Protect or Prepare?

Crop Insurance and Adaptation in a Changing Climate*

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Abstract

As climate risks intensify, governments increasingly subsidize insurance against weather shocks. While these subsidies improve financial protection against extreme weather events, they may reduce incentives for long-term adaptation to climate change. In this paper, I study how U.S. crop insurance subsidies impact agricultural adaptation. I develop and estimate a dynamic land use model that incorporates beliefs on climate, crop insurance, and government subsidies. I use the model to simulate future paths of production under alternative designs of crop insurance subsidies. Under the current design, funds increasingly flow to high-risk regions. As a result, farmers in riskier areas are more resistant to adaptation, which leads to higher public spending and more volatile output. I show that targeted subsidies—which adjust generosity based on regional climate trends—foster stability of agricultural production by encouraging crop switching patterns adapted to climate risk and increase welfare by 0.6 percentage points relative to the total value of agricultural output. Despite achieving better outcomes in aggregate, targeting penalizes farmers in the southern half of the U.S., which may lead to political resistance. I then consider an alternative in which subsidies are redistributed within states. This policy achieves 15% of the benefits obtainable under unconstrained targeting.

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1 Introduction

As a consequence of climate change, extreme weather events put a growing share of economic activity at risk, from agriculture to infrastructure or manufacturing (Allan et al., 2023; Balboni, 2019; Castro-Vincenzi, 2022). Increasingly, governments have stepped in to facilitate insurance coverage for homeowners, businesses, and farmers against adverse weather shocks. However, protection against today's weather shocks may distort economic incentives and slow down adaptation to shifting patterns of risks (Kousky et al., 2021; Hsiao, 2023). Therefore, the design and regulation of insurance against weather risk must balance protecting current assets with minimizing any dampening effects on long-term adaptation to climate change.

Agriculture is one of the industries most exposed to future climate risks, and in this paper, I study the impact of the design of the U.S. Federal Crop Insurance Program on agricultural adaptation. Through the program, the U.S. agricultural system receives 30% of the total federal support to U.S. agriculture (5-10 billion dollars per year between 2010 and 2020). These funds and their use remain an object of policy debate. Importantly, the current policy is not designed to adapt to significant shifts in climate conditions. Most subsidy dollars go to *today*'s high-risk regions, which may hinder the system's adaptation to *future* climate threats.

In this paper, I study the equilibrium interaction of land use and agricultural output with crop insurance design and beliefs over future weather. I develop and estimate a dynamic land use model that nests crop insurance decisions, weather shocks, and equilibrium crop prices. The model is designed to capture the key trade-off between protection against weather shocks and climate adaptation. Subsidies impact crop insurance decisions and indirectly influence land use decisions by altering the climate and price risks (and thus revenue risk) farmers face.

Using climate models to simulate future weather and agricultural productivity paths, I compute equilibrium outcomes across alternative scenarios. I find that the current design slows down adaptation and transfers increasingly more funds toward high-risk areas. Improving the targeting of crop insurance subsidies would increase aggregate efficiency at the cost of larger inequity across states. Nevertheless, targeting within states can still achieve better outcomes than the current design, which ignores future climate risks.

I collect detailed information on daily gridded weather, U.S. farmers' crop insurance and land use choices, and agricultural output. Consistent with the literature, I find that crops are differentially sensitive to extreme heat. Given the projected path of climate change, holding cropland area and agricultural technology fixed, these patterns suggest that grain yields will decrease by 10 to 40% by 2050; this would translate into an increase of 20% in crop insurance indemnities and the program's cost by 2050. However, I find evidence that, although crop switching is costly, farmers adjust to weather shocks by switching away from heat-sensitive crops. Finally, crop insurance subsidies interact with farmers' planting decisions: planted area increases by 0.2-3% in counties where premiums decrease by $10

(20% of paid premiums). Together, these facts motivate a model incorporating links between climate, insurance design, insurance choice, and land use choice to identify the impact of crop insurance subsidies on farmers' climate adaptation.

The model is made of two main blocks: pre-planting and a growing season. During the pre-planting season, the Risk Management Agency sets crop insurance premiums such that they are equal to expected insurance indemnities for each farmer.[1,2] Premium subsidies are set as a fixed share of insurance premiums. Farmers observe premiums and subsidies, past and current weather, and aggregate agricultural acres. Based on these observations, they form beliefs on the upcoming growing season yields and prices, understanding that international markets will clear. These beliefs are key to deciding which crops to sow or whether to leave land fallow. Insurance choice follows planting decisions.[3] During the growing season, weather realizes, and farmers harvest crops. Crop prices then result in equilibrium as a function of global production. Yields and prices jointly determine farmers' revenues and insurance payments.

Farmers' land use decisions are the result of optimal dynamic discrete choice. Today's land use influences the future because repurposing a field involves various switching costs, such as learning, equipment adjustments, or forming new trading partnerships. When choosing which crop to grow in a given year, farmers consider their expected revenues net of insurance premiums and indemnities, input cost per acre, and the discounted future value of growing that crop today. These objects are functions of the state space, which contains local weather, weather in other counties and abroad, aggregate cultivated areas, and crop insurance subsidies. Importantly, when making their planting decisions, farmers have rational expectation on their upcoming insurance choice.

Crop insurance demand takes planting decisions as given and follows a static discrete choice model. Each available insurance product combines a type of contract and a coverage level. When selecting a *yield protection* contract, farmers receive indemnities if their yields fall below a yield threshold, which increases in the coverage level. Instead, *revenue protection* contracts guarantee indemnities if farmers' revenues fall below a similar threshold; these plans protect farmers against both yield and price shocks. Insurance plans also differ in terms of premiums and subsidies. When making their crop insurance decision, farmers trade off subsidized premiums, expected revenues, and revenues risk (measured as the coefficient of

[1] The crop insurance system is actuarially fair and does not involve risk pooling across farms (U.S. Department of Agriculture, Economic Research Service, 2024).

[2] I treat each field as owned by a farmer who makes independent insurance and land use decisions. This is dictated by the need to limit the computation burden in the dynamic discrete choice model and by data availability considerations. I measure field-level land switching probabilities using satellite imagery and county-level insurance market shares. Farm structure is, therefore, not observed. In practice, I assume away the possibility for large farmers to hedge their risk outside of the crop insurance program by optimizing a portfolio of crops or resorting to other risk-smoothing financial tools. Section 4 discusses several factors that attenuate concerns arising from omitting such scale effects.

[3] The two-step timing of the model is consistent with observed farmers' behavior. Farmers do not grow seeds from their production to avoid cross-pollination and ensure the best performance possible. See Center for Farm and Food System article. Instead, they order seeds two to three months before the planting season. By contrast, farmers typically meet with a crop insurance agent the month before the regulated planting date, in late March-April for corn and soybeans. See article on important crop insurance dates.

variation). These outcomes are evaluated for every insurance option using beliefs on weather, yields, and prices in the upcoming growing season.

Estimation proceeds in three steps, following the model backward. First, I estimate farmers' short-run beliefs on growing season outcomes. Farmers form beliefs about yields based on historical weather-yield response functions estimated with annual county-level data. They form beliefs on crop prices using the price of crop futures available during the pre-planting season.[4] I combine the beliefs on yield and crop price with insurance indemnity schedules set by the Risk Management Agency will estimate farmers' beliefs on agricultural revenues, including insurance indemnity, for all insurance products. Finally, I compute *posted* crop insurance premiums per acre and verify that they are good predictors of *paid* premiums I observe in the data.

Second, I estimate insurance demand following Berry, Levinsohn, and Pakes (1995) and matching observed and predicted insurance market shares at the county level. Identification relies on cross-sectional and temporal variation in local and global weather. Farmers value insurance plans offering higher expected revenues and lower risk. They are premium-sensitive; their premium sensitivity is higher than the value they place on expected revenues. The estimates suggest that removing subsidies would reduce insurance take-up by 40%, a level broadly consistent with the insured share before the introduction of generous crop insurance subsidies in 1994, and would lower expected total net revenues by 3.5% per acre.

Third, I estimate the dynamic land use choice model matching observed and predicted conditional choice probability as in Hotz and Miller (1993). I assume that farmers have rational expectations over the evolution of the state space and that switching land use is a renewal action; continuation values difference out (Arcidiacono and Miller, 2011; Scott, 2013; Kalouptsidi, Scott, and Souza-Rodrigues, 2021). This estimator accommodates non-stationary state space and beliefs Arcidiacono and Miller (2019), yet it reduces to a linear regression. Identification comes from variations in world commodity prices over time and crop yields over space. I recover positive coefficients on agricultural revenues, consistent with an upward-sloping supply curve. Switching cost estimates reflect common crop rotation patterns. For instance, I estimate small switching costs between corn and soybeans, a cost-reducing rotation adopted by many farmers in the U.S. Overall, increasing subsidies by 10% increases cultivated acres by 0.1%. Crop-specific elasticities are comparable in magnitude to estimates in the literature (Yu, Smith, and Sumner, 2018).

The resulting empirical framework allows me to measure the impact of climate change and crop insurance policy on welfare. Welfare is the sum of the certainty equivalent of U.S. consumer surplus, farmer surplus, and government revenues. Increased *within-year* variability

[4] As I do not observe crop futures prices in counterfactuals, I develop a crop demand model where U.S. consumers have quasi-log-linear preferences over the bundle of agricultural goods and constant elasticity of substitution between crops. I calibrate the model to match U.S. crop price time series between 2005 and 2019, following (Costinot et al., 2016).

of agricultural production decreases surpluses of risk-averse farmers and consumers.[5] In each counterfactual, I simulate farmers' choices from 2020 to 2050. The evolution of local weather, worldwide agricultural production, and aggregate U.S. cropland areas enter the state space of farmers with rational beliefs. In contrast with estimation, I solve for continuation values in each county between 2020 and 2050. I assume farmers have accurate beliefs on the evolution of weather distributions in the U.S. and worldwide and autoregressive beliefs over aggregate corn, soybeans, and wheat acreages in the U.S (this is similar in spirit to Weintraub, Benkard, and Van Roy, 2008). Cultivated land outside the U.S. is treated as fixed.

A first set of results shows that climate change reduces U.S. agricultural welfare by 9.4% of the total value of baseline agricultural production annually, largely due to more frequent and severe weather shocks. Status quo crop insurance subsidies, proportional to premiums, further decrease welfare. In transferring government dollars to farmers and incentivizing the expansion of the cultivated area, which puts downward pressure on crop prices, these subsidies benefit farmers and consumers (+0.02% and +1.9%, respectively). However, the policy costs 4% of total agricultural output and incentivizes farming climate-sensitive crops in high-risk areas, which increases exposure of agricultural production to climate shocks.

I then consider a simple alternative design, consisting of a subsidy targeting rule based on climate risk trends. Under this scheme, counties receive different subsidies depending on whether they face increasing or decreasing climate risk over time. This approach approximates a forward-looking crop insurance policy design while maintaining a low-dimensional policy space. These targeted subsidies offer a more efficient allocation of government support, leading to better welfare outcomes than the status quo. A budget-neutral strategy—removing subsidies in counties with increasing climate risks while increasing them by 50% in counties with decreasing risks—increases welfare by 0.6 percentage points and reduces agricultural production variability. While most welfare gains are realized after 2040, targeting improves welfare at the onset of the study period. This suggests that policies fostering adaptation to climate change are not only transferring government funds from one generation to the next but can provide immediate efficiency benefits.

Nonetheless, targeted subsidies significantly reshape the geography of U.S. agriculture and have large distributional consequences. By design, the southern half of the U.S., which faces increasing climate risks, experience substantial reductions in government support under these policies. Conversely, U.S. states in the North, where farming conditions become more favorable, receive more government subsidies. This results in a less equitable distribution of government funds across U.S. states: the dispersion of equilibrium subsidy per acre increases by 140% compared to the status quo. In contrast, subsidies reallocated *within U.S. states* decrease concerns over political feasibility: most states included in the analysis see their

[5] Farmers trade off mean and risk of agricultural revenues when choosing their insurance plans. Consistently with the log utility parameterization of the crop demand model, which follows Costinot, Donaldson, and Smith (2016), consumers have a constant relative risk aversion parameter of 1.

funding increase under this scenario. Additionally, this alternative still achieves welfare gains compared to the status quo, albeit 85% lower than under unconstrained targeting.

This paper develops a new dynamic empirical framework for assessing government policies' role in distorting agricultural incentives and limiting adaptation to climate change. Adaptation reduces the consequences of climate change (Barreca et al., 2016; Nath, 2024; Bilal and Rossi-Hansberg, 2023; Cruz and Rossi-Hansberg, 2024), and in particular in the climatically-vulnerable agricultural sector (Costinot, Donaldson, and Smith, 2016; Rising and Devineni, 2020; Hultgren et al., 2022; Kala, 2017; Schulte et al., 2017; Taylor, 2022). However, distortionary government policies may displace incentives to adapt and exacerbate climate damages (Kousky, Luttmer, and Zeckhauser, 2006; Boustan, Kahn, and Rhode, 2012; Fried, 2022; Hsiao, 2023; Baylis and Boomhower, 2023; Hsiao, Moscona, and Sastry, 2024). While a large literature has documented the consequences of the U.S. Federal Crop Insurance Program on production and land use (Nelson and Loehman, 1987; Walters et al., 2012, Claassen, Langpap, and Wu, 2017; Yu, Smith, and Sumner, 2018), chemical application rates (Goodwin, Vandeveer, and Deal, 2004; Mieno, Walters, and Fulginiti, 2018), irrigation (Deryugina and Konar, 2017; Suchato et al., 2022), and vulnerability to weather shocks (Annan and Schlenker, 2015), these studies often rely on static or aggregate data, missing the rich dynamics and spatial heterogeneity of farmer responses. By combining detailed micro-data with an equilibrium model nesting land use and crop insurance choices, I provide a comprehensive analysis of how the U.S. Federal Crop Insurance Program distorts adaptation incentives today and in the future with climate change.

A growing body of literature emphasizes the advantages of environmental regulation targeting (Ostriker and Russo, 2022; Russo and Aspelund, 2024). Relatedly, mandated adaptation strategies are increasingly discussed as governments explore ways to foster climate adaptation (Mach et al., 2019; Baylis and Boomhower, 2022; Wagner, 2022, Behrer, Pankratz, and Park, 2024). My findings suggest that subsidy targeting can improve outcomes in the future by fostering long-term climate adaptation at the same time as delivering welfare improvements today. These insights underscore the potential of policy interventions that account for climate change's spatial and temporal complexities.

Methodologically, I draw on a large body of work that uses Euler equations to estimate dynamic discrete choice models (Aguirregabiria and Magesan, 2013; Kalouptsidi, Scott, and Souza-Rodrigues, 2021). I extend existing work on land use choice (Scott, 2013; Dominguez-Iino, 2023; Burlig, Preonas, and Woerman, 2024; Araujo, Costa, and Sant'Anna, 2024) by microfounding static payoffs to incorporate the role of crop insurance market and solving for counterfactuals outside of the steady state. I incorporate expectations over weather variability, a key market state variable, to discuss the future of agriculture under climate change.

2 Background on U.S. Crop Insurance

Farmland represents approximately 40% of the total contiguous U.S. area. Of these acres, 70% are planted with corn, soybeans, or wheat. Farmers must choose which crop to sow at the beginning of each calendar year,[6] with very little possibility of converting their decision by replanting in case of early crop failure.[7] This timeline makes planting decisions critical; these decisions must balance the benefits of periodic crop rotations,[8] expected changes in prices and yields.

Despite significant improvements in crop yields over the second half of the 20th century in the U.S., these remain sensitive to weather shocks. Temperatures exceeding 29-30°C (84-86°F) harm yields, particularly for corn and soybeans (Schlenker and Roberts, 2009; Gammans, Mérel, and Ortiz-Bobea, 2017). Therefore, a changing climate with increasing frequency of extreme heat events poses a significant risk to farmers' production and domestic agricultural output. During the worst year on record, 2012, half of the total crop losses nationwide were attributed to historical warming trends (Diffenbaugh, Davenport, and Burke, 2021).

To mitigate the (increasing) risks of uncertain yields and revenues, farmers can turn to crop insurance, offered to all farmers through a regulated, government-sponsored market. The Federal Crop Insurance Program was introduced in the 1930s as part of the New Deal following the droughts of the Dust Bowl and the Great Depression.[9] In 2010, 80% of American cropland was insured under the program, which represented 30% of the Farm Bill budget (between 5-10 billion USD per year between 2010 and 2020). Additionally, while 62% of farms producing row crops, such as corn, soybeans, and wheat, purchase federal crop insurance (Whitt, Lacy, and Lim, 2023), only around 25% of farmers are buying crop futures, options, or marketing contracts (MacDonald, 2020).

There are two main insurance contracts offered under the Multi-Peril Crop Insurance. Each available insurance product combines an insurance contract and a coverage level. Farmers who subscribe to a *yield protection* contract receive indemnities if their yields fall below a yield threshold—coverage levels times their historical yields—due to an environmental shock (drought, floods, extreme heat). Indemnity payments are the product of the yield shock

[6] One notable exception is winter wheat, which represents roughly 50% of wheat planted in my sample (Figure A2). Other wheat varieties are spring and durum, which follow corn and soybeans' planting/harvesting schedules. In the considered regions, winter wheat is planted in the fall and harvested a year later in August/September.

[7] After planting, the growing season spans April to September, after which yields and revenues are realized.

[8] Crop switching from one year to the next, known as crop rotation, is a common practice, followed by more than 80% of U.S. farmers (Wallander, 2013). Indeed, numerous studies have demonstrated the benefits of crop rotation, with the corn-soybeans rotation being particularly notable. These benefits include higher yields and lower rates of fertilizer use (Al-Kaisi et al., 2015; Bakhsh and Kanwar, 2007; Sindelar et al., 2015). Additionally, alternating active cropping with fallowness–practice by which the land is left uncultivated— can yield benefits, such as improved soil health and thus increased future yields (Ruis et al., 2023; Peng et al., 2024).

[9] More recently, the passage of the Federal Crop Insurance Reform Act in 1994 led to a spike in crop insurance subscriptions, reflecting the introduction of low-coverage, fully subsidized insurance and a temporary requirement that producers obtain insurance coverage to be eligible for other commodity support programs (Glauber, 2013). The Agricultural Risk Protection Act of 2000 increased crop insurance premium subsidies for plans with higher coverage.

(threshold minus realized yield) and the price of the crop future at the time of insurance subscription. *Revenue protection* contracts protect farmers against revenue loss due to either yield or crop price shocks.[10,11]

The Federal Crop Insurance Program is a public-private partnership. Farmers buy insurance policies from private insurers. The Risk Management Agency (RMA) acts as regulator and sponsor for the program. First, it mandates the types of insurance contracts that must be made available to farmers. Second, it determines farmers' premiums by setting subsidies and specific actuarial calculations. Third, the RMA supports private insurers by providing reinsurance and subsidies for their operating costs. These subsidies cover expenses such as monitoring compliance with RMA guidelines, including regulated planting dates, proper fertilization, pest control, and irrigation practices, all aimed at reducing the risk of fraud and moral hazard.

The Federal government provides premium subsidies which represent the largest share of total program costs.[12] These are calculated as a fixed share of insurance premiums and vary with the plan coverage (see Table A1 in Appendix). Premiums are based on a farmer's historical yields and harvest crop price projections and are set by the RMA such that they are equal to expected indemnities. Premiums can, therefore, be treated as exogenous in any given year, are decreasing in historical yields, increasing in coverage level, and higher for *revenue protection* than for *yield protection* insurance plans.[13]

3 Data and Motivating Evidence

3.1 Data

Climate. I obtain historical gridded weather data from (PRISM, 1985-2019). These data combine climate observations from a large monitoring network and climate models to produce spatially granular daily temperature and precipitation observations. In what follows, the two climate metrics I use are the number of extreme degree days and precipitation aggregated at the county level. Extreme degree days measure the exposure of a county to temperatures above 30°C; the measure increases by one if (i) the county temperature is above 31°C for

[10] Farmers do not receive indemnities in a year where yields are low, but crop prices offset the loss of income. However, they are compensated in years when prices are low enough to pull their realized revenue below the guaranteed revenue threshold.

[11] Both *yield and revenue protection* are indemnity-based insurance. The USDA also started offering index-based insurance products around 2000, but these products are not as popular: together, yield and revenue protection account for 85% of the total policies sold (Congressional Research Service, 2021; Zulauf et al., 2020).

[12] https://www.ers.usda.gov/topics/farm-practices-management/risk-management/crop-insurance-at-a-glance

[13] Additionally, premiums are regressive: a farmer insuring more acres will pay a smaller base rate. Farmers may also pool different crops under the same insurance policy to pool risks and cut costs. However, due to the lack of farm-level data in what follows, I model crop insurance premiums as a function of farmer's location, land quality, and expected local and global weather shocks (Section 4).

Table 1. Summary Statistics

Panel A: Climate	Mean	Median	Sd.
Extreme degree day (°C×day)	32.8	15.3	44.6
Precipitation (mm)	683.4	678.5	188.6
Panel B: Insurance	Mean	Median	Sd.
Share insured	0.77	0.82	0.20
Average coverage (%)	57.7	61.6	15.5
Number of products	11.5	12.0	2.4
Paid premiums per acre	16.0	15.1	5.9
Subsidy per acre	26.8	24.7	11.1
Claim per acre	33.1	14.0	56.6
Panel C: Ag. Outcomes	Corn	Soybeans	Wheat
Yields (tons/acre)	3.89	1.25	1.31
Production (million tons)	292	83	32
Exports (million tons)	44	37	15
Imports (million tons)	56	11	15
Price ($/ton)	163	364	192
Fraction of U.S. ag. acres in sample	0.90	0.88	0.59

Notes: Panels A and B present county-level statistics computed for the sample of counties in Appendix Figure A2. Extreme degree days is the number of 30-degree days during the growing season, measured in °C×day. Total growing season precipitation is measured in mm. Both measures are obtained from PRISM for the period 2008-2020. Insurance data are obtained from the Risk Management Agency Summary of Business. Panel C presents crop-level averages of agricultural outcomes. Data were obtained from the U.S. Department of Agriculture National Agricultural Statistics Survey.

a day or (ii) the temperature is 30.1°C for ten days.[14] In counterfactuals, I use weather projections from NASA Earth Exchange Global Daily Downscaled Projections (Thrasher et al., 2016-2050) under a moderate (RCP4.5) emission scenario. During the main estimation period (2008-2019), U.S. counties experienced an average of 33 extreme degree days during the growing season and received 690mm of precipitation (Table 1 panel A). However, climate is spatially heterogeneous: the standard deviation of extreme degree days is 1.3 times the average.

Land use. Land use data are obtained from a yearly land use classification of satellite imagery, the CropLand Data Layer (CDL) (Boryan et al., 2008-2021), available at a resolution of 30 meters. The CDL is produced using training and independent validation data from the Farm Service Agency Common Land Unit Program and the United States Geological Survey National Land Cover Database. The accuracy for crop-specific land cover ranges from 85% to 95%. These classifications are the basis for constructing transition probability between land covers (see Section 5.3). I reduce the resolution of the images to alleviate concerns about classification errors in the satellite images. I use the modal land use class in each 3×3 km^2

[14] https://www.ers.usda.gov/data-products/chart-gallery/gallery/chart-detail/?chartId=108037

(700 acres) pixel to resample the images.

