

Managing Heat Risk: Crop Insurance and Rural Economic Resilience

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Managing Heat Risk: Crop Insurance and Rural Economic Resilience*

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Abstract

This paper traces weather extremes through the Federal Crop Insurance Program (FCIP), the single largest form of federal support for US agricultural production, and into rural labor markets, estimating first how weather shocks drive FCIP enrollment and then how enrollment shapes the employment consequences of those same shocks. We combine policy-level FCIP enrollment records from 1991 to 2019 with establishment-level data on the near-universe of US businesses. We have two central findings. First, farmers respond to adverse weather and yield shocks by increasing insurance participation: a 10 percent yield decline increases insured acreage by approximately 4.9 percent for corn and 3.4 percent for soybeans. Projecting this response forward under RCP 4.5, climate-driven enrollment growth alone is estimated to raise program costs by 4–9 percent for corn and soybeans by midcentury, a magnitude comparable to fiscal analyses that attribute cost increases primarily to higher liabilities. Second, FCIP enrollment substantially mitigates the adverse effects of extreme heat on rural labor markets and generates positive spillovers to nontradable sectors, such as retail, hospitality, and health care. Our attribution exercise suggests that, during 2015–2019, the FCIP preserves about 95,000 rural jobs annually at an average program cost of roughly \$53,000 per job. These findings highlight the program’s role in supporting rural economic resilience and should be considered alongside fiscal sustainability concerns in ongoing policy discussions.

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1 Introduction

The Federal Crop Insurance Program (FCIP) is one of the most important agricultural support programs available to US farmers. Established in 1938 and greatly expanded in size and scope in the 1990s and 2000s, it offers financial protection against losses from drought, hail, wind, plant disease, and crop price fluctuations. It is administered by the US Department of Agriculture’s Risk Management Agency and available for 134 different commodities. In 2000–2022, an average 293 million acres of farmland were enrolled each year, comprising 81 percent of eligible acreage.

The FCIP is the single largest financial assistance program for agricultural producers, and its cost has risen sharply over the past two decades. According to a 2023 Government Accountability Office (GAO) report, it costs approximately \$14 billion annually in subsidies, with both indemnity payments and administrative costs increasing rapidly in recent years (Morris and Kaczmarek, 2023). Concerns over the rising fiscal costs and distortionary effects of subsidies on producer behavior have led to calls for reforms (Annan, 2024; Melear and Theodorou, 2024). As weather extremes intensify, these trends raise fundamental questions about how farmers use crop insurance as a financial safety net and what role the program plays in managing climate risk. Advocates for it, and for agricultural support programs more generally, often emphasize its purported broader economic benefits, especially in sustaining local rural economies. Whether the safety net benefits and local economic impacts justify the rising costs is unclear.

Research has largely focused on how crop insurance demand responds to prices, subsidies, or policy parameters, with less attention paid to dynamic responses after realized weather shocks and very limited empirical analysis of program impacts on local employment (Goodwin, 1993; Serra et al., 2003; O’Donoghue, 2014; Tsiboe and Turner, 2023). In particular, it remains unclear whether exposure to recent extreme weather leads farmers to adjust insurance coverage in subsequent years, despite its relevance for the program’s long-run costs and sustainability, and whether changes in coverage have measurable ancillary effects on job growth and other economic outcomes.

Given its size and scope, the FCIP is likely to have economic impacts that extend beyond the farm sector, as weather shocks to agriculture can propagate to local labor markets and nontradable industries through changes in farm income, employment, and consumption. By stabilizing farm revenues after adverse weather events, the FCIP may dampen these spillovers and enhance the economic resilience of rural communities. A 2013 White House report argues that FCIP indemnity payments help sustain business investment and household spending after natural disasters, thereby

protecting jobs in not only agriculture but also health care, entertainment, and food services (Executive Office of the President, 2013).

We address these research gaps by studying two related questions. First, we examine how farmers adjust their FCIP decisions in response to weather shocks experienced in the previous year, providing evidence on insurance take-up as a form of adaptation to increasing heat risk. Second, we analyze how FCIP enrollment affects outcomes in rural labor markets, distinguishing between direct effects on the agricultural sector and spillover effects on local nontradable sectors.

