Detecting Structural Change in the Demand for Multiple Peril Crop Insurance

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Abstract

Understanding what shapes producers' adoption of crop insurance is essential for evaluating the U.S. Federal Crop Insurance Program. This study analyzes county-level corn and soybean data from 1992 to 2023 using a high-dimensional panel regression with an unknown structural break to account for major policy changes following the 1994 Reform Act. The model selects key weather, soil, and market variables, allowing their effects to vary across policy regimes. Results show inelastic demand—average price elasticities of –0.031 for corn and –0.113 for soybeans—with significant heterogeneity across regions. High-return counties exhibit lower price responsiveness, while responses to moderate and extreme heat vary by crop type and policy period. The findings emphasize that farmers' production environment and policy context shape farmers' insurance decisions. While crop insurance enhances risk management, it may also affect regional crop diversity and the long-term sustainability of farming systems due to uneven responsiveness across producer types and locations.

Keywords: agricultural policy, subsidies, spatial distribution, premium rate, LASSO

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1 Introduction

The Federal Crop Insurance Program (FCIP) has emerged as the central pillar of U.S. agricultural risk policy. By 2023, the program provided coverage for 539 million acres of cropland—an 83% increase from a decade earlier (U.S. Department of Agriculture, Risk Management Agency, 2023) —and accounted for nearly 33% of all financial assistance distributed by the U.S. Department of Agriculture (USDA) between 2019 and 2023 (U.S. Government Accountability Office, 2024). These figures reflect the program's evolution from a modest yield insurance scheme to a multi-billion-dollar enterprise that now functions as a primary vehicle for stabilizing farm incomes and shaping risk behavior across U.S. agriculture.

This institutional expansion has generated a large body of research on the behavioral, economic, and environmental effects of crop insurance. Scholars have examined how insurance participation affects land use (Claassen et al., 2017; Miao et al., 2016), input intensity and farm management practices (Mieno et al., 2018; Yu et al., 2018; Deryugina and Konar, 2017; DeLay et al., 2023; Wang et al., 2021; Connor et al., 2022; Regmi et al., 2023), and enrollment in conservation programs(Fleckenstein et al., 2020). Others have explored how crop insurance creates or mitigates environmental externalities(Weber et al., 2016) or alters marketing decisions(Du et al., 2015). Despite this growing literature, relatively little is known about how the demand for crop insurance has evolved in response to major program reforms and shifting agro-climatic conditions. While a number of studies document price-inelastic demand for crop insurance (Goodwin, 1993; Coble et al., 1996; Richards, 2000; Goodwin et al., 2004; Woodard and Yi, 2020; Tsiboe and Turner, 2023a), these estimates often rely on cross-sectional or short panel data, and they generally assume stability in demand elasticity over time.

This assumption may be problematic given the scale of institutional changes since the 1990s. The Crop Insurance Reform Act of 1994, the Agricultural Risk Protection Act of 2000, and successive Farm Bills in 2008, 2014, and 2018 significantly altered the structure of the FCIP by expanding premium subsidies, broadening eligibility, and introducing revenue-based insurance products Protection Act of 2000, and the 2008, 2014, and 2018 Farm Bills (Glauber, 2013; Tsiboe and Turner, 2023b). Each reform potentially shifted the relative value of insurance for producers, thereby changing how they respond to premium rates and risk exposure. Yet few empirical models allow for structural breaks in demand elasticity or assess how environmental and economic variables interact with these institutional changes.

The current study addresses these gaps by examining the evolution of crop insurance demand between 1989 and 2023, a period that spans major policy reforms and rising climate risk. Specifically, this study estimates how participation rates and insured acreage respond to premium rates, expected returns, and agro-environmental conditions while allowing for endogenous structural changes in the relationship between these variables. The methodological approach combines high-dimensional panel data with desparsified LASSO estimation and structural break detection (Li and Yan, 2024), enabling us to identify shifts in demand behavior without relying on pre-imposed policy breakpoints. In doing so, the study captures how the determinants of insurance demand vary over time and across space, and under what conditions premium subsidies are more or less effective in encouraging participation.

The study makes three primary contributions to the literature. First, it provides the longest panel analysis of crop insurance demand to date, spanning 34 years and incorporating multiple institutional regimes. Unlike earlier studies that restrict analysis to pre- or post-2000 data, our framework endogenously detects structural changes and quantifies

shifts in responsiveness to program parameters. Second, the study includes a broader and more flexible set of agro-climatic and market variables than is typical in the literature. In particular, we incorporate nonlinear measures of weather risk—including degree days, extreme heat, vapor pressure deficit, and soil quality—interacted with economic variables to identify heterogeneous demand elasticities across counties. Third, we allow for nonlinear effects of extreme weather on insurance participation. As climate risks intensify, understanding how farmers adjust their risk management strategies in response to heat and drought conditions becomes increasingly important.

The results from this study reveal a major structural break in crop insurance demand around the 1994 Crop Insurance Reform Act. Following this reform, the price elasticity of demand for crop insurance—measured with respect to the net premium-changed substantially, particularly in high-risk and high-subsidy environments. Counties with greater exposure to heat stress and historical yield losses exhibited more inelastic responses to premium rate changes post-1995. We also find that self-selection into the program became more sensitive to agro-climatic factors after major reforms, suggesting that institutional changes reshaped both the intensive and extensive margins of insurance participation. These findings carry several implications. First, demand for crop insurance is not uniformly inelastic: responsiveness varies with both environmental conditions and policy design. Second, policies that reduce premium subsidies are unlikely to yield large cost savings in high-risk areas but may influence marginal participation in lower-risk zones. Third, climate risk interacts with institutional incentives in shaping farmers' insurance decisions, implying that future program reforms should account for the spatial heterogeneity of both economic and environmental conditions. More broadly, our results suggest that risk management behavior in agriculture is dynamic and context-dependent, responding not only to prices and subsidies but also to evolving perceptions of environmental volatility. By documenting how insur-

ance demand has evolved over three decades of policy change, this paper contributes to a more adaptive and empirically grounded understanding of agricultural risk policy in the United States.

The remainder of this paper is structured as follows. Section 2 reviews the evolution of the U.S. Federal Crop Insurance Program over time. Section 3 presents a conceptual framework illustrating how premium rates and heterogeneity in risk levels jointly influence the fraction of planted area insured—that is, the ratio of insured planted area to total planted area. Section 4 describes the data and outlines the estimation strategy. Section 5 reports the empirical findings. Finally, Section 6 offers concluding remarks and discusses policy implications.

2 Background

The U.S. Federal Crop Insurance Program (FCIP) experienced several major policy changes between 1989 and 2023, driven by national-level legislative actions that reshaped the program's structure (Serra et al., 2003; Glauber, 2013; Yu et al., 2018; Tsiboe and Turner, 2023b; USDA Economic Research Service, 2025). The landscape of federal crop insurance has changed dramatically over this period.

The Crop Insurance Reform Act of 1994 required producers to participate in crop insurance to qualify for certain federal farm program benefits. It also created the catastrophic coverage (CAT) option, offering a full subsidy rate that covered 50% of yield at 60% of the expected price, subject to an administrative fee. The Act further expanded coverage levels beyond CAT and authorized revenue protection products. In response to adverse weather and low prices, supplementary legislation in 1998 and 1999 provided ad hoc premium reductions for the 1999 and 2000 crop years (Glauber et al., 2002).

In 2000, the Agricultural Risk Protection Act (ARPA) converted these temporary premium reductions into formal provisions, leading to a 25% overall decrease in premium costs and a corresponding increase in subsidy rates (Yu et al., 2018). ARPA also broadened geographic availability, removed restrictions on livestock products, promoted private-sector product development, and authorized premium reduction plans, allowing approved insurance providers (AIPs) to offer lower premiums, thereby enhancing their competitive position. This legislation catalyzed an era of rapid expansion in product offerings, particularly revenue-based insurance products, and spurred a marked increase in program participation.

The 2008 Farm Bill abolished the premium reduction plans introduced under ARPA, reduced premium subsidies for area plans, and raised CAT fees. The 2014 Farm Bill further expanded the program by permitting higher coverage levels with lower deductibles, introducing shallow loss products such as the Supplemental Coverage Option and Stacked Income Protection, giving producers under certain conditions the ability to exclude low yields from their production history, linking premium subsidy eligibility to conservation compliance, and reducing subsidies for planting on native sod in some states.