Crop insurance. County-crop-level information on insurance enrollment, paid premiums, and indemnities comes from the RMA Summary of Business database for the years 2011-2019 (RMA, 2023b). The Actuarial Information Browser provides data on premium pricing variables and formulas (RMA, 2023a). Corn, soybeans, and wheat growers in the sample insured close to 80% of their planted acres, at 60% coverage (Table 1 panel B). On average, 11.5 insurance products have a positive market share out of 16 products included in the study. Paid premiums are 16 dollars per acre on average. However, government premium subsidies during the study period are large: posted premiums are closer to $40 per acre (or between 7 and 15% of farmers' revenues), and farmers pay less than 40% of their premiums. Finally, farmers claim 32 dollars per acre on average, and the program is actuarially fair: realized claims per acre are equal to the share of insured acres times premiums per acre. However, claims are more volatile than premiums, suggesting that premiums do not account for correlated risks.

Agricultural outcomes. I obtain county-crop-level average yields and crop prices from the annual National Agricultural Statistics Survey (1985-2020), prices of agricultural futures from the Chicago Board of Trade (1975-2020), and worldwide agricultural production and trade flows from FAO (2005-2020). U.S. corn yields are around 3.8 tons per acre, three times as large as soybeans and wheat yields (Table 1 panel C). Sampled counties mainly produce corn: 316 million tons of corn are produced in these counties on average between 2008 and 2019, 15% of which are exported. Overall, my sample of U.S. counties produces $51 billion of corn, followed by $30 billion of soybeans and $6 billion of wheat annually.

Land quality. The land use and crop insurance choice model (Section 4) incorporates persistent land quality heterogeneity. Soil Survey Staff (2024) produces a land quality map that is a function of time-invariant characteristics such as soil type, elevation, and ruggedness. The index ranges from 0 to 19. I select the median quality threshold and aggregate this index into two levels. The spatial distribution of high-quality land displays an East-West gradient (Figure A3).

Sample restrictions. As in Schlenker, Hanemann, and Fisher (2006), I focus on counties that follow relatively uniform agricultural practices, often referred to as "dry land farming". For this I consider counties to the East of the 100th meridian West. Moreover, I exclude counties where farming is negligible (i.e. less than 5% of the surface is farmed), and among the remaining counties I study those in which corn, soybeans, and wheat production represents at least 60% of the planted area between 2008 and 2019. This allows me to study the transition between the three largest crops in the U.S. and how this interacts with climate change and crop insurance design. Appendix Figure A2 displays the counties included in the analysis. These cover 90% (60%) of total corn and soybeans (wheat) production nationwide (Table 1).

3.2 Extreme Temperatures and Yields

Weather shocks impact crop yields, and there is consensus that climate change will decrease the yields of most commodity crops in the future (Schlenker, Hanemann, and Fisher, 2006; Rising and Devineni, 2020; Hultgren et al., 2022). These effects are heterogeneous across crops, linking changes in weather to changes in relative crop profitability and, ultimately, in crop choice.

Leveraging year-to-year variation in the county-level number of extreme degree days—above 30°C—during the growing season, I estimate, for each crop k:

$$\log \text{Yields}^k_{mt} = \beta^k \times \text{ExtremeDegreeDays}_{mt} + X_{mt} + \epsilon^k_{mt}, \tag{1}$$

where the dependent variable is the log of crop k yields in county m, in year t. The main variable on the right-hand side is the number of extreme degree days in county m, year t. X_{mt} includes county and year fixed effects and precipitation levels.

Results are reported in Table 2. In line with findings in the literature (see e.g. Schlenker and Roberts, 2009), I find that ten additional extreme degree days during the corn (soybeans) growing season reduce yields by 5.8% (6.0%). The effect of extreme weather on wheat yields is smaller (-1.6%), consistent with prior evidence (Gammans, Mérel, and Ortiz-Bobea, 2017).[15]

In interpreting these findings one may be concerned about the confounding effect of moral hazard induced by the availability and prevalence of crop insurance. After insuring their crops, farmers could lower their productive effort to collect indemnities. Because insurance take-up is likely to be higher in places with a larger propensity of weather shocks, this may lead to inconsistent estimates of the climate-yield relationships (β^k) in Table 2. I address this issue in Appendix A.4, where I exploit the 1994 reform, which resulted in a widespread but heterogenous increase in insurance take-up. Consistent with moral hazard, I find that yield responses to extreme degree days increase post-reform, especially for corn. However, the joint effect of the insurance and weather shocks on yields, estimated on the selected sample of counties described in Section 3.1, is one order of magnitude smaller than the direct effect of weather shocks and one order of magnitude smaller than previous estimates (Annan and Schlenker, 2015). I interpret this as evidence for a limited role of moral hazard, which may be consistent with the monitoring of insured farmers described in Section 2. In the remainder of the paper, I assume that insurance choices do not directly affect yields. I discuss the implications of this assumption in Section 4.3.

Table 2. Impact of Weather on Yields

Dependent Variable:	Log Yields		
Crop	Corn	Soybeans	Wheat
Extreme Degree Days	-0.0582***	-0.0598***	-0.0157***
	(0.0024)	(0.0022)	(0.0021)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	18,450	17,721	6,956
R^2	0.737	0.758	0.724

Notes: The sample includes all counties in Appendix Figure A2 between 1995 and 2019. Extreme degree days is the number of 30°C degree days measured during the growing season, expressed in tens. All specifications control for precipitation levels. Standard errors are clustered at the county level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

3.3 Climate Trends

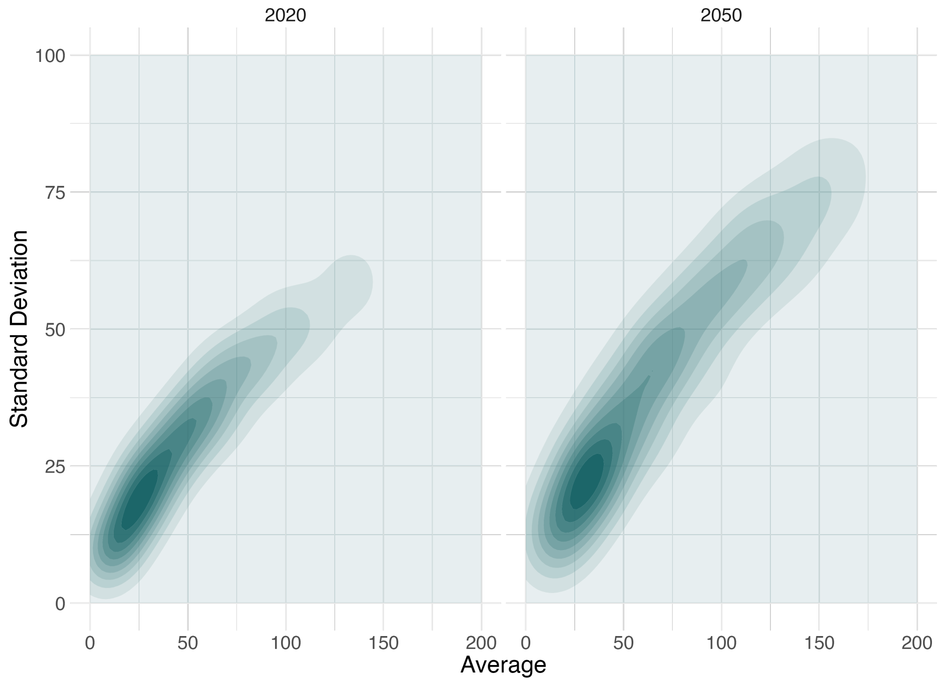
Climate models project the average worldwide temperature will increase by 1-3 degrees Celcius by 2050 (Science Framework Climate Working Group, 2016). This increase is accompanied by more frequent and severe extreme weather events. Figure 1 illustrates this shift for both extreme degree days and precipitation. Using projections from six global climate models for the U.S., I find that the average number of extreme degree days—30C degree days—increases across the U.S. from 50 to 84. Weather uncertainty also increases: the standard deviation of the number of extreme degree days almost doubles. Additionally, U.S. counties become drier (counties receive 313 mm/year of precipitation on average in 2020 against 300mm/year in 2050), and precipitation levels are more variable. Increasing climate uncertainty directly affects farmers' decisions: it worsens the reliability of medium-run weather predictions, which farmers use to decide which crop to grow and which insurance product to subscribe to during the pre-planting season.

However, the effects of climate change are heterogeneous. I define a climate risk index as the coefficient of variation of the number of extreme degree days. Figure 2 shows that climate risk trends differ across space. Weather in the southern half of the U.S. becomes increasingly difficult to forecast. The situation is the opposite in the North. Medium-run weather predictions are particularly relevant to farmers deciding which crop to grow at the beginning of the planting season.

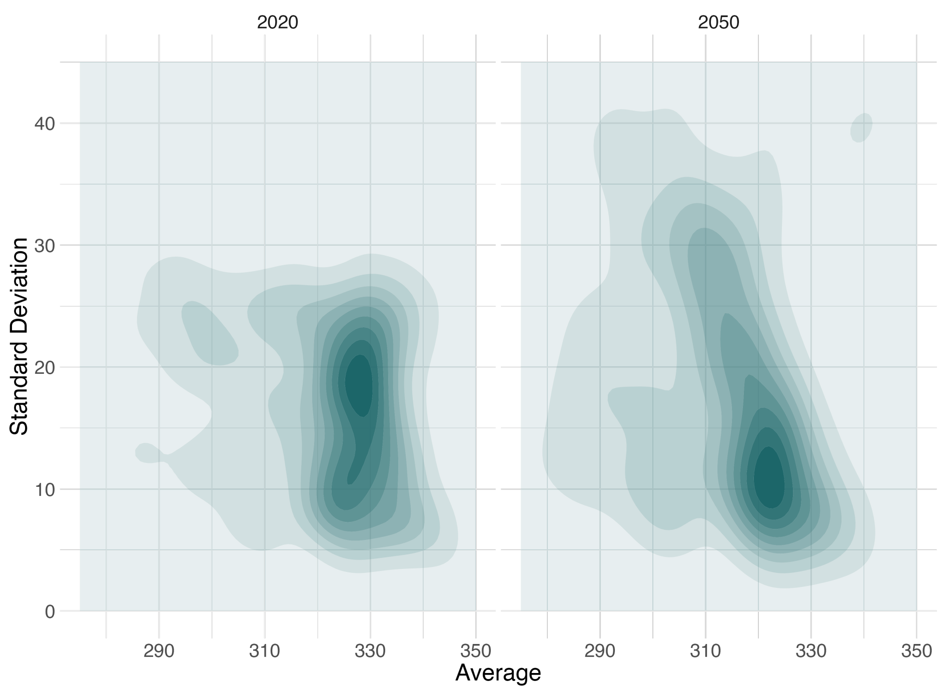
To quantify the potential impact of these trends in weather risk, I use the estimates of the crop-specific climate-yield relationships (β^k) from Table 2 to compute the changes in yields under future weather conditions holding fixed land use decisions to the status quo. I also

[15] Gammans, Mérel, and Ortiz-Bobea (2017) find a sensitivity of wheat to temperatures above 35°C half that of corn and soybeans above 30°C.

Figure 1. County-level Average Weather and Standard Deviation



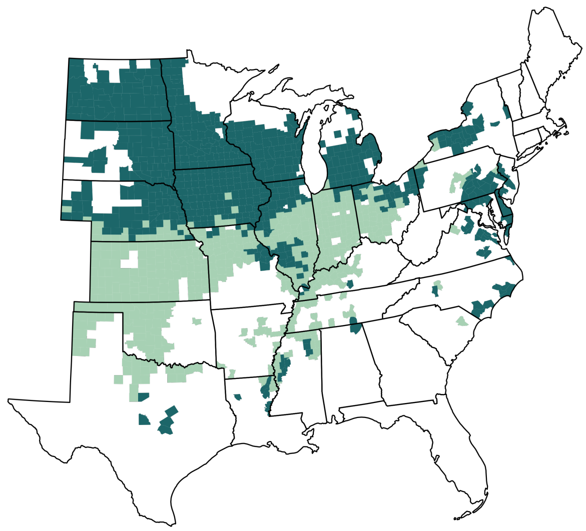
(a) Extreme degree days



(b) Precipitation

Notes: County-level average and standard deviation in the distribution of extreme degree days—30 Celsius degree-days, measured in $^{\circ}C\times$ day, and precipitation, in mm. The sample includes all counties in Appendix Figure A2. I include climate projections from 6 climate models under a moderate emission scenario (RCP4.5). See Appendix E.1 for details.

Figure 2. Trend in Climate Risk



Notes: Climate risk is measured as the ratio of standard deviation to average number of extreme degree days. Trends are measured over 2020-2050. I include climate projections from six climate models under a moderate emission scenario (RCP4.5). See Appendix E.1 for details. Climate risk measured in terms of precipitation (not shown) is correlated. Forecasting weather becomes increasingly difficult in the southern half of the U.S.

compute the corresponding changes in insurance premiums and indemnities holding fixed insurance choices. I find that holding planting, insurance and agricultural technology decisions fixed, predicted climate trends lower yields by 10-40% and increase insurance indemnities and premiums (and therefore government spending) by 20%.

3.4 Crop Switching and Costly Adaptation

As climate change increasingly threatens yields, farmers must adapt through various margins. Here, I focus on planting decisions, where farmers choose which crop to sow.Farming practices are also subject to adjustments I do not consider in this paper.[16]

To investigate how farmers adjust their planting decisions in response to expected weather shocks, I estimate for each crop k

$$\log \text{Acres}_{mt}^k = \beta_1^k \text{ExtremeDegreeDays}_{mt-1} + \beta_2^k \text{Premium}_{mt}^k + X_{mt} + \epsilon_{mt}^k, \tag{2}$$

where the dependent variable is the log of planted acres in county m at time t. The main right-hand side variable with coefficient β_1^k is the lagged number of extreme degree days as observed in the previous year, which I use to proxy for farmers' beliefs over extreme degree days in year

[16] Prior literature shows that this margin is somewhat limited, see, e.g., Burke and Emerick (2016).

Table 3. Impact of Weather and Premiums on Land Use Decisions

Dependent Variable:		Log Acres	
Crop	Corn	Soybeans	Wheat
Premium	-0.0040***	-0.0022*	-0.0297***
	(0.0008)	(0.0011)	(0.0046)
Lag Extreme Degree Days	-0.0150***	-0.0068***	0.0102***
	(0.0019)	(0.0019)	(0.0018)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	8,062	7,768	5,578
R^2	0.986	0.988	0.980

Notes: The sample includes all counties in Appendix Figure A2 between 2008 and 2019. Extreme degree days is the number of 30°C degree days measured during the growing season, measured in tens. Premium is the weighted average of land-quality specific insurance *subsidized* premiums, measured in tens of dollars, where weights are insurance take-up and county-level shares of land quality (see Section 5 for details). Standard errors are clustered at the county level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

t.[17] Equation (2) also includes, with coefficient β_2^k, the average subsidized insurance premium (weighted by insurance market shares in county m, year t). This assumes premiums are known when farmers make their planting decisions since the RMA posts estimates of premiums a few months before the planting season. X_{mt} includes county and year-fixed effects.

Results are presented in Table 3. I find that an additional ten extreme degree days in the previous growing season leads to a statistically significant acreage reduction for corn and soybeans (-1.5% and -0.6%, respectively). Wheat adjustment goes in the opposite direction (+1.0%). These heterogeneous effects are likely driven by the different sensitivities of each crop to extreme temperatures, as indicated by the results in Table 2.

The estimates of β_2^k show that higher crop insurance premiums reduce planted acreage. Quantitatively, an increase in premium by 10$ leads to an acreage decrease of 0.2-0.4% in corn and soybeans and -3% in wheat. These estimates imply that removing the subsidies would lead to reducing farmed land by 1.8% (3 million acres, approximately the area of Connecticut).[18]

Given the estimates of the parameters in equation (2), it is important to understand the costs incurred by farmers when changing their planting decisions in response to weather shocks or changes in insurance premiums. If adapting to climate trends involves significant switching costs, foregoing adaptation today may have ripple negative effects in the future due to path dependency.

[17] This assumption closely follows how I will model farmers' beliefs formation in Section 4.

[18] This back-of-the-envelope calculation is based on crop insurance subsidies covering, on average, 27$ and averaging over crop-specific acres (Table 1).

Table 4. Evidence of Costly Adaptation

Dependent Variable:		Log Acres	
Crop	Corn	Soybeans	Wheat
Extreme Degree Days - Five-year trend	-0.0143***	-0.0090***	0.0129***
	(0.0015)	(0.0014)	(0.0014)
Five-year trend	-0.0454***	-0.0689***	0.0762***
	(0.0058)	(0.0070)	(0.0056)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	18,188	17,277	13,470
Difference $\neq 0$ (p-value)	<0.0001	<0.0001	<0.0001

Notes: The sample includes all counties in Appendix Figure A2 between 1995 and 2019. In all specifications, I decompose extreme degree days (measured in tens) into climate norms and weather shocks. The 5-year moving average of extreme degree days is lagged by one year and captures the longer-run elasticity of acres to warming trends. Extreme Degree Days - Five-year trend is the difference between this value and the contemporaneous number of extreme degree days, lagged by one year. Standard errors are clustered at the county level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Here, I assess the magnitude of these switching costs leveraging variation in short-run weather shocks as distinguished from climate trends (Bento et al., 2023). Intuitively, if switching was costless, past warming should not impact planted acres when controlling for contemporaneous beliefs about extreme degree days, and vice versa.

I estimate

$$\log \text{Acres}^k_{mt} = \beta^k_{\text{short}} \times (\text{ExtremeDegreeDays}_{mt-1} - \text{Five-Year Trend}_{mt-1}) + \\ \beta^k_{\text{trend}} \times (\text{Five-Year Trend}_{mt-1}) + X_{mt} + \epsilon^k_{mt}, \quad (3)$$

where

$$\text{Five-Year Trend}_{mt-1} = \frac{1}{5} \sum_{s=-6}^{-1} \text{ExtremeDegreeDays}_{mt-s}.$$

Controlling for the average number of extreme degree days in the five years preceding year t (with coefficient β^k_{trend}) captures the effects of long-run shifts in climate.[19] The deviation from this trend, with coefficient β^k_{short}, is a proxy for farmers' beliefs over short-run weather shocks experienced by their county during the coming growing season.

Table 4 presents estimates of equation (3). For corn and soybeans, an additional ten extreme degree day difference between lag weather and the five-year average leads to reductions in

[19] In robustness (not shown), I change the averaging window from three to eight years to ensure that the auto-correlation of weather shocks does not drive results.

acreage by 1-1.4%. Conversely, wheat acreage increases by 1.3%. This suggests that farmers switch to crops better suited to warmer conditions.

Importantly, the effects of longer-run shifts in the number of extreme degree days on crop acreage are larger than short-term responses by a factor of three to seven. This is consistent with costly adaptation. While switching to wheat may avoid short-term revenue losses due to weather shocks, it incurs costs that farmers are willing to pay only in response to more persistent warming. In practice, these costs may include learning new techniques, acquiring different machinery, forming new trading partnerships, or waiting for the local support industry to adjust (Sayre, 2024).

Altogether, my results suggest that farmers can switch their crops in response to climate change. However, farmers in high-risk areas may delay or forego adaptation to climate change because switching is costly, and insurance premiums and subsidies adjust to crop failure risk. Insurance subsidies may, therefore, result in large future aggregate losses due to the predicted climate trends. In the rest of the paper, I build an empirical framework to quantify the impact of climate change on U.S. agriculture under alternative designs of crop insurance subsidies.

4 Empirical Model

4.1 Overwiew

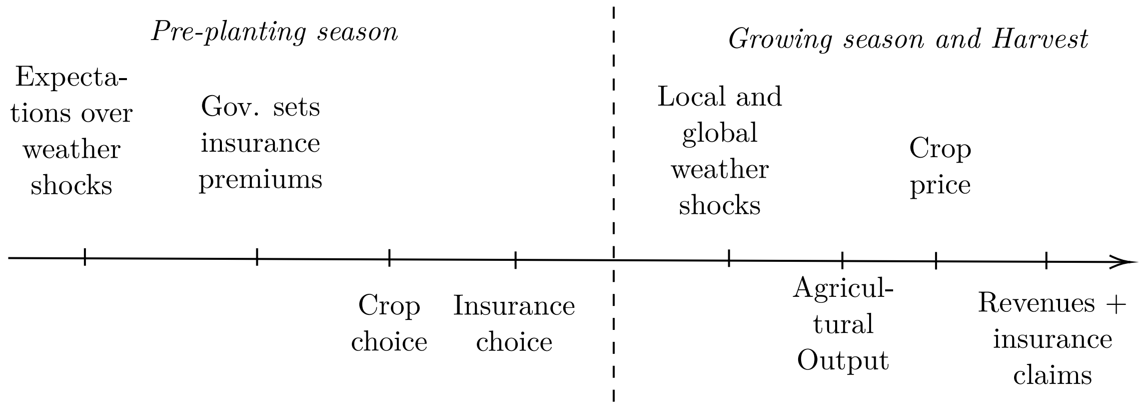
The model is composed of two blocks: a pre-planting period during which all farmers' decisions take place and a growing and harvest season during which production, prices, and profits are realized. The timeline is illustrated in Figure 3.

During the pre-planting season, farmers observe subsidized crop insurance premiums and form beliefs about (*i*) local weather shocks, (*ii*) weather shocks in other counties and abroad, and (*iii*) planted acres of each crop in the U.S. and abroad. Together, beliefs over these variables lead farmers to form beliefs over their individual production, as well as U.S. and foreign production. These ultimately result in beliefs over growing season revenues across alternative planting decisions. Farmers then make a land use decision, followed by a crop insurance decision.[20] Throughout my analysis, farmers are atomistic and farmers' decisions are modeled independently across mono-cultured, 700-acre fields.[21] After planting and insurance decisions are made, weather shocks, yields, prices, insurance indemnities, and profits are realized.

[20] Insurance choice follows planting decisions insofar farmers do not grow seeds from their own production (to avoid cross-pollination and ensure the best performance possible). Instead, they buy seeds 2-3 months before the planting season. In contrast, farmers typically meet with a crop insurance agent the month before the regulated planting date.

[21] First, it follows that farmers are price-takers. This assumption is common, and plausible given that agricultural commodity markets are highly integrated and that one agricultural field performance has a negligible effect on aggregate variables. Second, the independence assumption rules out risk hedging between fields. I discuss the implications of the omission of scale effects in Section 4.3.

Figure 3. Timing of Farmers' Decisions



4.2 Econometric Specification

I specify the primitives and distributional assumptions of the model proceeding backward along the timeline illustrated in Figure 3.

4.2.1 Growing Season and Harvest

During the growing season, local and global weather shocks realize. Given the land use decisions inherited from the pre-planting season, these shocks affect aggregate agricultural production. For the U.S., the total production of crop k in year t is

$$Q_t^{k,US} = \sum_{i \in US} \mathbf{1}\{\text{Farmer } i \text{ chooses } k\} \text{Yields}_{it}^k(\text{Weather}_{it}^{GS}) \tag{4}$$

where Weather_{it}^{GS} is the growing season weather experienced by farmer i in county m_i in year t. Crop prices equilibrate aggregate supply and demand, which I model adapting the agricultural trade model by Costinot et al. (2016) to the context of the U.S. In Appendix B I show that for crop k the price p_t^k must solve

$$Q_t^{k,US} - \text{Net Export}_t^k = \lambda \lambda_k \frac{\left(p_t^k\right)^{-\kappa}}{\sum_\ell \lambda_\ell \left(p_t^\ell\right)^{1-\kappa}}, \tag{5}$$

where $\lambda, \lambda_k, \kappa$ are parameters of the representative consumer's utility function, and net exports depend on foreign weather shocks holding fixed foreign land choice. See Appendix B for details.