Our analysis focuses on the eastern United States and relies on county-level measures constructed from spatially granular underlying data whenever possible. We use killing degree days (KDDs), a measure of cumulative heat exposure above the physiological tolerance point where additional temperature no longer contributes to growth and instead reduces yield, built around crop-specific damage thresholds estimated directly from the yield data and aggregated to counties using the spatial distribution of actual planted acreage. To study take-up, we pair these measures with policy-level FCIP records in a county–crop–year panel for corn and soybeans—the two largest US crops by acreage and revenue—and estimate the effect of last season’s realized yield on this year’s enrollment, instrumenting lagged yield with lagged weather. To study rural labor markets, we build a county–industry–year panel from establishment-level data, restricted to rural areas and disaggregated by industry, and ask whether heat depresses employment less where more cropland is insured, comparing the directly covered and spillover sectors against a set of control industries in the same county and year. Finally, we combine both estimates with downscaled climate projections under RCP 4.5 to extend enrollment, program costs, and employment effects to midcentury.

We find that farmers respond to adverse weather and yield shocks by increasing FCIP participation, primarily along the extensive margin: counties experiencing lower yields in the previous growing season enroll significantly more acres in the subsequent year, with our estimates implying that a 10 percent yield decline increases insured acreage by roughly 4.9 percent for corn and 3.4 percent for soy. Farmers do not, however, buy deeper protection on the land they already insure: yield losses leave the average coverage level (the percentage of expected yield or revenue guaranteed per acre) essentially unchanged. A complementary exercise attributes enrollment directly to warming: under RCP 4.5, we project temperature-driven uptake will reach 3.51 percent of corn and 8.43 percent of soy acreage by midcentury, raising expected annual program losses by about \$41.6 million for corn and \$38.1 million for soy (increases of 3.7 percent and 9.0 percent, respectively, relative to 2000–2025 baseline losses).

We further find that crop insurance plays an important protective role in insulating rural economies from the adverse effects of extreme heat shocks, which significantly depress employment and establishment growth in agricultural industries and, to a lesser extent, local nontradable sectors that are affected by agricultural activity and farm income. However, higher FCIP coverage substantially mitigates these effects through both insurance coverage and realized indemnity payments. The largest effects accrue to directly insured industries, with additional gains propagating to retail, accommodation, selected services, and other locally oriented sectors. Our estimates indicate that FCIP enrollment preserved approximately 67,000 jobs per year on average between 1991 and 2019, with spillover effects outside of agriculture accounting for the bulk of this, as these sectors employ a much larger share of the population. By midcentury under RCP 4.5, both the heat threat and FCIP’s protective benefit are projected to grow substantially, with annual jobs preserved rising to 110,000, of which the climate-driven increment grows roughly tenfold (from 5,400 to 50,000).

This paper contributes to several strands of the literature. First, it relates to a body of work examining FCIP impacts, which has primarily focused on farmers’ production decisions and farm-level outcomes. Studies find that FCIP participation leads to modest increases in planted acreage (e.g., [Goodwin, 1993](#); [Claassen et al., 2017](#); [Yu et al., 2018](#); [Shi et al., 2020](#)), but evidence on input use and production intensity remains mixed (e.g., [Horowitz and Lichtenberg, 1993](#); [Smith and Goodwin, 1996](#); [Deryugina and Konar, 2017](#); [Mieno et al., 2018](#)). Using farm-level longitudinal data from Kansas, [DeLay et al. \(2023\)](#) show that crop insurance indemnities help farmers manage liquidity constraints and smooth financial outcomes after adverse shocks. Our findings complement this literature by highlighting that farmers actively update their coverage in response to realized weather and yield shocks, underscoring the role of FCIP enrollment itself as a dynamic risk management decision.

Our paper also connects to an emerging literature on farmers’ adaptation and learning behaviors in response to short-run weather shocks. Studies have largely focused on adjustments in planting decisions, production practices, and consumption (e.g., [Ding et al., 2009](#); [Burke and Emerick, 2016](#); [Huang and Moore, 2018](#); [Ji and Cobourn, 2021](#); [Ahmed et al., 2023](#); [Cui and Tang, 2024](#)); we document adaptive responses in financial risk management through crop insurance participation.

By examining FCIP impacts on rural businesses and labor-market outcomes, we provide a unique lens on the connection between agriculture and the broader rural economy. Despite frequent assertions of such linkages,¹ empirical studies are relatively few, with much of the evidence based

¹For example, the USDA Economic Research Service regularly publishes reports describing trends in measures

on input–output models that rely on strong and largely untested assumptions about intersectoral relationships (Harrison, 1993; Paggi et al., 2011). Modeling-based studies generally suggest that crop insurance indemnity payments generate positive spillovers to other sectors (Leatham et al., 1997; Santangelo, 2019; Welch et al., 2024). In contrast, Weber et al. (2014) use the sharp increase in crop prices in the late 2000s and exploit variation across counties in agriculturally productive land to study the impacts of higher agricultural revenues on county economic outcomes in the US heartland, finding that higher revenues raise farm but generally not nonfarm income and employment. Their county-level data from the Bureau of Economic Analysis do not distinguish between urban and rural employment within counties, however, which may attenuate estimated nonfarm effects. Our analysis addresses this limitation by constructing industry-level establishment and employment measures restricted to rural areas within each county, allowing us to provide more targeted evidence.