These legislative changes had a profound impact on participation patterns. The compulsory CAT coverage in 1994, combined with subsidies for higher "buy-up" levels, drove insured acreage sharply upward. Although CAT enrollment declined after the mandate was repealed in 1996, subsequent subsidy increases—especially under ARPA—pushed total insured acreage to 293 million acres annually. The average annual FCIP participation from 2000 to 2022 covered 81% of eligible acres among producers of major field crops and a range of specialty crops across the United States. Given the price-inelastic nature of crop insurance demand, these participation gains came at the cost of rising marginal subsidies, while ad hoc disaster assistance continued despite high coverage rates (Knight and Coble, 1997; Glauber et al., 2002; Glauber, 2004). Nevertheless, even with higher participation,

advocates of disaster assistance argued for measures to "fill the hole in the safety net," emphasizing that insurance coverage remained low in high-risk areas and yield guarantees were inadequate in regions with frequent losses. Such assistance was viewed as a complement to, rather than a replacement for, crop insurance (Glauber, 2013).

Today, the vast majority of major crop acreage is insured under federally subsidized programs, with producers selecting from a range of yield- and revenue-based products at multiple coverage levels and unit structures. These developments underscore the need to reassess the drivers of insurance demand and to re-specify empirical models so they capture newly relevant variables and structural changes.

3 Theoretical Framework

We consider a representative risk-averse farmer who chooses the fraction of planted area that is insured, Q, to maximize expected utility *per acre*. All monetary values (revenue, cost, premium, and indemnity) are measured on a per-acre basis. For notational simplicity, the unit "per acre" is omitted in the subsequent derivations. The farmer's net income without insurance is given by

$$\pi_0 = Y - c, \tag{3.1}$$

where Y is crop revenue and c is fixed production cost. With insurance, net income becomes

$$\pi_I = Y - c - P_{\text{net}} + I, \tag{3.2}$$

where P_{net} is the net premium (the actuarially fair premium minus subsidy), and I is the indemnity payment. Let crop revenue without insurance be

$$Y = \bar{Y} + \varepsilon, \quad \varepsilon \sim N(0, \sigma^2),$$

where $\bar{Y}$ is the expected revenue and σ^2 is the variance of revenue. The parameter $r \in (0, 1]$ measures the risk exposure associated with each unit of the planted area. Purchasing crop insurance with the fraction Q proportionally reduces the farmer's exposure to yield risk by $(1 - rQ)$. Thus, the variance of net income with insurance is

$$Var(\pi) = \sigma^2(1 - rQ)^2.$$

For simplicity, the indemnity is assumed to be proportional to the risk level r and the fraction of the planted area Q:

$$E[I] = \alpha r Q, \quad Var(I) = \sigma^2 r Q, \tag{3.3}$$

where $\alpha > 0$ is the expected indemnity rate per unit risk and σ^2 captures the variance parameter.

The farmer's expected utility is expressed as a mean-variance function:

$$U(Q) = E[\pi] - \frac{\theta}{2} Var(\pi), \tag{3.4}$$

where $\theta > 0$ is the coefficient of absolute risk aversion.

Expected net income is

$$E[\pi] = \bar{Y} - c - P_{\text{net}}Q + \alpha rQ + (1 - rQ)\varepsilon, \tag{3.5}$$

and the variance of net income is

$$Var(\pi) = \sigma^2(1 - rQ)^2. \tag{3.6}$$

Substituting into the utility function gives

$$U(Q) = \bar{Y} - c - P_{\text{net}}Q + \alpha rQ - \frac{\theta}{2}\sigma^2(1 - rQ)^2. \tag{3.7}$$

Maximizing utility with respect to Q yields the first-order condition:

$$\frac{\partial U}{\partial Q} = -P_{\text{net}} + \alpha r + \theta\sigma^2 r(1 - rQ) = 0. \tag{3.8}$$

Solving for P_{net} gives:

$$P_{\text{net}} = \alpha r + \theta\sigma^2 r(1 - rQ). \tag{3.9}$$

Solving for Q gives the demand function:

$$Q(r) = \frac{1}{r} - \frac{P_{\text{net}} - \alpha r}{\theta\sigma^2 r^2}. \tag{3.10}$$

USDA crop insurance premiums are subsidized at rates that vary with the chosen coverage level but remain constant across crops and locations (Yu et al., 2018). Because farms with different risk levels tend to select different coverage levels, variation in risk expo-

sure indirectly affects the subsidy rate through coverage choice.[1] The net premium can be expressed as the difference between the actuarially fair premium and the subsidy:

$$P_{\text{net}}(r) = P(r) - S(r), \tag{3.11}$$

where both $P(r)$ and $S(r)$ are increasing in r, i.e., $\frac{dP}{dr} > 0$ and $\frac{dS}{dr} > 0$. Therefore, the net effect of risk on the net premium is:

$$\frac{dP_{\text{net}}}{dr} = \frac{dP}{dr} - \frac{dS}{dr}, \tag{3.12}$$

which may be positive or negative depending on the relative magnitude of subsidy and actuarial premium changes. The price elasticity of insurance demand is defined as:

$$E_{Q,P_{\text{net}}}(r) = \frac{\partial Q}{\partial P_{\text{net}}} \cdot \frac{P_{\text{net}}(r)}{Q(r)}. \tag{3.13}$$

Differentiating the demand function (3.10) with respect to P_{net} gives:

$$\frac{\partial Q}{\partial P_{\text{net}}} = -\frac{1}{\theta\sigma^2 r^2}. \tag{3.14}$$

Substituting into the elasticity formula yields:

$$E_{Q,P_{\text{net}}}(r) = -\frac{1}{\theta\sigma^2 r^2} \cdot \frac{P_{\text{net}}(r)}{Q(r)}. \tag{3.15}$$

[1] Although USDA crop insurance offers only a limited set of discrete coverage levels, our analysis uses county-level aggregated data. At this level of aggregation, the effective coverage level can be treated as a continuous variable, allowing us to capture its response to variation in risk exposure.

Substituting (3.10) back into (3.15) gives:

$$E_{Q,P_{\text{net}}}(r) = -\frac{P_{\text{net}}(r)}{\theta\sigma^2 r - P_{\text{net}}(r) + \alpha r}. \tag{3.16}$$

Taking the reciprocal of the elasticity expression yields:

$$\frac{1}{E_{Q,P_{\text{net}}}(r)} = -\frac{r}{P_{\text{net}}(r)}(\theta\sigma^2 + \alpha) + 1. \tag{3.17}$$

This implies that elasticity is jointly determined by the risk level r and the net premium $P_{\text{net}}(r)$. As r increases, the numerator in the first term of the inverse elasticity expression rises, which tends to reduce the absolute value of elasticity (i.e., demand becomes less sensitive to price). However, the response of $P_{\text{net}}(r)$ to changes in r is ambiguous. If the subsidy rate increases less rapidly than the actuarially fair premium, as shown in (3.12), then $P_{\text{net}}(r)$ may rise. If the net premium increases more rapidly than the risk level—i.e., if $P_{\text{net}}(r)$ grows faster than r such that the ratio $\frac{r}{P_{\text{net}}(r)}$ declines—then the impact of the risk component on the inverse elasticity is offset, resulting in a higher absolute value of elasticity.

In the empirical analysis, we estimate the response of the ratio of insured acreage to total acreage to changes in premium per acre and its interaction with various risk components. This allows us to assess how heterogeneity in risk exposure influences the elasticity of crop insurance demand.

4 Data and Empirical Methods

4.1 Data and Descriptive Statistics

Previous studies have used the proportion of planted or insurable acres that are actually insured as a proxy for the quantity of insurance purchased, thereby representing crop insurance demand or participation. We combine publicly available data on county-level insured acres (Risk Management Agency, 1989–2023) with data on county-level planted acres and yields for corn and soybeans (National Agricultural Statistics Service, 1989–2023). By merging these two sources, we construct the fraction of the planted area that is insured for each county, which is therefore available for the period 1989–2023. The two data sources derive county aggregates in different ways: the RMA data is the sum of all actual contracts[2] for a given year in the county. In contrast, the NASS data are derived from a representative subsample of farms participating in the Agricultural Survey every year, which is used to estimate county-level planted acreage. Due to the sampling nature of this approach, the estimates are subject to measurement error. In particular, if the NASS-based estimate of planted area understates the true value, the resulting insured fraction—calculated as the ratio of insured to planted acres—can exceed one.

