\beta + \phi \cdot \text{InnovationExposure}(q))$ where $\text{InnovationExposure}(q)$ is quantile q of the empirical distribution of $\text{InnovationExposure}_i$



(a) Unweighted



(b) Weighted by Initial Farm Area

Figure 5: **InnovationExposure$_i$ vs. Δ log Land Value per Acre: Non-Plains Counties.** The unit of observation is the county and each graph reports a partial correlation plot with state fixed effects. The sample includes all non-Plains counties. Coefficient estimates, standard errors, and *t*-statistics are reported at the bottom of each graph.

the coefficient estimate is small and statistically insignificant. Thus, exposure to Dust Bowl-induced innovation had no discernible impact in counties that were not facing environmental hardship. This null result makes it unlikely that terms of trade effects, which should affect all counties that grow a given crop, drive the estimates in Table 3.

Another possibility would have been for new technology to expand the land area on which damaged crops could be productively grown. US history is rife with examples of technological progress expanding the area on which agricultural production could take place, for example as settlers traveled West (Olmstead and Rhode, 2008). Even absent innovation, one adaptive response to the Dust Bowl might have been a re-allocation of production toward healthier land. This mechanism, however, also does not seem consistent with the data. I estimate the relationship between Dust Bowl exposure and cultivated area *outside* the Dust Bowl by combining data on crop-by-county planted areas from the 1929 and 1959 Censuses of Agriculture. Figure A2 displays the relationship between crop-level damage from the Dust Bowl and the change (1929-1959) in land area devoted to the crop in non-Plains counties (A2a) and in Plains counties with below-median land erosion (A2b). In both cases, the coefficient estimate is small in magnitude and indistinguishable from zero, suggesting a limited role for cross-crop production reallocation.

Together, these findings are consistent with the results from Sections 4.3.1 and 4.3.2, suggesting that technology development was driven by a rise in demand for specific technologies that would increase resilience on distressed land. I find no evidence that Dust Bowl-induced innovation exposure raised productivity on environmentally healthy land, or that it facilitated the re-allocation of production.

6 Conclusion

Innovation is a potentially crucial force driving adaptation in moments of catastrophe. The coronavirus pandemic has thrown into stark relief our economy's reliance on technological progress and ingenuity during and in the aftermath of major shocks. The idea that technology development may progress especially quickly during moments of great need has also guided much of the historical narrative about the growth of US innovation, and agricultural biotechnology in particular. However, little is known systematically about how innovation reacts to environmental distress or the extent to which directed technological change is an adaptive force in moments of crisis.

This paper documents a sharp re-direction of innovation in US agriculture during and in the aftermath of the Dust Bowl, perhaps the most extreme environmental crisis in American history. Technology development was directed toward crops that were more exposed to environmental distress, and research shifted toward technologies that would be most useful for environmental adaptation. Counties that, due to their crop composition, were best positioned to benefit from Dust Bowl-induced technological progress experienced more muted declines in land value and agricultural revenue, suggesting that innovation allowed production to adapt to the severe environmental shock.

While this paper investigates a historical episode of environmental catastrophe, modern crises may also require technological responses. Anthropogenic climate change is characterized not only by slow-moving changes in climate, but also by an increase in the number and severity of environmental disasters (Hsiang and Jina, 2014). Future health crises are also increasingly seen as a likely part of reality, potentially accelerated by environmetal change. By investigating the response of technology to a historical disaster—as well as the mechanisms underpinning the technological shift—this paper takes one step toward a more complete understanding of how invention shapes the human toll of crises.

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Online Appendix

A Supplementary Empirical Results

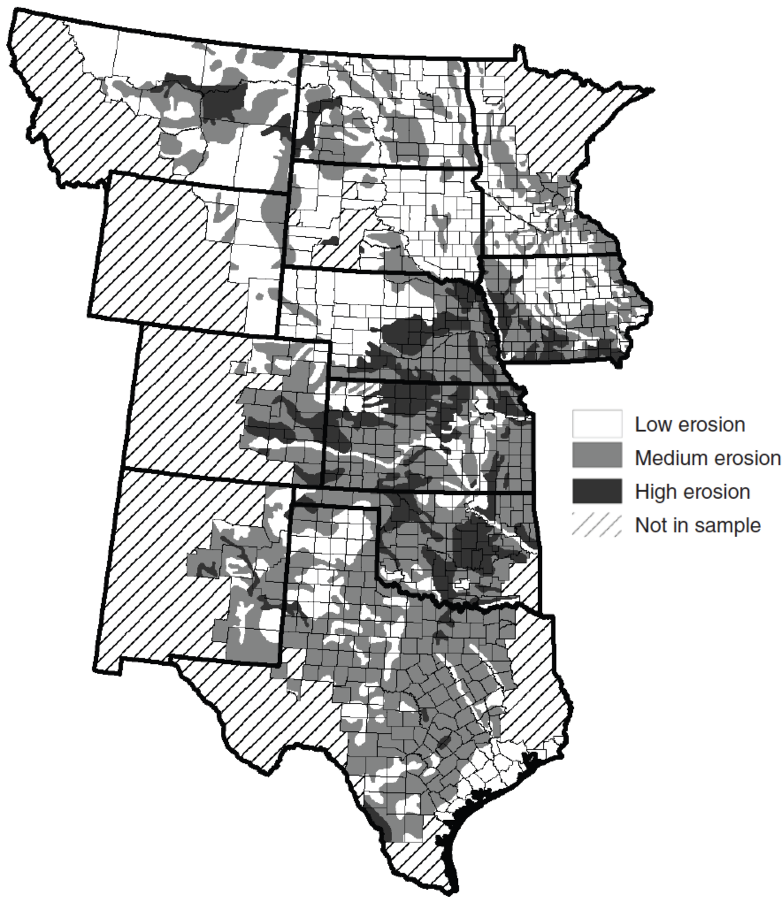
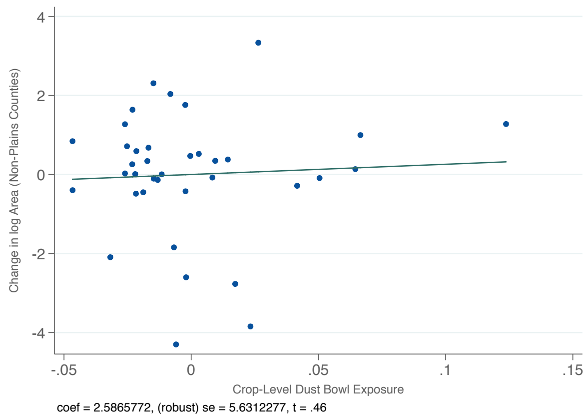
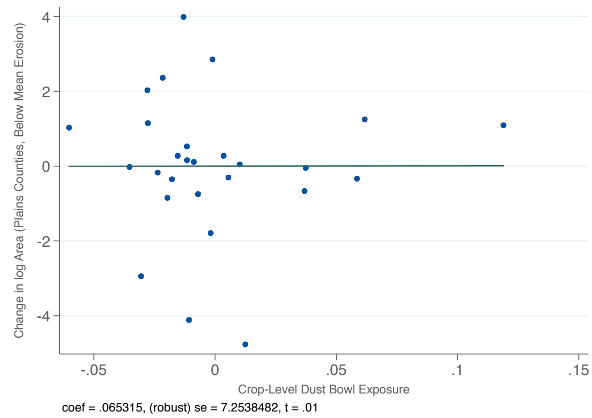


Figure A1: **Main Sample and County-Level Erosion.** This figure maps the Plains counties included in the empirical analysis. Counties are shaded by erosion level, where black corresponds to high erosion (greater than 75% topsoil eroded), grey corresponds to medium erosion (25-75% topsoil eroded) and white corresponds to low erosion (less than 25% topsoil eroded). This figure is reproduced from Hornbeck (2012a) and its original source is the US National Archives in College Park, Maryland.



