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

Jacob Moscona†

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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 and persistently re-directed 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 spurring innovation and the importance of endogenous technological progress as an adaptive force in the face of disasters.

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†MIT, email: moscon@mit.edu; website: https://economics.mit.edu/people/faculty/jacob-moscona

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 re-direction 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 crises.

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 (Haines et al., 2018). I use the share of the national land area devoted to each crop that experienced high levels of erosion as my main measure of crop-specific Dust Bowl exposure.

I then develop several complementary strategies to measure crop-specific innovation over time. 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*. This *List* 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.[2] This data set makes it possible to track the development of new crop varieties, which historical accounts suggest were the

[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.

[2] The *List* is compiled by the USDA from a broad range of sources, including "variety release notices, official journals, seed catalogs, and seed trade publications, as well as names cleared for use by seed companies."

primary technology used to adapt production to the changing environment, during a period without systematic patent or intellectual property protection for biotechnology (e.g., Crow, 1998; Sutch, 2011). I supplement the *Variety Name List* with three additional measures of innovation, including patents, which make it possible to investigate the re-direction of innovation across different types of technology (e.g., chemical technology, mechanical technology); research publications, which make it possible to study the effect on upstream science; and experimental records from US federal experiment stations, which make it possible to document the role of government-sponsored research.

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-exposed 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 0.32 standard deviation increase in new crop variety releases, corresponding to an 18% increase in technology development for the median-exposed crop in the sample. The positive effect of Dust Bowl exposure on innovation persisted long after the worst years of the Dust Bowl were over, potentially suggesting that the crisis led to a long-run shift in the direction of innovation and focus of technology development. In a set of sensitivity checks, I show that the findings are not driven by any small set of crops, outlier observations, or crop-level characteristics that might be associated with changing innovation trends.

I next investigate the types of innovation and technology development that underlie the baseline positive relationship between environmental damage and innovation. First, I show that the relationship between Dust Bowl exposure and innovation was strongest for crops for which hybrid varieties could be developed. This is consistent with historical accounts arguing that hybrid varieties were particularly beneficial on damaged topsoil and that the Dust Bowl was a major driver of hybrid variety demand and development (e.g., Crow, 1998). Second, using the patent data, I show that the Dust Bowl had a positive effect on patenting in soil modification and chemical technologies, but had little effect on mechanical technologies that are less relevant for adaptation. This heterogeneity across technology classes is consistent with demand for more environmentally-resilient technology driving the baseline finding rather than price effects or other crop-specific trends. Third, I find no evidence that the Dust Bowl shifted the focus of US breeding programs, suggesting that federal intervention does not drive the baseline results. Finally, I show that scientific publishing also shifted toward crops more exposed to the Dust Bowl and toward topics related to the climate and environment. This change in "upstream" scientific research may have also contributed to the persistent effect of the Dust Bowl on 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, the findings from the first part of the paper 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 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.

How specific was this new technology development to the ecological conditions of the Dust Bowl? Crop varieties are often bred for specific ecological conditions, and varieties that affect production resilience in one environment might not have productivity benefits in another (e.g., Griliches, 1957). There some evidence of a negative relationship between the average productivity and climate resilience of modern grain varieties in recent decades (Lobell et al., 2014). I find no evidence that Dust Bowl-induced innovation raised productivity *outside* the Dust Bowl counties, consistent with the environmental specificity of new technology: innovation exposure is not positively correlated with changes in agricultural land values outside the Plains region or in Plaints regions that were not exposed to high levels of erosion. 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 was directed toward raising production resilience on damaged land.

This paper builds on several bodies of work. First, it extends a large body of work studying adaptation to large environmental shocks (e.g. Hornbeck, 2012a,b; Moore and Lobell, 2014; Hsiang and Jina, 2014).[3] This study builds especially on Hornbeck (2012a), who investigates the short and long run impact of the Dust Bowl on Plains counties, and extends a broader body of work on the

[3]A broader literature studies the direct effect of the climate on US agriculture, including Mendelsohn et al. (1994); Schlenker et al. (2006); Deschênes and Greenstone (2007); Roberts and Schlenker (2011). Other work has investigated adaptation to climate change in agriculture, both in the US and around the world (e.g., Burke and Emerick, 2016; Costinot et al., 2016; Hultgren et al., 2022; Hsiao et al., 2024).

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 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. Most related on this topic is contemporaneous work investigating how agricultural innovation has shifted in response to slow-moving temperature change in recent decades and, based on those estimates, how innovation might be expected to shape the future economic consequences of global warming (Moscona and Sastry, 2023).

Second, this paper extends research investigating the direction of technological change (see Acemoglu, 2002, 2010). There has been a longstanding interest in the extent to which technological progress is driven by moments of crisis and how invention reacts at moments of scarcity or necessity (Rosen, 1994; Keller et al., 2003; Ruttan, 2006; Miao and Popp, 2014; Hanlon, 2015; Gross and Sampat, 2021, 2023a,b; San, 2023; Flynn et al., 2025). This study shows that innovation responded dramatically to environmental crisis, shaping its economic impacts over the subsequent decades. This took place largely in the absence of direct government support. Most prior work on innovation and the environment focuses on the development of emissions-mitigating technology in response to changing market incentives (e.g. Newell et al., 1999; Jaffe et al., 2003; Popp, 2002, 2004; Acemoglu et al., 2012; Aghion et al., 2016). This paper, in contrast, investigates the re-direction and development of adaptation technology, about which much less has been documented.

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 (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). The findings in this paper support the hypothesis that innovators reacted dramatically to environmental stress and document that early 20th century climate extremes had persistent effects on agricultural innovation.

The paper is organized as follows. Section 2 discusses the history of technology development in response to the Dust Bowl. 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

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, new fertilizer and chemical technologies also helped mitigate the effects of adverse environmental conditions on productivity. 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.

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." 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).

Crabb (1947, p. 165-166), who recounts the growth of Pioneer's breeding program, describes how 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." This narrative is not restricted to 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. There are also examples of government-led research reacting to the Dust Bowl. For example, 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).[4]

Pest outbreaks increased as a result of drought and soil erosion and were also the subject of new research investments.[5] 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

[4] Despite these successes, government innovation policy did not change 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 1930s and 40s (Nevins, 1962). I return to public sector innovation in Section 4.4.3.

[5] According to one observer writing in 1932, "For any one who has not seen an outbreak of grasshoppers it is very hard to visualize the damage done...Only when one goes through the country and works with the insect at a given place does a realization of the great destruction come to him" (Schlebecker, 1953, p. 91).

to drought and erosion in the Plains (Baveye et al., 2011).

Farmers themselves noted the increase in available technology during and after the Dust Bowl, as well as the importance of new technology in promoting environmental resilience. According to Walter Schmitt, who lived through the Dust Bowl in Nebraska on his family's farm:

> [B]efore the Dust Bowl days, farmers harvested about 35 to 40 bushels of corn per acre. Nebraska farmers now choose from many kinds of seeds that will grow in different soils and weather conditions, and will resist bugs and diseases, [a]long with hybrid seeds, innovations in irrigation, fertilizers and pesticides (Schmitt, 2003)

Anecdotally, new technologies helped mitigate damage from subsequent extreme weather events on the American Plains. While there were droughts of similar magnitude to the Dust Bowl in the 1950s and 1970s, they did not have nearly as extreme negative consequences for farmers and crop production did not suffer the same losses (Hansen and Libecap, 2004; Baveye et al., 2011). According to Schlebecker (1953, p. 91), "By 1950, just as another [grasshopper] plague was threatening to break out, the new insecticides were available to keep the grasshopper under control."

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. That said, this historical narrative runs counter to a common logic from models of directed technological change that innovation concentrates in the largest and most productive markets and therefore would shift *away* from crops and regions adversely affected by environmental destruction (Schmookler, 1966; Acemoglu, 2002). In Appendix B, I formalize the relationship between Dust Bowl exposure and innovation in a model of directed innovation, building most directly on the theory of equilibrium technological change developed in Acemoglu (2010) and its more recent application in Moscona and Sastry (2023). The model conveys that the predicted response of innovation to the Dust Bowl is ambiguous *ex ante*. Depending on the marginal effect of new technology on productivity is (on average) higher or lower on more environmentally degraded land, new innovation can either shift toward markets most negatively affected by the Dust Bowl—as suggested my historical accounts—or shift away from them—as implied by standard market size effects. Indeed, even as global warming has threatened agricultural productivity in recent decades, some evidence suggest that newer crop varieties have become *less* resilient to climate shocks in order to achieve higher average productivity (Lobell et al., 2014; Tack et al., 2016), leading to rising drought sensitivity overtime (Lobell et al., 2020) and complicating production in more heat-exposed regions. This theoretical ambiguity makes systematic, empirical analysis all the more crucial.

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). Figure A1 maps the share of total county land area under high and medium levels of erosion. Counties outside the Plains region used in the main analysis are covered with diagonal lines. 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. For example, measured erosion outside of the Plains region was not due to climate events during the early 1930s but rather captures prior land erosion that occurred for some other reason. Throughout the paper, I return to tests of potential bias due to this data feature.

Technology Development The main measure of technology development used in the analysis is the release of novel varieties using data from the United States Department of Agriculture (USDA) *Variety Name List*. The *List* catalogues 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 had an incentive to report new varieties for inclusion 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.[6] The key advantage of this data source is that it is possible to track innovation in seed varieties, which was anecdotally the most relevant technology for adaptation but cannot be measured with intellectual property data until the 1970s.

I supplement the *Variety Name List* with several additional measures of innovation and technology development. These make it possible both to corroborate the baseline estimates using alternative measurement strategies and to paint a more complete picture of how innovation reacted to environmental change. First, I compile data on crop-specific patenting in order to measure crop-level technology development across *multiple technology classes*. Using the database *PatSnap* (PatSnap Ltd., 2020), 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 (as in San, 2023; Moscona and Sastry, 2023). 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. The patent data are also useful for corroborating a version of the baseline results with an independent data set with more restrictive inclusion criteria. The downside to this strategy is that linking innovation to crops is not as straightforward as with varieties and requires relying on crop name mentions in the patent text. Second, I compile data on all research articles in the agricultural sciences from the Institute for Scientific Information's *Web of Science* database (Clarivate Analytics,

[6]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).

2020). The *Web of Science* combines article and citation information from 12,000 journals and 160,000 conference proceedings; I link all articles to crops by searching for the name of each crop in article titles.[7] Third, I use data on crop-specific experiments from US federal experiment stations (1910-1945), compiled by Kantor and Whalley (2019). Experiment-level information, including the crop of focus, were collected from individual reports published by each station. These data make it possible to investigate the extent to which public research contributes to the main finding.