Given the price p_t^k and realized yields, the total proceedings of a farmer i who planted k and selected crop insurance option j are equal to

$$R^k_{ijt} = \underbrace{p^k_t \times \text{Yields}^k_{it}(\text{Weather}^{GS}_{it})}_{\text{Revenues from crop sale}} + \underbrace{\text{Indemnity}^k_j \left(\text{Yields}^k_{it}(\text{Weather}^{GS}_{it}), p^k_t\right)}_{\text{Revenues from crop insurance}}, \tag{6}$$

obtained by adding up revenues from sales and crop insurance payments, if any.

4.2.2 Crop Insurance Demand

In the last stage of the pre-planting season, given crop choice k, farmer i must choose one insurance option $j \in \mathcal{J}$, or can remain uninsured $j = 0$. Each j is a pair of one of the two insurance types (revenue or yield; c.f. Section 2) and a coverage level. The insurance type determines whether the farmer is protected against yield shocks, or yield and price shocks. The coverage level dictates the generosity of indemnities when these shocks realize. Each of the two types of insurance can be paired with one of eight levels of coverage, ranging from 50% to 85%.

A farmer is characterized by their (persistent) land quality $\theta_i = \{H, L\}$ and county m_i, collected in the type $Z_i = (\theta_i, m_i)$. For insurance product j and crop k, farmer i's weather and aggregate production beliefs are such that the expected total revenue have mean and coefficient of variation equal to, respectively

$$\mathbb{E}^k_{jt}(Z_i) \equiv \mathbb{E}\left[R^k_{ijt}\middle|Z_i\right], \quad \text{and} \quad CV^k_{jt}(Z_i) \equiv \frac{\sqrt{\text{Var}\left[R^k_{ijt}\middle|Z_i\right]}}{\mathbb{E}^k_{jt}(Z_i)}.$$

The indirect utility for farmer i who planted crop k when selecting insurance j

$$u^k_{ijt}(Z_i) = \xi^k_{jt}(Z_i) + \underbrace{\beta^{\mathbb{E}}_\theta \mathbb{E}^k_{jt}(Z_i) - \beta^{CV}_\theta CV^k_{jt}(Z_i) - \alpha_\theta \text{Premium}^k_{jt}(Z_i))}_{\mu^k_{jt}(Z_i)} + \varepsilon^k_{ijt}, \tag{7}$$

where $\text{Premium}^k_{jt}(Z_i)$ is the subsidized insurance premium, ε^k_{ijt} is i.i.d. type 1 extreme value and the unobservable determinants of demand for insurance j are collected in $\xi^k_{jt}(Z_i) = \xi_t + \xi^k(m_i) + \xi^k_{jt}(m_i)$. For $j = 0$, $\text{Premium}^k_{0t}(Z_i) = \xi^k_{0t}(Z_i) = 0$.[22]

To make the planting decisions that I model next, farmers do not yet know the realizations of the idiosyncratic preference shocks ε^k_{ijt}, but have rational expectations about their future optimal crop insurance decision. That is, they know that if they select crop k the expected

[22] This specification of random utility for insurance can be micro-founded assuming that farmers are risk averse with CARA utility and revenue shocks are normally distributed. See Abaluck and Gruber (2011) for details.

total net revenues are

$$u^*_{kt}(Z) = \frac{1}{\alpha_\theta}\mathbb{E}_\varepsilon\left[\max_j u^k_{jt}(Z)\right] = \frac{1}{\alpha_\theta}\ln\left(\sum_j \exp\left(\xi^k_{jt}(Z) + \mu^k_{jt}(Z)\right)\right). \tag{8}$$

4.2.3 Dynamic Crop Choice

During the pre-planting season, farmer i must choose among four possible, mutually exclusive land uses $k \in \mathcal{K} = \{\text{corn, soybeans, wheat, fallow}\}$.[23] This choice is dynamic because choosing crop k affects not only expected profits in the current year but also future payoffs due to switching costs.

Specifically, at the beginning of year t crop choice must take into account the vector of state variables s_{it}, which contains the farmer's past land use, local weather shocks, weather shocks in other counties and abroad, aggregate acreage planted for each crop in the U.S. and abroad, crop insurance subsidies, and k-specific idiosyncratic shocks ϵ_{ikt}.[24] As is common, I assume the state space joint density function is conditionally independent and that ϵ_{ikt} is i.i.d type 1 extreme value.

Farmer i of land quality θ with state variables s_{it} realizes per-payoff payoffs at the end of year t that depend on the choice k equal to

$$\begin{aligned} \Pi_\theta(k, s_{it}) &= \pi_\theta(k, s_{it}) + \epsilon_{ikt}, \quad \text{where} \\ \pi_\theta(k, s_{it}) &= \underbrace{\phi^k_\theta(s_{it})}_{\substack{\text{switching}\\ \text{cost}}} + \underbrace{\gamma^k_\theta + \gamma^u_\theta u^*_{kt}(Z_i) + \gamma^c_\theta c_{kt}(Z_i) + \eta_{kt}(Z_i)}_{\text{static profits net of switching cost}}. \end{aligned} \tag{9}$$

The switching cost $\phi^k_\theta(s_{it})$ depends on the previous-year planting decision recorded in s_{it}, decision k and land quality θ. Static profits net of switching cost are a linear function of the expected total net revenues as defined in (8), a vector of observed cost measures $c_{kt}(Z_i)$, and the term $\eta_{kt}(Z_i)$ unobserved by the econometrician but known to the farmer.

By the Bellman's principle of optimality,

$$V_\theta(s_{it}) = \max_{k\in\mathcal{K}}\{\Pi_\theta(k, s_{it}) + \delta\mathbb{E}[V_\theta(s_{it+1})|s_{it}, s_{it-1}, ...]\} \tag{10}$$

where $V_\theta(s_{it})$ is the expected discounted stream of profits under optimal behavior. The chosen k on the right-hand side is recorded in s_{it+1}. The discount factor δ is treated as known and equal to 0.9.

[23] In practice, fallow corresponds to one of the following: pasture, cover crops, and fallow. I exclude forests and built areas from the analysis.

[24] This simplified state space—instead of tracking all cultivated acres in every county, farmers track U.S. aggregated acres in the spirit of Weintraub, Benkard, and Van Roy (2008)—makes the problem computationally tractable.

4.3 Discussion

The crop demand model outlined in Section 4.2.1 and Appendix B assumes that consumption in year t equals agricultural production in year t. In other words, I rule out the possibility of storing crops for future consumption. This assumption may lead to underestimating the elasticity of substitution across crops and exaggerating price volatility (Zuniga et al., 2024). To assuage this concern, in estimation, farmers form beliefs over crop prices using the price of crop futures during pre-planting; futures prices should correctly reflect expectations about storage, trade flows, and domestic and foreign production. However, ruling out storage may lead to overestimating the effect of crop insurance subsidies on crop prices and, ultimately, consumer surplus and welfare.

Throughout the analysis, I assume that farmers make independent insurance and land use decisions across fields. The following factors attenuate the concern that this approach may omit scale effects in planting and insurance choices.[25] First, the spatial concentration of larger farms (see Appendix Figure A4 and Tscharntke et al., 2005) implies that state-crop fixed effects partly account for farm size heterogeneity. Second, augmenting yield models by including the county-level share of large farms, only marginally increases the performance of the models I adopt, which controls for the share of high-quality land, omitting farm size.[26] Third, the literature (see e.g. MacDonald, 2020) suggests that farmers tend to see their various risk-hedging options as complements, limiting the concern that other risk-hedging solutions influence their crop insurance choice.[27]

As mentioned in Section 3, I assume that yield functions are independent of farmers' insurance decisions. Including moral hazard would lead to higher estimates of farmers' taste for insurance coverage ($\beta^{\mathbb{E}}$ and β^{CV}), which would increase the estimated effect of crop insurance subsidies on farmer surplus. On the other hand, the subsidies would further increase the volatility of agricultural output and lower the surplus of risk-averse consumers.

Finally, I assume that farmers (and the government) have rational beliefs on climate change. If, instead, I assumed that farmers do not expect climate change, I would estimate larger switching costs: farmers would expect future yields to be higher than they are, yet I observe low crop switching probabilities. The resulting higher switching costs would reinforce path dependency, increasing the likelihood that crop insurance subsidies could lock the U.S. agricultural system into a low-adaptation trajectory, potentially leading to significant welfare losses.

[25] Concern is that large farms may have greater access to alternative risk-hedging solutions such as futures and options markets or diversifying their crop mix over multiple fields. Omission of scale effects may result in underestimating farmers' distaste for revenue risk and overestimating premium sensitivity—thus leading to inflated impacts of crop insurance subsidies on the agricultural system. Additionally, observed low crop switching probability is rationalized by larger switching costs when it could be explained by portfolio diversification.

[26] The relative difference in R^2 of 0.8‰.

[27] For robustness, in Appendix C I re-estimate crop insurance demand on the subsample of counties with a low share of large farms.

5 Estimation

Estimation proceeds in three steps. First, I estimate farmers' short-run beliefs on growing season outcomes and compute the crop insurance plan characteristics. Second, I estimate crop insurance demand, allowing for persistent observed heterogeneity in land quality. Finally, I estimate the parameters of the dynamic crop choice model.

5.1 Short-run Beliefs and Insurance Characteristics

For each insurance option j, I need to recover farmers' beliefs on agricultural revenues, as captured by $\mathbb{E}^k_{jt}(Z_i)$, and $CV^k_{jt}(Z_i)$. These statistics are functions of two underlying distributions: quality-crop-county-year-specific yields and year-specific crop prices. I estimate both distributions using information available to farmers pre-planting. I assume the beliefs are exogenous from farmers' crop insurance and land use decisions, i.e., yields do not depend on insurance take-up as discussed in Section 3 above, and farmers are price-takers.

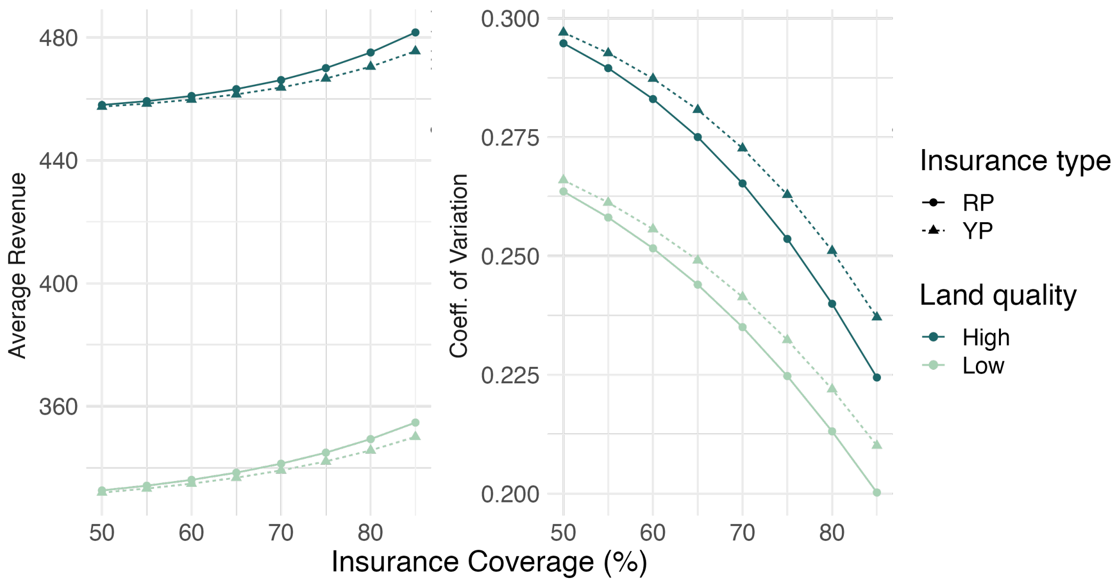
Beliefs on yields combine weather predictions with agronomic knowledge. Based on pre-planting weather and past years' growing season weather, I model farmers as forming rational expectations about the range of temperatures and precipitation levels for the upcoming growing season. These are then combined with estimates of weather-yield relationships to obtain beliefs on yield. Beliefs on crop prices are instead derived from the prices of pre-planting crop futures using a quantile random forest model.[28] I discuss details and goodness of fit in Appendix C.

I combine the beliefs on yield and crop price with insurance indemnity schedules set by the RMA to estimate $\mathbb{E}^k_{ijt}$ and CV^k_{ijt} for every j, including the uninsured option. The resulting estimates exhibit intuitive patterns. For a given coverage level, revenues associated with *yield protection* insurance plans are lower and more variable than those associated with *revenue protection* (Figure 4). Within each insurance type, $\mathbb{E}^k_{jt}$ (CV^k_{jt}) increases (decreases) with coverage level. Low-quality farmers expect lower revenues on average.

To complete the measurement of the right-hand side variables in equation (7), I calculate posted crop insurance premiums for each county and for each land quality. For this, I assume that farmers and the RMA have the same beliefs on growing season outcomes, and since the Federal Crop Insurance Program is actuarially fair, insurance premiums equal expected indemnities. This implies that premiums do not provide additional information on local yields and crop prices to farmers. In Appendix C, I verify that this procedure performs well in predicting the paid premiums that I directly observe in the data.

[28] In the counterfactual scenarios discussed in Section 6, I introduce an alternative process for the formation of farmers' beliefs on crop prices. Specifically, farmers' beliefs on aggregate cultivated acreage and weather shocks, combined with crop demand (as outlined in Section 4.2.1), shape their beliefs on crop prices.

Figure 4. Insurance Characteristics



Notes: This figure plots the beliefs farmers form on growing season revenues during the pre-planting season. The average revenues and coefficient of variation are computed for all insurance types and coverage levels included in the analysis. Each dot is the average over all counties in the sample (see Figure A2) in 2016.

5.2 Crop Insurance Demand

The crop insurance demand specification implies that the share of farmers of type Z growing crop k who choose insurance plan j in year t is given by

$$\sigma_{jt}^{k}(Z) = \frac{\exp(\xi_{jt}^{k}(Z) + \mu_{jt}^{k}(Z) - \mu_{0t}^{k}(Z))}{1 + \sum_{j \neq 0} \exp(\xi_{jt}^{k}(Z) + \mu_{jt}^{k}(Z) - \mu_{0t}^{k}(Z))} \tag{11}$$

where $\mu_{jt}^{k}(Z) = \beta_{\theta}^{\mathbb{E}} \mathbb{E}_{jt}^{k}(Z) - \beta_{\theta}^{CV} CV_{jt}^{k}(Z) - \alpha_{\theta} \text{Premium}_{jt}^{k}(Z)$ and $\xi_{jt}^{k}(Z) = \xi_t + \xi^{k}(m) + \xi_{jt}^{k}(m)$.

I estimate model parameters using the generalized method of moment (GMM) following the standard approach for differentiated products demand (Berry, Levinsohn, and Pakes, 1995). I estimate parameters such that observed and modeled insurance shares equalize:

$$\sigma_{jmt}^{k} = \sum_{\theta = H,L} sh_{m\theta}\, \sigma_{jt}^{k}(Z) \tag{12}$$

where σ_{jmt}^{k} is the observed county-level market share of j, $sh_{m\theta}$ is the share of land quality θ in county m and $\sigma_{jt}^{k}(Z)$, defined in equation (11), is a function of the parameters $\{\beta_{\theta}^{\mathbb{E}}, \beta_{\theta}^{CV}, \alpha_{\theta}, \xi_{jt}^{k}(Z)\}$.

Table 5. Crop Insurance Demand Estimates

Variables	Parameters	High Quality	Low Quality
Expected Revenues	$\beta^{\mathbb{E}}$	0.03	0.12
		(2e-06)	(4e-06)
Coeff. of Var.	$-\beta^{CV}$	-0.01	-0.04
		(5e-06)	(7e-06)
Subs. Premiums	$-\alpha$	-0.05	-0.2
		(4e-06)	(5e-06)

Notes: The estimation sample includes all counties in Figure A2 between 2008 and 2019 for a total of 19,457 observations (crop × counties × year). Standard errors are robust to heteroskedasticity.

Identification. I form moments with insurance characteristics and transformations (Gandhi and Houde, 2019).[29] Because I include time and crop-state fixed effects, identification relies on random panel variation in worldwide weather, as well as cross-sectional and panel variation in local weather and weather variability. Local weather variability impacts the precision of yield beliefs, which determines the distance between each insurance product in the characteristics space: a spiked yield distribution shrinks the distance between products with different coverage levels, whereas a wide distribution increases it. Worldwide weather variability has a similar effect mediated through the spread of crop price distributions. Finally, the actuarial fairness property helps identify the premium elasticity.

Results. Table 5 shows the land-quality specific estimate parameters. Farmers value insurance plans offering higher expected revenues and lower risk. They are premium-sensitive; their premium sensitivity is higher than the value they place on expected revenues. Appendix Table C4 shows robustness to dropping counties where more than 10% of farms are more than 1000 acres. I find that small farmers have a higher willingness to pay for insurance, implying that large farmers may hedge climate risks through alternatives like crop diversification or futures markets. However, parameter estimates are similar to the full sample, suggesting limited scope for these alternatives.

In Appendix Table C5, I analyze the impact of removing crop insurance subsidies. On average, this reduces insurance take-up by 40% and expected total net revenues by 3.5% per acre.[30] Farmers on low-quality land insure at higher rates and benefit more from subsidies in the baseline; removing subsidies decreases net revenues u^* more than for high-quality farmers. The decrease in net revenues from removing subsidies is comparable to the decrease due to climate change-induced warming and variability for corn and soybean growers. On the other hand, wheat growers benefit from warming (+3.5%). These results do not account for

[29] Given model assumptions, all crop insurance characteristics, $\mathbb{E}^k_{jt}(Z)$, $V^k_{jt}(Z)$ and $\text{Premium}^k_{jt}(Z)$, are exogenous. Beliefs on yields are not impacted by insurance choice; farmers are atomistic so that crop prices are not influenced by the agricultural production of one individual farmer; premiums are equal to farmers' expected indemnities. Therefore, the model is just-identified with the three moments deriving from the three insurance characteristics. However, I construct additional moments using Gandhi and Houde (2019) instruments to improve the estimator's efficiency.

[30] Expected total net revenues is defined in equation 8.

land-use adjustments, which may mitigate aggregate effects.

5.3 Crop choice

I estimate the dynamic crop choice model in two steps, using conditional choice probabilities solution method (Hotz and Miller, 1993). First, I recover the conditional choice probabilities from satellite images. Second, I estimate the coefficients of the profit functions using standard panel techniques.

5.3.1 Conditional Choice Probabilities

I obtain field-level land use (corn, wheat, soybeans, and fallow) for all years between 2008 and 2019 from the CropLand DataLayer. Then, I use a trained random forest algorithm to generate conditional choice probabilities for each crop category based on the state space: latitude, longitude, soil quality, year, and previous land use.[31] The estimates of probability are well-calibrated. A back-of-the-envelope calculation suggests that around 14% (5%) of cropland has been planted continuously with corn (soybeans) over three years (Appendix Figure D2). These numbers align with survey results collected by the USDA Agricultural Resource Management Survey (Wallander, 2020).

5.3.2 Euler Equation in Conditional Choice Probability Estimator

Using the Euler equations in the Conditional Choice Probability estimator requires additional assumptions. First, I assume that switching land use is a renewal action (Scott, 2013; Kalouptsidi, Scott, and Souza-Rodrigues, 2021), a special case of finite dependence: taking action a in period t leads to the same distribution of states at the beginning of period $t+1$, regardless of which state the farmer was in during period $t-1$. Finite dependence accommodates non-stationary state space and beliefs (Arcidiacono and Miller, 2019). Second, I assume the state space density function satisfies the conditional independence assumption and follows a first-order Markov process, consistent with the hypothesis of atomistic farmers; c.f. Section 4.2.2.

Then, using the distributional assumption on the error term ϵ_{ikt}, I obtain a structural regression equation, which holds across county and land quality (see Appendix D.1 for details).

[31] This procedure has the advantage of disaggregating the conditional choice probabilities by land quality and reducing the occurrence of zero transition probability. Other smoothing approaches adopted in (Scott, 2013; Araujo, Costa, and Sant'Anna, 2024; Burlig, Preonas, and Woerman, 2024) rely on less flexible inverse-distance smoothing. Figure D1 shows the resulting county-level conditional choice probability.

For readability, I drop subscripts m and θ. For all past land use k and action a; $a \neq k$:

$$\underbrace{\ln \frac{\mathbb{P}_{kat}}{\mathbb{P}_{kkt}} - \delta \ln \frac{\mathbb{P}_{kat+1}}{\mathbb{P}_{aat+1}}}_{Y_{kat}} = (1-\beta)\phi^{ka} + \gamma^a - \gamma^k + \gamma^u(\underbrace{u^*_{at} - u^*_{kt}}_{X^u_{kat}}) + \gamma^c(\underbrace{c_{at} - c_{kt}}_{X^c_{kat}}) + \zeta_{kat} \quad (13)$$

where $\mathbb{P}_{kat}$ is the conditional choice probability, i.e., the probability of switching from land use k to a at time t and all other factors are as in equation (9). The error term ζ_{kat}, is a function of the unobserved returns η_{at} and η_{kt}, and farmers' expectational error—i.e., the difference between expected and realized value functions at time t.

Within location estimation. I use standard panel techniques to recover coefficients on time-varying regressors, γ^u and γ^c. This approach allows for systematic differences across locations in the unobservable returns η. Taking the difference Equation (13) between t and $t-1$ for both level of land quality, I estimate

$$\Delta_t Y_{kat} = \gamma^u \Delta_t X^u_{kat} + \gamma^c \Delta_t X^c_{kat} + \Delta_t \zeta_{kat} \quad (14)$$

where Y_{kat}, X^u_{kat} and X^c_{kat} are defined in equation (13). This differentiation introduces endogeneity: $\Delta_t \zeta_{kat}$ contains the expectational error which is correlated with e.g. u^*_{at} in $\Delta_t X^u_{kat}$. I address this concern by constructing lags of X^u and X^c, which I use as instruments for $\Delta_t X^u_{kat}$ and $\Delta_t X^c_{kat}$ (Anderson and Hsiao, 1981).[32]

Estimation of the switching costs in levels. Use $\hat{\gamma}$ and projecting the residuals from Equation (14) on crop transition indicators, I estimate for all $a \neq k$

$$Y_{kat} - \hat{\gamma}^u X^u_{kat} - \hat{\gamma}^c X^c_{kat} = \tau_{ka} + \zeta_{kat}. \quad (15)$$

I then recover the intercepts and switching costs, noticing that $\tau_{ka} = (1-\beta)\phi_{ka} + \gamma_a - \gamma_k$ and normalizing $\phi_{aa} = 0$ for all $a \in \mathcal{K}$. Additionally, I assume $\phi(., \text{fallow}) = 0$.

Identification. Coefficients on farmers' revenues and input costs are identified from cross-sectional and panel variations between crops. Weather shocks interacted with crop-specific yield-weather response functions offer the identifying variation. A common challenge in identifying crop choice models is that corn, soybeans, and wheat are substitutes in many use cases, e.g., cattle feed, which results in correlated crop price time series. The passage of the 2009 Renewable Fuel Standard in the U.S. helps identifying crop supply parameters (Roberts and Schlenker, 2013). This mandate, also knows as the ethanol mandate, increased demand for U.S. corn and, to a lesser extent, soybeans, participating in decoupling the crop price time series and helping identify γ^u. The marginal cost parameter is identified from cross-sectional

[32] For example, $\Delta_t X^u_{ka2010}$ is instrumented by X^u_{ka2008}; $\Delta_t X^u_{ka2011}$ is instrumented by X^u_{ka2009}, etc. These instruments are valid because information on X^u_{kat-2} is in the information set of farmers at $t-1$ and is thus uncorrelated with the expectational error between $t-1$ and t.