(a) Δ log Area in Non-Plains Counties



(b) Δ log Area in Low-Exposure Counties

Figure A2: **Crop-Level Damage vs. Δ Area Planted Outside Dust Bowl.** Partial correlation plots at the crop-level. The dependent variable is the change in log total area harvested (1929-1959) in (a) non-Plains counties or (b) Plains counties with below-mean land erosion. Coefficient estimates, standard errors, and *t*-statistics are reported at the bottom of each graph.

Table A1: Crop-Level Land Erosion: Balance Across Other Crop-Level Features

(1) Variable Name	(2) Sample Mean	(3) Correlation with High Erosion Exposure	(4) Variable Name	(5) Sample Mean	(6) Correlation with High Erosion Exposure
Single Stem Plant (0/1)	0.520	0.154**	Annual Plant (0/1)	0.535	-0.000950
		(0.0719)			(0.0388)
Min. Crop Cycle (Days)	82.80	0.386	Max. Crop Cycle (Days)	194.9	4.575
		(3.202)			(6.407)
Opt. Soil Depth (cm)	2.000	0.0590	Opt. Soil Salinity (dS/m)	1.023	-0.00352
		(0.0549)			(0.0123)
Temp. Opt. Range, Max. (°C)	26.12	0.610	Temp. Opt. Range, Min.	16.02	0.357
		(0.423)			(0.249)
Rain Opt. Range, Max. (mm)	1247	7.085	Rain Opt. Range, Min.	720.9	6.643
		(31.84)			(17.85)
pH Opt. Range, Max. (0-14)	6.895	0.0126	pH Opt. Range, Min.	5.868	0.242
		(0.0363)			(0.176)
Hybrid Compatible (Imperfect Flowers)	0.140	0.0380	Vegetative Reproduction	0.279	-0.0162
		(0.0276)			(0.0365)
log Area Harvested (1929)	11.78	0.250	log Crop Varieties Released (pre-1930)	1.711	0.0605
		(0.224)			(0.150)

Notes: The unit of observation is a crop. Columns 1 and 4 list a series of crop-level characteristics, and columns 2 and 5 report the sample mean of each corresponding characteristic. Columns 3 and 6 report estimates of the relationship between each characteristic and crop-level exposure to high levels of erosion. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A2: Dust Bowl Exposure and New Varieties: Controlling for Trends in State Shares

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable is New Varieties (asinh)					
$\text{Exposure}_c \times \mathbb{1}_t^{\text{Post 1930}}$	0.0727***	0.0859**	0.0912**	0.0558*	0.0564**	0.0744**
	(0.0234)	(0.0393)	(0.0412)	(0.0305)	(0.0261)	(0.0331)
Initial area weighted estimates:						
$\text{Exposure}_c \times \mathbb{1}_t^{\text{Post 1930}}$	*0.125****	*0.127****	*0.107****	*0.117****	*0.115****	*0.0880**
	(0.0222)	*(0.0311)*	*(0.0326)*	*(0.0328)*	*(0.0300)*	*(0.0451)*
Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Texas Share x Year Fixed Effects	Yes	No	No	No	No	No
Oklahoma Share x Year Fixed Effects	No	Yes	No	No	No	No
Kansas Share x Year Fixed Effects	No	No	Yes	No	No	No
New Mexico Share x Year Fixed Effects	No	No	No	Yes	No	No
Colorado Share x Year Fixed Effects	No	No	No	No	Yes	No
Nebraska Share x Year Fixed Effects	No	No	No	No	No	Yes
Crops	43	43	43	43	43	43
Observations	1,720	1,720	1,720	1,720	1,720	1,720
R-squared	0.663	0.663	0.663	0.675	0.675	0.669

Notes: The unit of observation is a crop-year. All specifications include crop and year fixed effects. The outcome variable is the inverse hyperbolic sine of the number of new varieties in a crop-year. The controls included in each specification are noted at the bottom of each panel. Each set of controls is the share of the crops national area planted in the listed state interacted with year fixed effects. Estimates of the coefficient of interest from analogous specifications in which the regression is weighted by each crop's initial area are also reported. Standard errors, clustered by crop, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A3: Dust Bowl Exposure and New Varieties: Falsification & Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is New Varieties (asinh)						
Exposure$_c$ x $\mathbb{1}_t^{Post\,1930}$	0.0627**	0.0793*	0.0700***	0.0661***	0.0835**	0.0698***	0.0800**
	(0.0254)	(0.0408)	(0.0235)	(0.0231)	(0.0338)	(0.0251)	(0.0328)
Exposure Outside Plains$_c$ x $\mathbb{1}_t^{Post\,1930}$	-0.00644						
	(0.00420)						
Low Exposure$_c$ x $\mathbb{1}_t^{Post\,1930}$		0.00261					
		(0.00815)					
Initial area weighted estimates:							
Exposure$_c$ x $\mathbb{1}_t^{Post\,1930}$	*0.117****	*0.139****	*0.0941***	*0.0616***	*0.130****	*0.0924***	*0.0674**
	(0.0247)	*(0.0260)*	*(0.0372)*	*(0.0297)*	*(0.0344)*	*(0.0413)*	*(0.0355)*
Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial Varieties x Year Fixed Effects	No	No	Yes	No	No	No	Yes
AAA Inclusion x Year Fixed Effects	No	No	No	Yes	No	No	Yes
Exposure$_c$ x WWII	No	No	No	No	Yes	No	Yes
Exposure$_c$ x Depression	No	No	No	No	Yes	No	Yes
Hybrid Compat. x Year Fixed Effects	No	No	No	No	No	Yes	Yes
Crops	43	43	43	43	43	43	43
Observations	1,720	1,720	1,720	1,720	1,720	1,720	1,720
R-squared	0.663	0.663	0.675	0.675	0.669	0.667	0.699

Notes: The unit of observation is a crop-year. All specifications include crop and year fixed effects. The outcome variable is the inverse hyperbolic sine of the number of new varieties in a crop-year. The controls included in each specification are noted at the bottom of each panel. Estimates of the coefficient of interest from analogous specifications in which the regression is weighted by each crop's initial area are also reported. Standard errors, clustered by crop, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A4: Dust Bowl Exposure and New Varieties: Excluding the Largest Crops