Agricultural Production Data on county-level outcomes are from the 1910-1959 rounds of the US Census of Agriculture (Haines et al., 2018). Variables constructed from the Census of Agriculture include the value of land, agricultural revenue, farm size, and measures of land use. 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 is 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:

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

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. $\mathbb{I}\{\text{Plains}_i\}$ is an indicator that equals one if a county is in the Plains region. $\text{High Erosion Share}_i$ 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 crop-level damage by Dust Bowl erosion.[8]

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

[7] While other academic publication databases rely predominately on modern digital scholarly metadata, which are much less likely to be available before the 1950s, Web of Science uses a series of additional sources and specialized databases to extend its historical coverage (e.g., the Science Citation Index Expanded (SCIE) and the Social Sciences Citation Index (SSCI), which date back to the 1900s). This make it an ideal source for measuring scientific trends during the first part of the 20th century.

[8] Appendix C discusses the underlying data used for this measure in more detail. Table A1 reports the full list of crops in the baseline analysis, along with its Dust Bowl exposure ranking and additional summary statistics.

during the later part of the sample period. 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 Results: 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 (1920-1960). 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 a measure of innovation (e.g., new variety releases) for crop c in year t.

The coefficient of interest is β. $\beta > 0$ implies that innovation was directed toward crops that were more damaged by the Dust Bowl, perhaps due to the heightened demand for resilient technology in Dust Bowl-affected regions; $\beta < 0$ implies that variety innovation was directed away from crops that were more damaged by the Dust Bowl, perhaps seeking greater profit opportunities in parts of the agricultural economy on more solid economic ground. The model presented in Appendix B clarifies these competing mechanisms and explains why either sign for β is possible *ex ante*.

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 $\tau \in \mathcal{T}^{pre}$, 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.

The key identifying assumption is that crops that were more versus less exposed to the Dust Bowl would have remained on similar trends after 1930 had the Dust Bowl never taken place. Thus, the main potential threat to identification is that exposure to the Dust Bowl disproportionately affected the crops in which innovation would have taken off after 1930, even in the absence of envi-

Table 1: Dust Bowl Exposure and New Crop Varieties

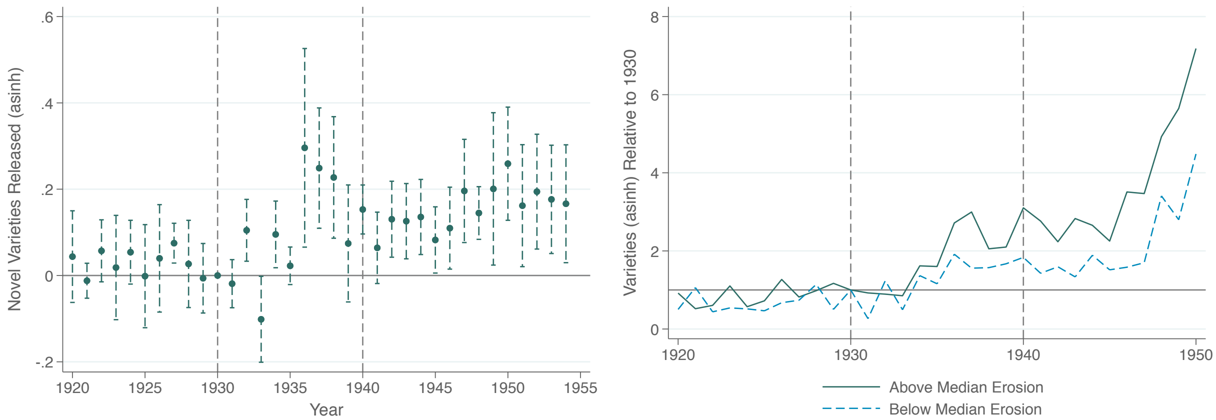
	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	New Varieties (asinh)		New Varieties (log)		New Varieties (count)
Specification:	OLS	OLS	OLS	OLS	PPML
$\text{Exposure}_c \times \mathbb{1}_t^{\text{Post 1930}}$	0.0694***	0.114***	0.0680**	0.133***	0.0750***
	(0.0242)	(0.0272)	(0.0320)	(0.0356)	(0.0283)
Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Weighting	None	Initial Area	None	Initial Area	None
Crops	43	43	43	43	43
Observations	1,720	1,720	799	799	1,720
R-squared	0.663	0.828	0.601	0.823	-

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, in columns 3-4 it is log of the number of new varieties, and in column 5 it is the number of new varieties in each crop-year. Columns 1-4 are estimated via OLS and column 5 is estimated via Poisson pseudo-maximum likelihood. Columns 2 and 4 are weighted by initial crop planted area. Standard errors, double clustered by crop and year, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

ronmental change. The relatively small number of crops (43), and the concentration of innovative activity throughout the sample period (1920-1960) in the most economically important crops, also raise the concern that the results are driven by spurious changes in innovation trends for a relatively small part of the sample. Table A2 document that crop-level exposure to the Dust Bowl is balanced across a range of crop-level characteristics, including proxies for crop-level market size (e.g., total harvested area and the number of released varieties during the pre-period), measures of sensitivity to environmental change (e.g., minimum rainfall requirement, maximum temperature resilience), and measures of technological capabilities (e.g., ease of hybridization). Nevertheless, throughout the empirical analysis, a key goal will be ruling out the possibility of a spurious relationship between Dust Bowl exposure and changing crop-level innovation trends during the 1930s.

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 sine of the) number of new agricultural varieties released for each crop in each year. 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 is not driven by crops that are a small share of national agricultural production. Columns 3-4 repeat the same specifications except using the log of the dependent variable and col-



(a) Event Study

(b) Raw Data Trend

Figure 1: **Dust Bowl Exposure and Innovation: Dynamics.** 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.

umn 5 uses a Poisson pseudo-maximum likelihood estimator, since the outcome is a count variable. 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. The estimates 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.

4.2.1 Dynamics

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 and remain that way for the subsequent decades. 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. While technology development in all crops was rising during the sample period (1920-1960), as has been the case for much of the 20th century, during the worst years of the Dust Bowl innovation in more vs. less exposed crops sharply diverged.

While variety development was directed toward Dust Bowl exposed crops starting at the height of the Dust Bowl, the effect also persisted after the Dust Bowl ended. There are several potential explanations for this. One is that, while the period of extreme weather and dust storms largely concluded in 1939, the effect on land quality persisted. Much of the land never recovered its topsoil (Worster, 2004, p. 24) and, 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 possibility is that research spurred by the Dust Bowl had a lasting impact on the scale and efficiency of R&D investments. Programs that were first financed and set up during the Dust Bowl continued to operate after the 1930s; 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.” Thus, major investments during the Dust Bowl might have had long run effects on research productivity. This dovetails with growing evidence from other contexts that changes in research investment can have lasting effects on innovation, even decades later (e.g. Gross and Sampat, 2023a, 2025; Antolin-Diaz and Surico, 2025). Consistent with this narrative about overcoming fixed costs to R&D, I find that the longer-run effects of the Dust Bowl on innovation were driven by crops with more limited pre-existing variety development prior to the Dust Bowl (Table A3). These are the crops whose future research costs may have been most affected by the “big push” provided by the Dust Bowl since investment had not yet taken off. That said, these findings are suggestive and a deeper understanding of the mechanisms underlying dynamic innovation spillovers and long-run effects of major R&D investments—which seems to be a common finding across contexts—is an important area for future work.

4.3 Sensitivity and Robustness

This section probes whether the data support a causal relationship between Dust Bowl exposure and crop-level innovation. The main goal of each empirical test reported in this section is to rule out the possibility that the findings are driven by changes in technology trends or opportunities across crops that may have spuriously correlated with Dust Bowl exposure but were not caused by environmental distress. First, I use a series of placebo exercises to rule out the possibility that the main results are simply picking up differential trends in crops that were grown on the Plains region where the Dust Bowl took place. Second, I show that the results are similar after controlling directly for a range of potential determinants of innovation trends, including crop-level market size, pre-period innovation, and hybridization potential. I also show that the results are similar after fully dropping sets of crops that might be on separate innovation trends, including the largest-market crops, grain crops, and highly traded crops. Third, I use a permutation test to verify that the results are not driven by spurious differential trends in any small set of crops and that the baseline standard errors achieve appropriate coverage. Finally, I use in-sample weather shocks to construct instruments for Dust Bowl exposure in order to make sure that the findings are not driven by reverse causality between technology use and soil erosion or any other feature of erosion measurement.

Crop Geography Placebo Test Since the Dust Bowl was concentrated in the Plains region, one possibility is that the Dust Bowl exposure measure is also picking up the crops that are disproportionately grown in the Plains region, which includes many major staple crops, rather than just their exposure to environmental catastrophe. These crops could be on separate innovation trends for reasons other than the impact of the Dust Bowl. To rule out this possibility, I compute a placebo measure that weights crop land area in each Plains county by the share of each Plains county that had *low* levels of erosion:

$$\text{Low Exposure}_c = \sum_i \frac{L_{ic}}{\sum_{i'} L_{i'c}} \cdot \mathbb{I}\{\text{Plains}_i\} \cdot \text{Low Erosion}_i \tag{4.3}$$

If the main results capture changing trends in innovation for Plains crops, then Low Exposure_c should also be positively associated with innovation after the Dust Bowl. However, I find no relationship between this placebo measure and variety development (Figure A2, bar 2).

I also 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. Crop-level exposure to medium levels of erosion is estimated using (4.3), except low erosion is replaced with medium erosion. While the impact of medium erosion exposure is positive (Figure A2, bar 3), the impact of high erosion exposure is larger in magnitude and the difference is statistically significant ($p < 0.05$). These findings further support the argument that the extent of environmental damage was the cause of technology development.

Accounting for Alternative Drivers of Innovation Next, I investigate the robustness of the baseline result to controlling for crop-level characteristics beyond crop geography that might have influenced innovation trends even in the absence of the Dust Bowl. Table A2 highlights that many of these characteristics are not correlated with Dust Bowl exposure, making it unlikely that they underlie the main result. I next investigate this possibility systematically by controlling for a series of crop-level characteristics interacted with a full set of year fixed effects (see Figure A3).

First, I control for pre-period crop variety releases (bar 2), flexibly capturing any innovation trends correlated with baseline differences in technology development (e.g., if innovation took of during the 1930s for crops in which innovation had already been most or least concentrated). Second, I account for differential crop-level exposure to the New Deal by controlling for crop-level inclusion in the 1933 Agricultural Adjustment Act (AAA) (bar 3).[9] Third, I account for the fact that certain crops may have been more exposed to national or international markets, which could effect crop-level price and demand trends, by controlling for whether or not the crop is perishable (i.e., ease of trade) and whether or not the crop was included in national trade statistics prior to the Dust Bowl (United States Department of Agriculture, 1936) (bar 4).[10] Fourth, I control for indicators for Depression and WWII years interacted with a full set of crop fixed effects to flexibly capture the differential effect of these shocks on crop-level trends (bar 5). While there is no reason *ex ante* why

[9]The AAA, which was the only New Deal program to have a crop-specific policy component, was initiated prior to the worst years of the Dust Bowl and before the extent and distribution of its damage was known. Nevertheless, it might have affected innovation incentives and also spuriously correlate with Dust Bowl exposure. While the AAA could have had independent effects on crop-level innovation, for example by increasing the market size of relevant technologies, the similar result after including these controls suggests that the main result is not biased by the effect of the AAA.