Table 6. Dynamic Crop Choice Estimates

Parameters	High Quality	Low Quality
γ^u	0.0026	0.0031
γ^c	-0.0022	-0.0020
γ^{Corn}	-1.07	-1.48
γ^{Soybeans}	-1.67	-1.36
γ^{Wheat}	-1.53	-1.39
ϕ(Corn, Fallow)	-6.18	-6.40
ϕ(Wheat, Fallow)	-5.35	-7.48
ϕ(Soybeans, Fallow)	-6.43	-7.20
ϕ(Soybeans, Corn)	-0.02	0.01
ϕ(Wheat, Corn)	-3.98	-3.71
ϕ(Corn, Soybeans)	-0.16	-0.31
ϕ(Wheat, Soybeans)	-2.58	-3.43
ϕ(Soybeans, Wheat)	-1.47	-0.74
ϕ(Corn, Wheat)	-2.46	-2.26

Notes: The table presents the results from the estimation of Equations (14) and (15). γ^u and γ^c are estimated with an instrumented panel estimator Anderson and Hsiao (1981). The F-stat are 815 and 960 for high- and low-quality, respectively. The estimation sample includes all counties in Figure A2 between 2011 and 2019.

variation in input prices resulting from exogenous supply chain and labor market conditions. Switching costs and crop-specific intercepts match the residual variation.

Results. Table 6 presents the estimated parameters. The positive coefficients on the expected utility derived from agricultural production and insurance give an upward-sloping supply curve. The negative crop-specific parameters capture the intercept of the cost function; the input cost structure is relatively similar across the three modeled crops. Switching cost estimates reflect common crop rotation patterns. For example, I estimate small switching costs between corn and soybeans, a well-known cost-reducing rotation adopted by many farmers in the U.S. I find that switching from corn to soybeans is 100 less costly for high-quality farmers than switching from corn to wheat. Appendix Table D1 shows that the estimated model predicts conditional choice probabilities highly correlated with the ground truth (0.8 on average across land use and land quality, with an R^2 of 0.7).

I compute aggregate long-run land use elasticities with respect to a permanent increase in crop insurance subsidies by 10% for all insurance plans. Appendix D.4 details the computation. This intervention increases total cultivated acres by 0.4%. Corn, soybeans, and wheat farmers have 0.02, 0.06, and 0.01 elasticities, respectively, similar in magnitude to those estimated by Yu, Smith, and Sumner (2018).

6 Crop Insurance Subsidies in a Changing Climate

6.1 Simulating the Future and Computing Welfare

To solve for counterfactual paths of farmers' decisions and agricultural outcomes between 2020 and 2050, I parametrize farmers' beliefs on the evolution of the state variables. First, I assume farmers have perfect foresight on crop insurance subsidies: the U.S. Department of Agriculture commits to a path of subsidies for the period.[33] Second, farmers have accurate beliefs on local and global climate. At any point in time, farmers know the path of weather distributions in their county and for all countries worldwide. For the scenarios with climate change, beliefs are derived from climate models; see Appendix F for details. Third, I assume constant cultivated area in countries outside the U.S. and constant exogenous export and import shares of agricultural commodities.[34] Finally, farmers form auto-regressive beliefs on the path of aggregate crop acres in the U.S. Using these beliefs, along with yield models (Section 5.1) and the crop demand model (Section 4.2.1), farmers form beliefs on local yields and crop prices, which inform their insurance and land use decisions. Counterfactual results do not account for technological change or population growth.

In 2050, I assume weather distributions stabilize, and farmers make choices facing a stationary state.[35] I solve the Bellman equation in the terminal year, and then, using initial belief parameters, I recover the value functions backward. I simulate farmers' land use choices, update the belief parameters using the simulated data, and repeat until convergence.

Welfare is measured in terms of net benefits: it is given by the sum of the certainty equivalent of U.S. consumer surplus, the certainty equivalent of farmer surplus, and government revenues.[36] The certainty equivalent of consumer surplus is the compensating variation needed to maintain baseline utility, adjusted by the risk premium, a function of *within-year* consumption mean and variance.[37] The variance of agricultural consumption directly results from the impact of weather variability on local and global yields and, ultimately, crop prices. Intuitively, consumption variance and the risk premium are greater the higher the share of U.S. production in counties with high weather unpredictability. Farmer surplus is the flow profits defined in Equation (9), and government spending is the product of subsidy rates, premium per acre, insurance take-up, and acres. Appendix F provides details.

[33] Additionally, I assume government policies in the rest of the world are fixed. Counties outside the selected sample (Figure A2) receive status quo subsidies (Table A1) in all counterfactual scenarios.

[34] This is a strong assumption that I plan to relax in future iterations. One tractable solution would be to model the rest of the world on an exogenous trend of acres.

[35] This is broadly consistent with the assumptions of the RCP4.5 scenario I use to obtain climate model temperature and precipitation projections: this scenario assumes that carbon emissions stabilize around 2050.

[36] Offering crop insurance premium subsidies also impacts the rest of the world's consumer and producer surplus. I do not consider this part of welfare when computing optimal policies: the crop demand model detailed in Section B is fairly stylized, making prices in the rest of the world imprecisely calibrated.

[37] Given log utility (Section 4.2.1), consumers have a constant relative risk aversion parameter of 1. Consumer's risk premium is $1/2(\sigma^C/\mu^C)^2$, where μ^C is the mean of agricultural consumption and σ^C is the standard deviation. Then, the consumer surplus is given by $CS = CS^{\text{RiskNeutral}}(1 - \text{Risk Premium})$.

Table 7. Impact of Crop Insurance Subsidies on Welfare and Agricultural Output

Scenario	**Climate Change:** **Subsidies:**	No Status Quo (Level)	No None (Δ%)	Yes Status Quo (Δ%)	Yes None (Δ%)	Yes Targeted (Δ%)	Yes Block-Targ. (Δ%)
Panel A: Welfare		-	1.5	-9.4	-6.6	-8.8	-9.3
	Gov. Spending	2,500	-4.0	0.7	-4.0	0.6	0.9
	Farmer Surplus	3,160	-0.04	0.01	-0.01	0.02	0.02
	Consumer Surplus	-	-2.5	-8.8	-10.5	-8.2	-8.5
Panel B: CS Decomposition							
	Risk Neutral Baseline	-	-2.5	-7.2	-9.1	-6.9	-7.0
	Adjustment for Risk Aversion	-	0.04	-1.6	-1.4	-1.3	-1.5
Panel C: Agricultural outcomes							
Cultivated Area	Acres	108	-3.9	-0.4	-3.8	-0.1	0.0
Corn	Acres	65	-5.2	-1.1	-5.5	-0.5	-0.7
	Price	166	2.8	0.8	4.4	0.8	0.8
Soybeans	Acres	40	-1.9	-0.2	-2.2	-0.2	0.3
	Price	425	4.2	2.1	5.8	1.9	1.9
Wheat	Acres	3	-1.0	11.4	11.5	9.8	11.4
	Price	251	2.1	1.2	3.5	1.2	1.2

Notes: Column *status quo/no climate change* presents baseline outcomes. Government spending and farmer surplus are expressed in million dollars, areas as in a million acres, and prices in dollars per acre. *Targeted* subsidies are 15% (150%) of the status quo (Appendix Table A1) in counties with increasing (decreasing) climate risk. *Block targeted* subsidies are 45% (150%) of the status quo in counties above (below) the median climate risk trend by state. In scenarios without climate change, climate is as in 2016-2020, both in the U.S. and worldwide. In scenarios with climate change, climate evolves as projected by six climate models under RCP 4.5 (see Appendix E).
Panel A shows average annual welfare differences between counterfactual crop insurance subsidy scenarios and the baseline. These differences are expressed in the percent of total production (in million dollars) under the status quo/no climate change scenario. Aggregate welfare is decomposed into government, consumer, and producer gains defined in Appendix F.1. Panel B breaks down the effect of subsidies and climate change on the change in consumer surplus, expressed as before in the percent of total baseline agricultural value (in million dollars). The consumer surplus is given by $CS = CS^{\text{RiskNeutral}}(1 - \text{Risk Premium})$ = Risk Neutral Baseline + Adjustment for Risk Aversion. The risk premium is $1/2(\sigma^C/\mu^C)^2$, where μ^C is the mean of agricultural consumption and σ^C is the standard deviation. Panel C presents percent differences in agricultural outcomes under counterfactual crop insurance policies and the baseline.

6.2 Climate Change Impacts on Agriculture

To test the model's predictions against literature estimates on the impact of climate change on agriculture, I compare two scenarios. One assumes no climate change from the baseline period 2016-2021, while the other follows projections from various climate models (see Section E.1). In both cases, the U.S. government continues to provide crop insurance premium subsidies to farmers (Appendix Table A1).

Overall, climate change reduces welfare by 9.4% of total output at baseline (in dollars) annually between 2020 and 2050 (Table 7, panel A). This translates into a 0.5% reduction in agriculture's contribution to U.S. GDP, consistent with previous estimates in the literature.[38] For instance, EPIC (2021) predicts that climate change will reduce U.S. GDP by 1 to 4% annually.

Worsening growing conditions lower consumer welfare by 8.8%. Smaller cultivated areas increase crop prices, reducing baseline consumer surplus by 7.2%. Additionally, increased climate variability under climate change decreases the surplus for risk-averse consumers by another 1.6 percentage points.

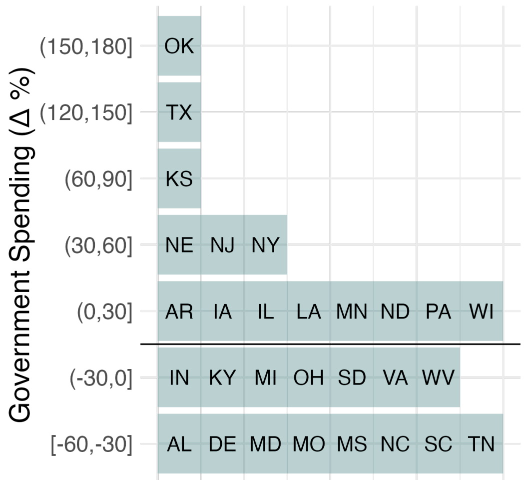
As warming severely impacts corn and soybean yields, farmers increasingly shift away from these crops as climate change worsens (Table 7, panel C).[39] Corn acreage decreases by 1%, and soybean acreage by 0.2% annually as farmers turn to more wheat. However, the rise in wheat acreage does not compensate for the reduction in corn and soybeans, leading to a 0.4% decline in total cultivated area. Consistent with patterns of warming and weather risk (Figure 2), corn and soybean growers are increasingly concentrated in the northern U.S. (Appendix Figure F2).

6.3 Impact of Status Quo Subsidies on Welfare and Adaptation

Crop insurance subsidies negatively affect welfare (Table 7, panel A). In a scenario where the climate remains at the 2016-2020 average through 2020 to 2050, removing status quo subsidies increases welfare by 1.5% of total agricultural output under the status quo (in dollars). However, this policy change harms both farmers (-0.04%) and consumers surplus (-2.5%). The reduction in consumer surplus stems from a decrease in cultivated acres: cultivated land declines by 4%, pushing crop prices up. Corn sees the largest decline in acreage (-5.2%), followed by soybeans (-2%) and wheat (-1%). This reduction in cultivated acreage occurs primarily in the Midwest, where corn production is most prevalent and which receives the largest share of subsidy dollars under the status quo (Appendix Figure F3). This pattern aligns with discussions on Farm Bill reform, which suggest that wealthier corn growers in the Corn Belt benefit most from crop insurance subsidies (Bekkerman et al., 2018).

[38] Agriculture's contribution to U.S. GDP is $1.5 trillion in 2024. See EPA website.
[39] See yield models in Section 3 and Appendix C.

Figure 5. Government Subsidies over Time and Space



Notes: The figure shows the percent change in government spending received by U.S. states between 2020-2030 and 2040-2050. Government spending is the weighted sum of subsidies, where the weights are equilibrium insurance take-up and planted acres.

Under climate change, the negative impact of status quo subsidies on welfare worsens. Removing these subsidies increases welfare by 2.8% in the climate change scenario (net of the direct effect of warming), compared to 1.5% under no climate change. Warming and increased climate risk increase crop insurance premiums, escalating government spending. Without subsidies, the U.S. government saves 4.7% in spending under climate change, compared to 4% without climate change.

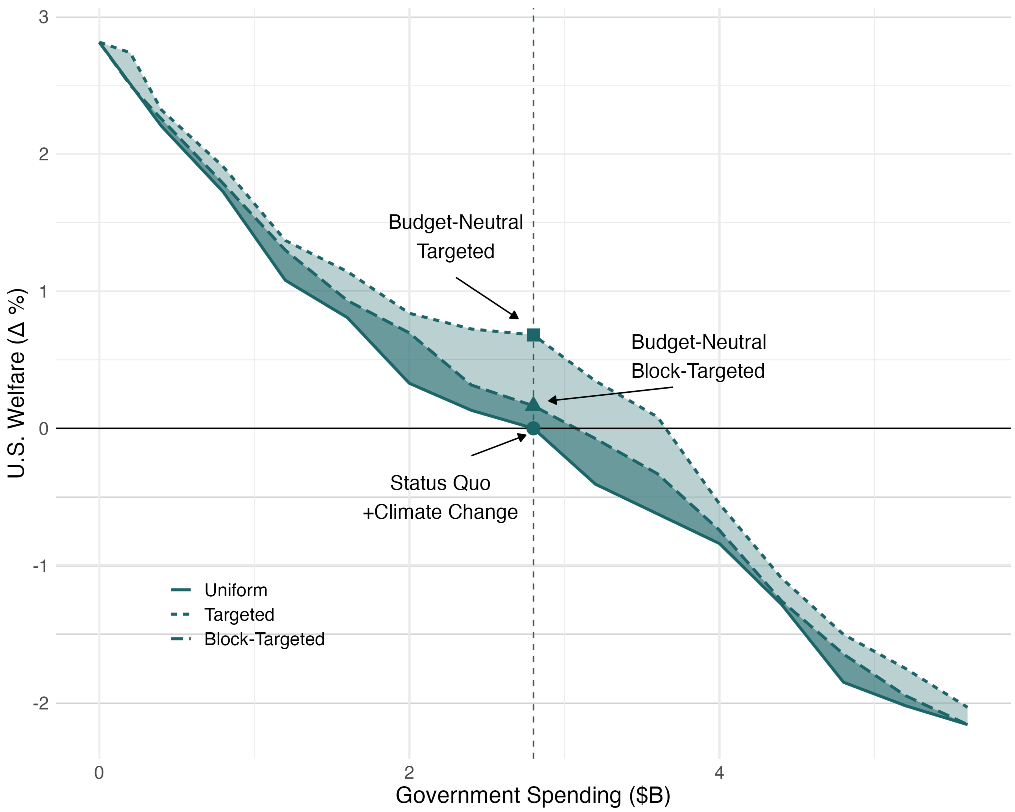
Subsidies also incentivize farmers to grow crops in riskier areas. Figure 5 shows that states experiencing worsening climate risk (e.g., Texas, Kansas, Oklahoma, and to a lesser extent, Nebraska; see Figure 2) are the primary beneficiaries of these subsidies. As a result, a combination of warming, costly crop switching, and the continuation of status quo subsidies places the agricultural system on a riskier trajectory. The consumer surplus risk adjustment—a measure of agricultural output volatility—decreases by 0.2% when subsidies are removed under a changing climate, compared to a reduction of only 0.04% without climate change (Table 7, panel B).

Overall, these findings support the hypothesis that crop insurance subsidies increase moral hazard in land use decisions. By exposing agriculture to greater weather-related risks, particularly under climate change scenarios, the subsidies lead to large net welfare losses.

6.4 Targeting Subsidy on Climate Risk Trends

Can subsidy targeting improve welfare outcomes and adaptation to climate change? I compare the welfare impacts of status quo (spatially uniform) versus targeted policies under

Figure 6. Welfare against Government Spending, under Climate Change



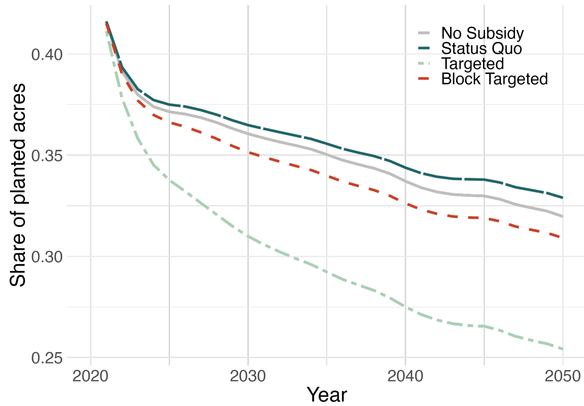
Notes: The figure plots the maximum welfare gains attainable, compared to the baseline, for all given levels of government spending for uniform subsidies, targeted, and block-targeted subsidies. Welfare is the sum of the certainty equivalent of consumer surplus, the certainty equivalent of farmer surplus, and government revenues. The y-axis is the annual 2020-2050 average difference in welfare between counterfactual subsidy schedules and the baseline, expressed in percent of total U.S. agricultural production (in dollars) under the baseline scenario. In the baseline scenario, climate changes under a moderate emission scenario (see Appendix E), and the U.S. government does not offer crop insurance premium subsidies. Targeted subsidies adjust based on a county risk trend. Block-targeted subsidies reallocate subsidies based on risk trend *within U.S. states*. *Status quo* (circle) are described in Table A1. *Budget-Neutral Targeted* subsidies (square) are 15% (150%) of the status quo in counties with increasing (decreasing) climate risk. *Budget-Neutral Block-targeted* subsidies (triangle) are 45% (150%) of the status quo in counties above (below) the median climate risk trend by state.

climate change. Targeting rules can take many forms and be adjusted over time. To simplify, I assume that at the start of the period in 2020, the government announces a subsidy schedule for the entire 2020-2050 period. I also allow subsidies to vary between counties based on decreasing or increasing climate risk *trends*.[40] This approach aims to quantify the importance of designing crop insurance subsidies accounting for climate change dynamics. Counties in the south (north) of the U.S. face more (less) unpredictable weather over time (Figure 2). In the targeted policy scenarios, subsidies differ between these two groups of counties.

Subsidy targeting improves welfare compared to the status quo. Figure 6 plots the maximum welfare gains attainable under climate change at various levels of government spending

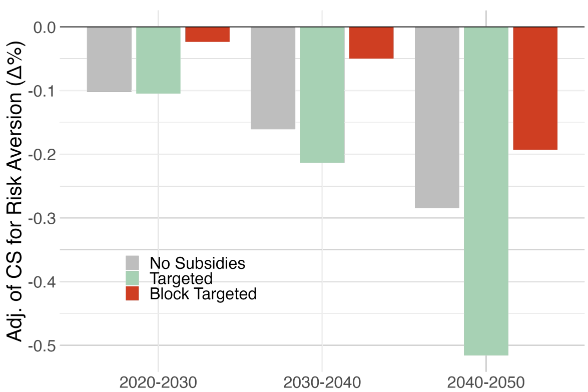
[40] As in Section 3, climate risk is the ratio of the standard deviation to the average number of extreme degree days in each county.

Figure 7. Share of Planted Acres in Risky Counties

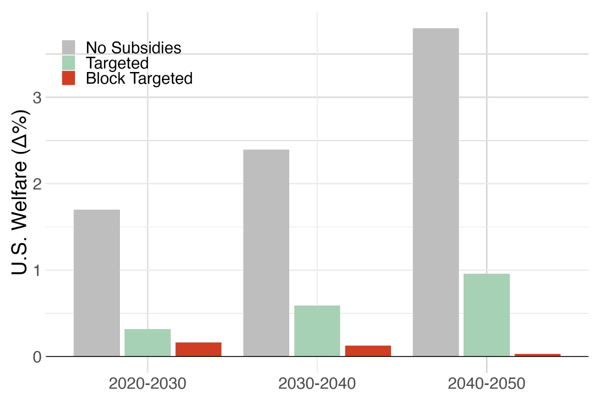


Notes: The figure shows the share of agricultural acres planted in the county on an increasing risk trend over time. *Targeted* subsidies are 15% (150%) of the *status quo* in counties with increasing (decreasing) climate risk. *Block targeted* subsidies are 45% (150%) of the status quo in counties above (below) the median climate risk trend by state.

Figure 8. Agricultural Production Stability and Welfare over Time



(a) Adjustment of Consumer Surplus for Risk Aversion



(b) Welfare

Notes: Panel (a) shows the change in the adjustment of consumer surplus for risk aversion under various counterfactual scenarios, i.e., how an increase in climate risk exposure translates into consumer surplus losses. Panel (b) shows the welfare gains from reforms of the status quo subsidies over time. Changes in both panels (a) and (b) are expressed in percent of the total value of agricultural production (in million dollars) in the baseline scenario. In the baseline scenario, climate changes under a moderate emission scenario (see Appendix E), and the U.S. government offers status quo crop insurance premium subsidies (Table A1). *Targeted* subsidies are 15% (150%) of the *status quo* in counties with increasing (decreasing) climate risk. *Block targeted* subsidies are 45% (150%) of the status quo in counties above (below) the median climate risk trend by state.

for uniform and targeted subsidies. While offering uniform subsidies decreases welfare as established in Section 6.3, a welfare-enhancing targeted subsidy schedule exists at any given spending level.

Focusing on budget-neutral reforms, I find that removing all subsidies from counties on a riskier trend and increasing them by 50% in counties where climate risk decreases over time improves welfare by 0.6% compared to the status quo. I refer to this approach as the *targeted* policy. Under this policy, farmer surplus doubles (Table 7, panel A), and consumer surplus rises by 0.6 percentage points. This improvement is driven by an increase in cultivated areas, which raises consumer surplus by 0.3% compared to the status quo under climate change, and a reduction in production volatility, further increasing consumer surplus by 0.3% (Table 7, panel B).

By targeting crop insurance subsidies based on climate risk trends, the government incentivizes farmers to relocate production to safer counties. Figure 7 shows that the share of agricultural output produced in risky counties drops sharply under *targeted* subsidies. In 2020, 43% of acres are planted in counties where weather risk is increasing. By 2050, this share decreases to 26%, a seven percentage point reduction compared to the status quo.

As a result, consumer surplus losses from agricultural output volatility decrease over time (Figure 8, panel (a)), and welfare improvements are largest in later decades (Figure 8, panel (b)). However, targeting also boosts welfare from the outset of the study period. This suggests that policies of mandated adaptation, often discussed during Farm Bill negotiations—and exemplified by the targeted policy in this paper—are not merely transfers between generations.

6.5 Political Barriers to Targeting and Alternatives

The *targeted* subsidies result in significant reallocation of government funds across regions. Figure 9 shows the percent change in government spending by U.S. states compared to the status quo. Southern states, where weather risk increases the most (e.g., Arkansas, Texas, Oklahoma), experience substantial reductions in government spending, ranging from 35 to 90%. In contrast, Northern states (e.g., Wisconsin and Michigan) see increases in government funding. Overall, twenty-one of the twenty-seven states included in the analysis experience a decrease in equilibrium funding under the *targeted* policy, leading to a more unequal distribution of subsidies. Specifically, the standard deviation of subsidy per acre increases by 140% compared to the status quo. Although the *targeted* policy achieves welfare gains without additional aggregate government spending, it creates a less equitable distribution of subsidies than the status quo. This could trigger political resistance from U.S. states that see their funding reduced.