	(1)	(2)	(3)	(4)
	Dependent Variable is New Varieties (asinh)			
	Excluding 25% Largest Crops by Pre-Period Area		Excluding 50% Largest Crops by Pre-Period Area	
$\text{Exposure}_c \times \mathbb{1}_t^{\text{Post 1930}}$	0.144**	0.191**	0.201**	0.265**
	(0.0536)	(0.0764)	(0.0720)	(0.103)
Crop Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
All Additional Controls	No	Yes	No	Yes
Observations	1,280	1,280	840	840
R-squared	0.620	0.676	0.572	0.644

Notes: The unit of observation is a crop-year. All specifications include crop and year fixed effects. The outcome variable is the inverse hyperbolic sine of the number of new varieties in a crop-year. The controls included in each specification are noted at the bottom of each panel. In columns 1-2, the sample excludes the 25% of crops with the largest pre-period national land area, and in columns 3-4 the sample excludes crops with above median pre-period area. Standard errors, clustered by crop, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A5: Dust Bowl Exposure and New Varieties: Het. by Hybrid Ease

	(1)	(2)
	Dependent Variable is New Varieties (asinh)	
$\text{Exposure}_c \times \mathbb{1}_t^{\text{Post 1930}}$	0.0510**	0.0532**
	(0.0239)	(0.0242)
$\text{Exposure}_c \times \mathbb{1}_t^{\text{Post 1930}} \times \text{Hybrid}_c$	0.0945***	0.0831**
	(0.0292)	(0.0392)
Crop and Year Fixed Effects	Yes	Yes
Initial Varieties x Year Fixed Effects	No	Yes
AAA Inclusion x Year Fixed Effects	No	Yes
Hybrid Compat. x Year Fixed Effects	Yes	Yes
Crops	43	43
Observations	1,720	1,720
R-squared	0.669	0.695

Notes: The unit of observation is a crop-year. All specifications include crop and year fixed effects. The outcome variable is the inverse hyperbolic sine of the number of new varieties in a crop-year. The controls included in each specification are noted at the bottom of each panel. Standard errors, double-clustered by crop and year, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A6: Dust Bowl Exposure and New Varieties: Het. by Pre-Period Innovation

	(1)	(2)
	Dependent Variable is New Varieties (asinh)	
$\text{Exposure}_c \times \mathbb{1}_t^{1930s} \times \text{Pre-Period Varieties}_c$	0.000499	0.000808
	(0.000339)	(0.000810)
$\text{Exposure}_c \times \mathbb{1}_t^{1940s} \times \text{Pre-Period Varieties}_c$	-0.000518	0.000698
	(0.000629)	(0.00108)
$\text{Exposure}_c \times \mathbb{1}_t^{1950s} \times \text{Pre-Period Varieties}_c$	-0.00321*	-0.00460**
	(0.00162)	(0.00189)
Crop Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Controls	None	All
Observations	1,720	1,720
R-squared	0.680	0.709

Notes: The unit of observation is a crop-year. All specifications include crop and year fixed effects. The outcome variable is the inverse hyperbolic sine of the number of new varieties in a crop-year. The controls included in each specification are noted at the bottom of each panel. The three reported coefficients are the effect of the triple interaction between Dust Bowl exposure, pre-period variety releases, and indicators for the 1930s, the 1940s, and the 1950s respectively. Standard errors, double clustered by crop and year, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A7: Dust Bowl Exposure and Mechanical vs. Bio-Chemical Patents: Direct Effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Mechanical Patents (asinh)			BioChem Patents (asinh)		
	Baseline		Citation Weighted	Baseline		Citation Weighted
$\text{Exposure}_c \times \mathbb{1}_t^{\text{Post 1930}}$	-0.0299***	-0.0231**	-0.0281*	0.0447*	0.0420*	0.0588**
	(0.00856)	(0.00858)	(0.0161)	(0.0242)	(0.0225)	(0.0268)
Crop and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
All Additional Controls	No	Yes	Yes	No	Yes	Yes
Observations	1,720	1,720	1,720	1,720	1,720	1,720
R-squared	0.714	0.734	0.617	0.567	0.627	0.542

Notes: The unit of observation is a crop-year. All specifications include crop and year fixed effects, as well as the set of controls listed at the bottom of each column. In columns 1-2 and 4-5, the dependent variable is the (asinh) number of patents; in 3 and 6 it is the (asinh) citation-weighted number of patents. In columns 1-3, dependent variables are constructed from all mechanical harvesting and post-harvest patents (A01D,F,G) and in columns 4-6, they are constructed from all biological and chemical patents (A01H,N). Standard errors, clustered by crop, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A8: Dust Bowl Exposure and Biotechnology Development: IV Estimates using 1930s Weather

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	New Varieties (asinh)			Number of Innovations in the Crop-Year-Class Bin (asinh): BioChem and Planting Patents vs. Mech Patents		
Estimator:	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
$\text{Exposure}_c \times \mathbb{1}_t^{\text{Post 1930}}$	0.0456*	0.0829**	0.0551*			
	(0.0269)	(0.0403)	(0.0286)			
$\text{Exposure}_c \times \mathbb{1}_t^{\text{Post 1930}} \times \mathbb{1}_k^S$				0.0405**	0.0742***	0.0359**
				(0.0192)	(0.0186)	(0.0174)
Initial area weighted estimates:	*0.138***	*0.179***	*0.122****	*0.0747***	*0.0956***	*0.0783****
	(0.0540)	*(0.0670)*	*(0.0346)*	*(0.0293)*	*(0.0432)*	*(0.0250)*
Excluded Instuments:	Extreme drought; severe drought	Temp. SD; Palmer drought index	Extreme drought; severe drought; temp SD; Palmer drought index	Extreme drought; severe drought	Temp. SD; Palmer drought index	Extreme drought; severe drought; temp SD; Palmer drought index
K-P F-Statistic	9.73	10.335	10.947	6.729	7.055	7.259
Crop Fixed Effects	Yes	Yes	Yes	-	-	-
Year Fixed Effects	Yes	Yes	Yes	-	-	-
Crop x Year Fixed Effects	-	-	-	Yes	Yes	Yes
Crop x Technology Class Fixed Effects	-	-	-	Yes	Yes	Yes
Year x Technology Class Fixed Effects	-	-	-	Yes	Yes	Yes
Crops	43	43	43	43	43	43
Observations	1,720	1,720	1,720	8,815	8,815	8,815