Our findings also connect to a broader literature on the role of insurance in supporting community financial resilience and economic recovery after adverse shocks. A growing body of evidence shows that insurance payments can stabilize household finances and sustain local economic activity after disasters. For example, higher insurance coverage has been shown to increase households’ ability to participate in local economies and support business activity after floods (You and Kousky, 2024), and insurance payouts played a central role in economic recovery after the earthquake in Christchurch, New Zealand (Nguyen and Noy, 2020). Related work finds that flood insurance reduces mortgage delinquency and financial distress among affected households (Gallagher and Hartley, 2017; Kousky et al., 2020), and cross-country evidence suggests that economies with higher insurance penetration experience smaller real economic losses after disasters (von Peter et al., 2012; Melecky and Raddatz, 2015). More broadly, these findings echo evidence from unemployment insurance, which generates spillovers through local demand stabilization (Di Maggio and Kermani, 2016; Hellwig, 2021). Our results extend this literature by showing that crop insurance similarly buffers rural labor markets, transmitting risk protection to the broader local economy.

The remainder of this paper is organized as follows. Section 2 provides background on the program. Section 3 describes our data sources and procedures. Section 4 discusses our estimation framework for both analyses. Section 5 presents and interprets the results. Section 6 concludes.

of economic output for rural areas, including its annual “Rural America at a Glance” report. The 2024 edition is available at <https://www.ers.usda.gov/publications/pub-details?pubid=110350>.

2 Policy Background

The FCIP is the primary source of crop insurance for farmers to manage weather- and market-related income risks. Administered by USDA’s Risk Management Agency (RMA), it provides protection against yield losses, price declines, and revenue shortfalls caused by weather, pests, and market volatility. Although private insurance companies deliver and service policies, the federal government subsidizes, reinsures, and regulates them. Participation is voluntary, and farmers can choose among yield-only, revenue-based, livestock, whole-farm, and area-trigger products. Policies typically indemnify farmers when realized yields or revenues fall below a guaranteed level based on historical yield averages, futures market prices, and the elected coverage level.

Although the program was instituted by the 1938 Federal Crop Insurance Act, meaningful nationwide uptake did not occur until the 1980s and 1990s, when multiple legislative reforms expanded access and increased subsidization. In 1994, the Federal Crop Insurance Reform Act introduced a fully subsidized catastrophic coverage to producers, protecting them against severe losses (over 50 percent of yield) for just an administrative fee and no premium cost. This provision dramatically increased participation. Farm Bills in 1996, 2000, 2008, 2014, and 2018 continued to raise premium subsidies, expand eligible crops, and introduce supplemental revenue policies. In recent years, the federal government pays roughly 60 percent of producers’ premiums, and participation is pervasive: in crop year 2019, it insured \$116 billion worth of crops and livestock, including over 85 percent of planted acres for corn, soybeans, cotton, and wheat ([Rosch, 2021](#)).

Debates around the Farm Bill in 2026 continue to weigh the FCIP’s fiscal costs and economic benefits. On one hand, the program enhances the resilience of the agriculture sector by reducing farm income volatility and may also mitigate the downstream effects of agricultural losses from weather and pest shocks on local labor markets, input suppliers, and nonfarm service sectors. On the other hand, critics argue that subsidized insurance may distort production decisions by encouraging cultivation on marginal lands, weaken incentives for on-farm risk mitigation, and disproportionately benefit large and capital-intensive operations ([Annan and Schlenker, 2015](#); [Lusk, 2017](#); [Wu et al., 2020](#); [Azzam et al., 2021](#); [Biram et al., 2024](#); [Obolensky, 2024](#)). The FCIP also represents a substantial and growing share of Farm Bill spending: CBO’s February 2026 baseline projects nearly \$156 billion over fiscal year 2027–2036, roughly 11 percent of the \$1.4 trillion in total projected Farm Bill outlays and the single largest mandatory farm program outside of nutrition assistance and commodity support ([Congressional Budget Office, 2026](#)). These costs have also risen sharply,

up 17 percent, or \$23 billion, from the January 2025 baseline, due largely to legislated expansions in premium support and coverage eligibility ([Congressional Budget Office, 2026](#)). Layered onto this legislated growth is a climate-driven long-term cost trend: a 2022 Office of Management and Budget analysis of climate risk exposure to the federal government projected a 3.5–22 percent increase in premium subsidies by 2080 ([OMB, 2022](#)). These trends suggest that rising costs reflect at least two compounding pressures—ongoing legislative expansion of subsidies and a climate-driven shift in the underlying loss distribution—raising the question of long-term fiscal stability of the program.