[10]While systematic data on trade across crops is limited during the early 20th century, existing evidence suggests that trade in the most Dust Bowl exposed crops was relatively limited. Import and export statistics were only systematically collected for twelve of the 43 crops in the baseline sample, and total exports of many of these crops were limited at the time of the Dust Bowl; for example, net exports of corn represented 0.8% of production in 1925 and 0.29% of production in 1932 (United States Department of Agriculture, 1936). The shares are slightly larger for wheat (13.8% and 4.4%) but similar for oats (2.8% and 0.4%) and buckwheat (0.1% and 0.4%), for example.

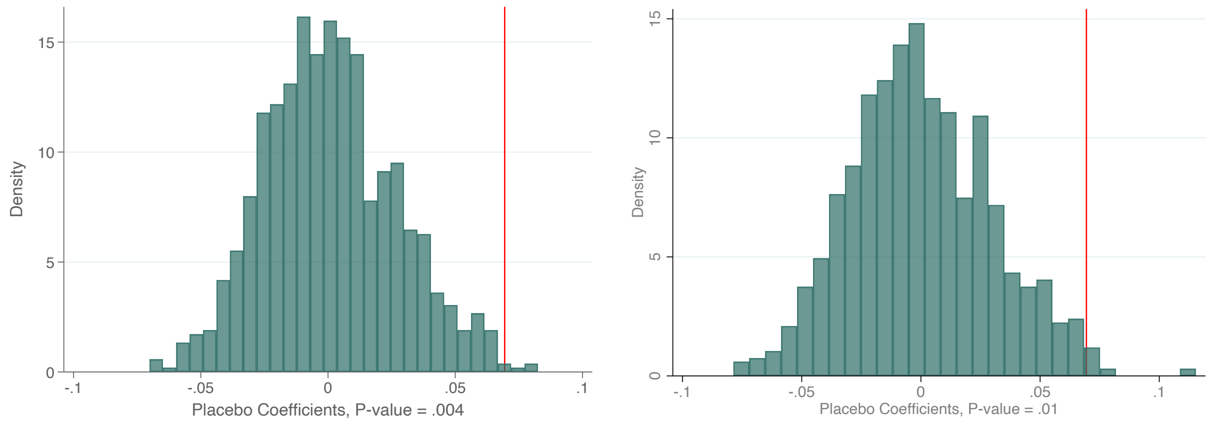
this should relate to Dust Bowl exposure, it could have differentially affected crop-specific demand in ways that spurred innovation. Fifth, I address the fact that the development of hybrid crop varieties began to take off during the 1930s, most famously in the case of corn (Griliches, 1957). While a range of case-study evidence suggests might have been an *outcome* of Dust Bowl-induced demand for more resilient seed varieties (May, 1949; Sutch, 2011), I control directly for the key crop-level characteristic that makes hybridization possible—the absence of perfect flowers—in order to rule out any confounding effect (bar 6).[11] Sixth, I control for a grain crop indicator (bar 7), and finally, I control for all preceding controls at once (bar 8). In all cases, the coefficient of interest remains similar and, if anything, it increases in magnitude when all controls are included.

Next, I show that the results are similar if I fully exclude from the sample crops that might have seen expanded market opportunities during the early 20th century, and hence different innovation trends, even in the absence of the Dust Bowl (see Figure A4). First, I drop the crops with the largest pre-period land area (bar 2). Second, I further drop all grain crops, which were disproportionately grown in the Plains region (bar 3). The estimates are also similar after dropping each major grain crop one-by-one.[12] Third, I exclude the most traded crops (United States Department of Agriculture, 1936) (bar 4). Finally, I show that the results are similar after making all sample restrictions at once (bar 5) and after further including all controls from Figure A3 (bar 6).

Permutation Test Given the relatively small sample size, it is also important to make sure that the results are not driven by a small number of crops that happen to have both been highly exposed to the Dust Bowl and also experience a trend break in innovation. To investigate this issue systematically, I conduct a permutation test that randomly re-assigns the Dust Bowl exposure measure across crops and re-estimates the baseline regression equation (4.1) using these alternative treatment assignments (see Imbens and Rubin, 2015, on the usefulness of this approach for small samples). If the true coefficient estimate is in the right tail of the placebo coefficient distribution, it would indicate that the precision of the baseline estimate is not driven by a relatively small set of crops or by random chance, since this small set would also have a high treatment value across many randomized draws. The full set of placebo coefficients is reported in Figure 2. The actual coefficient estimate is reported with the red line and is in the far-right tail of the distribution, both when no additional controls are included (Figure 2a) and when all of them are (Figure 2b). The set of placebo coefficients is centered around zero. This analysis suggests that the baseline result represents a systematic and precise relationship between Dust Bowl exposure and innovation.

[11] 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—which makes hybridization much more feasible (e.g. Wright, 1980; Butler and Marion, 1985). I use data from Moscona (2024), which goes into greater detail about this distinction, to construct the hybrid feasibility control.

[12] For example, the coefficient estimate corresponding to column 1 of Table 1 is 0.062 after dropping wheat, 0.091 after dropping sorghum, 0.058 after dropping corn, 0.069 after dropping soybeans, 0.068 after dropping oats, 0.070 after dropping barley, 0.070 after dropping rice, 0.069 after dropping rye, and 0.061 after dropping all aforementioned crops.



(a) No Added Controls

(b) All Additional Controls

Figure 2: **Falsification Tests.** Histogram of placebo estimates of β from Equation 4.1 after Exposure$_c$ was randomized across crops. The results from 1000 randomizations are reported as the green histogram and the true estimate of β is marked with a red line. Panel 2a reports results using the baseline difference-in-differences specification and Panel 2b reports estimates from a specification that also includes all additional controls listed in Figure A3. The implied randomization inference p-value is reported beneath each x-axis.

Measurement of the Environmental Shock One shortcoming of the measure of Dust Bowl exposure is that the USDA soil maps capture cumulative erosion as of the mid-1930s, much of which (in the Plains region) was caused by the Dust Bowl but some of which likely pre-dated the Dust Bowl. I use two strategies to make sure that the results are not driven by differences across crops that are more or less exposed to cumulative erosion. First, I show that the results are also very similar using exogenous weather shocks from the 1930s to construct instruments for Dust Bowl exposure (Table A4). 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.[13] Second, I construct a measure of exposure to erosion *outside* of the Plains counties, where cumulative erosion was mostly unrelated to the environmental shock of the 1930s. Figure A2 (fourth bar) shows that there is no relationship between this crop-level measure of exposure to cumulative erosion and innovation, suggesting that the baseline results do not capture differences between crops that happen to be grown on land with more versus less cumulative erosion.

4.4 Types of Technology and Innovation

Having established the baseline relationship between Dust Bowl exposure and variety development, this section investigates in greater detail the specific types of innovation that were most responsive to the Dust Bowl. First, I focus on the potentially important role played by hybrid crop

[13] I construct crop-level measures of weather severity by aggregating county-level weather data from Vose et al. (2014) using Equation 3.1; as weather variables, I use the standard deviation of local temperature and the Palmer drought index.

varieties, which historical accounts suggest were more resilient to climate extremes. Second, I use patent data to study the response of types of technology other than crop varieties. Third, I investigate whether government research at experiment stations were an important mechanism. Finally, I study whether there was any impact on upstream scientific research. The main conclusion from this analysis is that the response seems to be stronger in types of research and technology development most relevant for environmental adaptation, suggesting that the main results are driven by innovators responding to heightened demand in environmentally-damaged areas.

4.4.1 Hybrid Varieties

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). Anecdotally, hybrids were "strikingly more resistant" in the face of environmental degradation (Crow, 1998) and hence among the most productive seed varieties in the Dust Bowl's aftermath. If innovators were responding to technology demand in environmentally distressed part of the country, we might expect there to be a larger response for hybrid varieties.

Since it is not possible to directly measure which varieties are hybrids, to investigate whether the re-direction of variety development was driven by hybrid varieties I exploit variation across crops in the ease of hybrid development and check whether the baseline results are stronger for more "hybrid suitable" crops. In particular, the development of hybrid varieties is easier and much less costly when a crop has imperfect flowers (i.e., when the male and female parts are on different parts of the plant) since it is possible to separately capture the male and female genetic material. Thus, imperfect flower structure serves as a fixed crop-level proxy for the feasibility of hybridization, and the crops for which hybrid varieties were developed during the period (e.g., corn) all have imperfect flowers (see Wright, 1980; Butler and Marion, 1985; Moscona, 2024).[14]

Figure A5 reports estimates of Equation 4.1 that include an interaction term between Dust Bowl exposure and a crop-level imperfect flower ("hybrid feasibility") indicator. While there is a positive and significant coefficient for hybrid-infeasible crops, suggesting that the baseline results are not solely driven by hybrid development, the response was significantly larger for hybrid-feasible crops. These findings suggest that hybrid variety development played a particularly important role in the innovative response to the Dust Bowl.

4.4.2 Patenting and Non-Variety Technologies

In addition to shifting focus across crops, technology development may have also re-directed toward technologies that are most useful for adapting to environmental change. Varieties of hybrid crops are one such example. More generally, the Dust Bowl may have led to broader shifts in focus

[14] While it would also be interesting to measure the number of hybrid and non-hybrid varieties released for each crop directly, to my knowledge these data do not exist until varieties entered the patent record during the 1980s.

toward certain types of technologies that are more relevant for adaptation to environmental change (e.g., varieties), and away from other technologies that are not (e.g., tractors, harvesters).

To investigate this possibility—and, more generally, to study the impact of the Dust Bowl on technologies other than plant varieties—I use data on agricultural patenting. I use the cooperative patent classification (CPC) of each patent to classify each patent into mechanical technologies (e.g., harvesters), post-harvest and processing technologies, and soil-modification and chemical technologies (e.g., fertilizers, pesticides).[15] Table A5 reports the effect of crop-level exposure to the Dust Bowl on citation-weighted patenting in each technology class. I find no effect of Dust Bowl exposure on mechanical or post-harvest technologies (column 1). However, I find a positive effect of the Dust Bowl on soil modification and biological and chemical technologies, mirroring the baseline results on crop varieties (column 2). The finding seems to be driven especially biological and chemical technology development (column 3). Intuitively, these types of technology are more relevant to environmental adaptation and thus may have been more responsive to demands for more resilient production technology. These findings are also consistent with Hayami and Ruttan (1971) and Ruttan and Hayami (1984), which argue that biological and chemical technology development increases in response to relative land scarcity (e.g., land degradation caused by the Dust Bowl), while mechanical technology development increases in response to relative labor scarcity.