Notes: The unit of observation is a crop-year in columns 1-3 and a crop-year-technology class in columns 4-6. Columns 1-3 include crop and year fixed effects and columns 4-6 include all two-way fixed effects. In columns 1 and 4 the excluded instruments are months of extreme drought per acre and months of severe drouht per acre, interacted with the post-period indicator and both the post-period indicator and land-complementing class indicator respectively. In columns 2 and 5, the excluded instruments are the average standard deviation in temperature and the average Palmer drought index , interacted with the post-period indicator and both the post-period indicator and land-complementing class indicator respectively. Finally, in columns 3 and 6, all four instruments (interacted appropriately) are included. Estimates of the coefficients of interest from analogous specifications in which the regression is weighted by each crop's initial area are also reported. Standard errors, clustered by crop, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A9: Comparing Exposure to Medium and High Levels of Erosion

	(1)	(2)	(3)	(4)
	Dependent Variable is New Varieties (asinh)			
High Exposure$_c$ x $\mathbb{1}_t^{Post\,1930}$	0.0694***		0.114***	
	(0.0243)		(0.0274)	
Medium Exposure$_c$ x $\mathbb{1}_t^{Post\,1930}$		0.0155**		0.0193
		(0.00604)		(0.0168)
T-statistic of difference	*2.152*		*2.946*	
Crop Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Weighting	None	None	Initial Area	Initial Area
Crops	43	43	43	43
Observations	1,720	1,720	1,720	1,720
R-squared	0.663	0.660	0.828	0.818

Notes **:** The unit of observation is a crop-year. All specifications include crop and year fixed effects. The outcome variable is the inverse hyperbolic sine of the number of new varieties in each crop-year. In columns 1 and 3 the independent variable of interest is the main indepenent variable throughout the paper, the share of the crop's land under high levels of erosion. In columns 2 and 4 the independent variable of interest is the share of the crop's land under medium levels of erosion. In columns 1-2 the regression is unweighted and in columns 3-4 it is weighted by crops' area harvested during the pre-period. Standard errors, clustered by crop, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A10: Dust Bowl Exposure and Patented Technologies: Citation Weighted

	(1)	(2)
	Citation-Weighted Patents in the Crop-Year-Class Bin (asinh)	
	Bio-Chemical Patents vs. Mechanical Harvest + Post-Harvest Patents	
$\text{Exposure}_c \times \mathbb{1}_t^{\text{Post 1930}} \times \mathbb{1}_k^S$	0.0357*	0.0783***
	(0.0178)	(0.0205)
Crop x Year Fixed Effects	Yes	Yes
Crop x Technology Class Fixed Effects	Yes	Yes
Year x Technology Class Fixed Effects	Yes	Yes
Weighting	None	Initial Area
Crops	43	43
Observations	15,867	7,052
R-squared	0.725	0.785

Notes: The unit of observation is a crop-year-technology class. All specifications include crop-by-year fixed effects, crop-by-technology class fixed effects, and year-by-technology class fixed effects. The outcome variable is the inverse hyperbolic sine of the number of citation-weighted patents in a crop-year-class bin. Standard errors, double clustered by crop and year, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A11: Dust Bowl Exposure and Patented Technologies: Private vs. Public Sector

	(1)	(2)	(3)	(4)
	Patent Assignee:			
	Private Firms		Govt. & University	
$\text{Exposure}_c \times \mathbb{1}_t^{\text{Post 1930}} \times \mathbb{1}_k^S$	0.0188*	0.0305***	0.000232	0.000618
	(0.0103)	(0.0106)	(0.000380)	(0.00101)
Crop x Year Fixed Effects	Yes	Yes	Yes	Yes
Crop x Technology Class Fixed Effects	Yes	Yes	Yes	Yes
Year x Technology Class Fixed Effects	Yes	Yes	Yes	Yes
Weighting	None	Initial Area	None	Initial Area
Observations	8,815	8,815	8,815	8,815
R-squared	0.703	0.668	0.273	0.273

Notes: The unit of observation is a crop-year-technology class and all two-way fixed effects. In columns 1-2, the dependent variable is all patents assigned to private-sector firms. In columns 3-4, it is the number of patents assigned to government organizations and universities/colleges. Standard errors, clustered by crop, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A12: Dust Bowl Exposure and US Station Experiments

	(1)	(2)	(3)	(4)
	Experiments (asinh)		Any Experiment (0/1)	
	Panel A: All Experiment Stations			
High Exposure$_c$ x $\mathbb{1}_t^{Post\,1930}$	-0.00775	-0.000547	0.000127	-0.00134
	(0.00869)	(0.00917)	(0.00386)	(0.00787)
R-squared	0.705	0.736	0.533	0.571
	Panel B: Experiment Stations in Dust Bowl States			
High Exposure$_c$ x $\mathbb{1}_t^{Post\,1930}$	-0.0146	-0.0148*	-0.00422	-0.00928
	(0.0105)	(0.00745)	(0.00534)	(0.00623)
R-squared	0.630	0.714	0.548	0.608
Crop and Year Fixed Effects	Yes	Yes	Yes	Yes
All Additional Controls	No	Yes	No	Yes
Observations	1,548	1,118	1,548	1,118

Notes: The unit of observation is a crop-year. All specifications include crop and year fixed effects, abd columns 2 and 4 also include all baseline controls. In columns 1-2, the outcome variable is the inverse hyperbolic sine of the number of experiments and in columns 3-4, it is an indicator that equals one if at least one experiment was conducted and in column 3 it is the inverse hyperbolic sine of the citation-weighted number of articles. Standard errors, clustered by crop, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A13: Dust Bowl Exposure and Scientific Articles

	(1)	(2)	(3)
	Dependent Variable Is:		
	Articles (asinh)	Any Articles (0/1)	Citation Weighted Articles (asinh)
High Exposure$_c$ x $\mathbb{1}_t^{Post\,1930}$	0.0502**	0.0169***	0.0688*
	(0.0244)	(0.00408)	(0.0352)
Crop and Year Fixed Effects	Yes	Yes	Yes
All Baseline Controls	Yes	Yes	Yes
Observations	1,548	1,548	1,548
R-squared	0.661	0.517	0.575

Notes: The unit of observation is a crop-year. All specifications include crop and year fixed effects, as well as all baseline controls. In column 1, the outcome variable is the inverse hyperbolic sine of the number of new articles; in column 2, it is an indicator that equals one if at least one article was published; and in column 3 it is the inverse hyperbolic sine of the citation-weighted number of articles. Standard errors, clustered by crop, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A14: Standard Error Adjustments for Spatial Correlation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Coefficient estimate t-statistic						
	Kernel distance for spatial correlation (km):					State-Year and County	State
	200	*300*	*400*	*500*	*1000*		
t-statistic	2.93	2.70	2.77	3.52	3.98	2.37	2.74
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Round x State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Coefficient estimate t-statistics from the baseline county-level specification (with log of agricultural land values as the dependent variable) with alternative standard error clustering strategies. Columns 1-5 follow Hsiang (2010)'s implementation of Conley (2008) standard errors, for five different values of the kernel cut off distance (measured in km). In columns 6 and 7, standard errors are double clustered by state-year and clustered by state respectively.