3 Data

3.1 FCIP Enrollment and Indemnities

We measure FCIP enrollment using the RMA’s Summary of Business dataset, available from 1989 onward.² The dataset reports acreage insured, premium, subsidy, liability, and indemnity by crop, county, year, insurance plan type, and coverage level.

To analyze the effects of past heat shocks, we construct two measures of FCIP uptake by crop, county, and year: (i) total insured acres (the extensive margin) and (ii) the average coverage level among insured acres (the intensive margin). Because different crops have different sensitivity to heat, we separately examine insurance uptake for corn and soybeans, the two largest US crops in terms of acreage and revenues.

To analyze the effects on rural business and employment outcomes, we develop a county-level measure of overall FCIP protection as the share of each county’s enrolled cropland across all crops for each year. To measure total cropland, we use the maximum cropped area observed 2008–2019 in the Cropland Data Layer.³ This approach follows [Annan and Schlenker \(2015\)](#).

We also obtain FCIP indemnities data from the Summary of Business, which report payments by crop, county, year, and cause of loss. The dominant causes are “drought and high temperature” and “excess moisture.” We aggregate indemnities across crops to the county–year level.

3.2 Weather Data

We construct high-resolution measures of agricultural heat exposure using daily minimum and maximum temperature data from [PRISM Climate Group \(2023\)](#) at approximately 4km spatial res-

²<https://www.rma.usda.gov/tools-reports/summary-of-business>.

³https://www.nass.usda.gov/Research_and.Science/Cropland/Release/index.php.

olution. For each grid cell, we model the full daily temperature curve and calculate exposure in 1°C bins across the growing season, allowing us to recover the distribution of temperatures experienced by each crop. These grid-level measures are aggregated to county–crop–year using weights based on crop-specific planted area from the Cropland Data Layer ([USDA National Agricultural Statistics Service, 2022](#)), ensuring that weather exposure reflects where production actually occurs.

To construct temperature shock measures that are most relevant for yield risk, we take a data-driven approach. Using historical county-level yields, we estimate nonlinear temperature–yield relationships and identify the crop-specific threshold at which heat becomes damaging: 27°C for corn and 30°C for soybeans, consistent with the literature ([Schlenker and Roberts, 2009](#); [Schauberger et al., 2017](#)). Based on these thresholds, we construct KDDs and growing degree days (GDDs), which captures beneficial heat accumulation below the threshold. By combining fine spatial and temporal granularity with empirically derived biological cutoffs, these two measures more closely align with crop response mechanisms and improve the ability to detect heat impacts on insurance take-up and rural economic outcomes. Full methodological details are provided in Appendix B.

We apply an analogous aggregation scheme to construct measures of precipitation, calculating total and squared growing-season rainfall over cropped area in each county-year. These measures allow us to control for rainfall using a quadratic function.

For analyses of rural business and employment outcomes that are not crop specific, we construct county-level weather measures by averaging corn- and soy-specific KDDs and precipitation exposures, weighted by each crop’s planted acreage.

3.3 Agricultural Outcomes

County-level yield data for corn and soybeans are obtained from the USDA National Agricultural Statistics Service County Agricultural Production Survey for 1981–2022 ([USDA National Agricultural Statistics Service, 2023](#)). Yields are measured in bushels per harvested acre and reported as annual county averages. These data offer a consistent measure of realized agricultural productivity across major producing counties.

3.4 The National Establishment Time Series (NETS)

To measure rural economic outcomes, we use the NETS Database, which contains establishment-level data on every US establishment (private and government) 1990–2022. It allows us to observe employment levels for each establishment, emergence of new establishments during the sample

period, and whether existing ones continue their operation each year. The data provide industry classification at the 6-digit NAICS code level, number of employees in each year, and precise location (both street address and latitude/longitude). The database is based on archival Dun and Bradstreet data, originally collected for business analytics purposes. Compared to restricted-access government establishment-level data, such as the Census Bureau’s Longitudinal Business Database (LBD), NETS has two key advantages in our setting. First, the LBD covers nonfarm private establishments only, whereas NETS covers the full universe of establishments, including those in the agricultural industry, public, and nonprofit sectors. This is crucial for studying the direct impacts of the FCIP on agriculture. Second, NETS includes more comprehensive records of small businesses and thus better represents rural economies (Neumark et al., 2007; Walls et al., 2020).

We filter out establishments in urban areas. We use the urban-rural classification by the Census Bureau, which defines an urban area as a densely settled core of Census blocks based on housing unit and/or population density.⁴ We also restrict the sample to before 2020 to exclude economic disruptions from the COVID-19 pandemic.