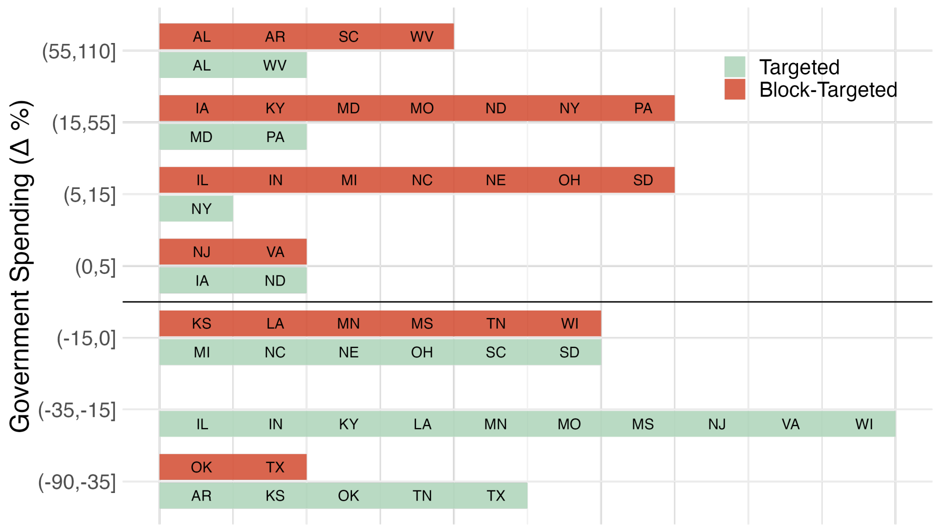
I explore an alternative targeting strategy in which subsidies vary between counties above or below the median weather risk trend within each U.S. state (Appendix Figure F5).[41] I adopt this block-targeting approach to approximate the political economy constraints often associated with large Farm Bill reforms.[42]

While block-targeting improves welfare compared to uniform subsidies, the efficiency gains

[41] This approach creates different subsidy schedules for northern and southern counties within states, reflecting the North-South gradient of weather risk.

[42] A recent example of difficult negotiations involves the allocation of $20 billion from the Inflation Reduction Act for climate-smart agriculture. The Farm Bill expired in 2023 and was extended by one year, but as of October 2024, negotiations continue. See American Progress article.

Figure 9. Crop Insurance Subsidies across Space under Counterfactual Policies



Notes: The figure shows the percent change in government spending by U.S. states between counterfactual targeted policies and the status quo. Government subsidies are the product of crop acres, insurance premiums, take-up, and subsidies, and are average over 2020-2050. Figure A2 describes the sample of considered counties. *Status quo* are described in Table A1. *Targeted* subsidies (square) are 15% (150%) of the *status quo* in counties with increasing (decreasing) climate risk. *Block targeted* subsidies are 45% (150%) of the status quo in counties above (below) the median climate risk trend by state.

are smaller than those achieved under unconstrained targeting (Figure 6). The budget-neutral *block-targeted* policy sets subsidies at 45% (150%) of the status quo in counties above (below) the state-level median climate risk trend. However, this policy achieves only 15% of the efficiency gains of the *targeted* policy. The welfare losses are largely due to the impact of reduced agricultural stability on consumer welfare (Table 7 panel B). Although *block-targeted* subsidies encourage some reallocation of agricultural production to safer areas within states, the potential for this reallocation is much smaller than under unconstrained targeting (Figure 7). By the end of the period, the share of production in risky counties remains five percentage points higher than under the *targeted* policy. As shown in Figure 8, panel (b), welfare under the *block-targeted* policy converges toward that of the status quo, in contrast to the paths obtained after removing subsidies or under *targeted* subsidies.

Nevertheless, with state-level targeting, over half of the twenty-seven U.S. states experience government spending changes of less than 15% in either direction (Figure 9). In comparison, under the *targeted* policy, only nine states see such limited changes. Moreover, under *block-targeted* subsidies, all but eight states receive increased funding, while Oklahoma and Texas lose the most subsidies under both policies. Relative to the status quo, the dispersion of equilibrium subsidies per acre increases by 50% under *block-targeting*, compared to a 140% increase under the unconstrained *targeted* policy. Collectively, these outcomes suggest that block-targeting may be more politically acceptable.

7 Conclusion

This paper develops a dynamic framework to assess the impact of government crop insurance subsidies on agricultural land use and insurance choice in the face of climate change. I show that current crop insurance subsidies—uniform across space—fail to incentivize farmers long-term adaptation to evolving climate risks. While the subsidies improve farmer and consumer surplus by increasing cultivated acreage and putting downward pressure on crop prices, the gains decrease over time as climate change unfolds and weather shocks become more extreme and frequent.

I propose a subsidy targeting rule based on climate risk trends to improve the status quo. This approach approximates a forward-looking design for crop insurance subsidies while maintaining a low-dimensional policy space. These targeted subsidies, aligned with regional climate risk trends, significantly improve welfare. In contrast to uniform subsidies encouraging production in high-risk areas, targeted policies that reduce subsidies in increasingly vulnerable regions and increase them in safer areas lead to more efficient agricultural outcomes. However, such policies also come with challenges, including potential reductions in crop diversity and spatial inequities that could spark political opposition. An alternative that reallocates government subsidies within states reduces concerns about political acceptability at the cost of 85% of the gains in efficiency and agricultural stability afforded by unconstrained targeting.

Overall, the findings highlight the importance of designing crop insurance policies that consider both the immediate need for farmer risk protection and the long-term sustainability of agricultural practices in the face of climate change. However, reforming crop insurance policy comes with an equity-efficiency trade-off.

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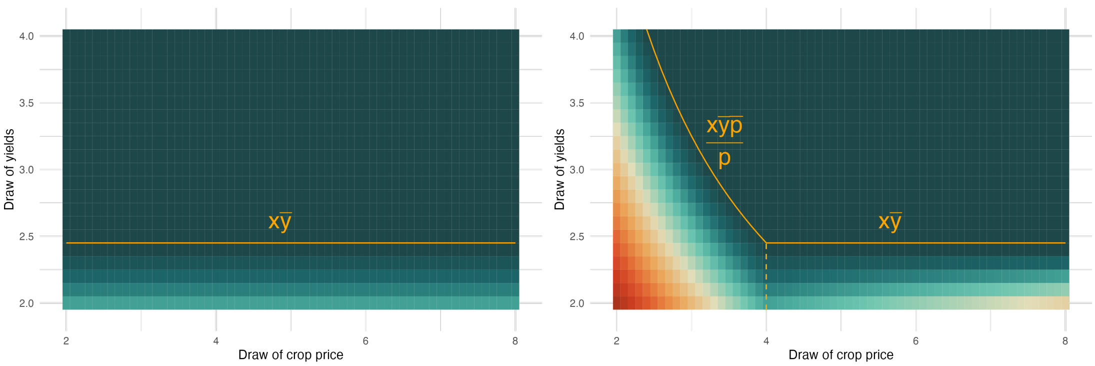
A Background and Data - Supplementary Material

A.1 The U.S. Federal Crop Insurance Program

Figure A1. Illustration of Insurance Indemnities



(a) Yield Protection (b) Revenue Protection

Notes: Simulated indemnity schedules under Yield (Panel a) and Revenue Protection (Panel b). When subscribing to insurance, farmers choose between Yield and Revenue Protection, each subdivided into eight levels of coverage x. Combined with historical yields $\bar{y}$ and projected prices $\bar{p}$ –known at the time of subscription–, these insurance plans result in different indemnity schedules. For exposition, I use $\bar{y} = 3$, $x = 0.8$ and $\bar{p} = 4$. If realizations of yield y and price p fall below the solid black line, farmers are eligible for indemnities. In the case of Revenue Protection, the guaranteed revenue is computed using the maximum between the price at the time of harvest and the projected price: the indemnity schedule differs to the left and the right of the dashed line ($p = \bar{p}$).

Table A1. Crop Insurance Subsidies 2011-2022

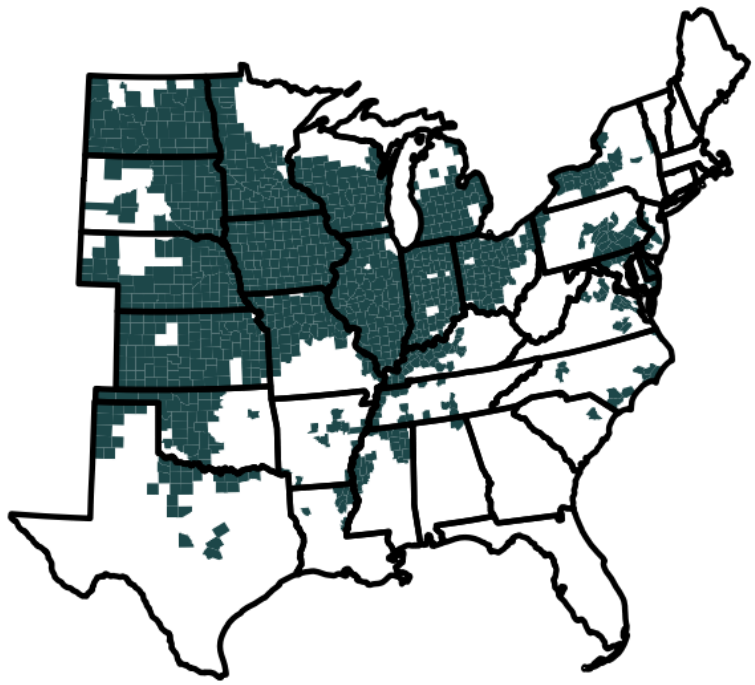
Coverage Level	Subsidy
0.50	0.67
0.55	0.64
0.60	0.64
0.65	0.59
0.70	0.59
0.75	0.55
0.80	0.48
0.85	0.38

Notes: Subsidies are determined in the Farm Bill. Data was obtained from actuarial data from the USDA Risk Management Agency.

A.2 Sample Restrictions

A county is included in the sample if (i) it is to the West of the 100$^{\text{th}}$ meridian, (ii) at least 5% of the area of the county is classified as agricultural land in the CDL for all years in the sample (2008-2020), and (*iii*) if at least 60% of the agricultural area corresponds to one of the selected three crop (corn, wheat, soybeans) for all years in the sample. Figure A2 shows the selected counties.

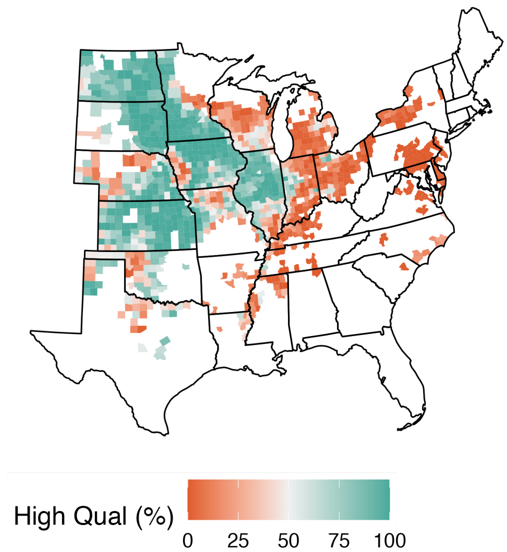
Figure A2. Selected Counties



Notes: A county is selected in the sample if (*i*) it is to the West of the 100$^{\text{th}}$ meridian, (*ii*) at least 5% of the area of the county is classified as agricultural land in the CDL for all years in the sample (2008-2020), and (*iii*) if at least 60% of the agricultural area corresponds to one of the selected 3 crop (corn, wheat, soybeans) for all years in the sample.

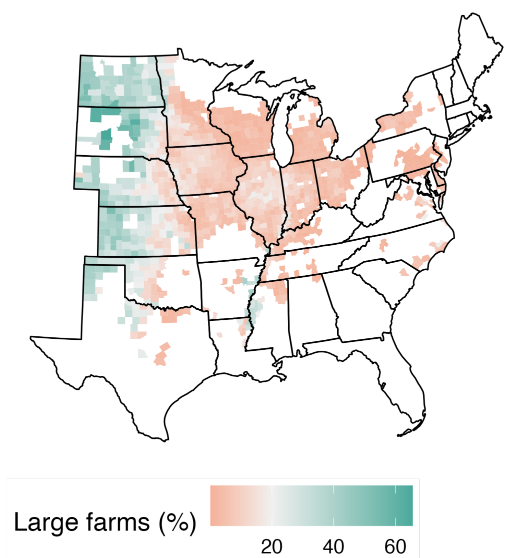
A.3 Spatial Distribution of Land Quality and Farm Size

Figure A3. Share of high-quality land in selected counties



Notes: Data was obtained from Soil Survey Staff (2024). The land quality map is a function of time-invariant characteristics such as soil type, elevation, and ruggedness. The index ranges from 0 to 19. I select the median quality threshold and aggregate this index into two levels (High/Low).

Figure A4. Share of farms with more than 1000 acres



Notes: Data was obtained from the U.S. Census of Agriculture in 2012.

A.4 Motivating Evidence - Crop Insurance and Moral Hazard

When farmers insure their crops, they may be less likely to put effort into their agricultural production. Because insurance take-up is likely to be higher in places with a larger propensity of weather shocks, this may lead to omitted variable bias in the climate-yield relationship. Following Annan and Schlenker (2015), I investigate the importance of moral hazard in my sample and estimate

$$\log \text{Yields}^k_{mt} = \beta^k_1 \text{ExtremeDegreeDay}_{mt} + \beta^k_2 \text{ShareInsured}^k_{mt} + \beta^k_3 \text{ExtremeDegreeDay}_{mt} \times \text{ShareInsured}^k_{mt} + X^k_{mt} + \epsilon^k_{mt} \quad \text{(A1)}$$

where the dependent variable is the log of yields of crop k in county m at time t. The main parameter of interest β^k_3 captures the effect of the interaction between weather shocks—measured by the number of extreme degree days expressed in hundreds—and the share of insured planted acres. X_{mt} contains county-specific quadratic time trends and county- and year-fixed effects. The identifying assumption is that endogenous insured share and yields are jointly independent of the weather shocks.

Results are presented in Table A2 for the sample of counties included in the analysis (Figure A2). Consistent with Annan and Schlenker (2015), I find that corn yields are more sensitive to weather shocks in counties where the share of agricultural acres insured is higher. This suggests that farmers withhold effort in years when yields are negatively affected by weather shocks *and* in counties where insurance take-up is high. However, the interaction effect is one order of magnitude smaller than the direct effect of weather shocks on yields and is smaller than estimated in Annan and Schlenker (2015). Additionally, I do not detect an effect of the interaction of weather shock and insured share on soybeans or wheat yields.

In a second exercise, I relax the strong identifying assumption of equation (A1) in an event-study design leveraging variation in insurance take-up encouraged by the Federal Crop Insurance Reform Act in 1994, borrowing from Havnes and Mogstad (2011).

After the passage of the Act, the insured share increased by 120% on average. I cut the sample (Figure A2) in counties above versus below the median of insurance share *growth* between 1994 and 1996. Figure A5 shows the time series of the average insured share for corn pre- and post-reform for both groups of counties. The graphs move in parallel before the reform, with take-up highest in counties where subsequent take-up growth is lowest. The insured share in treatment counties (above median) kinks heavily after the reform, and the insured share in the two groups converges. This illustrates that the study compares counties that differ distinctly in terms of changes in insurance coverage within a narrow time frame.

Then, I study the impact of weather on crop yields pre- and post-reform in each of the two

Table A2. Effect of insurance share on crop yields

Dependent Variable:		Log Yields	
Crop	Corn	Soybeans	Wheat
Extreme Degree Days	-0.0456***	-0.0616***	-0.0107***
	(0.0021)	(0.0025)	(0.0017)
Insured share	-0.0056	-0.0950***	-0.1209**
	(0.0222)	(0.0251)	(0.0553)
Extreme Degree Days × Insured share	-0.0080***	0.0028	0.0033
	(0.0019)	(0.0021)	(0.0034)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	29,815	28,279	16,431
R^2	0.765	0.765	0.724

Notes: Figure A2 shows the sample of included counties. Extreme degree days measure crop exposure to temperatures above 30°C during the growing season and are expressed in tens. Insured share is computed by dividing the total number of planted acres of crop k in county m in year t by the average number of planted acres of crop k between 1989 and 2019 (Annan and Schlenker, 2015). All regressions control for precipitation levels and the interaction between precipitation and insured share. Standard errors are clustered at the county level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

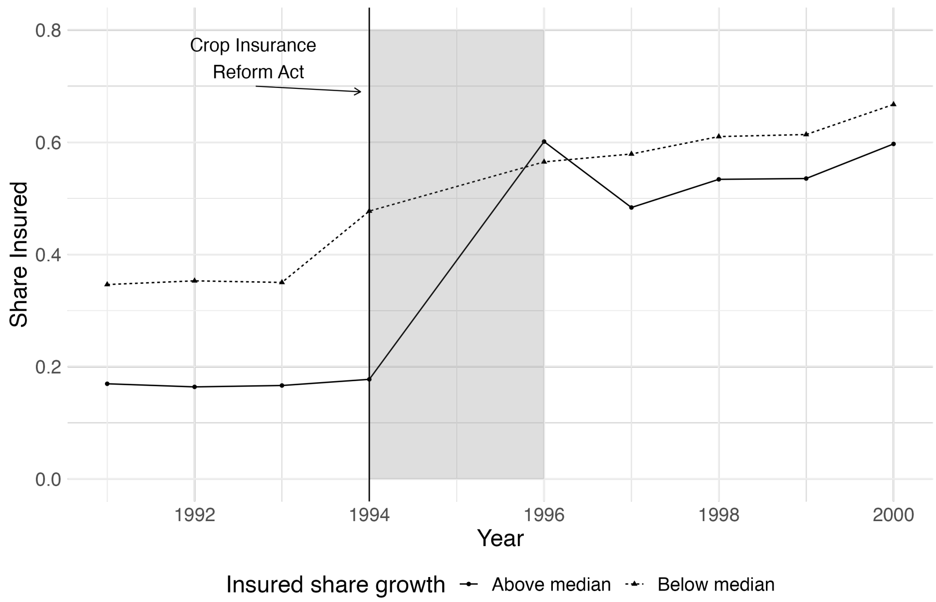
groups of counties, G_q where $q \in \{\text{above, below median}\}$. I estimate

$$\log \text{Yields}^k_{mt} = \lambda^k_1 \text{ExtremeDegreeDay}_{mt} \times \mathbf{1}[m \in G_q] + \\ \lambda^k_2 \text{ExtremeDegreeDay}_{mt} \times \text{Post} \times \mathbf{1}[m \in G_q] + X^k_{mt} + \epsilon^k_{mt} \quad \text{(A2)}$$

where Post is a dummy equal to one if $t >= 1995$. X^k_{mt} contains county- and year-fixed effects and controls for pre- and post-reform insured shares and precipitation levels. These controls assuage some of the concerns that the time trend in yields differs by, e.g., farmer's ability, while there are systematic differences in farmer's ability between treatment and comparison counties. Results are robust to changing the cutoff year for Post to 1995 and dropping insured share controls.

Estimation results for equation (A2) are presented in Table A3. In the pre-period, counties with a higher insurance baseline ("below") have a larger elasticity of corn yield to extreme degree days. This may be explained by selection—farmers in more vulnerable county-year insure their production at a higher rate—or moral hazard—in counties with a higher share of insurance, farmers reduce their effort. Consistent with the moral hazard channel, I find that counties in the "above" group see the largest increase in yield sensitivity to heat post-reform. However, similar to the previous exercise (Table A2), the effect is small, an order of magnitude smaller than estimated in (Annan and Schlenker, 2015). Soybean yields exhibit the opposite patterns, which suggests that moral hazard does not play as large a role. Finally,

Figure A5. Insured share of corn acres by treatment group



Notes: Sampled counties (Figure A2) are grouped into four quartiles of insurance adoption by corn growers following the reform of the Federal Crop Insurance Program in 1994. Counties in the first quartile see their adoption *decrease* post-reform, while counties in the fourth quartile see the largest increase in insurance take-up. Similar graphs can be produced for soybeans and wheat growers but are omitted for conciseness. Extreme degree days are measured in tens over the growing season (May-October).

Table A3. Effect of weather shocks on yields pre- and post-insurance reform Act (1994)

Dependent Variable:		Log Yields	
Crop	Corn	Soybeans	Wheat
Extreme Degree Days × Below	-0.0604***	-0.0759***	-0.0117***
	(0.0045)	(0.0039)	(0.0023)
Extreme Degree Days × Above	-0.0445***	-0.0640***	-0.0092***
	(0.0035)	(0.0043)	(0.0019)
Extreme Degree Days × Below × Post	-0.0018	0.0121***	0.0033*
	(0.0032)	(0.0032)	(0.0017)
Extreme Degree Days × Above × Post	-0.0100***	0.0040	-0.0036**
	(0.0027)	(0.0035)	(0.0015)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	27,453	24,963	14,195
R^2	0.736	0.736	0.696

Notes: Counties in the sample (Figure A2) are grouped in two sets: counties above versus below the median of insurance share *growth* between 1994 and 1996 (see Figure A5). Extreme degree days measure crop exposure to temperatures above 30°C during the growing season, and is expressed in hundreds. Standard errors are clustered at the county level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

although the effect is small, wheat yields are more sensitive to heat in counties that adopt insurance post-reform.

Overall, these results suggest that in counties sampled for this analysis, the RMA, which takes many precautions to audit insured farmers, successfully limits farmers' ability to decrease their efforts following insurance enrollment (see Section 2). As a result, in the rest of the paper, I disregard this the role of this phenomenon in distorting crop insurance and land use decisions.

B Crop Demand - Supplementary Material

I model aggregate demand for crops in the U.S. A representative American consumer solves the following problem:

$$\max U_t = \max C_t^0 + \lambda \ln \left(\left[\sum_k \lambda_k^{\frac{1}{\kappa}} C_t^{k\,\frac{\kappa-1}{\kappa}} \right]^{\frac{\kappa}{\kappa-1}} \right) \tag{B1}$$

$$\text{s.t.} \quad C_t^0 + \sum_k p_t^k C_t^k \leq Y_t \qquad \text{(Budget constraint)}$$

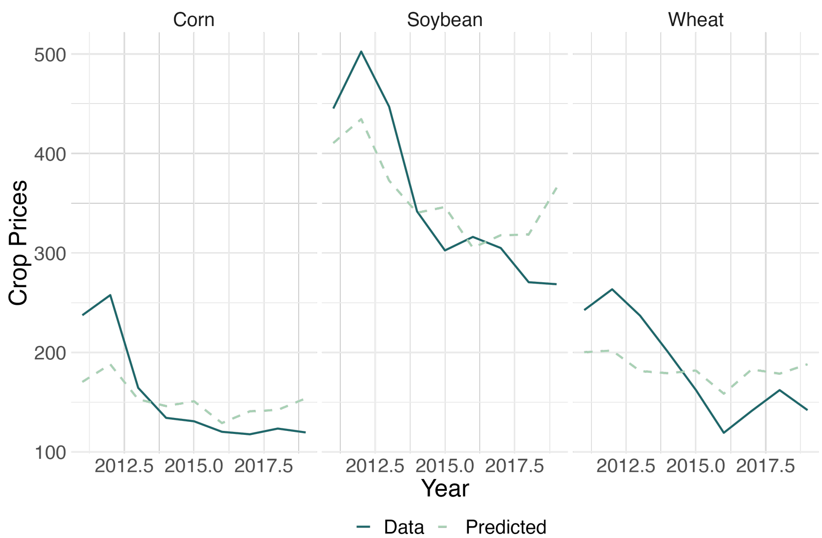
$$C_t^k = Q_t^{k,US}(1 - \underbrace{X^k}_{\substack{\text{U.S. export}\\ \text{share}}}) + \sum_{c \neq U.S.} \underbrace{M^{k,c}}_{\substack{\text{U.S. import}\\ \text{share from } c}} Q_t^{k,c} \qquad \text{(Market clearing)}$$

where C_t^0 and C_t^k are the consumption of the outside good and crop k in year t, respectively. Preferences over various crop has constant elasticity of substitution $\kappa > 0$. The nest between the outside good and the composite agricultural good is quasi-linear, meaning there is no income effect: the total demand for agricultural goods depends on a demand shifter λ. The small expenditure share on agricultural goods in the United States justifies this assumption. Finally, the preference parameters λ_k are crop-specific demand shocks. p^k denotes U.S. crop prices ; $Q_t^{k,US}$ and $Q_t^{k,c}$ denote country-level aggregate crop production in year t. These aggregate quantities are a function of weather shocks in the U.S. and abroad. X^k and M^k are export and import shares of crop k from and to the U.S. I assume that these shares are time-invariant over the study period 2008-2019.[43]

I normalize the price of the outside, non-agricultural good to 1: $p_t^0 = 1$. Then, maximizing

[43] I do not allow trade flows to adjust endogenously to production level, and importantly in counterfactuals, to future climate change. This is a strong assumption that I am working on relaxing.