Methodologically, this set of estimates also suggests that the baseline result is not driven by aggregate trends in crop-level innovation or demand, which would have plausibly affected all technology areas. Instead, the effect is concentrated in the technologies that were most likely to be relevant for environmental adaptation. To make this point explicitly, I estimate an augmented version of the baseline specification, in which the unit of observation is a crop-year-technology triplet:

$$y_{xct} = \alpha_{cx} + \delta_{tx} + \gamma_{ct} + \psi \cdot \text{Exposure}_c \cdot \mathbb{I}_t^{\text{Post 1930}} \cdot \mathbb{I}_x^{\text{Adapt}} + \epsilon_{kct} \tag{4.4}$$

where now x indexes CPC classes and $\mathbb{I}_x^{\text{Adapt}} = 1$ for soil modification and chemical technologies (CPC classes A01B, A01C, A01H and A01N). γ_{ct} fully absorbs all crop-specific trends, crop price changes which could be one mechanism driving the baseline estimates. The coefficient of interest ψ captures the extent to which technology development in more-exposed crops increased disproportionately in adaptation-relevant areas compared to mechanical and post-harvest technology development. I find that ψ is positive and highly significant (column 4), suggesting that technology development increased significantly more in adaptation-relevant technologies in crops more exposed to the Dust Bowl. This finding also confirms that the main results are not driven by any spurious differential trends across crops or by crop-level price changes, both of which are fully absorbed by the crop-year fixed effects. Instead, the results are driven by higher demand for specific technologies that reduce the marginal effect of environmental damage.[16]

[15] I identify patents in CPC classes A01D, and A01G as mechanical technologies; A01F as post-harvest technologies; and A01B, A01C, A01H and A01N as soil modification (A01B, C) and biochemical technologies (A01H, N).

[16] This finding also suggests that changes in domestic or international trade, which could mediate the effect of local environmental damage on crop prices, are unlikely to drive the main results. This is consistent with Figures A3 and A4 showing that the main results are similar after controlling for proxies for crop-level trade.

4.4.3 Federal Experiment Stations

There are some examples of particularly resilient crop varieties emerging from government-funded breeding programs (see Section 2). To investigate whether federal breeding and experimentation responded systematically to the Dust Bowl, I turn to independently collected data on experiments conducted on US federal experiment stations, originally compiled by Kantor and Whalley (2019), and identify the crop that was the focus of each experiment. Panel A of Table A7 reports estimates of Equation 4.1 in which the dependent variable captures the number of experiments related to each crop. Panel B is identical to Panel A, except that the outcome variables measure experiments only in stations located in Dust Bowl states (see Figure A1), which might be more likely to shift focus in response to the Dust Bowl. The estimates are all small and statistically indistinguishable from zero. One explanation for the limited response is that federal researchers were instructed to focus on basic, rather than applied, research, and to not "focu[s] research on solving local problems" (Nevins, 1962). During the Dust Bowl, they also focused disproportionately on documenting the value of production adjustment rather than new technology (Stephens, 1937).

4.4.4 Scientific Research

To this point, the results have focused on technology development, in the form of new seed varieties and patents. Here, I investigate whether scientific research shifted in response to the Dust Bowl. Upstream scientific research may have reacted to changes in the demand for new knowledge induced by environmental change. The Dust Bowl could have also made certain topics more salient in ways that percolated upstream to affect the focus of scientific research. 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.[17] I also identify the articles that mention keywords related to the environment in order to study whether there was a rise in agricultural science related to the climate.[18]

I find that crop-level exposure to the Dust Bowl increased scientific research, and this is especially true for research related to the environment (Table A6). These results depart from prior work on directed technical change, which focuses on the development of new technology rather than the production of new scientific knowledge (e.g. Acemoglu and Linn, 2004; Hanlon, 2015). Moreover, this shift in scientific research may have contributed to the long-run effect of the Dust Bowl on innovation (Figure 1) and, more generally, may be important part of the short and long run response of technology to major crises. Understanding how science responds to downstream technological opportunities seems like an interesting area for future work.

[17] Article abstracts are not available for the vast majority of articles before 1950, and are not available for any articles during the pre-period in the difference-in-differences design (before 1930).

[18] My keyword search is to require at least one of the following terms in the article title: drought, erosion, climate, temperature, rain, dust, wind.

5 Results: Adaptation

Did the major shift in the direction of technology in response to the Dust Bowl shape its economic consequences? This section studies the role of innovation in mitigating the Dust Bowl's economic harm. I investigate the county-level impact of the Dust Bowl and compare its impact in counties that were differentially exposed to the re-direction of innovation documented above. I find that exposure to new innovation substantially mitigated the negative economic consequences of the Dust Bowl.

5.1 Empirical Strategy

5.1.1 Measurement

The two key ingredients for this part of the empirical analysis are a measure of local exposure to the Dust Bowl and local exposure to induced innovation. To measure local exposure to the Dust Bowl, I use the share of county-level land exposed to high levels of topsoil erosion (following Hornbeck, 2012a). To measure local exposure to Dust Bowl-induced innovation, I calculate the extent to which the crops cultivated in each county were exposed to the Dust Bowl *on average* across all counties. Counties that cultivated crops more exposed to the Dust Bowl 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 that were 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 measure the innovation exposure of each 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 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.[19]

5.1.2 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 census rounds, and s 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.

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

Panel A of Table 2 presents long difference estimates of Equation 5.2 in which only the first and last Census round in which each outcome variable is recorded is included in the sample.[20] 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. The results are similar when the outcome variable is the (log of the) value of land per acre (column 2), or when the outcome variable is (log of) in-sample agricultural revenue (column 3) or agricultural revenue per acre (column 4).[21]

[19] The geographic distribution of innovation exposure is displayed in Figure A6.

[20] 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. In Table 2, standard errors are clustered by crop, but Table A8 shows that the precision of the baseline estimates is very similar after adjusting the standard errors for spatial correlation (see Conley, 1999; Hsiang, 2010).

[21] An alternative approach could be to use actual variety releases for each crop to construct a measure of innovation exposure and use this, instrumented with the measure in Equation 5.1, in estimates of Equation 5.2. There are a few shortcomings to this approach. First, it requires using multiple instruments (innovation exposure and its interaction) for multiple endogenous variables. Second, many varieties are unrelated to environmental adaptation, making this an imprecise measure of the conceptually relevant object. Third, most variety releases are concentrated in a relatively small

Table 2: 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
	Panel A: Effects of Dust Bowl and Innovation Exposure			
$\text{Erosion}_i \times \mathbb{1}_t^{\text{Post 1930}}$	-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
	Panel B: Pre-trends for Innovation Exposure			
$\text{Erosion}_i \times \text{InnovationExposure}_i$	0.0925	1.035	1.189	2.287
	(3.649)	(3.881)	(6.111)	(4.579)
State Fixed Effects	Yes	Yes	Yes	Yes
Observations	796	796	796	796
R-squared	0.469	0.488	0.269	0.365

Notes: The unit of observation is a county-year in Panel A and a county in Panel B. All estimates are from long differences specifications. In Panel A, the starting year is either 1920 or 1925 and ending year either 1940 or 1959, depending on data availability. In Panel B, the dependent variable is the change in each outcome variable between 1910 and 1930. 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.

Panel B of Table 2 shows that there do not seem to be any pre-existing trends in the relationship between innovation exposure and county-level outcomes. Each column reports the relationship between $\text{Erosion}_i \cdot \text{InnovationExposure}_i$, the independent variable of interest in Panel A, and the change in each outcome variable between 1910 and 1930. In all cases, the coefficient estimates are small in magnitude compared to Panel A and statistically indistinguishable from zero.

Figure 3 illustrates the magnitude of the innovation effect, using the specification from column 1 of Panel A of Table 2. 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

set of crops, so estimates could be driven simply by differential trends in specialization in those crops. Nevertheless, to pursue this strategy, I construct a direct measure of exposure to varieties released during the sample period:

$$\text{VarietyExposure}_{it} = \sum_c \frac{L_{ic}}{L_i} \cdot \log(\text{Varieties Released}_{ct})$$

and report estimates in Table A9 that instrument for regressors that include $\text{VarietyExposure}_{it}$ with analogous regressors that include $\text{InnovationExposure}_{it}$ from Equation 5.1. The estimates are qualitatively very similar to the baseline results, even after controlling for trends in baseline production shares for the crops with the highest number of variety releases (Panel B). Coefficient estimates imply that a 1% increase in variety development reduces the marginal effect of Dust Bowl erosion on agricultural output by 1-2%.

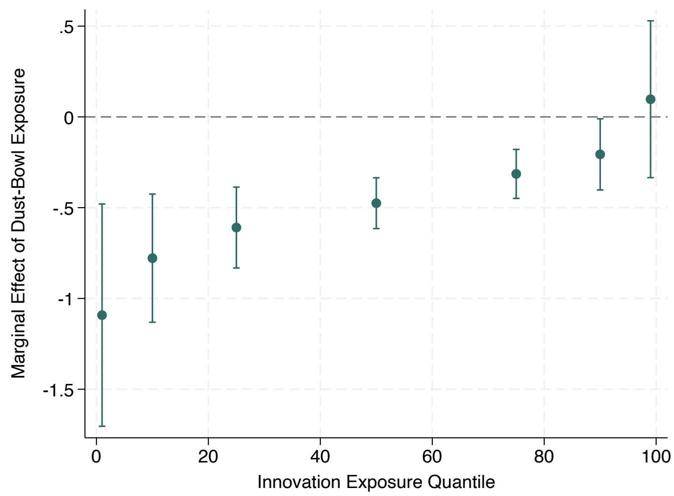


Figure 3: **Quantitative Impact of Innovation Exposure.** The points display the marginal impact of Dust Bowl exposure (y-axis) by innovation exposure quantile (x-axis). Marginal effects are estimated using Equation 5.2, evaluated at various percentiles of the innovation exposure distribution. Innovation exposure is defined in Equation 5.1 and the reported coefficients correspond to the 1st, 10th, 25th, 50th, 75th, 90th and 99th percentile effects. 95% confidence intervals are reported.