To address this issue, we follow the approach of Annan and Schlenker (2015) and construct the denominator as the maximum reported planted acreage in each county across the

[2]The total insured acreage is calculated based on a selection of major insurance plans that have been available and widely adopted during the study period. These plans include: Actual Production History (APH), Crop Revenue Coverage (CRC), Revenue Assurance (RA), Income Protection (IP), Indexed Income Protection (IIP), Group Risk Plan (GRP), Group Risk Income Protection (GRIP), Revenue Protection (RP), Revenue Protection with Harvest Price Exclusion (RP-HPE), Yield Protection (YP), Area Revenue Protection (ARP), Area Revenue Protection with Harvest Price Exclusion (ARP-HPE), Area Yield Protection (AYP), Margin Protection (MP), and Margin Protection with Harvest Price Option (MP-HPO). These plans have evolved over time — some were introduced, replaced, or consolidated into more modern policies. Many of the older plans (e.g., CRC, RA) have been phased out or consolidated into Revenue Protection in the 2000s. We focus on this subset of plans to ensure consistent coverage of the most relevant insurance products over the 1989–2023 period.

previous, current, and subsequent years.[3] This procedure helps mitigate the impact of sampling noise in the NASS data. Nevertheless, some observations still yield insured fractions exceeding one. To avoid implausibly high values and ensure the insured share remains bounded between zero and one, we cap the ratio at one whenever it exceeds that threshold.

The USDA subsidizes a substantial share of crop insurance premiums, resulting in net premiums paid by producers that are often considerably lower than the actuarially fair rates. Accordingly, the key price measure in our estimation is the net premium per insured acre, defined as the gross premium minus the subsidy amount on a per-acre basis. In addition, the gross premium per insured acre is included in the set of control variables to account for potential effects beyond the net price. To ensure comparability over time, both premium and subsidy amounts are deflated using the Producer Price Index (PPI) for farm products, with 1982 as the base year.[4]

In addition to quantity and premiums, we consider several risk components in the pricing of insurance that are conceptually relevant to insurance purchase decisions. The Loss Ratio (LR) is defined as the ratio of total indemnity payments to total premiums. For example, an LR of 0.5 indicates that \$0.50 of every premium dollar is paid out in claims. This metric reflects the cost of claims to the insurer relative to the revenue generated from premiums. The LR serves as an indicator of the underlying risk environment: a persistently high LR reflects elevated indemnity risk relative to premiums, whereas a low LR suggests a comparatively lower likelihood of loss.

Weather information, especially extreme weather events, and their impacts on crop insurance programs are also considered. The "Parameter-Elevation Regression on Inde-

[3] Annan and Schlenker (2015) show that while insured acreage increased substantially from 1989 to 2013, planted acreage remained relatively stable over time. We partially adopt their strategy by assuming that the planted area does not vary significantly over a three-year window at the county level.

[4] PPI data for farm products are obtained from the U.S. Bureau of Labor Statistics.

pendent Slopes Model" (PRISM) data have been widely used in previous studies (e.g., Schlenker and Roberts (2009), Annan and Schlenker (2015)). We primarily utilize data from PRISM to calculate the moderate heat degree days (10–29 °C for corn and 10–30 °C for soybeans, both measured in thousands), extreme heat degree days (above 29 °C for corn and 30 °C for soybeans, both measured in thousands), and accumulated precipitation (in mm), following Schlenker and Roberts (2009).

Weather variability can influence producers' beliefs and expectations about future production risks, which in turn shape their decision-making and observed outcomes (Hsiang, 2016). Consequently, it is reasonable to expect that climate-relevant variables—such as temperature extremes and precipitation patterns—may directly affect producers' crop insurance decisions. To capture this effect, we include a set of weather variables measured over the growing season (April to September) in the preceding year, including monthly cumulative precipitation, monthly moderate heat degree days, and monthly extreme heat degree days.[5] While premium rates reflect the actuarial cost of coverage, they do not directly capture heterogeneity in expected returns to insurance or differences in weather-related beliefs across producers.

We examine the role of lagged variables in crop insurance as potential determinants of the dependent variable. In particular, lagged expected return and historical weather variability may be strongly correlated with producers' underlying risk preferences, thereby influencing their willingness to purchase crop insurance. Following the approach of Goodwin (1993), we incorporate a measure of historical indemnity experience to better proxy for perceived insurance value. Specifically, we construct an expected loss ratio, defined as the average realized loss ratio in a county over the previous four years. This variable re-

[5]For the selection of monthly extreme heat degree days, we exclude April, as soybean observations are consistently zero in this month and nearly all corn observations are also zero.

flects farmers' expectations of receiving indemnities in excess of premium payments and, as such, serves as a proxy for the perceived profitability of insurance. It thereby captures a key component of the decision to participate in the crop insurance program. Formally, the expected loss ratio for county i in year t, denoted as $\textit{ExpLossRatio}_{it}$, is defined as:

$$\text{ExpLossRatio}_{it} = \frac{1}{4} \sum_{s=t-4}^{t-1} \text{LR}_{is}$$

where LR_{is} denotes the *loss ratio* (i.e., indemnities divided by total premiums) for county i in year s.

Analogously, we construct expected weather-related variables to capture climate risks that may influence insurance participation. In particular, we calculate the expected number of extreme heat degree days and moderate heat degree days during the growing season by averaging values over the previous four years. For instance, the expected extreme heat exposure is defined as:

$$\text{ExpExtremeHeat}_{it} = \frac{1}{4} \sum_{s=t-4}^{t-1} \text{ExtremeHeatDegreeDays}_{is}$$

where $\text{ExtremeHeatDegreeDays}_{is}$ denotes the number of degree days above 29 °C or 30 °C in the growing season in county i, year s.

This averaging process over the preceding four years mitigates the influence of transitory shocks or exceptional losses that may occur in any single year. The $\textit{ExpLossRatio}_{it}$ variable is used to allow heterogeneous premium elasticities: producers with different expectations of returns (as proxied by historical loss ratios) may respond differently to changes in insurance premiums. To account for this, we include interaction terms between premium per acre and the $\textit{ExpLossRatio}_{it}$ variable in the demand equation. Similarly, we interact premiums with the expected extreme and moderate heat exposure measures, allow-

ing premium responsiveness to vary by climate-related risk.

To facilitate interpretation relative to state-level baselines, we demeaned the constructed variables—Expected Loss Ratio, Expected Extreme Heat, and Expected Moderate Heat—at each year within each state. Specifically, each variable was normalized by subtracting the corresponding annual state-level mean. As a result, counties with positive demeaned values are those that have historically experienced higher-than-average loss ratios or heat exposure relative to other counties in the same state and year. Conversely, counties with demeaned expected risk values below zero have received lower indemnities relative to premiums or experienced fewer extreme or moderate heat degree days compared to the state average.

We then construct interaction terms between premium per acre and the normalized variables. Under this specification, the coefficient on premium per acre alone captures the baseline premium elasticity at the state average level of loss risk and climate risk. Deviations from this baseline, as captured by the interaction terms, reveal whether farmers in counties with above- or below-average risk exhibit systematically different demand responses—suggesting the presence of adverse selection in the premium-setting process.

In addition, we calculate the average yield over the preceding four years, which may provide information to producers regarding expected yields in the upcoming season. This is because soil moisture deficiencies, adverse growing conditions, and other disaster-related impacts often persist beyond the year of occurrence. Consequently, producers who have recently experienced unfavorable agronomic conditions—relative to neighboring regions—may exhibit heightened sensitivity to crop insurance programs. Thus, the yield variable is, to some extent, also correlated with the local risk environment. We incorporate four additional weather indices developed by the National Climatic Data Center (NCDC) to capture local and regional drought and moisture anomalies. These indices—defined in detail in Table 1—include the Palmer Drought Severity Index (PDSI), Palmer Hydrological Drought

Index (PHDI), Palmer "Z" Index (ZNDX), and the Modified Palmer Drought Severity Index (PMDI). They are available at multiple spatial resolutions, including climatic divisions, state, regional, and national levels, and are reported on a monthly basis.