Figure B1. Realized versus predicted crop prices



Notes: Predicted crop prices (dotted line) against observed crop prices (solid line). The calibrated crop demand model replicates the price spikes due to shocks to agricultural production in 1983 and 2012 and explains 76% of crop price variation.

the consumer utility given in Equation (B1), I get, for each k,

$$Q_t^{k,US} - \text{Net Export}_t \equiv Q_t^{k,US}(1 - X^k) + \sum_{c \neq U.S.} M^{k,c} Q_t^{k,c}$$
$$= \lambda \lambda_k \frac{p_t^{k^{-\kappa}}}{\sum_k \lambda_k p_t^{k^{1-\kappa}}}. \tag{B2}$$

I calibrate the elasticity of substitution between crops to the value estimated by Costinot et al. (2016): $\kappa = 2.82$. Then, I estimate $\lambda = \sum_k p_k(Q_t^{k,US} - \text{Net Export}_t)$ using production and trade flows data on corn, wheat, and soybeans production from FAOSTAT and crop prices from the Chicago Board of Trade.

With the estimate of λ, I calibrate crop-specific demand shocks λ_k by iterating the fixed point defined by Equation (B2). Figure B1 presents the predicted crop prices (dotted line) against observed crop prices (solid line). The model replicates the price spikes due to shocks to agricultural production in 1983 and 2012 and explains 76% of crop price variation.

C Short-run Beliefs and Crop Insurance Choice - Supplementary Material

Farmer's planting season beliefs over end-of-growing season yields and crop prices interacted with the crop insurance program design form the insurance plan characteristics used by farmers to decide whether and how much to insure their production.

Once the two underlying distributionsquality-county-crop-year-level yields and crop prices are estimated using data from the information set of farmers at pre-planting, I compute the expected revenues and risk under various insurance plans. Following the parameterization in Section 4, I need to recover, for each insurance plan and the outside option, the average and variance of the expected revenue distribution, $\mathbb{E}_{jt}(Z_i)$, and $V_{jt}(Z_i)$.

Using the same beliefs, the U.S. government sets crop insurance premiums $P_{jt}(Z_i)$ at the beginning of the planting season. The insurance program is actuarially fair, and premiums equal the expected indemnity payment.

Estimating the distribution of farmers' beliefs on revenues proceeds in three steps. First, I recover county-level yield distributions from realized yield and weather data. I make sure the estimated yield beliefs are well-calibrated: when interacting with insurance design, they must imply that the resulting expected indemnities are correlated with the realized insurance indemnity payments I observe in the data. Second, I recover crop price distributions from out-of-gate and futures price data. Finally, I combine these distributions with insurance plan characteristics to recover moments from the distribution of revenues that enter the crop insurance demand model.

C.1 Weather predictions

At the beginning of the growing season, farmers form beliefs about the weather in the coming growing season (April-October). They use observations of the current planting season (PS) weather and past growing season (GS) weather:

$$\text{ExtremeDegreeDay}_{mt}^{GS} = f(\text{Climate}_{mt}^{PS}, \text{Climate}_{mt-1}^{GS}) + X_m + \nu_{mt} \tag{C1}$$

$$\text{Precipitation}_{mt}^{GS} = g(\text{Climate}_{mt}^{PS}, \text{Climate}_{mt-1}^{GS}) + X_m + \nu_{mt} \tag{C2}$$

where *Climate* is a vector containing information on precipitation levels, the number of extreme degree days and the number of growing degree days (10°C-30°C degree days). I assume f and g are linear functions of weather. X_m is a vector of controls that includes measures of county-level elevation and ruggedness. Table C1 presents the results. These parsimonious models capture a large share of the variation in extreme temperature and precipitation (74% and 52%, respectively).

I obtain the predicted climate variable for the coming growing season from the estimated models, the basis of farmers' beliefs on average yields. Then, I obtain the covariance of the residuals and draw from the county-level joint distribution of errors to recover distributions of county-level predicted weather. The variance of these distributions maps into farmers' beliefs on the variance of the yield distributions. Farmers' expected yield distribution will have a larger variance in counties with more unpredictable weather.

Table C1. Weather models

Dependent Variables:	Extreme degree day^{GS}	Precipitation^{GS}
Model:	(1)	(2)
Lag precipitation^{GS}	0.0117***	0.4166***
	(0.0006)	(0.0035)
Lag extreme degree day^{GS}	0.6205***	-0.3869***
	(0.0035)	(0.0211)
Lag growing degree day^{GS}	0.0191***	-0.0186***
	(0.0004)	(0.0025)
Precipitation^{PS}	-0.0459***	0.4072***
	(0.0012)	(0.0070)
Extreme degree day^{PS}	12.18***	-17.58***
	(0.2759)	(1.670)
Growing degree day^{GS}	0.0338***	0.2903***
	(0.0018)	(0.0108)
Observations	77,550	77,550
R^2	0.738	0.518

Notes: The models are estimated on the sample of counties shown in Figure A2 and with data obtained from PRISM PRISM (2014) between 1985 and 2020. All specifications include elevation and ruggedness controls. Extreme degree days is the number of 30°C degree days. Growing degree days is the number of 10°C to 30°C degree days. Precipitation is measured in mm and includes both snow and rain. Standard errors are robust. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

C.2 Yield models

I estimate yield models linking growing season weather with crop yields. I obtain data on realized average yields in each US county for all crops and years between 2011 and 2019 from the USDA NASS. For each crop k, I compute the land quality-specific average yields:

$$\log \text{Yield}_{mt}^{k} = \beta_{1k}\,(sh_m^H \times \text{ExtremeDegreeDays}_{mt}^{GS}) + \beta_{2k}\,(sh_m^H \times \text{Precipitation}_{mt}^{GS}) + \alpha_m + \epsilon_{mt}^{k} \quad \text{(C3)}$$

where the dependent variable is the log of crop yields in county m at time t.

ExtremeDegreeDays^{GS} and Precipitation$_{mt}^{GS}$ are the number of extreme degree days (30°C degree days) and precipitation levels recorded during the growing season (April-October). sh_m^H is the share of high-quality land in county m.

Table C2 presents the results for the three considered crops. In line with the literature,

Table C2. Yield models

Dependent Variable:		log Yields	
Model:	Corn	Soybeans	Wheat
Extreme degree day^{GS}	-0.0063***	-0.0040***	-0.0018***
	(0.0003)	(0.0002)	(0.0001)
Precipitation^{GS} (100 mm)	0.01***	0.0032*	-0.03***
	(0.0025)	(0.0017	(0.0026)
Extreme degree day^{GS}	-0.0001	-0.0024***	0.0008***
× High-Quality share	(0.0005)	(0.0003)	(0.0003)
Precipitation^{GS} (100mm)	0.0050	0.02***	0.03***
× High-Quality share	(0.0041)	(0.0035)	(0.0055)
County FE	Yes	Yes	Yes
Observations	12,197	10,941	9,245
R^2	0.721	0.770	0.786

Notes: The models are estimated on the sample of counties shown in Figure A2 and with data obtained from PRISM (PRISM, 2014) and USDA NASS between 2011 and 2020. Extreme degree days is the number of 30°C degree days. Precipitation is measured in mm and includes both snow and rain. Standard errors are robust. Standard errors are robust. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

degree days above 30°C are detrimental to yields (Schlenker and Roberts, 2009). Weather is a larger determinant of corn and soybean yields than wheat yields. Corn and soybeans planted on high-quality land are more sensitive to extreme heat, while wheat on high-quality land is more resilient.

In the last step, I allow farmers on different land quality to have different yield intercepts by projecting the county-fixed effects on the county-level share of high-quality land.

C.3 Yield beliefs

I assume that yield uncertainty comes from two sources: (i) weather unpredictability—growing season weather is predicted with an error during the pre-planting season—and (ii) other factors, containing, e.g., pest contamination.

I recover the effect of weather unpredictability on yield uncertainty (i) by combining pre-planting and past weather data with weather forecast models (equations (C1) and (C2)), and yield models (equation (C3)). Specifically, I obtain the distribution of predicted growing season weather by resampling the errors of the weather model. I combine the beliefs on weather with yield models to obtain each quality farmer's beliefs on yields. I allow the weather prediction errors to be correlated across the various weather variables. In equation (C3), I set $sh^H = 1$ to predict farmers' yields on high-quality land and $sh^H = 0$ for farmers on low-quality land.

Other stochastic factors (ii) may influence yields and lead to underestimating beliefs spread. However, modeling all such factors is challenging. I remedy this issue by calibrating a reduced-form uncertainty parameter to match the expected insurance indemnity payments implied by the yield beliefs with the observed realized indemnity payments. The estimation of this uncertainty parameter proceeds in two steps. First, I recover the total yield uncertainty σ—inclusive of weather unpredictability—in each county, year, crop, and coverage level. However, the estimates are not land-quality specific. In RMA data, I observe the number of *yield protection* policies sold with coverage level $x =$ in county m in year t , $n_{mt}(x)$. I observe the number of these insured farmers who receive indemnities $n_{mt}^{ind}(x)$. In other words, I observe for all coverage level x the number of acres whose yields fell below the threshold: coverage level x times guaranteed yields $\overline{\text{Yield}}_{mt}$. I omit subscripts m and t for readability. I assume beliefs on yields are normal. Then, $n^{ind}(x)$ follows a Bernoulli distribution with probability $\phi^{\sigma}(x\overline{\text{Yield}})$ where ϕ^{σ} is the CDF of a normal distribution of known averagethe county level yields, and unknown variance σ. σ is the crop-, county- and year-specific uncertainty parameter I want to estimate. The likelihood of the data is given by:

$$f(n^{ind}|\sigma) = \prod_{x=0.5}^{0.85} \phi^{\sigma}(x\overline{\text{Yield}})^{n^{ind}}(1-\phi^{\sigma}(x\overline{\text{Yield}}))^{(n-n^{ind})}$$

The likelihood expression relies on the assumption that farmers do not adjust their production practices depending on their coverage level: the draws from the Bernoulli distributions are independent across x. As mentioned in Section 2, I assume that insurance choice does not influence yields. Using an inverse gamma prior for distribution of the standard deviation $f(\sigma)$, I maximize the posterior distribution $f(n^{ind}|\sigma)f(\sigma)$.

In the second step, I remove the influence of weather unpredictability from the estimates of σ. I assume that this additional uncertainty is uncorrelated with weather unpredictability.

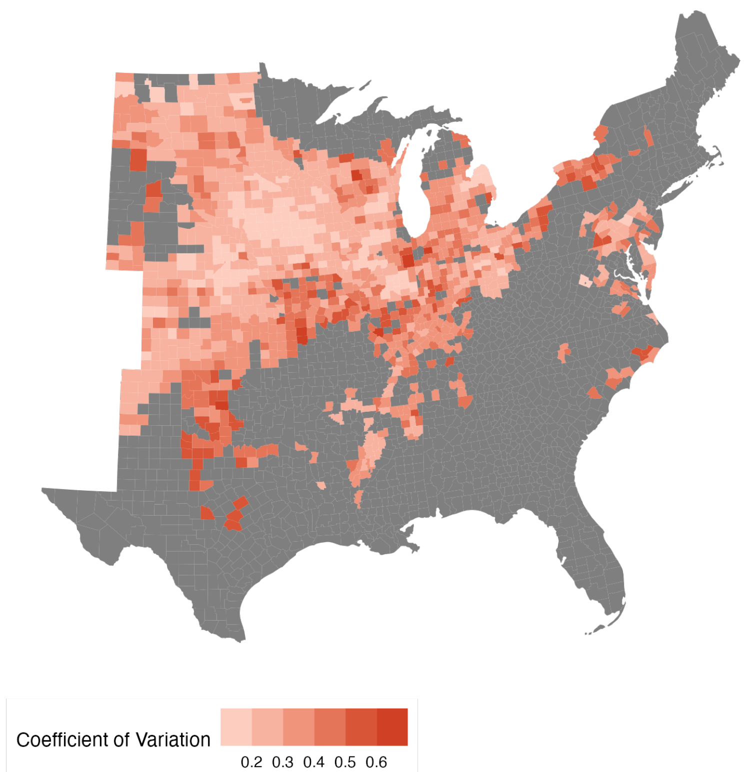
The fitted models provide estimates of farmers' beliefs in *all* selected U.S. counties, not limited to counties that have historically cultivated the considered crop. Obtaining counterfactual yield beliefs is crucial to estimating the dynamic crop choice model: estimation relies on comparing the profits farmers *expect* to earn.[44] These beliefs vary at the land quality-crop-year level.

Given farmers' beliefs on yields, I recover the predicted coefficient of variation for corn yields—ratio of standard deviation to mean corn yields (Figure C1). They broadly agree with the USDA estimation of risks (Harwood et al., 1999): corn yields are less variable in the Midwest than in the South of the US. I further validate the estimated distribution by comparing the implied average indemnity per acre with realized indemnity claims obtained from the Risk Management Agency database (Table C3). The correlation of 0.7 suggests that the estimation method recovers indemnity levels of the same order of magnitude as those reported

[44] In counties with missing fixed effects, I impute them with the state average.

by the Risk Management Agency. The coefficient of determination of 0.23 suggests that the above estimation method captures only a subset of the yield variability. This discrepancy comes in part from the fact that while the model of yields is suitable to capture trends and average effects, it will underestimate the tail events that are responsible for the large indemnities reported by the RMA. Given the paper's focus on climate change and trends in the U.S. agricultural system, which I study in counterfactuals, adopting this definition of yield variability is justified.

Figure C1. Pre-planting Beliefs on Corn Yields Risk in 2015



Notes: The coefficient of variation is the ratio of standard deviation and the mean of the yield distribution. It is a unitless measure of growing season agricultural risk that farmers have available at time of planting. Farmers use this information to choose which crop to grow and which insurance to subscribe to if any. Importantly, I verify that the measure of risk presented here is comparable to USDA measurements (Harwood et al., 1999).

Table C3. Comparison between expected indemnities with realized indemnity

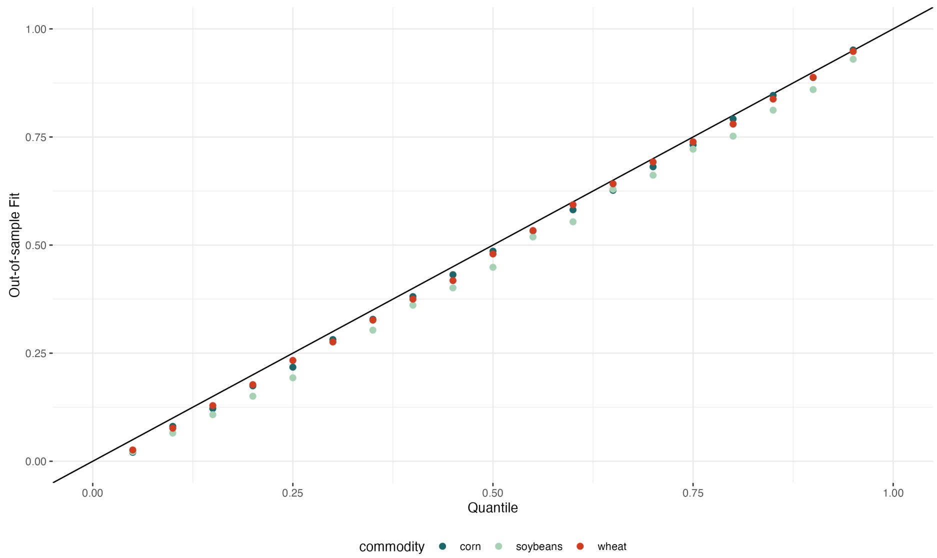
Dependent Variable:	Indemnity per acre - Data
Model:	(1)
Constant	5.102***
	(0.1294)
Indemnity per acre - Estimated	0.7225***
	(0.0025)
Observations	262,465
R^2	0.238

Notes: With the estimated yield distribution, I compute the implied expected indemnity per acre in every county for each crop, year and land quality. I then recover the average expected indemnity by computing the land-quality weighted county average of expected indemnities. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

C.4 Beliefs on crop prices

Farmers form beliefs on crop prices based on crop futures published during the pre-planting season. To estimate the model, I assume that farmers' beliefs are stationary and can be derived from prices of crop futures. Moreover, I assume crop prices are homogenous across space, and beliefs are undifferentiated between high- and low-quality farmers. I recover farmers' beliefs using quantile random forests (Athey, Tibshirani, and Wager, 2019). Figure C2 shows the out-of-sample fit of each quantile of the price distribution. The distributions of corn, soybeans, and wheat prices are well-calibrated. For example, 10% of the observations of corn prices over 2007-2019 fall below the estimated 10th percentile of the corn price distribution. I assume the beliefs on crop price distribution are the same between high- and low-quality farmers.

Figure C2. Crop Price Beliefs - Out-of-sample fit



Notes: Calibration of the crop-price distribution prediction using quantile random forest. The regressors are future prices available to farmers pre-planting. The distributions of corn, soybeans, and wheat prices are overall well-calibrated: around 50% of the observations of state-level crop-specific prices over 2007-2019 fall below the estimated 50th percentile for that crop-year-state combination.

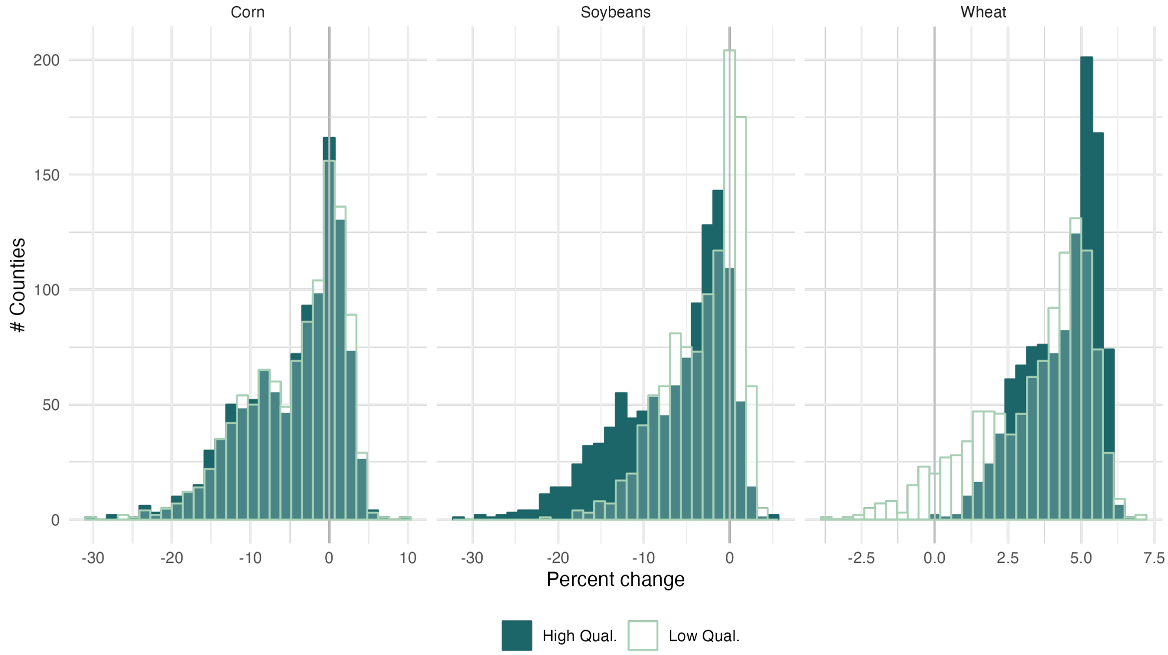
C.5 Beliefs on Revenues

Figure C3 shows the change in average and variance of expected revenues between 2020 and 2050, holding worldwide corn, soybeans, and wheat acreage constant. I let county-level yield adjust as in Figure E2, and crop prices adjust following domestic and worldwide agricultural production shocks.[45] Expected revenues for corn and soybeans decrease on average while they increase for wheat. The combination of two factors explains that discrepancy. First, wheat yields are less sensitive to weather shocks than corn and soybeans: wheat yields do not decrease as much as corn and soybeans yields following climate change. Second, corn and soybean prices follow an upward trend because of the decreases in yields, and because the three crops are fairly substitutable in their use, wheat prices follow a similar upward trend. The changes are more pronounced for farmers on high-quality land.

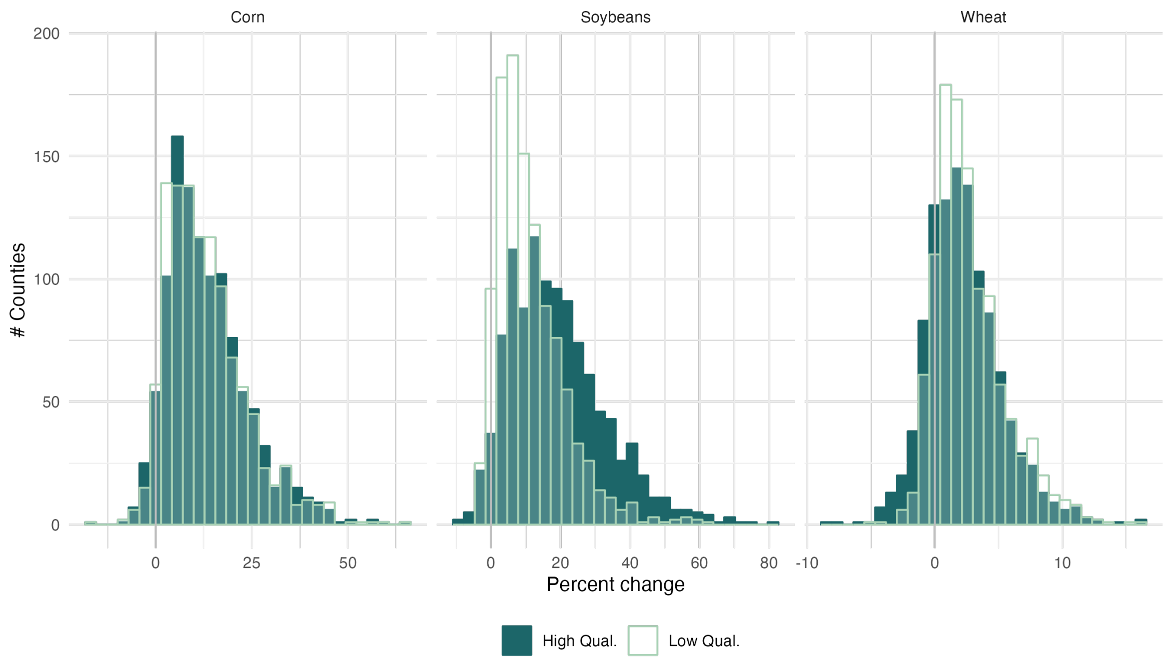
Revenue variance increases for all three crops. As weather becomes more unpredictable, yield and price variability increase, increasing revenue variance. These changes are comparable across land quality.