Next, we classify establishments into aggregate industries using their NAICS code,⁵ mostly following the standard two-digit NAICS sector but with more granularity in the agriculture sector (see Table 1), and calculate total employment and establishments with at least two employees⁶ at the aggregate industry, county, and year level to form the core of our estimation dataset.

As shown in Table 1, we assign aggregate industries into three groups depending on their hypothesized treatment effect. The first includes the agriculture and adjacent industries that we expect to directly benefit from the protective effect of FCIP enrollment. The second comprises industries in the local nontradable sector, including retail, accommodation and food services, health care, and education, that could be affected by spillover effects from FCIP enrollment. The third incorporates industries for which FCIP should have no effect, including mining, manufacturing, and public administration; it serves as a control group.

⁴See <https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural.html> for more details.

⁵The NAICS code follows a hierarchical structure, where the first two digits represent sectors, the first three represent subsectors within the sectors, and so on. For a full list of two-digit NAICS sectors, see <https://www.census.gov/programs-surveys/economiccensus/year/2022/guidance/understandingnaics.html>.

⁶We count establishments with more than one employee because we want to focus on those that create employment opportunities at the local labor market.

Table 1: Industry Treatment Group Classification

Description	NAICS code
A. Direct Effect—Agriculture and Adjacent Industries	
Crop Production	111
Animal Production and Aquaculture	112
Fishing and Hunting	113-114
Support Activities for Agriculture and Forestry	115
Ag-related Wholesale	
Grocery and Related Product Merchant Wholesalers	4244
Farm Product Raw Material Merchant Wholesalers	4245
Farm and Garden Machinery and Equipment Merchant Wholesalers	423820
Farm Supplies Merchant Wholesalers	424910
B. Spillover Effect—Local Nontradable Sector	
Retail	44-45
Finance and Insurance	52
Other Real Estate and Rental and Leasing	53
Educational Services	61
Health Care and Social Assistance	62
Accommodation and Food Services	72
C. No Effect—Control Industries	
Mining, Quarrying, and Oil and Gas Extraction	21
Manufacturing	31-33
Public Administration	92

4 Econometric Framework

In this section, we outline the econometric framework for the two main analyses. First, we examine how recent heat shocks affect farmers’ take-up of FCIP as a tool to manage temperature-induced production risks. Second, we assess how FCIP participation influences the resilience of rural business establishments to extreme heat events.

4.1 Heat Shocks, Crop Yields, and Insurance Take-Up

This analysis focuses on corn and soybean production, with heat exposure, yields, and crop insurance uptake all measured by crop at the county-year level. For each crop, we estimate the following specification:

$$Uptake_{ct} = \alpha_1 GDD_{c,t-1} + \alpha_2 KDD_{c,t-1} + \alpha_3 Prcp_{c,t-1} + \alpha_4 \ln(PlantAcres_{ct}) + \delta_c + \lambda_t + \varepsilon_{ct} \quad (1)$$

The outcome $Uptake_{ct}$ is either log insured acres or average coverage level across all insured acres in county c and year t . Insurance uptake is modeled as a function of the previous growing season’s GDDs ($GDD_{c,t-1}$) and KDDs ($KDD_{c,t-1}$). GDDs measure the cumulative warmth above a crop’s minimum growth threshold, used to predict development stages, like flowering or harvest. KDDs measures the cumulative cold (or extreme heat) below (or above) a plant’s safe threshold, used to estimate the risk of frost or heat damage. Other weather controls include a quadratic function of total precipitation (Prp_{ct}) and log planted acres in the current year ($\ln(PlantAcres_{ct})$). The model also includes county and year fixed effects to control for cross-sectional variation in climate conditions and general changes over time that affect all counties, such as changes in FCIP subsidy level, commodity prices, or other macroeconomic shocks. Standard errors are clustered by state.

As we hypothesize that previous year’s weather affects insurance uptake through its impacts on previous year’s crop yield, we can cast the estimation in a two-stage-least-squares (2SLS) framework, where we estimate the relationship between yield and weather shock in the first stage:

$$Yield_{ct} = \beta_1 GDD_{ct} + \beta_2 KDD_{ct} + \beta_3 Prp_{ct} + \beta_4 \ln(PlantAcres_{ct}) + \delta_c + \lambda_t + \varepsilon_{ct}, \quad (2)$$

which simply replaces the outcome in Equation (1) with contemporaneous crop yields. In the second stage, we estimate the relation between uptake and lagged yield using the following equation:

$$Uptake_{ct} = \gamma_1 \widehat{Yield}_{c,t-1} + \gamma_2 \ln(PlantAcres_{ct}) + \delta_c + \lambda_t + \varepsilon_{ct}. \quad (3)$$

Essentially, we use lagged weather variables to instrument for lagged crop yield and estimate its effect on crop insurance uptake decision in the next crop year. Compared to the reduced-form regression, the 2SLS framework requires two assumptions. First, the instruments are relevant (i.e., weather shocks are strong drivers of crop yields). Equation (2) is similar to the regressions employed in a large literature that establishes that weather shocks, especially extreme heat, strongly affect crop yields. The second assumption is an exclusion restriction, that weather shocks do not affect uptake through channels other than their impacts on crop yields.