PDSI is a widely used meteorological drought index that quantifies the severity of wet and dry spells based on a water balance model. It captures the cumulative effect of precipitation and temperature anomalies but does not account for human interventions such as irrigation or water infrastructure. PHDI, similar in structure to PDSI, is designed to assess longer-term hydrological drought conditions. It reflects imbalances in moisture supply and demand but excludes anthropogenic influences such as irrigation or reservoir operations. ZNDX (Palmer Z-Index) measures short-term moisture anomalies by comparing actual monthly conditions to climatological normals. It is responsive to isolated monthly deviations (e.g., a single wet month within a drought) and serves as an indicator of current moisture anomalies. PMDI is an operationally enhanced version of the PDSI developed by the National Weather Service Climate Analysis Center. It blends information from the wet and dry components of the PDSI, weighted by the probability that a given wet or dry spell is ongoing. During stable periods, PMDI equals the PDSI; however, it diverges during transitional phases, providing a smoother representation of changing drought conditions (Heddinghaus and Sabol, 1991).

All indices are constructed as continuous variables, but each captures a distinct dimension of drought or moisture conditions. Following the approach of Karl (1986), we transform these continuous measures into discrete categorical variables to reflect better meaningful thresholds for classifying drought severity and wetness levels. In addition to the above climate and risk variables, several economic and farm characteristic variables are conceptually relevant to crop insurance purchases. The average of the preceding four years' yield is used to measure farmers' expected yields.

Cumulative Freq. (%)	**PHDI / PMDI / PDSI Range**	**Category**	**Z Index Range**
> 96	> 4.00	Extreme Wetness	> 3.50
90–95	$[3.00, 3.99]$	Severe Wetness	$[2.50, 3.49]$
73–89	$[1.50, 2.99]$	Mild to Moderate Wetness	$[1.00, 2.49]$
28–72	$[-1.49, 1.49]$	Near Normal	$[-1.24, 0.99]$
11–27	$[-2.99, -1.50]$	Mild to Moderate Drought	$[-1.99, -1.25]$
5–10	$[-3.99, -3.00]$	Severe Drought	$[-2.74, -2.00]$
< 4	< -4.00	Extreme Drought	< -2.75

Table 1: Classification of Wet and Dry Periods Based on Palmer Drought Indices and Z Index (Karl, 1986)

Another key component of the empirical specification is the inclusion of long-run soil characteristics as control variables. These variables are sourced from the National Resources Inventory (NRI) and capture essential aspects of land quality. The dataset includes factors such as soil erodibility, slope, water-holding capacity, and conservation practices (e.g., the P-factor), which reflect the physical and agronomic constraints relevant to crop production.

Market conditions are represented using fertilizer prices, crop prices for corn and soybeans, and the ratio of corn to soybean prices. These data are obtained from the World Bank Commodity Price Database (commonly referred to as the "Pink Sheet") and are measured in February of each year to reflect pre-planting expectations. As these prices are reported at the national level, they are treated as county-invariant in the analysis.

Figures A.1 and A.2 present the county-level distributions of seven variables used in the estimation: relative insured acres, premium per acre, average historic yield, subsidy per acre, expected loss ratio, expected growing season moderate heat degree days, and expected growing season extreme heat degree days. The maps are shown separately for corn and soybean samples, covering county-level observations from 1992 to 2023. Premium rates alone may not fully reflect heterogeneity in the expected returns to insurance across

producers. Temperature-based risk measures, such as degree days, capture a different dimension of production risk and exhibit spatial variation that is not necessarily aligned with the distribution of expected returns. Consequently, incorporating weather-based indicators is necessary, as spatially heterogeneous climatic conditions may interact with or confound the elasticity of crop insurance demand. Figures A.1 and A.2 present the county-level distributions of seven key variables for the corn and soybean samples, respectively, over the period 1992–2023: (1) relative insured acres, (2) premium per acre, (3) average historic yield, (4) expected loss ratio, (5) expected growing season moderate heat degree days, and (6) expected growing season extreme heat degree days.

The spatial distributions of average relative insured acres with respect to premium rates and historic yields do not reveal a uniformly perceived negative relationship between price and demand, nor between yield and participation. In the Corn Belt, Southern states, and the Delta region, the correlation between average relative insured acres and premium rates is mixed. In contrast, in other regions the correlation is in some cases even positive. Similarly, the relationship between average relative insured acres and historic yields is also mixed across these major production regions, but in other areas, it is generally negative. Moreover, the three risk-related variables—expected loss ratio, expected growing-season moderate heat degree days, and expected growing-season extreme heat degree days—exhibit markedly different distributional patterns. Given this heterogeneity, restricting the empirical specification to an interaction between premium and expected loss ratio alone would be incomplete. Accordingly, we allow the price sensitivity of insurance demand to vary along all three risk dimensions by including interactions between the net premium and each risk measure in the specification.

The demand model for relative insured acres is estimated using a high-dimensional panel regression framework that allows for an unknown structural change. Our empirical

analysis relies on county-level annual observations of relevant insurance experience for corn and soybeans separately. Definitions of the explanatory variables and the corresponding summary statistics are reported in Table A.1, A.2 and listed all other control variables we mentioned above. In our setting, with $p = 73$ variables (including the intercept), the presence of one potential structural break doubles the number of parameters to $2p = 146$ when accounting for both pre- and post-break regimes. This dimensionality is consistent with a high-dimensional framework. The subsequent subsection outlines the econometric model utilized and discusses the potential challenges of conducting statistical inference in such a situation.

4.2 Shrinkage Estimation of High-Dimensional Models with Structural Change

High-dimensional regression models are widely employed in the analysis of macroeconomic and financial panel data. This study addresses the estimation challenges that arise when the model may contain a single unknown structural break. Given the high dimensionality of the covariates described above and the possibility of such breaks, our approach focuses on the simultaneous selection of relevant explanatory variables and the detection of parameter changes across two regimes (i.e., pre-break and post-break). To this end, we employ the Lasso (Least Absolute Shrinkage and Selection Operator) method. Originally introduced by Tibshirani (1996), Lasso has become a widely used technique for model selection in high-dimensional settings. It achieves variable selection and regularization simultaneously by imposing an ℓ_1-penalty on the magnitude of the regression coefficients, thereby shrinking some coefficients to exactly zero and identifying a sparse model. Building on model and variable selection, Lasso can also be applied to identify unknown struc-

tural breaks. In the context of regression models with unknown structural changes—also referred to as change point models—Lasso has been shown to reliably detect structural breaks and estimate the associated regression coefficients (see, e.g., Cheng et al. (2016); Qian and Su (2016); Lee et al. (2016); Callot et al. (2017)).

More formally, we consider the following panel data model, commonly referred to as a regression model with an unknown structural change or change point:

$$Y_{it} = \begin{cases} X_{it}'\boldsymbol{\beta}_0 + U_{it}, & \text{if } t < \tau_0, \\ X_{it}'(\boldsymbol{\beta}_0 + \boldsymbol{\delta}_0) + U_{it}, & \text{if } t \geq \tau_0. \end{cases} \tag{4.1}$$

Here, Y_{it} is the outcome variable for county i in year t, X_{it} is a p-dimensional covariate vector (i.e., the set of explanatory variables), $\boldsymbol{\beta}_0$ denotes the pre-break coefficient vector, and $\boldsymbol{\delta}_0$ captures the change in coefficients after the unknown break point τ_0. The post-break coefficient vector is thus given by $\boldsymbol{\beta}_0 + \boldsymbol{\delta}_0$. U_{it} is the idiosyncratic error term. Let $\boldsymbol{\beta}_0^{(j)}$ or $\boldsymbol{\delta}_0^{(j)}$ denote the j-th element of the vector. We distinguish between two types of coefficient changes (or instabilities):

- **Type-I change:** $\boldsymbol{\beta}_0^{(j)} \neq 0$ and $\boldsymbol{\delta}_0^{(j)} \neq 0$, indicating a change in the magnitude of an existing covariate's effect at τ_0.
- **Type-II change:** $\boldsymbol{\beta}_0^{(j)} = 0$ and $\boldsymbol{\delta}_0^{(j)} \neq 0$, implying that a previously irrelevant covariate becomes active after the change point.