Table A15: Innovation and Adaptation: Flexible Output Prices Controls

	(1)	(2)	(3)	(4)
Dependent Variable:	log Value of Land and Buildings per Acre	log Value of Land per Acre	log Total Revenue	log Total Revenue per Acre
$\text{Erosion}_i \times \mathbb{1}_t^{\text{Post 1930}}$	-1.330***	-1.006***	-1.735***	-1.301***
	(0.415)	(0.328)	(0.521)	(0.466)
$\text{Erosion}_i \times \mathbb{1}_t^{\text{Post 1930}} \times \text{InnovationExposure}_i$	13.43***	9.058**	16.86***	12.67**
	(5.034)	(3.839)	(6.047)	(5.439)
County Fixed Effects	Yes	Yes	Yes	Yes
Census Round x State Fixed Effects	Yes	Yes	Yes	Yes
Output Price Aggregate	Yes	Yes	Yes	Yes
$\text{Erosion}_i \times \mathbb{1}_t^{\text{Post 1930}} \times$ Output Price Aggregate	Yes	Yes	Yes	Yes
Observations	1,592	1,592	1,592	1,592
R-squared	0.953	0.975	0.885	0.924

Notes: The unit of observation is a county-year. All estimates are from long differences specifications; the starting year is either 1920 or 1925 and ending year either 1940 or 1959, depending on data availability. The sample of counties was selected as in Hornbeck (2012). All specifications include county fixed effects and census round-by-state fixed effects. Each specification also includes the county-by-year level agricultural output price measure and this measure interacted with Dust Bowl exposure. The dependent variable is listed at the top of each column. Standard errors, clustered by county are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A16: Innovation and Adaptation: Panel Estimates

	(1)	(2)	(3)	(4)
Dependent Variable:	log Value of Land and Buildings per Acre	log Value of Land per Acre	log Total Revenue	log Total Revenue per Acre
$\text{Erosion}_i \times \mathbb{1}_t^{\text{Post 1930}}$	-0.736***	-0.678***	-1.068***	-0.764**
	(0.214)	(0.217)	(0.393)	(0.316)
$\text{Erosion}_i \times \mathbb{1}_t^{\text{Post 1930}} \times \text{InnovationExposure}_i$	5.224**	4.759*	8.663*	5.596
	(2.498)	(2.525)	(4.593)	(3.664)
County Fixed Effects	Yes	Yes	Yes	Yes
Census Round x State Fixed Effects	Yes	Yes	Yes	Yes
Observations	7,959	3,184	7,164	7,164
R-squared	0.960	0.960	0.892	0.923

Notes: The unit of observation is a county-year. All estimates are from panel estimates including all census rounds for which each dependent varaible was recorded. The sample of counties was selected as in Hornbeck (2012). All specifications include county fixed effects and census round-by-state fixed effects. The dependent variable is listed at the top of each column. Standard errors, clustered by county, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A17: Innovation and Adaptation: Excluding State $\times$ Round Fixed Effects

	(1)	(2)	(3)	(4)
Dependent Variable:	log Value of Land and Buildings per Acre	log Value of Land per Acre	log Total Revenue	log Total Revenue per Acre
$\text{Erosion}_i \times \mathbb{1}_t^{\text{Post 1930}}$	-2.390***	-1.588***	-2.448***	-1.852***
	(0.531)	(0.451)	(0.568)	(0.527)
$\text{Erosion}_i \times \mathbb{1}_t^{\text{Post 1930}} \times \text{InnovationExposure}_i$	22.49***	16.05***	21.85***	16.11***
	(6.301)	(5.285)	(6.558)	(5.978)
County Fixed Effects	Yes	Yes	Yes	Yes
Census Round Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,592	1,592	1,592	1,592
R-squared	0.900	0.926	0.865	0.909

Notes: The unit of observation is a county-year. All estimates are from long differences specifications; the starting year is either 1920 or 1925 and ending year either 1940 or 1959, depending on data availability. The sample of counties was selected as in Hornbeck (2012). All specifications include county fixed effects and census round fixed effects. The dependent variable is listed at the top of each column. Standard errors, clustered by county are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A18: Innovation and Adaptation: Controlling for Policy

	(1)	(2)	(3)	(4)
Dependent Variable:	log Value of Land and Buildings per Acre	log Value of Land per Acre	log Total Revenue	log Total Revenue per Acre
$\text{Erosion}_i \times \mathbb{1}_t^{\text{Post 1930}}$	-1.398***	-0.947***	-1.505***	-1.159**
	(0.450)	(0.322)	(0.529)	(0.479)
$\text{Erosion}_i \times \mathbb{1}_t^{\text{Post 1930}} \times \text{InnovationExposure}_i$	11.70**	7.740**	13.51**	10.25*
	(5.235)	(3.787)	(6.211)	(5.592)
County Fixed Effects	Yes	Yes	Yes	Yes
Census Round Fixed Effects	Yes	Yes	Yes	Yes
AAA Payments x Round Fixed Effects	Yes	Yes	Yes	Yes
Relief Spending x Round Fixed Effects	Yes	Yes	Yes	Yes
New Deal Loans x Round Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,584	1,584	1,584	1,584
R-squared	0.950	0.975	0.885	0.924

Notes: The unit of observation is a county-year. All estimates are from long differences specifications; the starting year is either 1920 or 1925 and ending year either 1940 or 1959, depending on data availability. The sample of counties was selected as in Hornbeck (2012). All specifications include county fixed effects and census round fixed effects. All specifications also include AAA payments, relief spending, and new deal loans, interacted with a full set of census round fixed effects. The dependent variable is listed at the top of each column. Standard errors, clustered by county are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A19: Innovation and Adaptation: "Leave-State-Out" Estimates

	(1)	(2)	(3)	(4)
Dependent Variable:	log Value of Land and Buildings per Acre	log Value of Land per Acre	log Total Revenue	log Total Revenue per Acre
$\text{Erosion}_i \times \mathbb{1}_t^{\text{Post 1930}}$	-1.412***	-0.956***	-1.694***	-1.286***
	(0.450)	(0.324)	(0.536)	(0.480)
$\text{Erosion}_i \times \mathbb{1}_t^{\text{Post 1930}} \times \text{InnovationExposure}_i$	12.21**	8.011**	15.97**	11.97**
	(5.321)	(3.864)	(6.361)	(5.672)
County Fixed Effects	Yes	Yes	Yes	Yes
Census Round x State Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,592	1,592	1,592	1,592
R-squared	0.953	0.975	0.885	0.924

Notes: The unit of observation is a county-year. All estimates are from long differences specifications; the starting year is either 1920 or 1925 and ending year either 1940 or 1959, depending on data availability. The sample of counties was selected as in Hornbeck (2012). All specifications include county fixed effects and census round-by-state fixed effects. Innovation exposure is estimated excluding crop-level damage in the county's state. The dependent variable is listed at the top of each column. Standard errors, clustered by county, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A20: Innovation and Adaptation: Comparing High and Medium Levels of Local and Aggregate Exposure