Finally, we use our estimates from Equation (1) to conduct a historical attribution of FCIP uptake to changing temperatures and project it for corn and soy to 2050 under climate change. We begin by constructing a county-specific temperature baseline using mean GDD and KDD over the pre-2000 period and restrict the analysis to counties with planted acreage in the last 10 observed years. We then conduct the historical attribution by generating two predictions of FCIP

coverage for every county-year and crop: from realized GDD and KDD and from the county’s baseline values. To convert predictions of log acres covered back to levels, we apply a smearing factor recovered from the residuals to correct for retransformation bias (Duan, 1983) and cap total coverage at observed planted acres. We treat the difference between the two predictions as the share of FCIP enrollment attributable to temperature.

To project FCIP coverage forward under climate change, we calculate county-level GDD and KDD for 2020–2050 under RCP 4.5 from a probability-weighted ensemble of the 21 CMIP5 climate projections in the NASA Earth Exchange Global Daily Downscaled Projections dataset, downscaled to a $0.25^\circ \times 0.25^\circ$ resolution. Following Rasmussen et al. (2016), each projection is assigned a probabilistic weight so that the ensemble’s distribution of global mean surface temperature is consistent with that of a probabilistic simple climate model. We allow planted acreage to increase over time using a linear trend estimated from the historical time series. For each year, we again predict covered acres twice, once at projected GDD and KDD and once at the pre-2000 baseline values, and take the difference as the projected temperature-driven change in FCIP coverage.

4.2 Crop Insurance Take-up and Rural Business Establishments

This analysis is conducted at the county–year level and does not differentiate across crops, reflecting our focus on the broader rural economy. Our primary regression specification is

$$\begin{aligned}
Growth_{ict} = & \beta_1 KDD_{ct} + \beta_2 Cover_{ct} + \beta_3 KDD_{ct} \cdot Cover_{ct} + \\
& \beta_4 KDD_{ct} \cdot Direct_i + \beta_5 Cover_{ct} \cdot Direct_i + \beta_6 KDD_{ct} \cdot Cover_{ct} \cdot Direct_i + \\
& \beta_7 KDD_{ct} \cdot Spillover_i + \beta_8 Cover_{ct} \cdot Spillover_i + \beta_9 KDD_{ct} \cdot Cover_{ct} \cdot Spillover_i + \\
& X_{ct}\gamma + \alpha_{ic} + \theta_{st} + \delta_{it} + \varepsilon_{icst}.
\end{aligned} \tag{4}$$

The outcome $Growth_{icst}$ is the growth rate of either employment or number of establishments with at least two employees in industry i , county c , and year t . We model the outcome as a function of a fully saturated set of interactions between KDDs (KDD_{ct}), share of cropland covered by the FCIP ($Cover_{ct}$), and indicators of industry treatment groups ($Direct_i$ and $Spillover_i$).

Crop insurance protects farmers against negative shocks to crop yields and farm revenues, and a leading cause of loss is drought and high temperature. The model estimates these effects in two coefficients of interest. β_4 , which corresponds to the interaction between KDDs and the direct

treatment group, captures the primary effect of extreme heat on agriculture and adjacent industries. β_6 captures the protective effect of crop insurance by further interacting this term with the share of cropland insured under FCIP. These coefficients represent effects relative to the control industries, which are treated as the reference group in this regression.

The effects of both extreme heat and crop insurance might affect agricultural workers' disposable income and consumption decisions, which might spill over to the nontradable sector in the local economy. To allow the spillover effects to differ from the direct effects, we include a parallel set of interactions that replace the direct treatment indicator with the spillover treatment indicator, where the coefficients of interest β_7 and β_9 have similar interpretations as β_4 and β_6 , respectively.

The other terms in the model serve as controls for the underlying correlations between insurance decisions, weather risk, and local economic conditions. For example, $Cover_{ct}$ controls for the endogeneity of insurance decision to local economic conditions. Its interaction with KDD accounts for the possibility that more vulnerable industries or counties might choose more coverage. Similarly, its interaction with the industry treatment group indicators allows for endogenous insurance decisions based on sectoral composition. The model also includes controls at the county-year level (X_{ct}), including a quadratic function of growing season precipitation and log planted acres.