Under a type-I instability, the effect of a covariate changes in magnitude after the structural break.[6] In contrast, type-II instability corresponds to the emergence of new covariates entering the model only after the break point. Clearly, if $\boldsymbol{\delta}_0^{(j)} = 0$, then the j-th variable's

[6]Within type-I changes, a special case exists when $\boldsymbol{\beta}_0^{(j)} \neq 0$, $\boldsymbol{\delta}_0^{(j)} \neq 0$, but $\boldsymbol{\beta}_0^{(j)} + \boldsymbol{\delta}_0^{(j)} = 0$, implying that a previously relevant covariate becomes inactive after the change point.

effect remains unchanged across the break. Moreover, if $\boldsymbol{\delta}_0 = 0$, this implies the absence of any structural break in the model.

We employ the two-step estimation approach of Lee et al. (2016). In the first step, for each τ denoting a candidate break date, we estimate the parameters $\widehat{\boldsymbol{\beta}}(\tau)$ and $\widehat{\boldsymbol{\delta}}(\tau)$ as follows:

$$\widehat{\boldsymbol{\beta}}(\tau),\, \widehat{\boldsymbol{\delta}}(\tau) := \arg\min_{\boldsymbol{\beta},\boldsymbol{\delta}} \left\{ \frac{1}{nT} \left[\sum_{t=1}^{\tau-1} \sum_{i=1}^{n} \left(Y_{it} - X_{it}'\boldsymbol{\beta}\right)^2 + \sum_{t=\tau}^{T} \sum_{i=1}^{n} \left(Y_{it} - X_{it}'(\boldsymbol{\beta}+\boldsymbol{\delta})\right)^2 \right] + \lambda \left(\|\boldsymbol{\beta}\|_1 + \|\boldsymbol{\delta}\|_1 \right) \right\} \tag{4.2}$$

where λ is the tuning parameter, which can be selected using criteria such as the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), cross-validation, or the plug-in procedure (PI). We choose BIC for tuning parameter selection in (4.2).

In the second step, we select $\hat{\tau}$ as the estimate of τ_0 that minimizes:

$$\hat{\tau} := \arg\min_{\tau} \left\{ \frac{1}{nT} \left[\sum_{t=1}^{\tau-1} \sum_{i=1}^{n} \left(Y_{it} - X_{it}'\widehat{\boldsymbol{\beta}}(\tau)\right)^2 + \sum_{t=\tau}^{T} \sum_{i=1}^{n} \left(Y_{it} - X_{it}'(\widehat{\boldsymbol{\beta}}(\tau) + \widehat{\boldsymbol{\delta}}(\tau))\right)^2 \right] + \lambda \left(\|\widehat{\boldsymbol{\beta}}(\tau)\|_1 + \|\widehat{\boldsymbol{\delta}}(\tau)\|_1 \right) \right\} \tag{4.3}$$

However, the estimates $(\widehat{\boldsymbol{\beta}}(\tau),\, \widehat{\boldsymbol{\delta}}(\tau),\, \hat{\tau})$ obtained from the Lasso procedure are generally not root-n consistent and do not yield asymptotically normal estimators of the parameters of interest. This limitation arises primarily from the omitted variable bias introduced by the shrinkage penalty in the Lasso objective function. Such bias complicates the derivation of the estimator's limiting distribution and poses a challenge for valid statistical inference (van de Geer et al., 2014; Leeb and Pötscher, 2008). Although post-Lasso estimators—i.e., ordinary least squares (OLS) regression estimates obtained after variable selection via Lasso—are widely used in empirical research (Leeb and Pötscher, 2005), concerns remain regarding their inferential validity. The asymptotic distribution of this type

of post-Lasso estimator is valid only pointwise and does not provide uniformly valid inference for the regression coefficients (Pötscher and Leeb, 2009; Leeb and Pötscher, 2008). Uniformly valid inference ensures that the coverage probabilities of confidence intervals or the rejection rates of hypothesis tests are accurate across a broad class of data-generating processes, rather than at a fixed parameter value. This is particularly important in post-selection settings, where standard asymptotic approximations may fail to account for the model selection step, leading to misleading inference unless properly corrected.

To overcome the issue of pointwise valid inference for the regression coefficients and confidence interval construction, bias-correction procedures are necessary. However, high-dimensional models introduce additional complications: when the number of regressors is large relative to the sample size, the sample covariance matrix becomes reduced rank. In such settings, standard inference techniques are no longer applicable and require methodological adjustments.

To de-bias the Lasso estimator and obtain heteroskedasticity-robust standard errors in the presence of structural breaks, an approximate inverse of the potentially singular sample covariance matrix is required. Li and Yan (2024) propose a method specifically designed for change point models, extending the framework of van de Geer et al. (2014) by constructing an approximate inverse via a 2-by-2 block matrix formulation. This approach accounts for structural shifts in parameters and facilitates valid inference in high-dimensional settings. For a detailed discussion of inference in high-dimensional change point regression models and related extensions, we refer interested readers to Li and Yan (2024). These extensions are beyond the scope of the present study and are therefore not discussed in detail.

5 Results and Discussion

Recognizing that our high-dimensional dataset encompasses a rich set of weather indicators, market conditions, and county-level soil characteristics, we are able to mitigate potential endogeneity concerns partially. A key source of such endogeneity stems from the role of "risk" in determining insurance premiums: omitting certain risk components can lead to potential omitted variable bias. By exploiting the richness of our dataset—which incorporates an extensive set of weather, market, and soil characteristics—rather than imposing a parsimonious specification, we are able to more comprehensively account for these risk factors and thereby mitigate the endogeneity concern. The approach we use here jointly selects the most relevant variables from an extensive pool of candidates and permits coefficients to vary across pre- and post-break regimes, yielding a more flexible specification while controlling for overfitting.

The estimation results for the corn sample reported in Table A.4 indicate the presence of a structural change in the demand model in 1995. This break is consistent with the enactment of the Federal Crop Insurance Reform and Department of Agriculture Reorganization Act of 1994, signed into law by President Bill Clinton on October 13, 1994, and implemented beginning with the 1995 crop year. Consistent with prior literature, this policy change represents the most significant reform in the past 35 years in terms of crop insurance policy parameters, program participation, and product diversity—as illustrated in Figure 1 of Tsiboe and Turner (2023a)—as well as in subsidy rates, as displayed in Figure 1 of Yu et al. (2018).

The estimated coefficient on the premium per acre suggests that, at the state-average level of expected returns to insurance, moderate heat exposure, and extreme heat exposure, the implied price elasticity of insurance demand is -0.031, which is statistically significant.

This estimate suggests that a 1% decrease in the net premium rate is associated with a 0.031% increase in relative insured acreage, implying a price elasticity of demand for relative insured acreage with respect to the net premium rate of –0.031 and indicating inelastic demand consistent with previous studies.

The interaction term capturing heterogeneous responses to premium changes across counties with different historical expected returns to insurance indicates that counties with higher historical expected returns exhibit less price elasticity of insurance demand. This finding is broadly consistent with the earlier results of Goodwin (1993). By contrast, the interaction term reflecting heterogeneous responses across counties with varying historical extreme-heat risk suggests lower price elasticity of insurance demand in counties with high extreme-heat risk. However, this estimate is not statistically significant.

Following the implementation of the 1994 Act, the estimated demand elasticity becomes -0.104. Post-break estimates also indicate that counties with historical returns above the state average remain less price elastic to changes in premiums. Moreover, the moderating effect of expected returns on price elasticity of insurance demand appears to be stronger in the post-break period. In addition, the interaction terms reveal that counties with higher historical extreme-heat risk are significantly less price elastic for crop insurance after the reform. Similarly, counties experiencing more frequent moderate-heat conditions also exhibit greater price inelasticity. Given that moderate heat is generally conducive to crop growth, a higher price elasticity of demand for crop insurance with respect to the net premium would be expected in such regions. The observed lack of increased elasticity may reflect the offsetting influence of net premium adjustments under favorable growing conditions, thereby mitigating the elasticity-enhancing effect of moderate heat, as discussed with equation (3.17) of Section 3.