	(1)	(2)	(3)	(4)
Dependent Variable (Long Difference Estimates):	log Value of Land and Buildings per Acre	log Value of Land per Acre	log Total Revenue	log Total Revenue per Acre
High Erosion$_i$ x $\mathbb{1}_t^{Post\,1930}$	-1.344***	-0.909***	-1.590***	-1.163**
	(0.427)	(0.308)	(0.538)	(0.472)
High Erosion$_i$ x $\mathbb{1}_t^{Post\,1930}$ x High CropMixDamage$_i$	9.743**	6.470*	12.69**	9.257*
	(4.961)	(3.644)	(6.232)	(5.464)
Medium Erosion$_i$ x $\mathbb{1}_t^{Post\,1930}$	0.140	0.104	0.357	0.446
	(0.288)	(0.219)	(0.353)	(0.333)
Medium Erosion$_i$ x $\mathbb{1}_t^{Post\,1930}$ x Medium CropMixDamage$_i$	-1.760	-1.133	-2.778**	-2.619*
	(1.125)	(0.851)	(1.398)	(1.346)
t-statistic of difference between φ and φ^{med}	*2.261*	*2.032*	*2.422*	*2.110*
County Fixed Effects	Yes	Yes	Yes	Yes
Census Round x State Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,592	1,592	1,592	1,592
R-squared	0.953	0.975	0.888	0.925

Notes: The unit of observation is a county-year. All specifications are long differences estimates between 1920 or 1925 and 1940 or 1959 depending on data availability. The sample of counties was selected as in Hornbeck (2012). All specifications include county fixed effects and census round-by-state fixed effects. The dependent variable is listed at the top of each column. Standard errors, clustered by county are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A21: Innovation and Adaptation to the Dust Bowl: Heterogeneity by Farm Size

	(1)	(2)	(3)	(4)
Dependent Variable:	log Value of Land and Buildings per Acre	log Value of Land per Acre	log Total Revenue	log Total Revenue per Acre
$Erosion_i$ x $\mathbb{1}_t^{Post\,1930}$ x $InnovationExposure_i$ x Above Med. $Size_i$	34.23**	22.38**	10.80	11.19
	(13.41)	(11.11)	(15.84)	(15.14)
County Fixed Effects	Yes	Yes	Yes	Yes
Round x State Fixed Effects	Yes	Yes	Yes	Yes
Relief Controls x Round FE	Yes	Yes	Yes	Yes
Observations	1,584	1,584	1,584	1,584
R-squared	0.952	0.977	0.889	0.927

Notes: The unit of observation is a county-year. All estimates are from long differences specifications; the starting year is either 1920 or 1925 and ending year either 1940 or 1959, depending on data availability. The sample of counties was selected as in Hornbeck (2012). Above Med. Farm is an indicator that equals one if the average farm size in a county in 1930 (measured as total county revenue divided by the number of farms) is above the within-sample median. Standard errors, clustered by county, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

B Omitted Proofs

B.1 Proposition 1

Suppose there is a shift from $F(.)$ to $F^{DB}(.)$ where F first order stochastic dominates $F^{DB}(.)$. Define θ as the technology level in the equilibrium before the Dust Bowl and θ^{DB} as the technology level in the equilibrium after the Dust Bowl. We assumed that $G(.)$ is concave and twice continuously differentiable and that the cost of innovation $C(\theta)$ is convex and differentiable. Therefore, a necessary and sufficient condition that equilibrium technological progress is the solution to the innovator's profit maximization problem is satisfied if the following first order conditions hold:

$$p^{\frac{1}{\alpha}} \int G_2(A_i, \theta) dF(A) = \frac{d}{d\theta} C(\theta)$$

$$p^{\frac{1}{\alpha}} \int G_2(A_i, \theta^{DB}) dF^{DB}(A) = \frac{d}{d\theta} C(\theta^{DB})$$

First, consider the case where $G_{12} < 0$ and suppose that $\theta > \theta^{DB}$. Since F first order stochastic dominates F^{DB}, it must be true that

$$\int G_2(A_i, \theta) dF(A) \leq G_2(A_i, \theta) dF^{DB}(A)$$

Moreover, since $\theta > \theta^{DB}$ and G is concave in θ, it is also the case that

$$\int G_2(A_i, \theta) dF^{DB}(A) \leq G_2(A_i, \theta^{DB}) dF^{DB}(A)$$

Combining both expressions with the first order conditions above:

$$\frac{d}{d\theta} C(\theta^{DB}) = G_2(A_i, \theta^{DB}) dF^{DB}(A) \geq \int G_2(A_i, \theta) dF^{DB}(A) \geq \int G_2(A_i, \theta) dF(A) = \frac{d}{d\theta} C(\theta)$$

However, by assumption, $\theta > \theta^{DB}$ and since $C(.)$ is convex, this implies that

$$\frac{d}{d\theta} C(\theta) > \frac{d}{d\theta} C(\theta^{DB})$$

This is a contradiction and implies that $\theta^{DB} \geq \theta$, as desired.

Now consider the case where $G_{12} \geq 0$ and suppose that $\theta < \theta^{DB}$. By analogous arguments to the first case, it must be true that

$$\int G_2(A_i, \theta) dF(A) \geq G_2(A_i, \theta) dF^{DB}(A)$$

and that

$$\int G_2(A_i, \theta) dF^{DB}(A) \geq G_2(A_i, \theta^{DB}) dF^{DB}(A)$$

Combining these inequalities with the first order conditions:

$$\frac{d}{d\theta} C(\theta^{DB}) = G_2(A_i, \theta^{DB}) dF^{DB}(A) \leq \int G_2(A_i, \theta) dF^{DB}(A) \leq \int G_2(A_i, \theta) dF(A) = \frac{d}{d\theta} C(\theta)$$

However, by assumption, $\theta < \theta^{DB}$ and since $C(.)$ is convex, this implies that

$$\frac{d}{d\theta} C(\theta) < \frac{d}{d\theta} C(\theta^{DB})$$

This is a contradiction and implies that $\theta^{DB} \leq \theta$, as desired. This completes the proof.

C Detailed Data Description and Balance

County-level erosion was measured using data from detailed Reconnaissance Erosion Surveys, digitized in map form by Hornbeck (2012a). These maps were constructed from direct measurement by specialists sent to each county. The first surveys of this kind were carried out during the mid-1930s; as a result, the data capture cumulative erosion prior to this point and not the erosion that took place since the start of the Dust Bowl period. The original map was constructed by the Soil Conservation Service (SCS) from the individual soil survey reports; this was then traced and merged with county boundaries using Geographical Information Systems (GIS) software (Hornbeck, 2012a, p. 1484). For each county, it is possible to measure the share of land under high, medium, and low levels of topsoil erosion at the time of the survey. The sample of Dust Bowl counties included in the analysis also follows the methodology outlined in Hornbeck (2012a, p. 1484) to identify the set of contiguous and ecologically similar Plains counties.