[45] See Appendix B for a detailed description of the crop demand model linking worldwide weather shocks to crop prices.

Figure C3. Revenue change 2020-2050



(a) Average

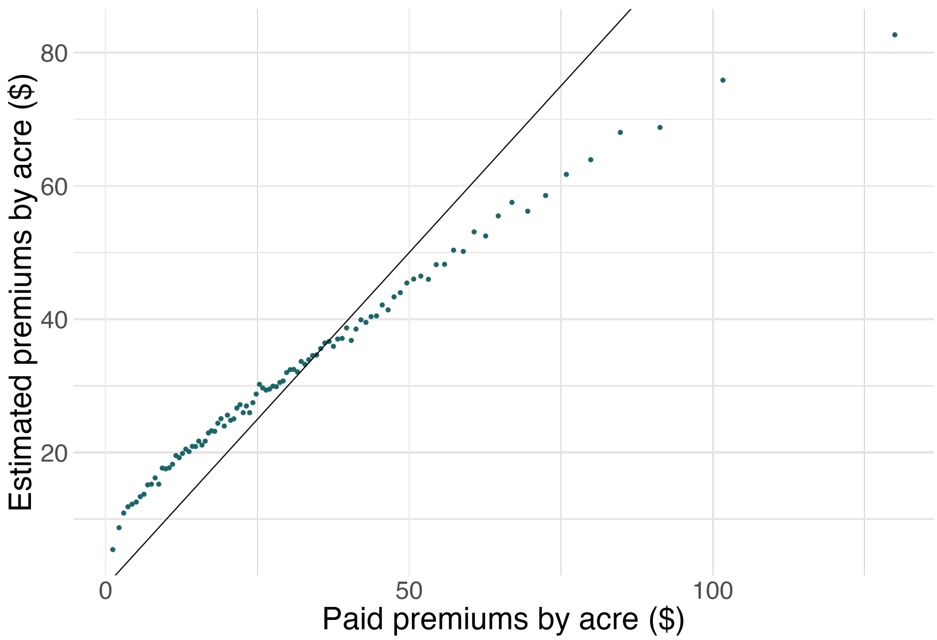


(b) Coefficient of Variation

Notes: This figure plots the distribution of the change of average revenues and change in revenue risk between 2020 and 2050, holding worldwide corn, soybeans, and wheat acreage constant. I let county-level yield adjust as in Figure E2, and crop prices adjust following domestic and worldwide agricultural production shocks. Section B describes the crop demand model linking worldwide weather shocks and crop prices.

C.6 Premiums

Figure C4. Observed versus estimated premiums



C.7 Estimation Results

Table C4. Crop Insurance Demand Estimates - Robustness

Quality:	Any	High Qual.	Low Qual.	High Qual.	Low Qual.
Sample:	All	All		Share Large Farms < 10%	
Expected Revenues	0.033	0.030	0.12	0.019	0.1195
	(0.0007)	(2e-06)	(4e-06)	(5.0e-06)	(6.0e-06)
Coeff. of Var.	-0.061	-0.014	-0.04	-0.047	-0.0079
	(0.0015)	(5e-06)	(7e-06)	(1.2e-05)	(1.1e-05)
Subs. Premiums	-0.063	-0.047	-0.17	-0.026	-0.1552
	(0.0012)	(4e-06)	(5e-06)	(8.0e-06)	(7.0e-06)
Year FE	Yes	Yes	Yes	Yes	Yes
State x Crop FE	Yes	Yes	Yes	Yes	Yes
Observations	21,788	19,457	19,457	11,788	11,788
Estimator	Logit	GMM		GMM	

Notes: The estimation sample in columns 1-3 includes all counties in Figure A2 between 2008 and 2019. In columns 4 and 5, I further restrict the sample to counties in which less than 10% of farms are 1,000 acres and above. The number of observations is the number of crop × counties × year. Standard errors are clustered at the state level in column 1 (logit estimator) and robust in columns 2-5 (GMM).

Table C5. Demand elasticities to subsidies and implication for farmer surplus

		Removing premium subsidies (2011-2019)				Effect of climate change (2020-2050)
		Share Insured		Producer welfare ($ per acre)		Producer welfare ($ per acre)
Commodity	Quality	Baseline	Change (%)	Baseline	Change (%)	Change (%)
Corn	High Qual.	0.7	-28.6	435.3	-3.2	-3.44
Corn	Low Qual.	0.8	-70.0	428.4	-2.9	-3.65
Soybeans	High Qual.	0.8	-10.9	373.6	-1.8	-5.19
Soybeans	Low Qual.	0.8	-32.5	253.7	-2.9	-2.68
Wheat	High Qual.	0.5	-16.9	299.0	-1.9	3.79
Wheat	Low Qual.	0.7	-47.5	157.0	-5.4	3.28

Notes: The table presents changes in insurance take-up and producer surplus implied by the removal of crop insurance subsidies or by climate change. In all cases, crop acreage is maintained to their average level during 2011-2019. In the climate change scenario, status quo subsidies are maintained and climate projections are obtained from six global circulation models (Appendix E.1). The *Baseline* columns report the unweighted average insurance take-up and producer surplus in dollars per acre implied by the crop insurance demand estimates in Table 5, columns 3 and 4. The sample includes all counties in Figure A2.

D Dynamic crop choice - Supplementary material

D.1 Derivations

Value function and conditional choice probabilities

Recall that the vector of state variables $s_t(Z_i) = s_{it}$ contains information on local and global climate, aggregate (country-level) land use, crop insurance subsidies, farmers past land use k, and crop-specific idiosyncratic shock ϵ_{iat}. Let $V_\theta(s_{it})$ be the value function of the dynamic programming problem, i.e., the expected discounted stream of profits under optimal behavior for land quality θ. By Bellmans principle of optimality,

$$V_\theta(s_{it}) = \max_{a \in \mathcal{K}} \{\Pi_\theta(a, s_{it}) + \delta \mathbb{E}[V_\theta(s_{it+1}) | s_{it}, s_{it-1}, ...]\} \tag{D1}$$

I define the ex-ante value function:

$$\bar{V}_\theta(s_{it}) = \int V(s_\theta(s_{it}) dF^\epsilon(\epsilon) \tag{D2}$$

The conditional value function is given by

$$v_\theta(s_{it}) = \pi_\theta(a, s_{it}) + \delta \mathbb{E}[\bar{V}_\theta(s_{it+1}) | s_{it}] \tag{D3}$$

where $\pi_\theta(a, s_{it}) = \bar{\pi}_\theta(a, s_{it}) + \eta_\theta(a, s_{it})$. In what follows, I use subscripts t, k, and a to indicate dependence time, past land use and action (chosen land use). All objects depend on Z_i (farmer's county and land quality). The agents optimal policy is given by the probability of choosing a given the state (CCP):

$$\mathbb{P}_{kat} = \int \mathbf{1}\{v_{kat} + \epsilon_{at} \geq v_{ka't} + \epsilon_{a'mt}, \forall a' \in \mathcal{K}\} dF^{\epsilon}(\epsilon) \tag{D4}$$

Finally, define $\psi_{kat} := \psi(\mathbb{P}_{kat})$ derived from F^{ϵ} such that:

$$\bar{V}_{kt} = v_{kat} + \psi_{kat}, \forall k \in \mathcal{K} \tag{D5}$$

Equation (D5) states that the ex-ante value function $\bar{V}$ equals the value obtained by choosing a today and optimally thereafter (v_{kat}) plus a correction term (ψ_{kat}) because choosing action a today is not necessarily optimal.

Deriving the structural equation of regression To identify the model with ECCP equations, I assume that the controlled state k satisfies the finite dependence property. In particular, I assume that switching land use is a renewal action, a special case of one-period finite dependence (Arcidiacono and Miller, 2011). Action K is a renewal action if, taking action K in period t leads to the same distribution of states at the beginning of period $t+1$, regardless of which state the agent was in during period $t-1$. Combining Equations (D3) and (D5) I get:

$$\psi_{kat} = \bar{V}_{kt} - \pi_{kat} - \delta\mathbb{E}[\bar{V}_{at+1}|a, k, t] \tag{D6}$$

$$:= \bar{V}_{kt} - \pi_{kat} - \delta(\bar{V}_{at+1} + \underbrace{e^{V}_{katt+1}}_{\substack{\text{Prediction error} \\ \text{conditioned on } \omega, k \text{ and } a}}) \tag{D7}$$

Equation (D7) uses the realized values of agents future expected payoffs $\bar{V}_{at+1}$ as a noisy measure of agents expected future payoffs. This allows the relaxation of typical assumptions about how agents form beliefs about the evolution of the market-level state variables.

I then eliminate $\bar{V}_{kt}$ from Equation (D7) by taking the difference between any two choices a and a' starting from the same land use k:

$$\psi_{ka't} - \psi_{kat} = \pi_{kat} - \pi_{ka't} - \delta(e^{V}_{ka'tt+1} - e^{V}_{katt+1}) - \delta(\bar{V}_{a't+1} - \bar{V}_{at+1}) \tag{D8}$$

Finally, I decompose the last term of equation, $V_{a't+1} - V_{at+1}$, using finite dependence and Equation (D6) recursively (Arcidiacono and Miller, 2011): for all $j \in \mathcal{K}$,

$$\bar{V}_{a't+1} - \bar{V}_{at+1} = \psi_{a'jt+1} - \psi_{ajt+1} + \pi_{a'jt+1} - \pi_{ajt+1} - \\ \delta\underbrace{\left(\mathbb{E}[\bar{V}_{jt+2}|j, a', t+1] - \mathbb{E}[\bar{V}_{jt+2}|j, a, t+1]\right)}_{=0 \text{ by finite dependence}} \tag{D9}$$

Plugging (D9) in (D8):

$$\psi_{ka't} - \psi_{kat} - \delta(\psi_{ajt+1} - \psi_{a'jt+1}) = \pi_{kat} - \pi_{ka't} - \delta(\pi_{a'jt+1} - \pi_{ajt+1}) - \delta(e^V_{ka'tt+1} - e^V_{katt+1}) \quad \text{(D10)}$$

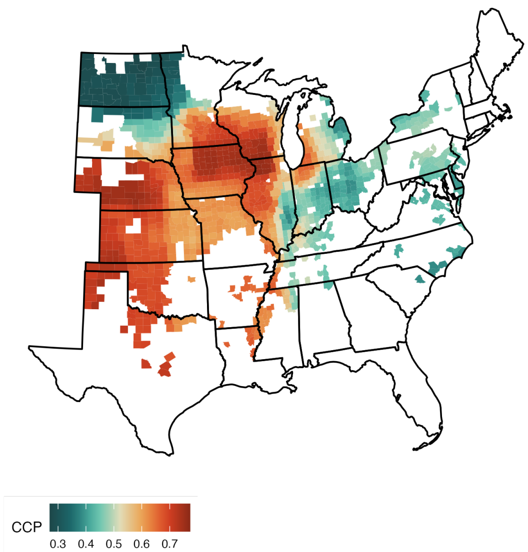
Because ϵ follows a Gumbel distribution, $\psi_{kat} = \gamma - \ln \mathbb{P}_{kat}$ where γ is the Euler constant. I obtain a structural regression equation using this distributional assumption as well as the parameterization of the profits (see Section 4). For $a' = k$ and $j = a$, I get for all $a, k \in \mathcal{K}; a \neq k$:

$$\boxed{\underbrace{\ln \frac{\mathbb{P}_{kat}}{\mathbb{P}_{kkt}} - \delta \ln \frac{\mathbb{P}_{kat+1}}{\mathbb{P}_{aat+1}}}_{Y_{kat}} = (1-\delta)\phi_{ka} + \gamma_a - \gamma_k + \gamma^u(\underbrace{u^*_{at} - u^*_{kt}}_{X^u_{kat}}) + \gamma^c(\underbrace{c_{at} - c_{kt}}_{X^c_{kat}}) + \zeta_{kat}} \quad \text{(D11)}$$

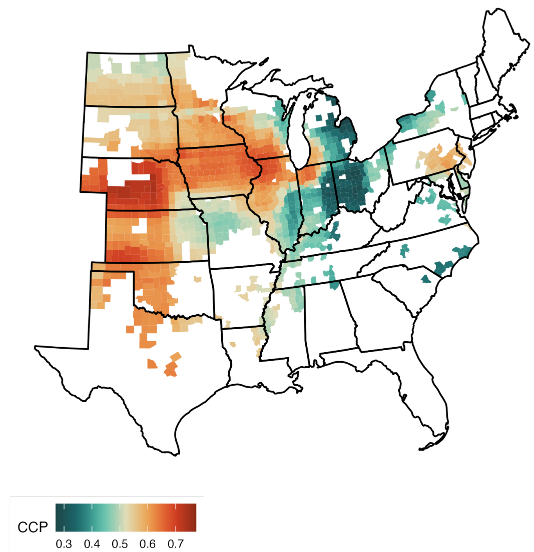
where $\zeta_{kat} = \eta_{at} - \eta_{kt} + \delta(e^V_{katt+1} - e^V_{kktt+1})$.

D.2 Estimation results

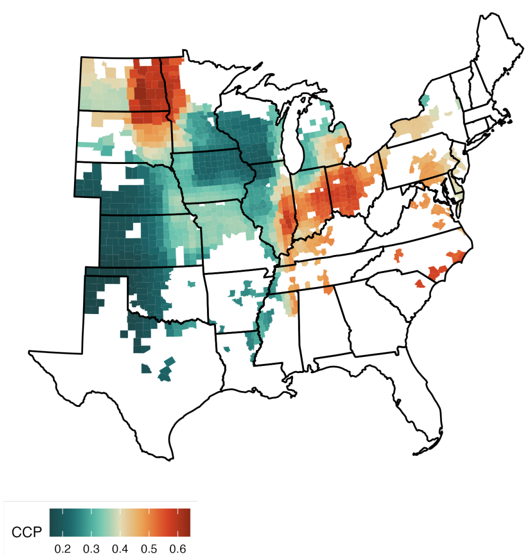
Figure D1. County-level conditional choice probabilities



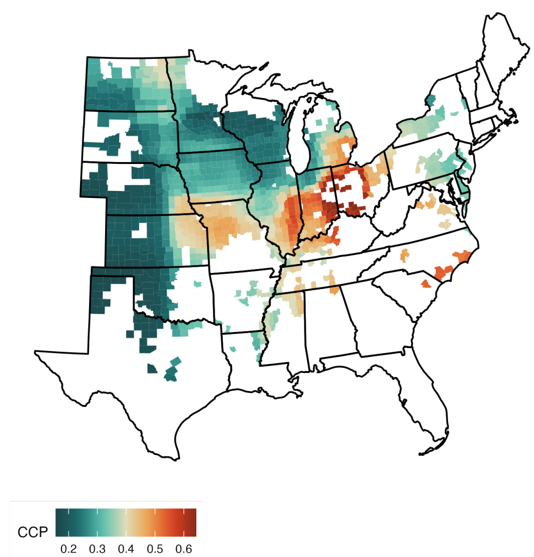
(a) Corn on Corn - High land quality



(b) Soybeans on Corn - Low land quality



(c) Corn on Soybeans - High land quality



(d) Soybeans on Corn - Low land quality

*Notes:*The map shows the spatial distribution of conditional choice probability in 2015 for a selection of land use transitions.

Figure D2. Matrix of transition probabilities

Notes: The transition probabilities are averaged across space and time (2008-2020). A back-of-the-envelope calculation suggests that around 16% of cropland is continuously planted with corn over three years. These numbers align with survey results collected by the USDA Agricultural Resource Management Survey (Wallander, 2020).

D.3 Model Fit

I compute the dynamic model fit by comparing the conditional choice probability predicted by the estimated model with data. I obtain data on conditional choice probability using the CropLand Data Layer (see Section 5.3 for details). Using the counterfactual algorithm described in Section 6.1, I obtain implied equilibrium conditional choice probability in 2021 under status quo subsidies and climate change. That is, I assume farmers expect climate change to happen as is projected by climate models (see Appendix E) under a moderate emission scenario and U.S. government policies to remain as in the estimation period between 2020 and 2050. Table D1 shows that for both low- and high-quality land, the estimated model predicts conditional choice probability highly correlated with the ground truth (0.7 on average, with a R^2 of 0.6).

Table D1. Model fit

Dependent variable:	Conditional Choice Probability (Observed)				
Action:	Any	Corn	Soybeans	Wheat	Other
Panel A: θ =High					
Intercept	0.032***	0.121***	0.028***	0.015***	−0.107***
	(0.002)	(0.004)	(0.003)	(0.002)	(0.003)
CCP (Model)	0.873***	0.679***	1.218***	0.774***	1.034***
	(0.004)	(0.010)	(0.015)	(0.009)	(0.006)
Observations	17,584	4,396	4,396	4,396	4,396
R^2	0.751	0.692	0.500	0.576	0.905
Panel B: θ =Low					
Intercept	0.030***	0.074***	0.064***	0.021***	−0.089***
	(0.001)	(0.003)	(0.004)	(0.002)	(0.003)
CCP (Model)	0.765***	1.382***	1.959***	0.871***	0.629***
	(0.005)	(0.012)	(0.018)	(0.012)	(0.006)
Observations	17,584	4,396	4,396	4,396	4,396
R^2	0.702	0.492	0.592	0.614	0.876

Notes: Ground-truth conditional choice probability for 2021 are estimated using the CropLand Data Layer (Section 5). Panel A (B) shows the fit results for the CCP on high (low)-quality land. I compute the model-implied CCP using the algorithm described in Section 6.1. The estimation sample includes all counties in Figure A2 between 2011 and 2019. Standard errors are clustered at the state level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

D.4 Land use elasticity to subsidy increase

I compute the long-run elasticities of land use with respect to crop insurance subsidies by comparing farmers' equilibrium land use choices in 2021. Using the counterfactual algorithm described in Section 6.1, I compute the equilibrium acres for each crop k and each farmer land quality Z under status quo subsidies ($acres_k(Z)$) and status quo subsidies increased by 10% ($\widetilde{acres}_k(Z)$). As a reminder, farmer type concatenates their county and land quality. I assume that farmers expect the climate to remain as in 2016-2021 for the period 2020-2050.

The land use elasticity for each crop k is:

$$\frac{1}{\sum_Z acres_k(Z)} \sum_Z [\widetilde{acres}_k(Z) - acres_k(Z)] \frac{\sigma_j(Z) * Subs_j}{\widetilde{\sigma}_j(Z) * \widetilde{Subs}_j(Z) - \sigma_j(Z) * Subs_j(Z)} \tag{D12}$$

where $Subs_j(Z)$ and $\widetilde{Subs}_j(Z)$ are the subsidies and counterfactual subsidies for insurance product j for farmer type Z. $\sigma_j(Z)$ and $\widetilde{\sigma}_j(Z)$ are equilibrium insurance take-up for product j and farmer type Z.

A permanent 10% increase in subsidies leads to an increase in corn acreage by 0.2% for corn, 0.06% for soybeans and 0.03% for wheat. These elasticities are comparable in magnitude to those implied by the reduced form exercise in Section 3 or estimated by Yu et al. (2018) using variation in subsidy level over time.

E Simulating the future - Supplementary Material

In this section, I describe my treatment of the data from climate models (GCMs) under a medium forcing scenario (RCP4.5). RCP 4.5 is a stabilization scenario: the radiative forcing level stabilizes at 4.5 W/m2 before 2100 by employing various technologies and strategies for reducing greenhouse gas emissions.

E.1 County-level Yield Distributions

Future weather. I get gridded daily weather data from six climate models (GCMs).[46] Data are available for the period 2016-2050. I aggregate the data at the county level and get six weather paths, one for each GCM.

Yield distribution projections. Combining the six paths of pre-planting weather with yield models, I obtain six sets of average and standard deviation of yields for each county in the US and each year between 2016 and 2050. I sample from these six distributions and compute an overall average and standard deviation of yield for each county in the US and each year between 2016 and 2050. The uncertainty in yields comes from across model variation and from uncertainty in the end-of-growing-season yield prediction at planting time.

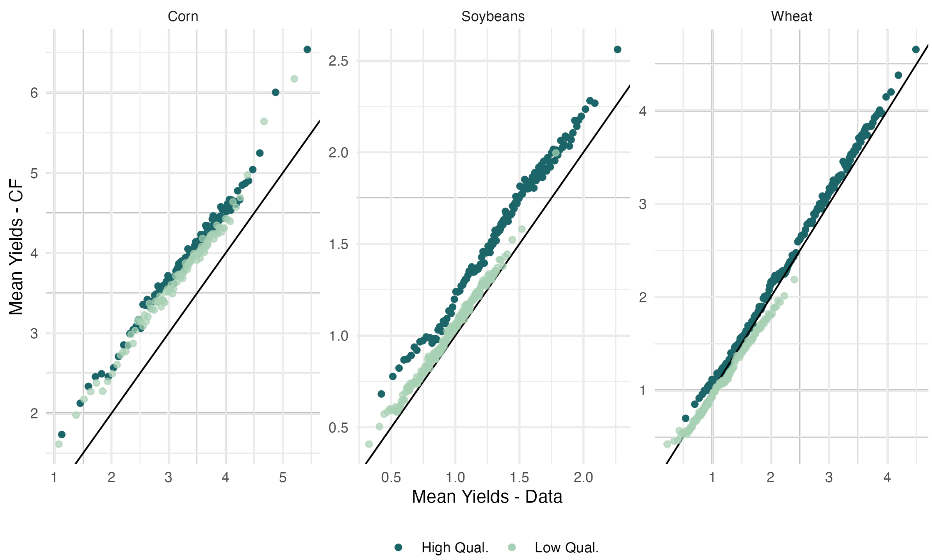
Fit. Figure E1 displays the fit of the procedure against the average and standard deviation estimated in Section 5.1 and derived from climate observations from PRISM. Overall, the yield distributions obtained using modeled and observed weather paths agree on 2016-2019 (R-squared of 0.94 for average yields and 0.85 for standard deviation).

Spatial distribution of yields under climate change. Using weather projections from climate models and yield models, I compute the path of yield distribution between 2020 and 2050. All crops included in the analysis see their yields drop in the future due to the increased frequency and severity of extreme heat and lack of precipitation (Figure E2(a)). The effects of climate change are not homogenous across crops, land quality, and space. Counties in

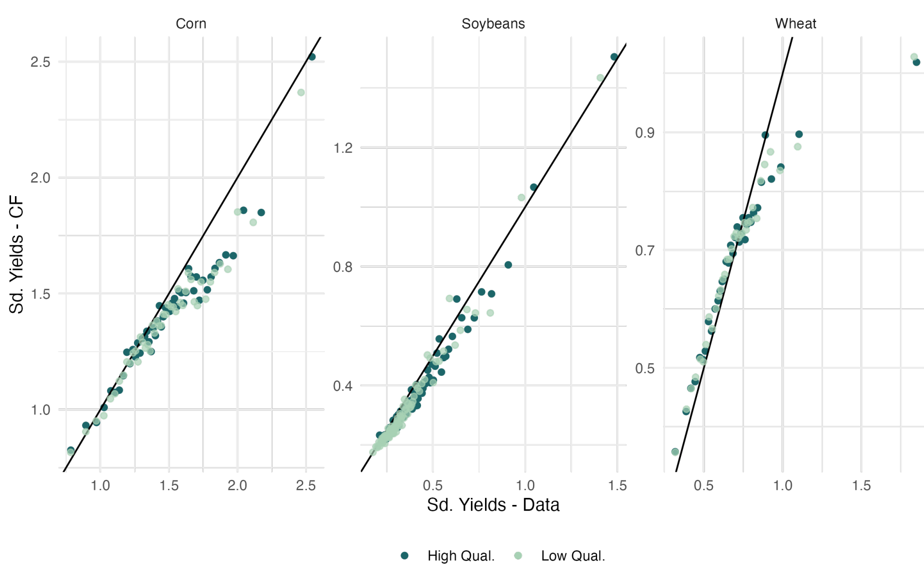
[46] I use ACCESS1-0, BNU-ESM, CCSM4, CESM1-BGC, MIROC_ESM, NorESM1-M.

the South see their yields decrease more sharply than in the North (Figure E3), and corn and soybean yields decrease more than wheat yields. Yields of crops grown on high-quality land tend to decrease more than yields grown on low-quality plots. Growing season weather becomes more variable and unpredictable, and the standard deviation of pre-planting yield distribution beliefs increases for the three crops (Figure E2(b)).