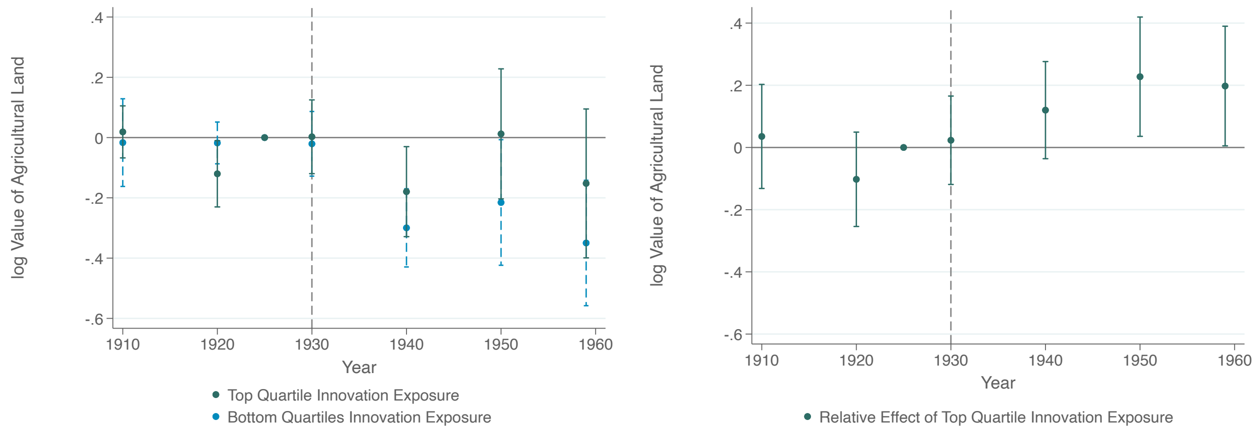
exposure distribution.[22] The marginal impact of land erosion for a county with median innovation exposure is under half that of a county at the bottom of the innovation exposure distribution. Moreover, counties at the highest part of the innovation exposure distribution experienced no discernible long run decline in land value as a result of the Dust Bowl (top right). Thus, directed technology drove substantial heterogeneity in the downstream economic impact of the Dust Bowl.

In Appendix E, I discuss additional results that further probe the sensitivity of the county-level estimates. These include replicating the findings using the full panel of census rounds, rather than long difference estimates (Table A10); re-producing all estimates without state-by-time fixed effects (Table A11); 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 A12). 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 A13). Dovetailing with the analogous crop-level estimates, this is consistent with directed innovation in response to environmental catastrophe driving adaptation.

5.2.1 Dynamics

Figure 4 displays the dynamic relationship between Dust Bowl exposure and the value of agricultural land. Figure 4a reports the effect of Dust Bowl exposure over time, separately for counties in the top quartile of innovation exposure ("high innovation exposure") and counties in the bottom three quartiles of innovation exposure ("low innovation exposure"). Prior to 1930, the two sets of

[22] In particular, Figure 3 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) Top and Bottom Quartiles Innovation Exposure (b) Relative Effect of Top Quartile Innovation Exposure

Figure 4: **Innovation Exposure and Land Values: Dynamic Effects.** Figure 4a reports the effects of Dust Bowl exposure in each decade separately for counties in the top quartile and bottom three quartiles of innovation exposure. Figure 4b reports the differential effect of Dust Bowl exposure between these two sets of counties. That is, it reports coefficient estimates on the interaction between Dust Bowl exposure, an indicator for being in the top quartile of the innovation exposure distribution, and decade indicators. 95% confidence intervals are reported for all coefficients.

counties were on similar trends. However, their trends diverge in 1940, a decade after the start of the Dust Bowl, and diverge even further in 1950 and 1960. The negative effect of Dust Bowl exposure persists in low-innovation exposed countries, while it declines in magnitude over time in high-innovation exposed counties. By the 1950s, the effect of Dust Bowl exposure on high-innovation exposed counties it not statistically distinguishable from zero.

Figure 4b reports the differential effect of the Dust Bowl over time in high- vs. low-innovation exposed counties. This corresponds exactly to the difference between the two sets of coefficients from Figure 4a in each decade. Again, it is possible to see that the two sets of counties were on similar trends prior to the Dust Bowl. However, the Dust Bowl had a a substantially weaker effect on more innovation-exposed counties. The gap between the two sets of counties widened over time, perhaps as more innovation-exposed counties adopted and incorporated new technology subsequent decades while less innovation-exposed counties remained economically depressed.

5.2.2 Mechanisms and Potential Threats to Interpretation

The main threat to the interpretation is that innovation exposure may be correlated with other county-level dynamics, especially changes in producer prices caused by the Dust Bowl itself. Since all estimates control for the direct 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 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 compared to counties that were less exposed to the Dust Bowl. To address this potential concern, 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.[23] I then control directly for county-level changes in output prices, as well as the interaction between 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. This result makes it unlikely that producer price changes are driving the effects in Table 2.

As noted above, price effects are only a threat to interpretation if their impact on profits is larger in more Dust Bowl-exposed counties. One reason this might be true is if credit constraints limited Dust Bowl-exposed farms from adjusting to environmental damage, but higher output prices relieved some of these constraints and facilitated production adjustment. If this is true, then estimates of ϕ would be largest for the most constrained farms or for countries with the most limited potential access to credit. I investigate this possibility in two ways.

First, I investigate heterogeneous effects based on pre-period average farm size (see Table A14). If the findings are driven by counties with smaller farms, which are more likely to be constrained, it could indicate that price effects might be driving the relationship between innovation exposure and agricultural outcomes. However, for all outcome variables, the estimates are larger for counties with larger farms, and in half of the columns the difference is statistically significant. These results are inconsistent with price effects driving the result since they suggest that the findings are driven by least-constrained farms. Moreover, they are consistent with the induced innovation hypothesis to the extent that larger farms are better able to access improved technology.

Second, I directly measure local bank access and bank suspensions using data from Federal Deposit Insurance Corporation (1992) and repeat estimates of equation 5.2 after restricting the sample to counties with above or below median exposure to banks or to bank suspensions. I find no evidence that the effects are driven by the counties with more limited bank access—the effect size is virtually identical for both sets of counties across all proxies for credit access (see Figure A7). Thus, price effects—and their potential interaction with heterogeneous credit constraints—do not seem to underlie the main findings.

A final potential threat to interpretation would be if the innovation exposure measure were spuriously correlated with New Deal policy developed in response to the Dust Bowl. However, the estimates are very similar after controlling flexibly for local government spending and a range of New Deal programs compiled by Fishback et al. (2005) (see Appendix E and Table A16). While these could be considered "bad controls" to the extent that New Deal spending and program take-up were an outcome of the economic damage from the Dust Bowl, the similar estimates suggest that

[23] 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.

differences in New Deal spending were not an important intervening mechanism for the baseline county-level results.

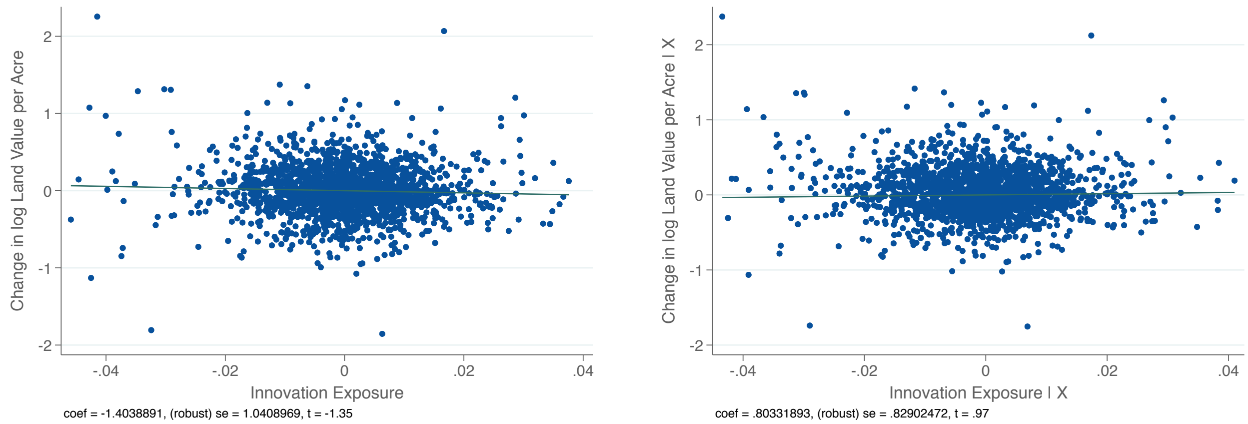
5.3 Mechanism: Resilience on Damaged Land and Context-Specific Technology

To this point, the results have focused on the impact of new technology in counties that were directly affected by the Dust Bowl. These new technologies may have also had benefits for farmers elsewhere in the country, to the extent that they were broadly applicable or were designed to expand production opportunities in places that were out of harm's way. However, there are also reasons to expect the effects to be concentrated in Dust Bowl-affected counties. First, historical evidence suggests that the main benefit of new technology was that it increased resilience on damaged land (Section 2). Second, the fact that technology development was focused on hybrids, and was directed *away* from harvesting technologies and *toward* biological, chemical, and planting technologies, suggests that a key goal of innovation was to promote adaptation and not raise productivity across the board (Section 4.4). Third, more generally, in the context of variety development, there is a strong context-specific component to the technology's benefits and productivity gains can be much lower in contexts that are geographically dissimilar from that for which the variety was designed (Griliches, 1957; Kantor and Whalley, 2019; Moscona and Sastry, 2025; Akerman et al., 2025).

This all suggests that technologies designed for adaptation to the Dust Bowl might have had a much more limited impact elsewhere in the country and in regions that were not facing environmental hardship. If Dust Bowl-induced innovation led to the adaptation of new technology to eroded Plains land, then we might expect innovation exposure as measured above to have a much weaker relationship with productivity gains elsewhere in the country.

To investigate this hypothesis, I directly estimate the relationship between innovation exposure and changes in land values in non-Dust Bowl counties. First, Figure 5 reports a partial correlation plot between county-level innovation exposure and county-level changes in land value in *non-Plains* counties (see Figure A1). 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, the coefficient estimate is small and statistically insignificant. Thus, exposure to Dust Bowl-induced innovation had no discernible impact in counties for which it was not intended. Moreover, even within the Plains region, the effects of induced innovation are largely contained within the counties that are exposed to high-levels (compared to medium levels) of erosion (see Appendix E). This is all consistent with the context-specificity of Dust Bowl-induced innovation and with new technology targeting the local conditions in areas most affected by the Dust Bowl. In terms of identification, this null result also makes it unlikely that terms of trade or price effects, which should affect all counties that grow a given crop, drive the estimates in Table 2.

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



(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.

to the Dust Bowl might have been a re-allocation of production toward healthier land. To test this, 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 A8 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 (A8a) and in Plains counties with below-median land erosion (A8b). 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 results suggest that technology development was driven by a rise in demand for specific technologies that would increase resilience on distressed Plains land. I find no evidence that Dust Bowl-induced innovation exposure raised productivity elsewhere in the country or that it facilitated the re-allocation of production.

6 Conclusion

Innovation is a potentially crucial force for adaptation in moments of climate catastrophe, reshaping the aggregate and distributional economic consequences of environmental disruption. 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 the growth of 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 shifted toward crops that were more exposed to environmental distress and 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 substantially mitigated the economic impacts of environmental distress.

While this paper investigates a historical episode of environmental catastrophe, modern crises are also accompanied by technological responses that shape their aggregate and distributional consequences. 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. Future health crises are also increasingly seen as a likely part of reality, potentially accelerated by environmental 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 environmental crises.