The estimation results for the soybean sample, presented in Table A.5, also indicate a

statistically significant structural change in 1995. At the state-average levels of expected returns to insurance, moderate heat exposure, and extreme heat exposure, the estimated coefficient on premium per acre implies a price elasticity of demand for insured acreage with respect to the net premium rate of –0.113, significant at the 1% level. This estimate suggests that a 1% reduction in the net premium rate is associated with a 0.113% increase in relative insured acreage—over three times the magnitude observed in the corn sample.

Pre-break estimates show that counties with higher historical expected returns, greater moderate-heat exposure, and lower extreme-heat risk tend to exhibit less price elasticity of crop insurance demand. This pattern broadly mirrors the corn results, except that moderate-heat exposure is more strongly associated with inelastic demand for soybeans insurance even before the policy reform.

Following the 1995 break, the average price elasticity of crop insurance demand becomes more negative, indicating a stronger demand response to premium changes. The inelastic effect of historical expected returns on elasticity remains, with high-return counties continuing to display lower sensitivity to price changes. However, post-reform results diverge from the corn findings in the weather variability interactions: counties with more frequent moderate-heat conditions and those facing higher extreme-heat risk both exhibit significantly greater price elasticity. This contrast may reflect differences in soybean physiology and market conditions, as soybeans are generally more heat-tolerant than corn, and producers in warmer regions may respond more aggressively to premium reductions when extreme weather risk increases. While the soybean estimates share key qualitative features with the corn results, the greater magnitude of the baseline price elasticity and the reversal in the weather interaction after the policy change suggest that crop heterogeneity plays a critical role in shaping insurance demand responses.

Overall, our evidence of inelastic demand for crop insurance for both corn and soybeans

is qualitatively consistent with earlier findings in Goodwin (1993); Coble et al. (1996); Goodwin et al. (2004); Woodard and Yi (2020); Tsiboe and Turner (2023a). Across both crops, producers with higher historical returns from insurance consistently exhibit lower price elasticity, a statistically significant pattern, and in line with existing studies. In contrast, the effects of moderate-heat and extreme-heat exposure on demand elasticity are more mixed, varying by crop type and by whether the period is before or after the structural break.

6 Conclusion

This study identifies several key environmental and risk factors that shape the heterogeneous nature of crop insurance demand across U.S. corn- and soybean-producing counties. Leveraging a high-dimensional dataset that integrates detailed weather indicators, market conditions, and county-level soil characteristics, we are able to account for important cross-sectional variation and mitigate potential endogeneity concerns stemming from unobserved "risk" components in premium determination. The application of a panel LASSO framework with an unknown structural break allows for the joint selection of relevant covariates and the estimation of regime-specific coefficients, yielding a flexible specification that accommodates both temporal shifts and spatial heterogeneity in demand responsiveness.

The results point to a statistically significant structural change in 1995, coinciding with the implementation of the Federal Crop Insurance Reform Act of 1994. For both corn and soybeans, the estimated price elasticities of crop insurance demand with respect to the premium after subsidy are negative and statistically significant, indicating inelastic demand for relative insured acreage under the federal crop insurance program. Producers with higher historical expected returns from insurance consistently exhibit lower price responsiveness, a finding that is robust across crops and periods and consistent with earlier

literature. However, weather variability interactions display more nuanced patterns: the effects of moderate-heat and extreme-heat exposure vary by crop type and by whether the period is before or after the policy reform, with soybeans showing a post-reform increase in elasticity under both moderate-heat and extreme-heat conditions.

The findings from this study have several important policy implications. First, the persistence of inelastic demand suggests that premium rate adjustments may have limited effects on insured acreage, especially in counties with historically high loss ratios. Second, the significant role of environmental variables in explaining crop insurance demand heterogeneity implies that current premium rating methodologies may not fully account for underlying weather variability and soil conditions, potentially leading to rate inaccuracies. As regional environmental differences are substantial—spanning the Corn Belt, Southern states, and the Delta regions—incorporating these factors more explicitly into actuarial models could improve both fairness and efficiency in crop insurance premium setting.

Finally, the observed structural break associated with the rapid expansion of the revenue insurance program underscores the sensitivity of crop insurance demand to major policy reforms. Future research could extend this analysis to other measures of crop insurance demand and participation variables and consider the role of supplemental insurance products. Such work would further inform the ongoing debate over the trade-off between program participation incentives and actuarial soundness, ensuring that federal crop insurance remains both financially sustainable and responsive to the evolving risk environment faced by U.S. agricultural producers.

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References

Annan, F. and Schlenker, W. (2015). Federal crop insurance and the disincentive to adapt to extreme heat. *American Economic Review*, 105(5):262–66.

Callot, L., Caner, M., Kock, A. B., and Riquelme, J. A. (2017). Sharp threshold detection based on sup-norm error rates in high-dimensional models. *Journal of Business & Economic Statistics*, 35(2):250–264.

Cheng, X., Liao, Z., and Schorfheide, F. (2016). Shrinkage estimation of high-dimensional factor models with structural instabilities. *The Review of Economic Studies*, 83(4):1511–1543.

Claassen, R., Langpap, C., and Wu, J. (2017). Impacts of federal crop insurance on land use and environmental quality. *American Journal of Agricultural Economics*, 99(3):592–613.

Coble, K. H., Knight, T. O., Pope, R. D., and Williams, J. R. (1996). Modeling farm-level crop insurance demand with panel data. *American Journal of Agricultural Economics*, 78(2):439–447.

Connor, L., Rejesus, R. M., and Yasar, M. (2022). Crop insurance participation and cover crop use: Evidence from indiana county-level data. *Applied Economic Perspectives and Policy*, 44(4):2181–2208.

DeLay, N. D., Brewer, B., Featherstone, A., and Boussios, D. (2023). The impact of crop insurance on farm financial outcomes. *Applied Economic Perspectives and Policy*, 45(1):579–601.

Deryugina, T. and Konar, M. (2017). Impacts of crop insurance on water withdrawals for irrigation. *Advances in Water Resources*, 110:437–444.

Du, X., Ifft, J., Lu, L., and Zilberman, D. (2015). Marketing contracts and crop insurance. *American Journal of Agricultural Economics*, 97(5):1360–1370.

Fleckenstein, M., Lythgoe, A., Lu, J., Thompson, N., Doering, O., Harden, S., Getson, J. M., and Prokopy, L. (2020). Crop insurance: A barrier to conservation adoption? *Journal of Environmental Management*, 276:111223.

Glauber, J. W. (2004). Crop insurance reconsidered. *American Journal of Agricultural Economics*, 86(5):1179–1195.

Glauber, J. W. (2013). The growth of the federal crop insurance program, 1990—2011. *American Journal of Agricultural Economics*, 95(2):482–488.

Glauber, J. W., Collins, K. J., and Barry, P. J. (2002). Crop insurance, disaster assistance, and the role of the federal government in providing catastrophic risk protection. *Agricultural Finance Review*, 62(2):81–101.

Goodwin, B. K. (1993). An empirical analysis of the demand for multiple peril crop insurance. *American Journal of Agricultural Economics*, 75(2):425–434.

Goodwin, B. K., Vandeveer, M. L., and Deal, J. L. (2004). An empirical analysis of acreage effects of participation in the federal crop insurance program. *American journal of agricultural economics*, 86(4):1058–1077.

Heddinghaus, T. R. and Sabol, P. (1991). A review of the palmer drought severity index and where do we go from here. In *Proceedings, 7th conference on applied climatology*, pages 242–46. Citeseer.

Hsiang, S. (2016). Climate econometrics. *Annual Review of Resource Economics*, 8(1):43–75.

Karl, T. R. (1986). The sensitivity of the palmer drought severity index and palmer's z-index to their calibration coefficients including potential evapotranspiration. *Journal of Applied Meteorology and Climatology*, 25(1):77 – 86.

Knight, T. O. and Coble, K. H. (1997). Survey of us multiple peril crop insurance literature since 1980. *Applied Economic Perspectives and Policy*, 19(1):128–156.

Lee, S., Seo, M. H., and Shin, Y. (2016). The lasso for high dimensional regression with a possible change point. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 78(1):193–210.

Leeb, H. and Pötscher, B. M. (2005). Model selection and inference: Facts and fiction. *Econometric Theory*, 21(1):21–59.