Figure E1. Fit of county-level yield distribution - Binsreg



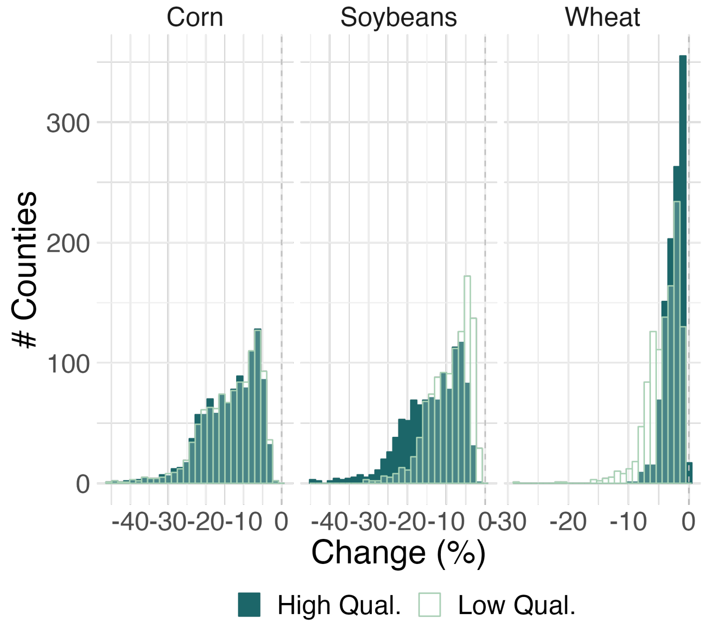
(a) County-level average yields



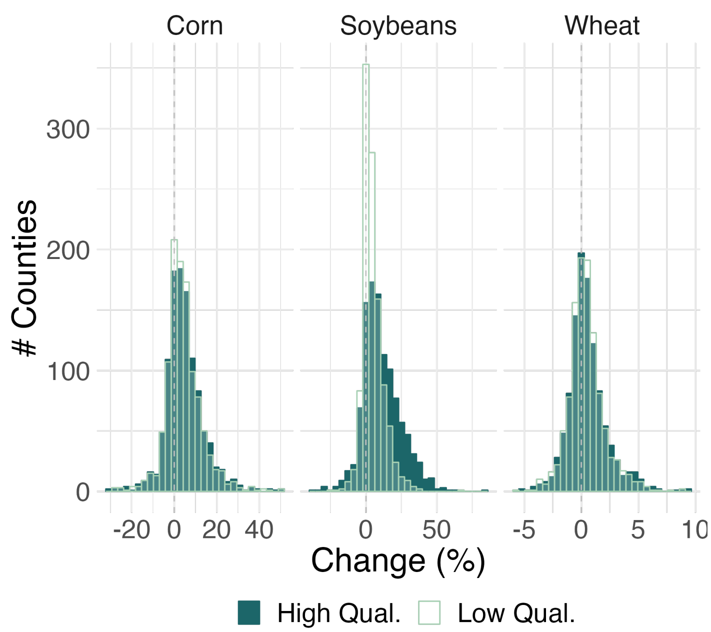
(b) County-level standard deviation of yields

Notes: Correlation between average and standard deviation of yields obtained using realized weather (x-axis) and modeled weather (y-axis) over the period 2016-2019. The coefficients of determination (R^2) are 0.94 for average yields and 0.85 for standard deviation.

Figure E2. Yield distribution change 2020-2050



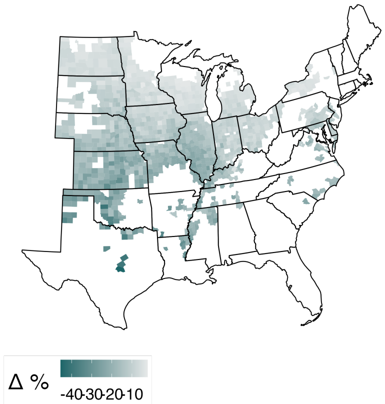
(a) Average



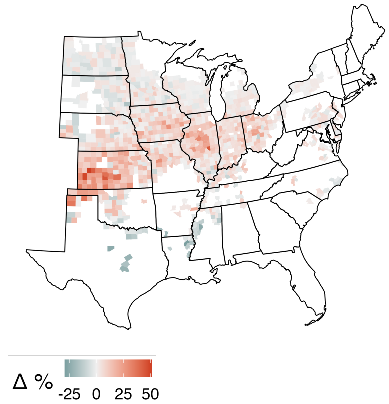
(b) Standard deviation

Notes: The figure shows the distribution of county-level change in the average and standard deviation of crop yields for both high- and low-quality land between 2020 and 2050. Climate evolves as projected by six general circulation models under a moderate emission scenario (RCP 4.5). The sample is restricted to counties shown in Figure A2.

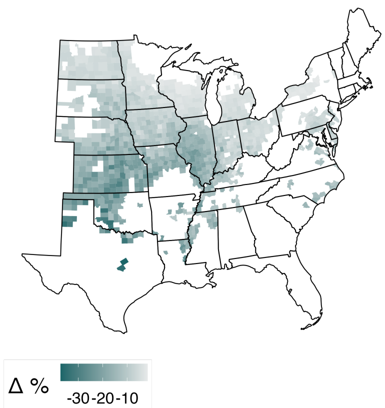
Figure E3. Spatial Yield Distribution Change 2020-2050



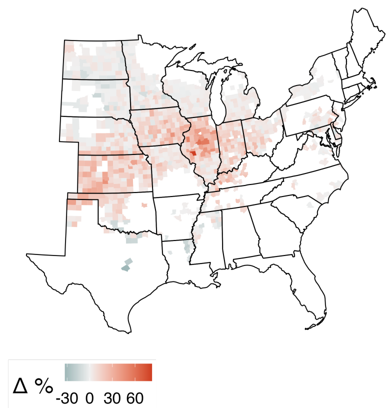
(a) Corn - Average



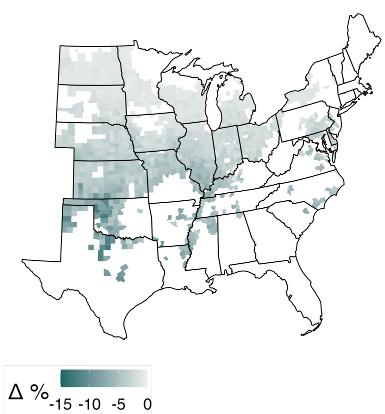
(b) Corn - Standard Deviation



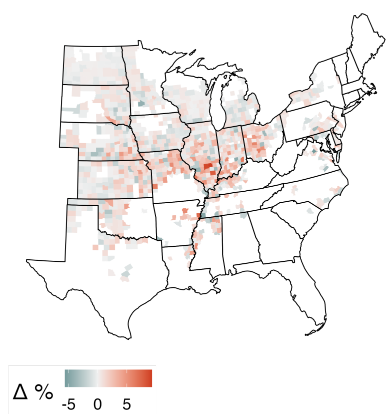
(c) Soybeans - Average



(d) Soybeans - Standard Deviation



(e) Wheat - Average



(f) Wheat - Standard Deviation

Notes: The maps show the spatial distribution of county-level change in the average and standard deviation of crop yields for both high- and low-quality land between 2020 and 2050. Climate evolves as projected by six general circulation models under a moderate emission scenario (RCP 4.5).

E.2 Country-level Yield Distributions

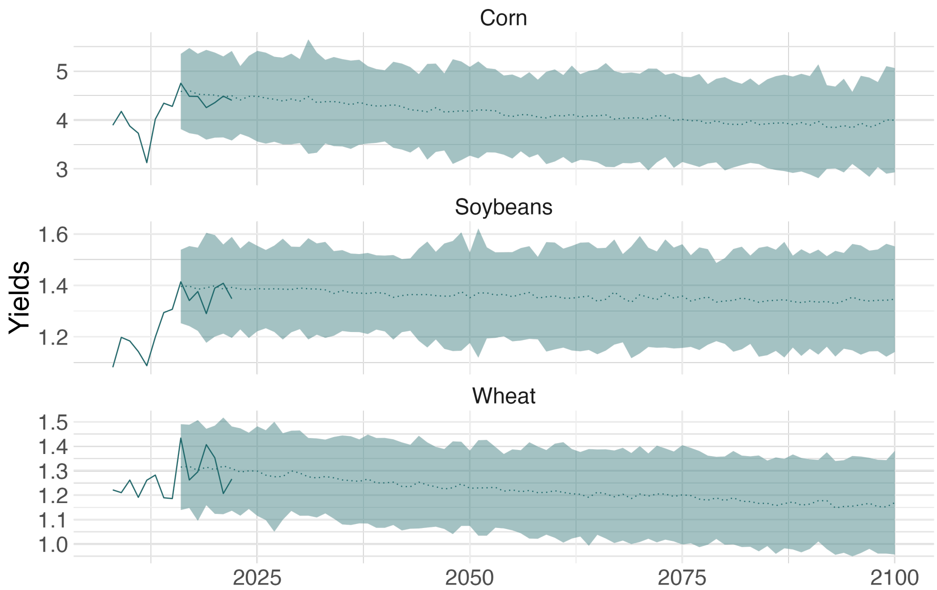
The approach uses the estimated yield-weather response and simulated future weather paths from the General Circulation Models to project future country-level yield distributions. Zuniga et al. (2024) generously shared these data. The procedure proceeds in two steps. First, weather simulations are augmented to account for weather variability. Second, yield variability not explained by the model is added by bootstrapping the residuals of the estimated yield-weather response.

Sampling future weather. Twenty-nine GCMs provide a path of future weather variables over 2020-2050. The number of simulations in a given year is augmented using a resampling procedure, allowing better capture of within-model weather variability. The resampling procedure uses permutations of weather draws within two years of the considered year. Importantly, this method conserves the matrix of covariance of weather.

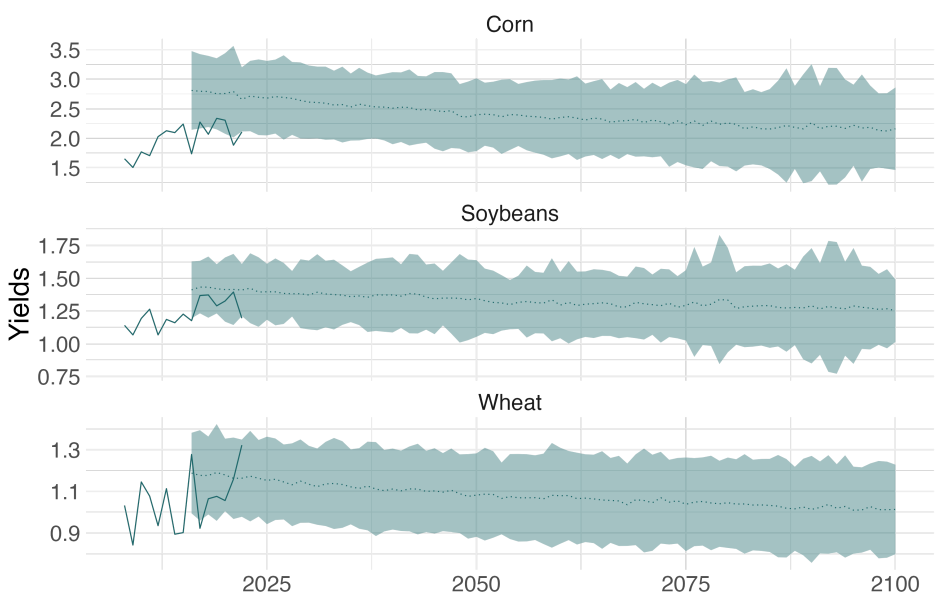
Bootstrap predictions. A sample of yield predictions is generated using a bootstrap procedure for each given weather path. The procedure samples the residuals at two stages: first, to account for parameter uncertainty, and second, to account for yield variability not explained by the model. This procedure also conserves the cross-sectional correlation of residuals.

Fit. Figure E4 presents the procedure's fit and the time series of the yield projections for two main agricultural producers: the US and Brazil. The model performs well in predicting average yields: the transition between observed data and climate models is seamless. The 0.05-0.95 percentile range covers the pre-2020 observed yield variability.

Figure E4. Fit and projections of country-level yield distributions



(a) United States



(b) Brazil

Notes: The solid line corresponds to country-level average yields for the three considered commodities. The dotted line is the average yields implied by the projections of 29 global circulation models under radiative forcing scenario RCP4.5. The shaded areas are the 0.05-0.95 percentile range. The data was generously shared by Zuniga et al. (2024).

F Results - Supplementary Material

F.1 Welfare Definition

I compute undiscounted total consumer surplus, producer surplus, and government spending. For a given year t:

$$CS_t = \beta \log\left(\frac{1}{P}\right)\left(1 - \frac{1}{2}\left(\frac{\sigma^C}{\mu^C}\right)^2\right) \tag{F1}$$

$$PS_t = \sum_i V_{it} \tag{F2}$$

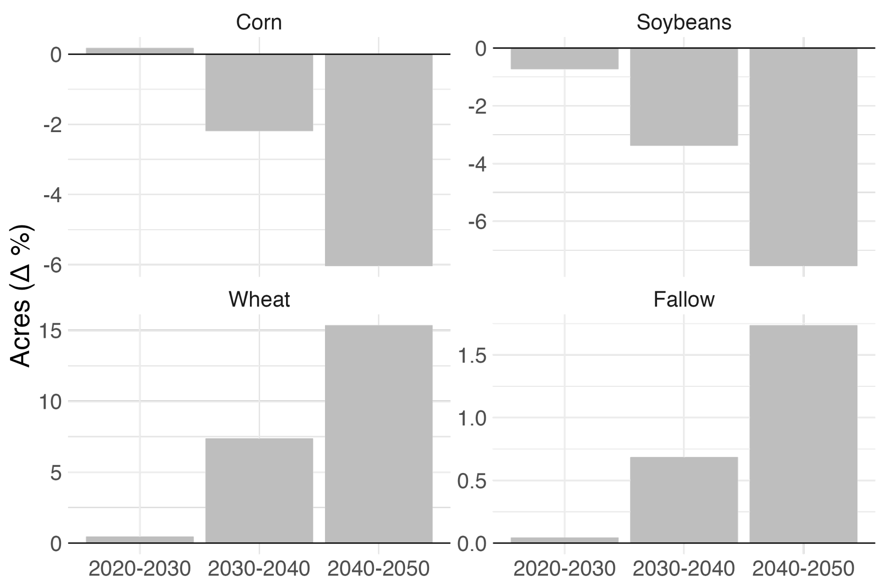
$$GS_t = \sum_i \sum_k \mathbf{1}[i \text{ chooses } k] \sum_j \mathbf{1}[i \text{ chooses } j] S^k_{jt}(Z_i) \tag{F3}$$

where β is defined in Equation B1 and P is the crop price index $\left[\sum_k \beta_k {p_k}^{1-\kappa}\right]^{\frac{1}{1-\kappa}}$.

The representative consumer has log utility over the composite agricultural good, implying that they have constant relative risk aversion with parameter 1. Consumer surplus is therefore adjusted by the risk premium, $0.5\left(\sigma^C/\mu^C\right)^2$, where μ^C and σ^C are the average and standard deviation of U.S. agricultural consumption. Importantly, the consumer surplus is defined up to a constant. Producer surplus is the sum of farmers' value functions. Finally, government spending is the sum of all crop-county-land quality-insurance specific subsidies S^k_{jt}.

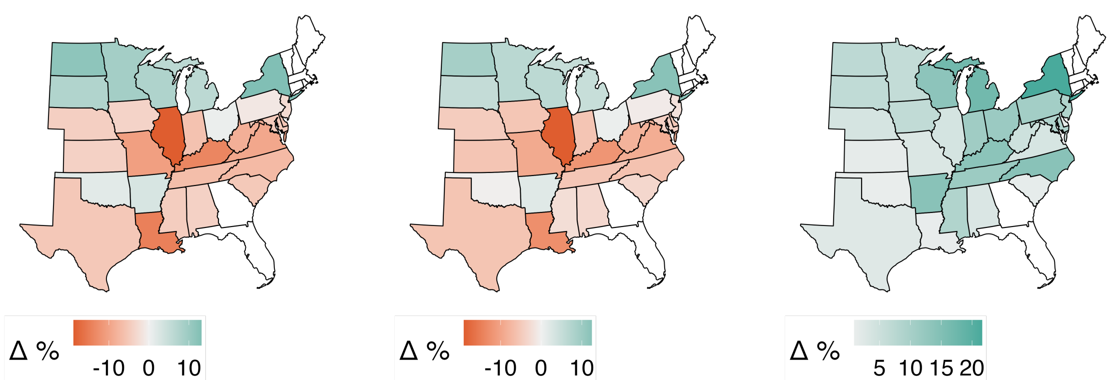
F.2 Climate Change Impacts on Agricultural System

Figure F1. Impact of Climate Change on Planted Acres Over Time



Notes: The figure shows the difference by decade in farmers' land use decisions between (i) a scenario in which climate does not change from the baseline period 2016-2021 and (ii) one in climate changes under a moderate emission scenario (Appendix E). In both scenarios, the U.S. government does not offer crop insurance subsidies. Farmers have accurate beliefs about the evolution of climate. As climate change unfolds, corn and soybeans growers, two crops negatively affected by extreme temperature, exit and are replaced by wheat farms, less sensitive to extreme heat (Tables 2 and C2). The total cultivated area decreases over time: more land is left fallow.

Figure F2. Impact of Climate Change on Planted Acres

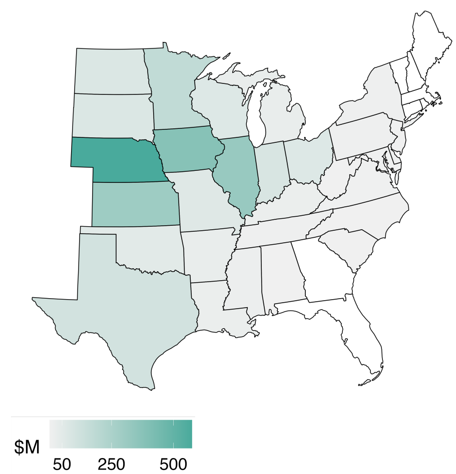


(a) Corn (b) Soybeans (c) Wheat

Notes: The maps show the difference by decade in farmers' land use decisions between (i) a scenario in which climate does not change from the baseline period 2016-2021 and (ii) one in climate changes under a moderate emission scenario (Appendix E), for the selected counties (Figure A2). In both scenarios, the U.S. government does not offer crop insurance subsidies.

F.3 Impact of Status Quo Subsidies, Absent Climate Change

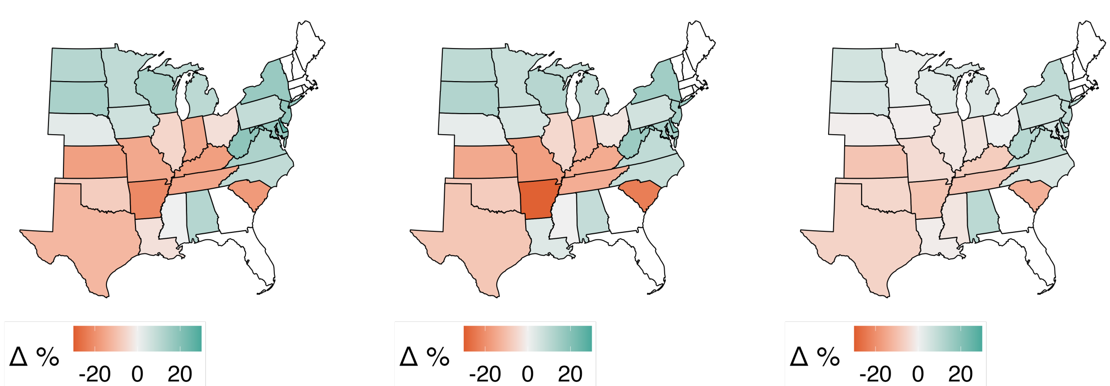
Figure F3. Distribution of Government Funds, Absent Climate Change



Notes: Government subsidies are the product of crop acres, insurance premiums, take-up, and subsidies, averaged over 2020-2050. Climate is measured in 2016-2021 using the climate projections from six global circulation models (see Section E.1).

F.4 Crop Insurance Policy Design Under Climate Change

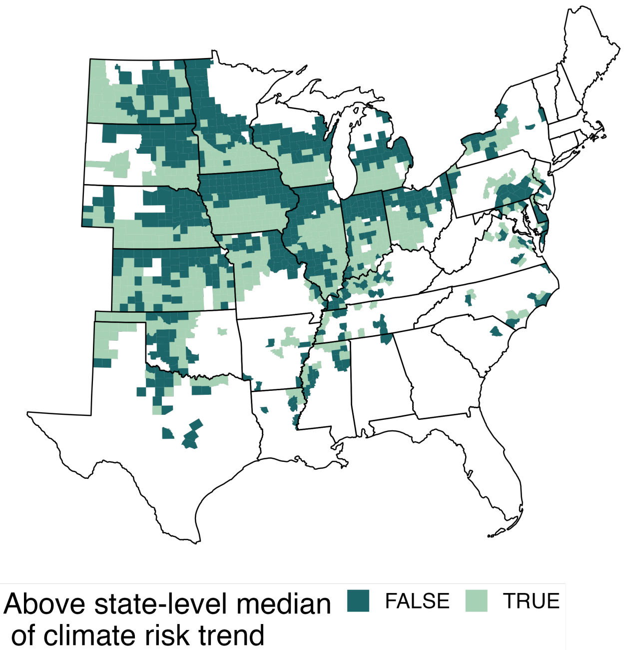
Figure F4. Impact of Targeted Subsidies on Planted Acres



(a) Corn (b) Soybeans (c) Wheat

Notes: The maps show the change in crop acres at the state level between *targeted* and *status quo* subsidies for the selected counties (Figure A2). Climate changes under a moderate emission scenario (see Appendix E). Subsidies in Status Quo are as in Table A1. *Targeted* subsidies (square) are 15% (150%) of the *status quo* in counties with increasing (decreasing) climate risk.

Figure F5. Clusters of counties for block-targeting of crop insurance subsidies



Notes: The figure shows the clusters of counties differentially targeted under *block-targeting*. Counties are divided into two groups: above or below the median climate risk trend by U.S. state. Weather risk is the ratio of standard deviation to the mean of the number of extreme degree days. Climate projections are obtained from six global circulation models under a moderate emission scenario (Appendix E). Climate risk trends are computed over 2020-2050 for the selected counties (Figure A2).