We also use a rich set of fixed effects to control for confounding factors varying across time, space, and industry. The industry-by-county fixed effects (α_{ic}) control for cross-sectional variation between economic growth and industry composition, the state-by-year fixed effects (θ_{st}) control for macroeconomic trends at the state level, and the industry-by-year fixed effects (δ_{it}) control for national trends in each industry.

As our main outcomes are growth rates, they might be subject to extreme values if an industry has very few establishments and jobs in a county. To alleviate this concern, we weight all the regressions using lagged employment or number of establishments. We also cluster the standard errors by county throughout to account for correlations within county, including those between industries and across time.

5 Results

5.1 Heat Shocks and Crop Insurance Take-Up

In this section, we examine how farmers' crop insurance decisions respond to weather conditions and realized crop yields in the previous growing season. We estimate the regressions outlined in

Section 4.1 using two separate county-by-year datasets constructed for corn and soybeans, each containing information on yields, heat exposure, and insurance uptake. Table A1 reports summary statistics for the two samples in separate panels.

The results for corn are reported in Table 2. Columns (1) and (2) present the OLS and 2SLS estimates, respectively, of the relationship between log FCIP-covered acres and lagged yield. In the 2SLS specification, lagged yield is instrumented using lagged weather shocks (KDDs, GDDs, and precipitation). Both estimates are negative and statistically significant, indicating that lower yields in the prior year lead to greater FCIP enrollment. The 2SLS estimate is roughly four times larger, suggesting that the OLS estimate likely understates the behavioral response. This pattern is consistent with attenuation due to classical measurement error in yields or omitted variables that are positively correlated with both yield potential and lower insurance demand. For example, counties with improving soil quality or production technologies may achieve higher yields while also perceiving less need for insurance, biasing the OLS estimate toward zero. By instrumenting yields with weather shocks—which affect yields exogenously but are plausibly uncorrelated with these latent characteristics—the 2SLS estimates more cleanly isolate the effect of yield losses on subsequent insurance uptake. The point estimate implies that a one-bushel-per-acre decline in yield increases FCIP-covered acres by approximately 0.4 percent, corresponding to a 4.9 percent increase for a 10 percent yield decline.

Column (7) reports the first-stage results, which relate yields to growing-season weather conditions. As expected, GDDs significantly increase yields and KDDs reduce them, and precipitation exhibits a significant nonlinear relationship with yield. One KDD has more than four times the marginal effect of one GDD on yields. The first-stage F-statistic of 29.43 confirms the strength of the instruments. Column (3) presents the corresponding reduced-form estimates, obtained by regressing log covered acres directly on weather shocks. Consistent with the first-stage results, FCIP enrollment increases significantly with KDDs and adverse precipitation conditions but shows no response to GDDs.

Columns (4)–(6) shift the focus to the average coverage level chosen within a county. Although both OLS and 2SLS estimates are positive, the magnitudes are economically small. The statistically significant 2SLS estimate implies that a 10 percent yield decline is associated with only a 0.0036-pp decrease in average coverage, against a sample mean of 66 percent. The reduced-form estimates in Column (6) are similarly negligible.

We can combine the estimated effects on the extensive margin (Column (2)) with those on the

Table 2: Variable Weather, Yield, and Federal Crop Insurance Program (FCIP) Take-Up for Corn

	<i>Dependent variable:</i>						
	ln(Covered Acres)			Coverage level			Yield _{t-1}
	OLS	2SLS	Reduced Form	OLS	2SLS	Reduced Form	Stage 1 (F = 29.43)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Yield _{t-1}	-0.001** (0.0005)	-0.004*** (0.001)		0.00002 (0.0001)	0.0003** (0.0001)		
GDD _{t-1}			0.00000 (0.0002)			0.0001*** (0.00003)	0.041*** (0.010)
KDD _{t-1}			0.001*** (0.0003)			0.00004* (0.00002)	-0.181*** (0.018)
Prcp _{t-1}			-0.001*** (0.0002)			-0.00002 (0.00002)	0.042*** (0.015)
Prcp _{t-1} ²			0.00000*** (0.00000)			0.000 (0.000)	-0.00003*** (0.00001)
ln(PlantAcres)	0.927*** (0.038)	0.932*** (0.042)	0.931*** (0.036)	0.008 (0.006)	0.007 (0.006)	0.008 (0.006)	0.844 (2.765)
Mean dep. var.	-	-	-	66.001	66.001	66.001	122.993
Observations	44,252	44,252	44,252	43,279	43,279	43,279	44,252
Adjusted R ²	0.940	0.939	0.941	0.816	0.813	0.819	0.770