The county-level erosion data are used to construct a crop-level measure of Dust Bowl exposure, as outlined in Section 3.2. This measure captures the share of total crop land area in the sample of Plains counties and under high levels of topsoil erosion. There is substantial variation across crops, ranging from zero exposure to 29.2% of national crop land area. The difference between the 90th and 10th percentile is 6.7% of national land area. The share of national crop land under high *or* medium levels of topsoil erosion ranges from zero to 72.51% and the difference between the 90th and 10th percentile is 31.66% of national land area.

While the main analysis does not require perfect balance across crops that were more or less exposed to erosion, and instead requires a parallel *trends* assumption, here I investigate in more detail any cross-sectional differences across crops that were more- or less-exposed to soil erosion during the Dust Bowl. In particular, I estimate the relationship between crop-level exposure to high levels of erosion—the main measure of crop-level Dust Bowl exposure—and a range of crop-level characteristics, controlling only for the share of each crops' land in Plains counties in order to absorb any mechanical relationship driven by the Dust Bowl's regional concentration. These estimates are reported in Table A1. The first six rows rely on crop-level biological and growing characteristics, compiled from the Food and Agriculture Organization's ECOCROP database, which contains information about plant-specific characteristics and growing conditions for over 2,500 species compiled from a range of expert agronomist surveys.[28]

Physiological characteristics of plants shape the structure, method, and demands of crop breeding; indeed, since much of variety development is designed to adapt plants to different ecological conditions, a crop's baseline optimal growing conditions play a major role in shaping the demands of research. The covariates included are: an indicator that equals one if a plant has a single stem, an indicator that equals one if a crop is an annual plant, the minimum and maximum crop cycle length, the optimal soil depth and salinity, and the upper and lower values for the crop's optimal temperature, rainfall, and pH range. The relationship is significant for just one variable (the single stem indicator), and the effect is very small relative to the sample mean. Moreover, while the significant coefficient could be due to random chance, all baseline estimates are very similar controlling for the single stem indicator interacted with year fixed effects (not reported).

[28]This data source is discussed at greater length in Moscona and Sastry (2021).

Next, I investigate the relationship between erosion exposure and a crop level hybrid compatibility indicator (as discussed in Section 4.2) and vegetative reproduction indicator—in both cases, the correlation is small and insignificant. Finally, I estimate the relationship between erosion exposure and two proxies for pre-determined crop-level market size: (log of) the total land area devoted to the crop and (log of) total varieties released prior to 1930. Again, in both cases the correlation is small in magnitude and statistically insignificant. Together, these results suggest that at the crop-level, exposure to Dust Bowl erosion is not related in any systematic or obvious way to a range of crop-level characteristics that affect the structure and demands of crop research.

D Crop Planting Patterns and the Dust Bowl

In this section, I investigate planting re-allocation during the study period and whether crop-specific reallocation might affect the interpretation of the results. First, I investigate the extent to which crop planting patterns persisted during the sample period. I construct a crop-by-county data set that reports the area devoted to each crop in each county in 1929—prior to the onset of disaster—and in 1959—the point I use as the end year for empirical analysis throughout the paper. I then estimate:

$$\log(\text{Area}_{i,c}^{1959}) = \xi \cdot \log(\text{Area}_{i,c}^{1929}) + \epsilon_{i,c} \tag{D.1}$$

if ξ is close to one, crop-reallocation was limited during the sample period and crop allocations at the start of the period closely resemble crop allocations throughout. Estimating (D.1) on the full sample of US counties, weighting each observation by its pre-period area, I find that $\xi = 1.112$; estimating an augmented version of (D.1) that includes crop and county fixed effects, I find $\xi = 0.949$. On average, crop allocations in 1929 closely resembled those in 1959.

Repeating the same two specifications on the sample of Plains counties used in the analysis, estimates of ξ are 1.103 and 1.017 respectively. I also find no evidence that the extent of persistence differed across counties depending on their exposure to land erosion. Including an interaction term between $\log(\text{Area}_{i,c}^{1929})$ and the share of county land area under high levels of erosion, I find that the coefficient on the interaction term is -0.008 with a standard error of 0.008. Together, these estimates suggest that crop planting allocations were strongly persistent during the sample period, and that the persistence of planting pattern was not different across counties that were more- or less-exposed to land erosion. This finding is consistent with narrative evidence discussed and referenced in Section 2.1 on the inter-generational persistence in crop choice and crop-specific expertise during the sample period (e.g. Schaper, 2012; Huffman, 2001, for a review).

A final concern might be, even if crop switching were limited on average, that the *potential* for crop switching were correlated with the baseline measure of crop-specific Dust Bowl exposure. If the most exposed crops were also the crops for which it is most difficult to shift production across locations, then this could be a key part of the mechanism and would be important to incorporate in the theoretical and empirical analysis. To investigate this, I test whether there is any relationship between crop-specific Dust Bowl exposure and the ease of crop switching. To proxy for the *ex ante* ease of crop switching for each crop c, I measure average share of cropland in each county devoted to crop c across all counties where c is grown. Intuitively, for higher values of this proxy, the locations where production can take place and set of other crops that require similar conditions are more limited. I then estimate the relationship between crop-specific erosion and crop-specific "switchability," controlling for log of total planted area in 1930. The relationship is small in magnitude, statistically insignificant, and negative, suggesting that if anything the more Dust Bowl exposed crops are *less* geographically constrained. The beta coefficient is -0.017 and the p-value is 0.886. Moreover, it is more straightforward to shift the production allocation of annual (as opposed to perennial) plants, and Table A1 (row 1) showed no evidence that crops more exposed to the Dust Bowl were more likely to be annual. Thus, it does not appear to be easier to shift the production of more Dust Bowl exposed crops *ex ante*.

Finally, I investigate the extent to which *ex post* persistence in crop planting patterns was related to crop-specific Dust Bowl exposure. I estimate an augmented version of Equation (D.1):

$$\log(\text{Area}_{i,c}^{1959}) = \sum_c \xi_c \cdot \Big(\log(\text{Area}_{i,c}^{1929}) \times \mathbb{I}_c \Big) + \alpha_c + \delta_i + \epsilon_{i,c} \tag{D.2}$$

Now, each ξ_c estimates the relationship between pre- and post- period planted areas for crop c. I then estimate the relationship between crop-specific Dust Bowl exposure and the $\hat{\xi}_c$'s:

$$\hat{\xi}_c = \pi \cdot \text{Exposure}_c + \epsilon_c \tag{D.3}$$

The estimated relationship π is statistically indistinguishable from zero (p = 0.71) and very small in magnitude; a one standard deviation increase in Dust Bowl exposure is associated with a 0.05 standard deviation in increase in $\hat{\xi}_c$. The results are qualitatively similar when the dependent variable in (D.3) is instead $|1 - \hat{\xi}_c|$ (p-value = 0.385), further indicating that there is no relationship between Dust Bowl exposure and the extent of crop switching.

Together, these null results suggest that the ease of crop reallocation and realized persistence of planting patterns in the data are not correlated with Dust Bowl exposure. This makes it unlikely that crop switching has a major impact on the paper's empirical estimates of interest and suggests that, consistent with the general results of Hornbeck (2012a), production re-allocation in response to the Dust Bowl was limited.