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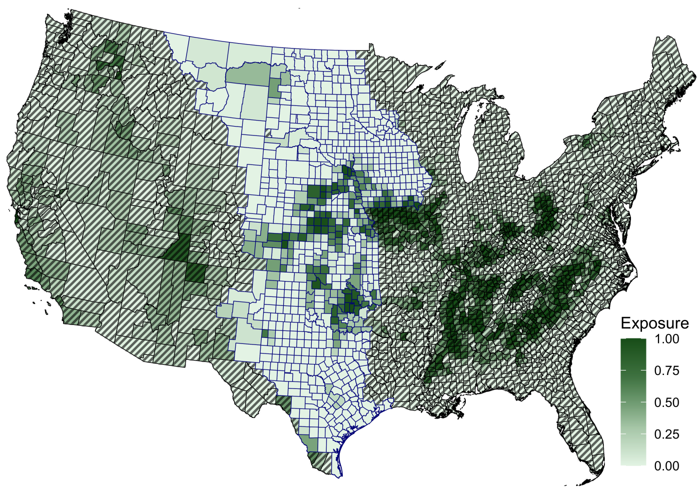
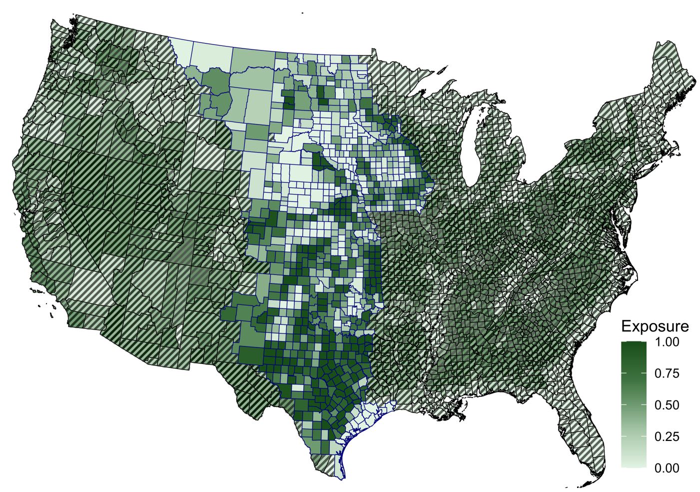
Online Appendix

A Supplementary Empirical Results



(a) Exposure to High Levels of Erosion (> 75% Topsoil Eroded)



(b) Exposure to Medium Levels of Erosion (25-75% Topsoil Eroded)

Figure A1: **Erosion Patterns and Main Sample.** This figure maps exposure to high (a) and medium (b) levels of topsoil erosion. Counties are shaded by the share of total county area exposed to each level of erosion, where darker shares of green correspond to higher shares. The underlying data are from Hornbeck (2012a) and its original source is the US National Archives in College Park, Maryland. The lighter counties are the Plains counties included in the main analysis.

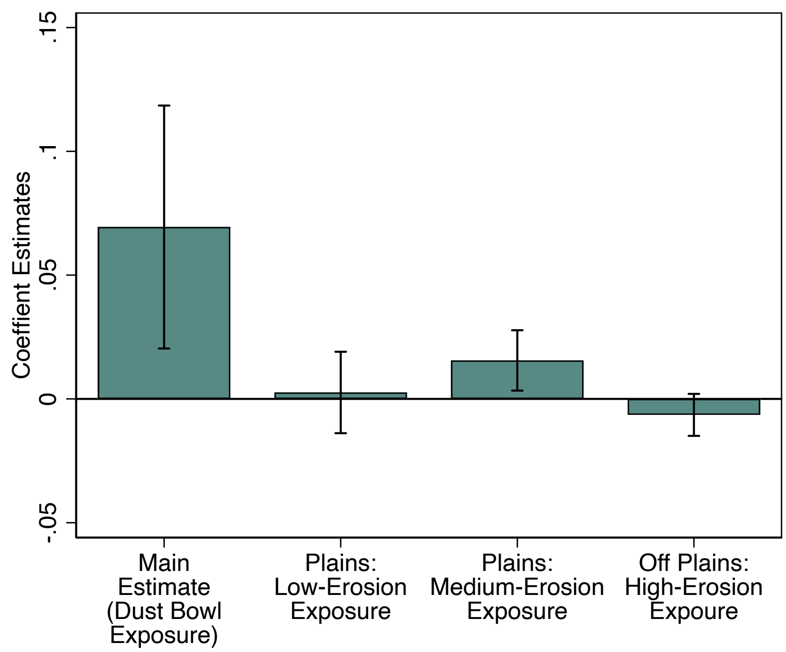


Figure A2: **Placebo Dust Bowl Exposure Estimates.** This figure reports estimates of Equation 4.1. The first bar reproduces the baseline estimate in which Dust Bowl exposure is computed as each crop's exposure to high levels of top soil erosion in Plains counties. The second bar reports the coefficient estimate using a measure of exposure computed as each crop's exposure to low levels of top soil erosion in Plains counties. The third bar reports the coefficient estimate using a measure of exposure computed as each crop's exposure to medium levels of top soil erosion in Plains counties. The fourth bar reports the coefficient estimate using a measure of exposure computed as each crop's exposure to high levels of top soil erosion *outside* of Plains counties. Standard errors are clustered by crop and 95% confidence intervals are reported.

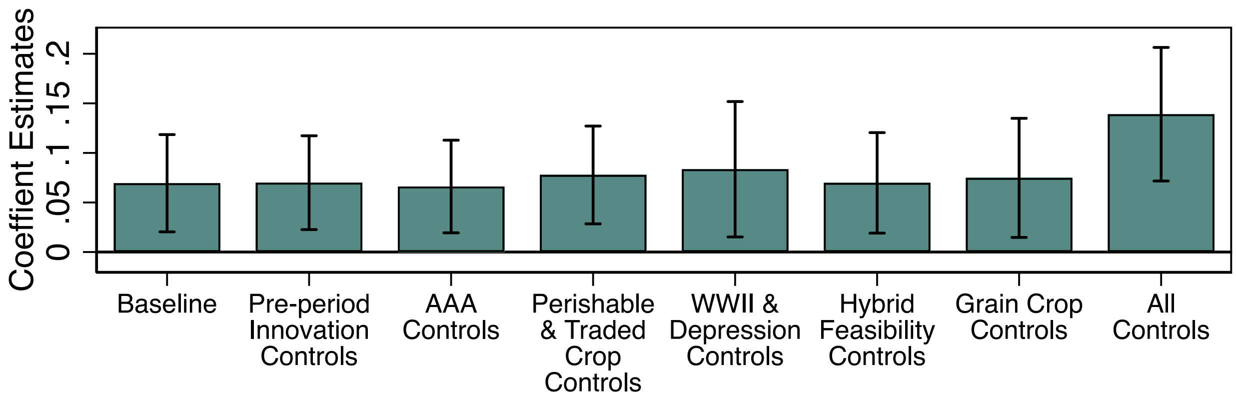


Figure A3: **Robustness to Controls.** This figure reports estimates of Equation 4.1 with additional controls added in each specification. The controls are pre-period crop-level variety releases interacted with year fixed effects (bar 2); an Agricultural Adjustment Act (AAA) inclusion indicator interacted with year fixed effects (bar 3); a perishable crop indicator interacted with year fixed effects as well as an indicator for inclusion in United States Department of Agriculture (1936) for years prior to the Dust Bowl interacted with year fixed effects (bar 4); indicators for the years of WWII (1941-1945) and the depression (1929-1939) interacted with crop fixed effects (bar 5); an indicator that equals one if a crop has imperfect flowers interacted with year fixed effects (bar 6); an indicator that equals one if a crop is a major grain (sorghum, corn, wheat, spelt, buckwheat, millet, rye, barley, oats, rice) interacted with year fixed effects (bar 7); and all previous controls combined (bar 8). Standard errors are clustered by crop and 95% confidence intervals are reported.

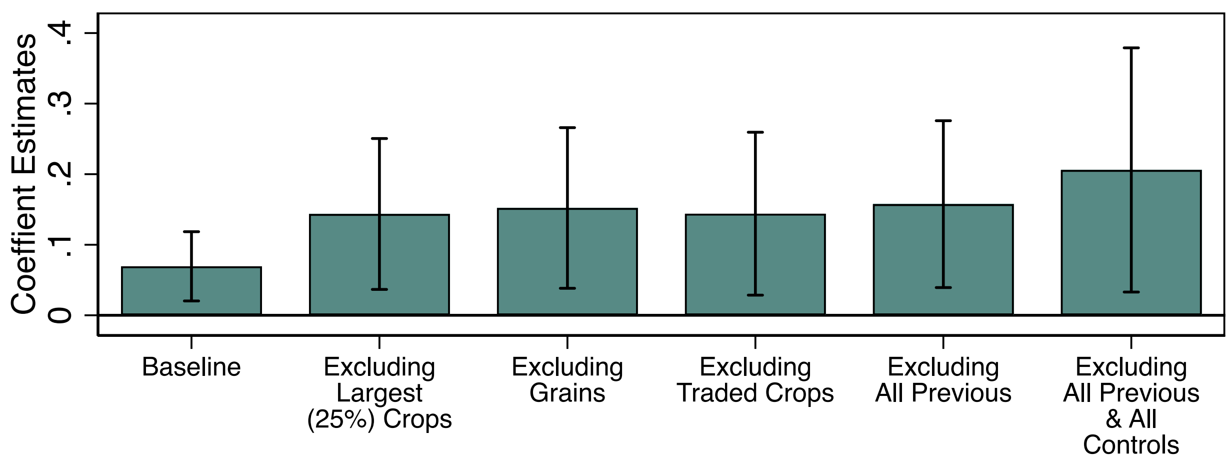


Figure A4: **Robustness to Sample Restrictions.** This figure reports estimates of Equation 4.1. The first bar repeats the baseline estimate. Bars 2-6 exclude from the sample the top 25% of crops by planted area in 1929 (bar 2); further exclude all grain crops (bar 3); further exclude all traded crops as recorded in United States Department of Agriculture (1936) for years prior to the Dust Bowl (bar 4); exclude all crops ever excluded in bars 2-4 (bar 5); and do the same while also controlling for all controls from Figure A3 (bar 6). Standard errors are clustered by crop and 95% confidence intervals are reported.