Leeb, H. and Pötscher, B. M. (2008). Can one estimate the unconditional distribution of post-model-selection estimators? *Econometric Theory*, 24(2):338–376.

Li, J. and Yan, H. (2024). Uniform inference in high-dimensional threshold regression models. arXiv preprint arXiv:2404.08105.

Miao, R., Hennessy, D. A., and Feng, H. (2016). The effects of crop insurance subsidies and sodsaver on land-use change. *Journal of Agricultural and Resource Economics*, pages 247–265.

Mieno, T., Walters, C. G., and Fulginiti, L. E. (2018). Input use under crop insurance: The role of actual production history. *American Journal of Agricultural Economics*, 100(5):1469–1485.

Pötscher, B. M. and Leeb, H. (2009). On the distribution of penalized maximum likelihood estimators: The lasso, scad, and thresholding. *Journal of Multivariate Analysis*, 100(9):2065–2082.

Qian, J. and Su, L. (2016). Shrinkage estimation of common breaks in panel data models via adaptive group fused lasso. *Journal of Econometrics*, 191(1):86–109.

Regmi, M., Tack, J., and Featherstone, A. M. (2023). Does crop insurance influence crop yield impacts of warming temperatures? a farm-level analysis. *Journal of the Agricultural and Applied Economics Association*, 2(4):808–822.

Richards, T. J. (2000). A two-stage model of the demand for specialty crop insurance. *Journal of agricultural and resource economics*, pages 177–194.

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

Serra, T., Goodwin, B. K., and Featherstone, A. M. (2003). Modeling changes in the us demand for crop insurance during the 1990s. *Agricultural Finance Review*, 63(2):109–125.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 58(1):267–288.

Tsiboe, F. and Turner, D. (2023a). The crop insurance demand response to premium subsidies: Evidence from us agriculture. *Food Policy*, 119:102505.

Tsiboe, F. and Turner, D. (2023b). Econometric identification of crop insurance participation. *Agricultural and Resource Economics Review*, 52(3):476–497.

U.S. Department of Agriculture, Risk Management Agency (2023). 2023 risk management agency accomplishments. Technical report, United States Department of Agriculture, Risk Management Agency. https://www.rma.usda.gov/sites/default/files/2024-05/RMA%202023%20Accomplishment%20Text.pdf.

U.S. Government Accountability Office (2024). Farm programs: Usda financial assistance to agricultural producers for fiscal years 2019–2023. Technical Report GAO-25-107174, U.S. Government Accountability Office.

USDA Economic Research Service (2025). Crop insurance at a glance. https://www.ers.usda.gov/topics/farm-practices-management/risk-management/crop-insurance-at-a-glance. Accessed: 2025-08-10.

van de Geer, S., Bühlmann, P., Ritov, Y., and Dezeure, R. (2014). On asymptotically optimal confidence regions and tests for high-dimensional models. *The Annals of Statistics*, 42(3):1166 – 1202.

Wang, R., Rejesus, R. M., and Aglasan, S. (2021). Warming temperatures, yield risk and crop insurance participation. *European Review of Agricultural Economics*, 48(5):1109–1131.

Weber, J. G., Key, N., and O'Donoghue, E. (2016). Does federal crop insurance make environmental externalities from agriculture worse? *Journal of the Association of Environmental and Resource Economists*, 3(3):707–742.

Woodard, J. D. and Yi, J. (2020). Estimation of insurance deductible demand under endogenous premium rates. *Journal of Risk and Insurance*, 87(2):477–500.

Yu, J., Smith, A., and Sumner, D. A. (2018). Effects of crop insurance premium subsidies on crop acreage. *American Journal of Agricultural Economics*, 100(1):91–114.

Tables and Figures

Table A.1: Corn: Summary Statistics of Key Variables

Variable	**Mean**	**SD**
Relative insured acres (1)	0.584	0.281
Premium per acre ($/acre)	7.100	3.981
Average historic yield (4-year lag, bu/acre)	125.999	35.429
Subsidy per acre ($/acre)	10.939	7.508
Expected loss ratio (1)	0.846	0.872
Expected growing season moderate heat degree days	1852.246	483.808
Expected growing season extreme heat degree days	5.196	15.006
Premium $\times$ demeaned expected loss ratio	0.230	5.148
Premium $\times$ demeaned expected moderate heat degree days	22.963	1285.222
Premium $\times$ demeaned expected extreme heat degree days	0.935	64.079

Table A.2: Soybeans: Summary Statistics of Key Variables

Variable	**Mean**	**SD**
Relative insured acres (%)	0.598	0.283
Premium per acre ($/acre)	5.191	2.710
Average historic yield (4-year lag, bu/acre)	38.409	9.776
Subsidy per acre ($/acre)	7.948	4.883
Expected loss ratio	0.722	0.692
Expected growing season moderate heat degree days	1869.895	445.821
Expected growing season extreme heat degree days	1.243	3.936
Premium $\times$ demeaned expected loss ratio	0.151	3.005
Premium $\times$ demeaned expected moderate heat degree days	-6.028	794.218
Premium $\times$ demeaned expected extreme heat degree days	0.117	14.255

Table A.3: Classification of Other Control Variables with Monthly Detail

Category	Variables
Input and Output Prices feburary	Natural gas price, Potash price, Diammonium phosphate price, Urea price, Corn (or Soybean) price, Corn-soybean price ratio
Land and Soil Characteristics	Cropland area, T factor (soil loss tolerance), R factor (rainfall erosivity), V factor (vegetative cover), K factor (soil erodibility), WC factor (wind erodibility), I factor (infiltration), Water erosion index, C factor (cover management), P factor (support practice), Slope length, Slope percent, Wind erosion index, WK factor, WL factor, WV factor
Drought and Moisture Indices (indicator variable)	PDSI (April, May, June, July, August, September), Z-Index (April, May, June, July, August, September), Hydrological Drought Index (April, May, June, July, August, September), Modified Drought Index (April, May, June, July, August, September)
Cumulative Precipitation	Cumulative precipitation (April, May, June, July, August, September)
Temperature Degree Days	Moderate heat degree days (April, May, June, July, August, September), Extreme heat degree days (May, June, July, August, September)

Table A.4: Main estimates of the effect on relative insured acres from the change-point model (Corn)

Variable	**Coefficient**
Pre-1995	
Premium per acre ($/acre)	-0.031***
	(0.001)
Average yield (4-year lag, bu/acre)	0.000
	(0.000)
Subsidy per acre ($/acre)	0.092***
	(0.002)
Premium $\times$ Expected loss ratio	0.013***
	(0.001)
Premium $\times$ Expected extreme-heat degree days	0.011
	(0.012)
Post-1995	
Post-1995 intercept	0.450***
	(0.049)
Premium per acre ($/acre), post-1995	-0.073***
	(0.001)
Average yield (4-year lag, bu/acre), post-1995	0.003***
	(0.000)
Subsidy per acre ($/acre), post-1995	-0.118***
	(0.001)
Premium $\times$ Expected loss ratio, post-1995	0.011***
	(0.001)
Premium $\times$ Expected moderate-heat degree days, post-1995	0.014*
	(0.008)
Premium $\times$ Expected extreme-heat degree days, post-1995	0.150***
	(0.022)

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Main estimates of the effect on relative insured acres from the change-point model (Soybeans)

Variable	**Coefficient**
Pre-1995	
Premium per acre ($/acre)	-0.113***
	(0.002)
Subsidy per acre ($/acre)	0.095***
	(0.002)
Premium × Expected loss ratio	0.013***
	(0.002)
Premium × Expected moderate-heat degree days	0.024**
	(0.010)
Premium × Expected extreme-heat degree days	-0.870***
	(0.015)
Post-1995	
Post-1995 intercept	0.662***
	(0.085)
Premium per acre ($/acre), post-1995	-0.071***
	(0.001)
Average yield (4-year lag, bu/acre), post-1995	0.014***
	(0.000)
Subsidy per acre ($/acre), post-1995	-0.182***
	(0.001)
Premium × Expected loss ratio, post-1995	0.018***
	(0.002)
Premium × Expected moderate-heat degree days, post-1995	-0.034***
	(0.013)
Premium × Expected extreme-heat degree days, post-1995	-0.075***
	(0.020)