E Sensitivity Analysis of County-Level Estimates

Alternative Specifications While the baseline county-level results report long difference estimates since technology development is a long-term process, full panel estimates are reported in Table A16. The coefficient estimates are intuitively smaller in magnitude than the long difference estimates, consistent with new technology accumulating over time, but the findings are qualitatively very similar.

There is a debate about the appropriateness of including state-by-time fixed effects in county-level analyses of US agricultural production (see Deschênes and Greenstone, 2007; Burke and Emerick, 2016). In particular, the concern is that state-by-time fixed effects absorb a large share of the variation in agricultural production and environmental shocks, making the remaining variation difficult to interpret. Table A17 reproduces the baseline results with only census round and county fixed effects; the results are very similar and if anything suggest a *larger* role for innovation in dampening the effect of the Dust Bowl on agricultural outcomes.

Controlling for New Deal Policy A potential concern is that the result is driven, in part, by government spending. It is might be the case that that counties that produced crops that were, on average, more affected, received more federal assistance. Particularly relevant is the AAA, which had a crop-specific component and might have disproportionately allocated funds toward counties whose crops were more damaged nationally (see Section 4.2). To address this, I control directly for several measures of New Deal spending at the county-level—including AAA spending—interacted with Census round indicators. This set of controls flexibly captures any dynamic impact of New Deal policy on county-level outcomes. These results are presented in Table A18 and the coefficients of interest remain similar.

Ruling Out Local Spillovers The innovation exposure measure (5.1) captures *national* Dust Bowl damage to each county's crop mix. Since innovation was re-directed toward more damaged crops, counties with higher innovation exposure have access to more Dust Bowl induced technology. The cultivation of certain crops, however, is concentrated in space and thus county-level innovation exposure may also capture the fact that nearby counties were exposed to the Dust Bowl; this could have a direct effect on agricultural production via local spillovers. To directly address this, I estimate a version of innovation exposure after dropping data from all other counties within the same state; this ensures that innovation exposure does not capture the Dust Bowl exposure of nearby counties. I replicate all baseline estimates using this alternative innovation exposure measure in Table A19 and the results are very similar.

Exploiting Variation in Dust Bowl Intensity In Section 4.2, I show that innovation was more strongly affected by crop-level exposure to areas with *high* levels of erosion than exposure to areas with *medium* levels of erosion. If innovation is driving the estimates of ϕ in Table 3, then the results should be weaker when the Dust Bowl exposure and innovation exposure are computed in terms of exposure to medium levels of erosion rather than high levels of erosion.[29] Analogous to the crop-level estimates, the *differential* effect of exposure to high and medium levels of Dust Bowl exposure—both in terms of the direct effect of the Dust Bowl and exposure to innovation—might do a better job holding other county-level features fixed and comparing more Dust Bowl-exposed and more

[29] Moreover, counties whose crop composition was very exposed to medium levels of erosion during the Dust Bowl may be a more appropriate comparison group for counties whose crop composition was exposed to high levels of erosion; this follows from the logic of the identification strategy in Hornbeck (2012a).

innovation-exposed counties to an appropriate control group. To investigate this, I estimate an augmented version of Equation 5.2:

$$
\begin{aligned}
y_{it} =& \alpha_i + \delta_{st} + \beta \cdot \left(\text{HighErosion}_i \cdot \mathbb{I}_t^{\text{Post 1930}}\right) + \gamma \cdot \left(\text{HighInnovationExposure}_i \cdot \mathbb{I}_t^{\text{Post 1930}}\right) + \\
& \phi \cdot \left(\text{Erosion}_i \cdot \mathbb{I}_t^{\text{Post 1930}} \cdot \text{HighInnovationExposure}_i\right) + \\
& \beta^{\text{med}} \cdot \left(\text{MedErosion}_i \cdot \mathbb{I}_t^{\text{Post 1930}}\right) + \gamma^{\text{med}} \cdot \left(\text{MedInnovationExposure}_i \cdot \mathbb{I}_t^{\text{Post 1930}}\right) + \\
& \phi^{\text{med}} \cdot \left(\text{MedErosion}_i \cdot \mathbb{I}_t^{\text{Post 1930}} \cdot \text{MedInnovationExposure}_i\right) + \epsilon_{it}
\end{aligned}
\tag{E.1}
$$

where "MedErosion$_i$" is the share of land in county i under medium levels of erosion from the Dust Bowl and "MedInnovationExposure$_i$" is analogous to InnovationExposure$_i$ except it captures the aggregate exposure of county i's crop mix to *medium* levels of erosion. Since innovative activity was most responsive to crop-level exposure to high levels of erosion, the exposure of county's crop composition to high levels of erosion should have a larger dampening effect on the Dust Bowl's impact than the exposure of a county's crop composition to medium levels of erosion. In the context of the estimating equation, this would mean that $\phi > \phi^{\text{med}}$.

Table A20 reports estimates of Equation (E.1). Across specifications, I find that $\phi > 0$; moreover, I also find that $\phi > \phi^{\text{med}}$ and that this difference is statistically significant across outcome variables. This more subtle set of results further points toward technology development as the key mechanism driving the estimates in Table 3.

E.1 Exploiting Variation in Farm Size

Not all farms might benefit equally from new innovation; in particular, larger farms were perhaps better able to afford, adopt, and incorporate new technology. Table A21 reproduces the baseline county-level results with the inclusion of an interaction term between the independent variable of interest—Erosion$_i \cdot \mathbb{I}_t^{\text{Post 1930}} \cdot$ InnovationExposure$_i$—and an indicator that equals one if a county's average farm size was above the within-sample median in 1929. The coefficient on the quadruple interaction is positive in all specifications and statistically significant in half. This suggests that, on average, counties with larger farms were better positioned to adapt to the Dust Bowl via the adoption of new technology.

This finding also supports interpretation of the baseline county-level result as the impact of induced innovation rather than output price changes. Recall that the concern is that innovation exposure may also be a shifter of county-level output prices; while I control in all specifications for the direct effect of innovation exposure, this channel could still bias the estimates if prices had a non-log-linear relationship with features of agricultural production. A primary reason this could be the case is if credit constraints limited farmers from adjusting production; farmers producing crops that were more damaged on average may have then been less constrained due to the increased price of their output. If this is true, the baseline estimates could be capturing the differential ability of farmers across counties to afford production adjustments rather than variation in the benefits of new innovation.

If the credit constraints channel were important, however, the baseline effects should be largest for counties with the *most* constrained farms. If, on the other hand, the channel is innovation, the baseline effect, if anything, would likely be larger for the *least* constrained farms since they would be better able to access and afford improved technologies. While ideally one would measure credit constraints at the county level and investigate whether more or less constrained counties are driving the result, to my knowledge a direct measure of credit constraints does not exist. Therefore, the fact that the baseline finding is stronger for counties with *larger* farms that are less likely to be constrained is inconsistent with the main results being driven by price effects and credit constraints.