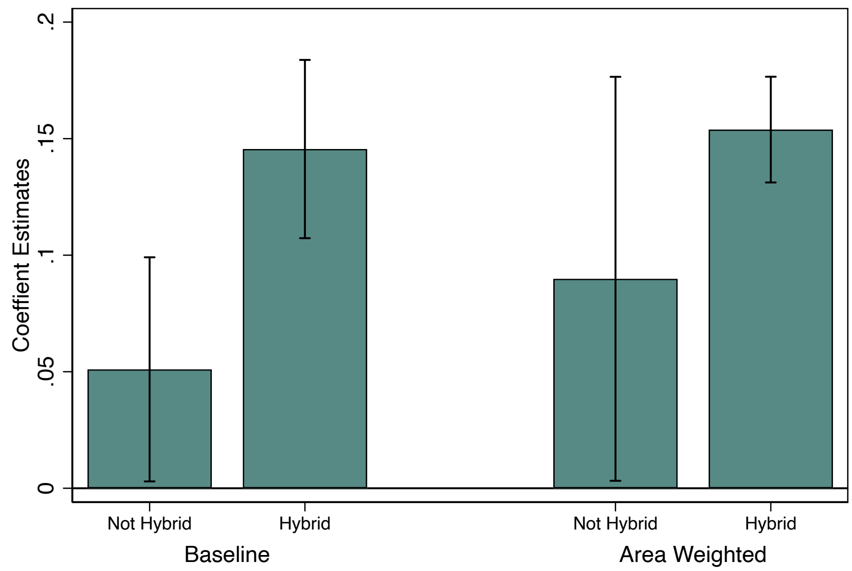


Figure A5: **Heterogeneity by Hybrid Feasibility.** This figure reports estimates of Equation 4.1 in which the main treatment variable is interacted with indicators for whether or not the crop is hybrid compatible (i.e., whether or not it has imperfect flowers). Crop fixed effects and year fixed effects interacted with the imperfect flower indicator are included in all specifications. Each pair of bars corresponds to a single regression estimate; the first set of bars is from an un-weighted regression and the second set of bars is from a regression weighted by pre-period crop area. In both cases, the difference between the bars is statistically significant ($p < 0.05$). Standard errors are clustered by crop and 95% confidence intervals are reported.

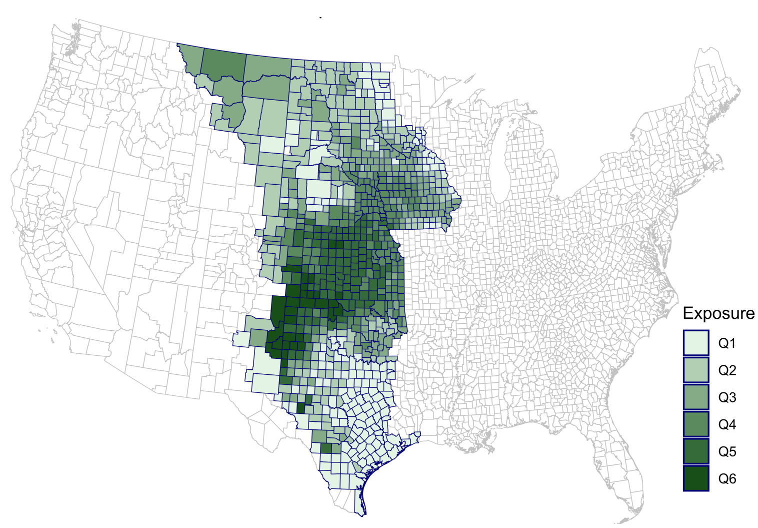


Figure A6: **Geographic Distribution of Innovation Exposure.** This map displays innovation exposure across all Plains counties in the main sample. Innovation exposure is computed using Equation 5.1 and color coded by quantile, where darker shares of green correspond to higher levels of innovation exposure.

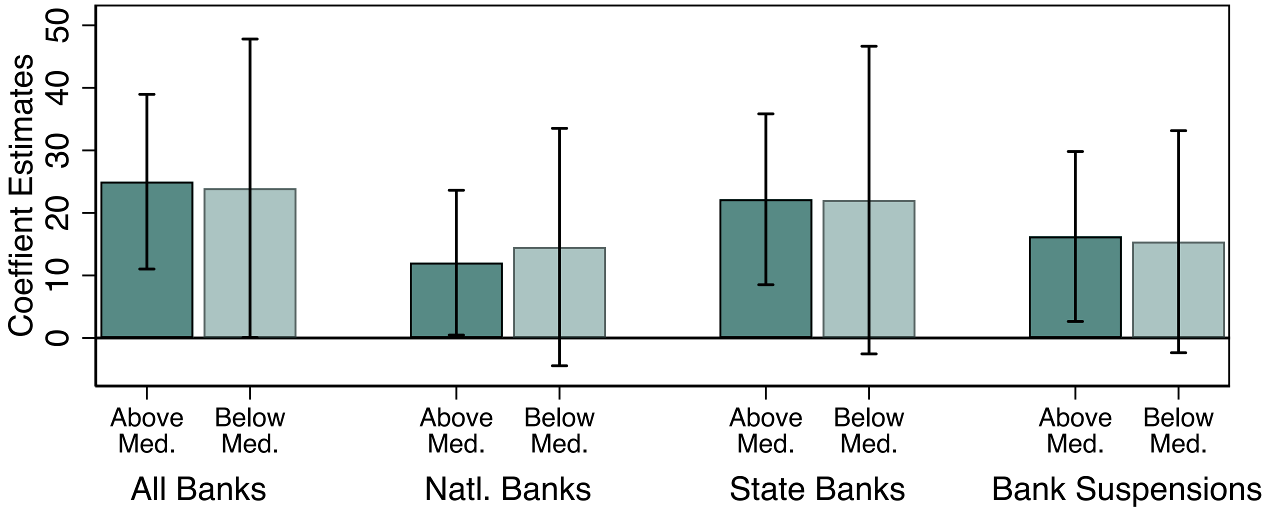
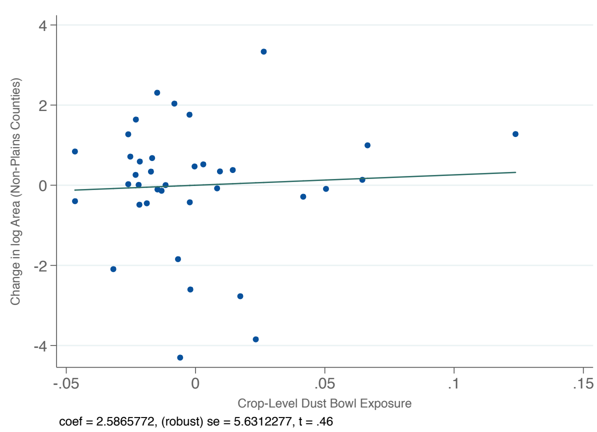
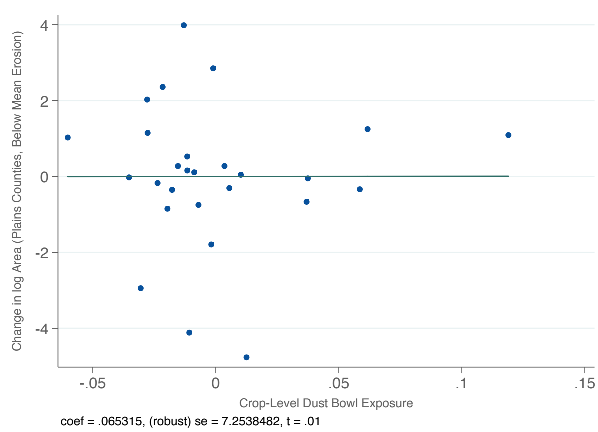


Figure A7: **Bank Access Sample Restrictions.** This figure reports estimates of ϕ from Equation 5.2. Each bar reports estimates from a restricted sample based on local bank access using data from Federal Deposit Insurance Corporation (1992). Bars 1-2 report estimates from specifications for counties with above versus below median total banks per capita; bars 3-4 report estimates from specifications for counties with above versus below median active national banks per capita; bars 5-6 report estimates from specifications for counties with above versus below median active state banks per capita; and bars 7-8 report estimates from specifications for counties with above versus below median bank suspensions per capita. Each measure is computed as the average over the decade prior to the Dust Bowl. Standard errors are clustered by county and 95% confidence intervals are reported.



(a) Δ log Area in Non-Plains Counties



(b) Δ log Area in Low-Exposure Counties

Figure A8: **Crop-Level Damage vs. Δ Area Planted Outside Dust Bowl.** This figure displays 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: List of Crops in Main Sample and Summary Statistics

Crop Name	Dust Bowl Exposure Ranking	log Area in 1929	Varieties Released 1930-1960	AAA Crop
Artichoke	43	8.822175	1	0
Asparagus	30	11.4592	12	0
Barley	9	16.33745	151	0
Beans	17	15.34646	221	0
Broccoli	6	7.286876	26	0
Brussel Sprouts	42	7.435438	4	0
Buckwheat	36	13.31806	1	0
Cabbage	27	12.04369	47	0
Carrots	25	9.7475	85	0
Cauliflower	14	9.871119	119	0
Celery	31	10.32551	65	0
Clover	8	15.52132	18	0
Collard	41	5.823046	3	0
Corn	2	18.23835	1247	1
Cucumber	23	11.32189	140	0
Eggplant	37	7.620215	38	0
Emmer and Spelt	13	12.63024	12	0
Flax	20	14.72065	47	0
Kale	40	6.617403	25	0
Lettuce	29	11.62355	126	0
Melons	11	11.72523	126	0
Oats	5	17.39564	218	0
Okra	32	8.235095	11	0
Onion	7	11.40831	184	0
Other Grasses	4	16.17317	28	0
Parsley	34	6.021023	6	0
Parsnip	35	5.817111	9	0
Peanut	15	14.66331	38	1
Peas	33	12.49933	188	0
Peppers	22	10.19836	150	0
Radish	24	8.007034	60	0
Rhubarb	28	8.110427	4	0
Rice	39	13.33934	42	1
Rye	16	14.88421	52	0
Sorghum	1	15.87801	75	0
Soybean	21	14.86947	17	0
Spinach	19	10.84404	43	0
Squash	12	8.920923	94	0
Timothy	18	16.97461	14	0
Tobacco	38	14.42538	44	1
Tomato	26	13.00397	514	0
Watermelon	10	12.52267	67	0
Wheat	3	17.87227	427	1

Notes: This table reports the crop name; Dust Bowl exposure ranking; (log of) total area planted in 1929, as measured in the 1930 Census of Agriculture; the total number of varieties released between 1930 and 1960; and an indicator that equals one if a crop was covered under the Agricultural Adjustment Act (AAA), for all crops included in the baseline analysis.