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

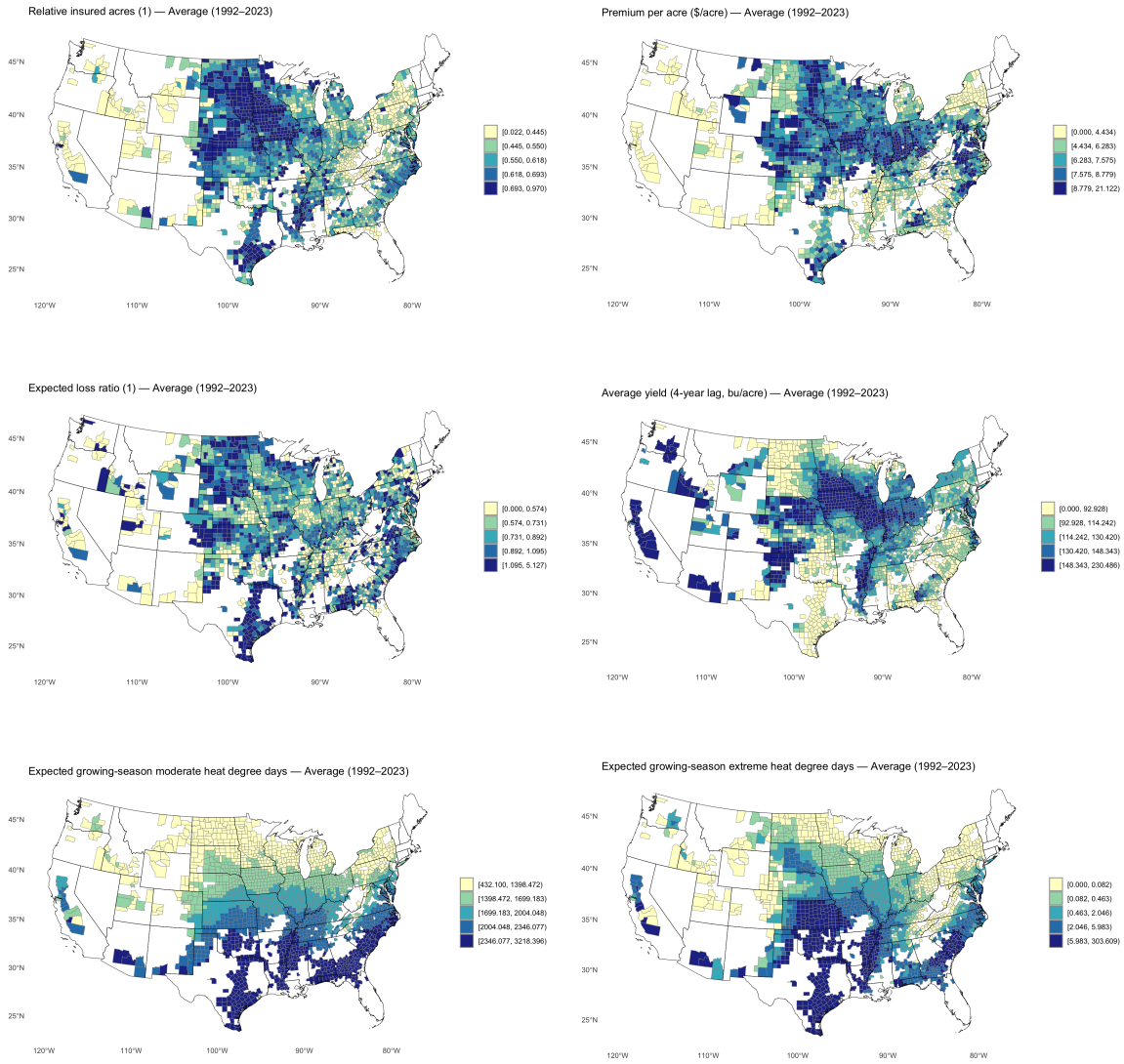


Figure A.1: Spatial distribution of selected variables for corn by county (1992–2023)

Note: Shaded counties indicate county-level average values for each variable over the period 1992–2023. The shading intensity corresponds to the magnitude of the average value for that variable; darker shades indicate higher values.

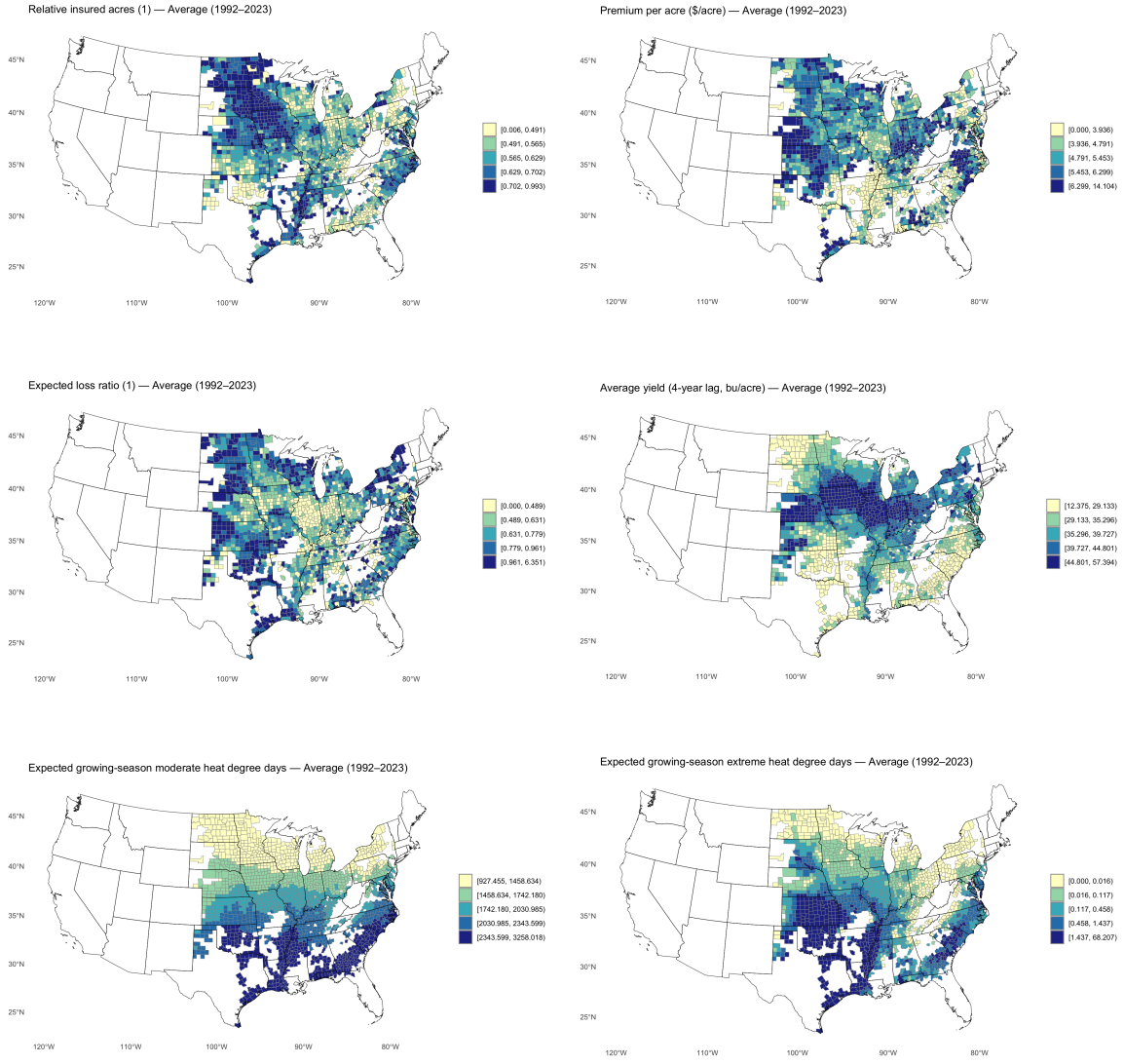


Figure A.2: Spatial distribution of selected variables for soybeans by county (1992–2023)

Note: Shaded counties indicate county-level average values for each variable over the period 1992–2023. The shading intensity corresponds to the magnitude of the average value for that variable; darker shades indicate higher values.