Table A2: 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 A3: 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	-0.000196
	(0.000339)	(0.000375)
$\text{Exposure}_c \times \mathbb{1}_t^{1940s} \times \text{Pre-Period Varieties}_c$	-0.000518	-0.000354
	(0.000629)	(0.000742)
$\text{Exposure}_c \times \mathbb{1}_t^{1950s} \times \text{Pre-Period Varieties}_c$	-0.00321*	-0.00218**
	(0.00162)	(0.000947)
Crop Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Observations	1,720	1,720
R-squared	0.680	0.689

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 three reported coefficients are the effect of the triple interaction between Dust Bowl exposure, pre-period variety releases (column 1) or an indicator for any pre-period variety releases (column 2), 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 A4: Dust Bowl Exposure and Biotechnology Development: Estimates using 1930s Weather

	(1)	(2)
Dependent Variable:	New Varieties (asinh)	
Estimator:	OLS (Reduced Form)	2SLS
Exposure$_c$ x $\mathbb{1}_t^{\text{Post 1930}}$		0.0829**
		(0.0403)
Palmer Drought Index$_c$ x $\mathbb{1}_t^{\text{Post 1930}}$	0.0961***	
	(0.0285)	
Temperature Standard Deviation$_c$ x $\mathbb{1}_t^{\text{Post 1930}}$	0.433**	
	(0.184)	
Excluded Instuments:		Palmer drought index; Temp. SD
K-P F-Statistic		10.335
Crop Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Crop x Year Fixed Effects	-	-
Crop x Technology Class Fixed Effects	-	-
Year x Technology Class Fixed Effects	-	-
Crops	43	43
Observations	1,720	1,720

Notes: The unit of observation is a crop-year and both columns include crop and year fixed effects. In column 2, the excluded instruments are the average standard deviation in temperature and the average Palmer drought index , interacted with the post-period indicator. Standard errors, clustered by crop and year, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A5: Dust Bowl Exposure and Patented Technologies

	(1)	(2)	(3)	(4)
	Outcome is log citation-weighted patents related to:			Outcome is log citation-weighted patents
	Mechanical and Post-Harvest Tech	Soil Modification and Bio / Chemical Tech	Only Bio / Chemical Tech	
$\text{Exposure}_c \times \mathbb{1}_t^{\text{Post 1930}}$	0.0163	0.0391**	0.149**	
	(0.0164)	(0.0165)	(0.0697)	
$\text{Exposure}_c \times \mathbb{1}_t^{\text{Post 1930}} \times \mathbb{1}_k^{S}$				0.292***
				(0.0592)
Crop Fixed Effects	Yes	Yes	Yes	-
Year Fixed Effects	Yes	Yes	Yes	-
Crop x Year Fixed Effects	-	-	-	Yes
Crop x Technology Class Fixed Effects	-	-	-	Yes
Year x Technology Class Fixed Effects	-	-	-	Yes
Observations	356	441	296	330
R-squared	0.643	0.434	0.475	0.863

Notes: The unit of observation is a crop-year (columns 1-3) or crop-year-technology class (column 4). Columns 1-3 include crop and year fixed effects and column 4 includes all possible two-way fixed effects. In column 1, the outcome is log of the number of mechanical and post-harvest technologies (A01D,F,G), in column 2 it is log of the number of soil modification and bio-chemical technologies (A01B,C,H,N) and in column 3, it is log of the number of bio-chemical technologies (A01H,N). In column 4, the outcome is log of the number of articles in the relevant technology class. $\mathbb{1}(k,S)$ is an indicator that equals onw for classes A01B,C,H,N. Standard errors, clustered by crop, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A6: Dust Bowl Exposure and Scientific Articles

	(1)	(2)	(3)	(4)
	Total Articles		Any Articles (0/1)	
	PPML	PPML	OLS	OLS
	All Articles	Environment-Related Articles	All Articles	Environment-Related Articles
$\text{Exposure}_c \times \mathbb{1}_t^{\text{Post 1930}}$	0.136***	0.457***	0.0145***	0.0186*
	(0.0451)	(0.103)	(0.00432)	(0.00928)
Crop and Year Fixed Effects	Yes	Yes	Yes	Yes
Pre-period articles x Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,296	609	1,548	1,548
R-squared			0.494	0.246

Notes: The unit of observation is a crop-year. All specifications include crop and year fixed effects, as well as pre-period article counts interacted with year fixed effects. In columns 1-2, the outcome variable is the total article count and PPML specifications are reported. In columns 3-4, the outcome is an indicator that equals one if at least one article was published and OLS specifications are reported. In columns 2 and 4, the outcome consists only of environment-related articles, as determined by a keyword search using all article titles for the following words or word segments: drought, erosion, climate, temperature, rain, dust, wind. Standard errors, clustered by crop, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A7: 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 $\mathbb{1}_t^{\text{Post 1930}}$	-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 $\mathbb{1}_t^{\text{Post 1930}}$	-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, and 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. Standard errors, clustered by crop, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A8: 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 A9: Innovation and Adaptation: Instrumented Variety Releases

	(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
	Panel A: No Added Controls			
Erosion$_i$ x $\mathbb{1}_t^{Post\ 1930}$	-1.416***	-0.964***	-1.660***	-1.265***
	(0.441)	(0.317)	(0.530)	(0.474)
Erosion$_i$ x $\mathbb{1}_t^{Post\ 1930}$ x Variety Exposure	1.699*	1.074*	2.138*	1.781*
	(0.937)	(0.592)	(1.169)	(1.052)
County Fixed Effects	Yes	Yes	Yes	Yes
Census Round Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,592	1,592	1,592	1,592
First Stage K-P F-statistic	8.4	8.4	8.4	8.4
	Panel B: Controlling for Trends in Top-Variety Crops			
Erosion$_i$ x $\mathbb{1}_t^{Post\ 1930}$	-8.901**	-3.613	-12.95**	-10.20**
	(4.332)	(2.511)	(5.964)	(4.891)
Erosion$_i$ x $\mathbb{1}_t^{Post\ 1930}$ x Variety Exposure	1.410**	0.568	2.048**	1.607**
	(0.704)	(0.410)	(0.969)	(0.794)
County Fixed Effects	Yes	Yes	Yes	Yes
Census Round Fixed Effects	Yes	Yes	Yes	Yes
Corn and Tomato Area x Crop Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,128	1,128	1,128	1,128
First Stage K-P F-statistic	10.12	10.12	10.12	10.12

Notes: The unit of observation is a county-year. All estimates are from long differences specifications where the starting year is 1920 and ending year either 1940 (column 2) or 1959, depending on data availability. In Panel B, pre-period areas of corn and tomato, interacted with a post-period indicator, are also included as controls. The sample of counties was selected as in Hornbeck (2012). All columns report IV-2SLS estimates in which Variety Exposure (and its interactions) are instrumented using InnovationExposure (and its interactions). 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 A10: 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
$Erosion_i$ x $\mathbb{1}_t^{Post\ 1930}$	-0.736***	-0.678***	-1.068***	-0.764**
	(0.214)	(0.217)	(0.393)	(0.316)
$Erosion_i$ x $\mathbb{1}_t^{Post\ 1930}$ x $InnovationExposure_i$	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 regressions 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 A11: Innovation and Adaptation: Excluding State × 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
$Erosion_i$ x $\mathbb{1}_t^{Post\ 1930}$	-2.390***	-1.588***	-2.448***	-1.852***
	(0.531)	(0.451)	(0.568)	(0.527)
$Erosion_i$ x $\mathbb{1}_t^{Post\ 1930}$ x $InnovationExposure_i$	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 A12: Innovation and Adaptation: "Leave-State-Out" Estimates

Dependent Variable:	(1) log Value of Land and Buildings per Acre	(2) log Value of Land per Acre	(3) log Total Revenue	(4) 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 A13: Innovation and Adaptation: High vs. Medium Levels of Local and Aggregate Exposure

Dependent Variable (Long Difference Estimates):	(1) log Value of Land and Buildings per Acre	(2) log Value of Land per Acre	(3) log Total Revenue	(4) log Total Revenue per Acre
$\text{High Erosion}_i \times \mathbb{1}_t^{\text{Post 1930}}$	-1.344***	-0.909***	-1.590***	-1.163**
	(0.427)	(0.308)	(0.538)	(0.472)
$\text{High Erosion}_i \times \mathbb{1}_t^{\text{Post 1930}} \times \text{High CropMixDamage}_i$	9.743**	6.470*	12.69**	9.257*
	(4.961)	(3.644)	(6.232)	(5.464)
$\text{Medium Erosion}_i \times \mathbb{1}_t^{\text{Post 1930}}$	0.140	0.104	0.357	0.446
	(0.288)	(0.219)	(0.353)	(0.333)
$\text{Medium Erosion}_i \times \mathbb{1}_t^{\text{Post 1930}} \times \text{Medium CropMixDamage}_i$	-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 A14: 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
$\text{Erosion}_i \times \mathbb{1}_t^{\text{Post 1930}} \times \text{InnovationExposure}_i \times \text{Above Med. Size}_i$	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.

Table A15: Innovation and Adaptation: Flexible Output Price 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: 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
$Erosion_i \times \mathbb{1}_t^{Post\,1930}$	-1.398***	-0.947***	-1.505***	-1.159**
	(0.450)	(0.322)	(0.529)	(0.479)
$Erosion_i \times \mathbb{1}_t^{Post\,1930} \times InnovationExposure_i$	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.

B Model

This section formalizes the relationship between Dust Bowl exposure and innovation in a model of directed technological change. 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. In one case of the model, consistent with the historical narrative presented in the main text, innovation increases in response to the Dust Bowl, driven by technologies that restore production resilience. In another case, however, the opposite happens and faltering producers are left behind as innovators flee the distressed sector.

B.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:

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

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.[24]

There is a representative innovator that determines both the price of T_i and the aggregate level of technological progress (θ) in order to maximize profits, and faces a marginal cost of technology

[24]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.

development $1-\alpha$ and a convex cost $C(\theta)$ of expanding the technological frontier. Substituting for technology input use from the farmer's maximization problem, the innovator's problem becomes:

$$\max_{q,\theta}(q-(1-\alpha))\alpha^{-1}p^{\frac{1}{\alpha}}q^{\frac{-1}{\alpha}}\int G(A_i,\theta)dF(A)-C(\theta) \tag{B.2}$$

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:

$$\max_{\theta} p^{\frac{1}{\alpha}}\int G(A_i,\theta)dF(A)-C(\theta) \tag{B.3}$$

Finally, assume that the price of the crop is determined by an inverse demand function $p=D(Y)$, 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.

B.2 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).

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. 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. □

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 in the main text, I do not find strong evidence of price effects driving the technological response to the Dust Bowl, I only mention them briefly here.[25]

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. Second, I explore several strategies to examine heterogeneity across crops and technologies that are more (or less) plausibly topsoil-substituting; this makes it possible to investigate the key mechanism and distinguish between the "marginal product" effects outlined in Proposition 1 and general equilibrium price effects.

[25] See Moscona and Sastry (2023) 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.

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. There is substantial variation across crops in exposure to high levels of erosion, ranging from zero exposure to 29.2% of national crop 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 A2. 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.[26]

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

[26]This data source is discussed at greater length in Moscona and Sastry (2023).

for the single stem indicator interacted with year fixed effects (not reported).

Next, I investigate the relationship between erosion exposure and a crop level hybrid compatibility indicator (as discussed in Section 4.2) and a 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:

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

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 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 of that crop can take place are more limited, and so it the set of other crops that require similar environmental conditions. 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 A2 (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 A10. 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 A11 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 might be the case 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 using data from Fishback et al. (2005), all 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 A16 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 A12 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 2, 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.[27] 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

[27]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).

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

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

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 A13 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 2.

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 A14 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.