Notes: This table reports estimates of the effects of lagged weather and yield shocks on FCIP takeup for corn. Columns (1) and (3) present OLS estimates based on Equation (3); Columns (2) and (4) report the corresponding 2SLS estimates. Columns (5) and (6) present reduced-form regressions as specified in Equation (1), and Column (7) reports the first-stage regression from Equation (2). Dependent variables are indicated in the top panel. Standard errors are clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

intensive margin (Column (5)) to estimate the total impact of yield on insurance coverage.⁷ Writing total coverage as $I \equiv A \times C$, the proportional response of I to yield is $\partial \ln I / \partial Y = \beta_A + \beta_C / \bar{C}$. Evaluated at the mean coverage level, a one-bushel-per-acre decline in yield raises total FCIP coverage by approximately 0.40 percent, corresponding to a 4.9 percent increase in total coverage for a 10 percent yield decline in the average county. Applying the reduced-form estimates in the same way, one additional KDD raises total coverage by roughly 0.10 percent, so that a 10 percent increase in KDDs raises coverage by about 1.3 percent in the average county. In both cases, the extensive margin accounts for essentially the entire response: the intensive-margin contribution is two orders of magnitude smaller and, if anything, slightly offsetting.

Table 3 reports analogous results for soybeans. The qualitative patterns closely mirror those observed for corn. Yield increases with GDDs, decreases with KDDs, and exhibits a nonlinear relationship with precipitation (Column (7)). The first-stage F-statistic is 54.89, again indicating strong instruments. In response to weather-driven yield losses, farmers increase the number of acres enrolled in FCIP: a 10 percent decline in yield is associated with a 3.0 percent increase in insured acreage under OLS (Column (1)) and a 3.4 percent increase under 2SLS (Column (2)). In contrast, average coverage level has no statistically or economically meaningful change (Columns (4)–(6)).

Appendix Table A2 reports an additional set of estimates examining the relationship between FCIP take-up and corn yields using a distributed lag specification. Although our baseline analysis focuses on responses to the most recent growing season, insurance decisions may reflect information accumulated over multiple seasons rather than a single year’s realization. Allowing yields to enter with multiple lags captures potential persistence, learning, and adjustment dynamics in insurance participation. Columns (1)–(3) use log FCIP-covered acres as the dependent variable and include one, two, and three lags of yield, respectively. Two notable patterns emerge. First, adding lags does not change the estimated coefficients on shorter lags, suggesting that excluding earlier yield realizations does not introduce meaningful omitted variable bias. Second, the coefficient on the most recent yield remains the largest in magnitude and most statistically significant across specifications. Together, these findings indicate that insurance decisions respond primarily to recent yield outcomes and support the validity of the baseline specification. Columns (4)–(6) report results for the average coverage level. Consistent with earlier findings, none of the yield lags are statistically significant.

⁷Let A denote covered acres, C the average coverage level, and total coverage $I \equiv A \times C$. Then $\frac{\partial I}{\partial Y} = C \cdot \frac{\partial A}{\partial Y} + A \cdot \frac{\partial C}{\partial Y}$. Let β_A denote the coefficient on lagged yield in the $\ln(\text{Covered Acres})$ regression (Column (2)) and β_C the corresponding coefficient in the coverage-level regression (Column (5)). Because the former is estimated in logs, $\frac{\partial A}{\partial Y} = \beta_A A$, and $\frac{\partial C}{\partial Y} = \beta_C$. Substituting and dividing through by I yields $\frac{\partial \ln I}{\partial Y} = \beta_A + \beta_C / \bar{C}$, where $\bar{C} = 66.0$ pp is the mean coverage level.

Table 3: Variable Weather, Yield, and FCIP Take-Up for Soybeans

	<i>Dependent variable:</i>						
	ln(CoveredAcres)			Coverage level			Yield _{t-1}
	OLS	2SLS	Reduced Form	OLS	2SLS	Reduced Form	Stage 1 (F = 54.89)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Yield _{t-1}	-0.008*** (0.001)	-0.009*** (0.002)		-0.0001 (0.0001)	0.0004 (0.0003)		
GDD _{t-1}			0.001*** (0.0001)			0.00000 (0.00002)	0.016*** (0.003)
KDD _{t-1}			0.003*** (0.0004)			-0.00003 (0.00004)	-0.078*** (0.008)
Prcp _{t-1}			-0.001*** (0.0002)			0.00002 (0.00002)	0.032*** (0.003)
Prcp _{t-1} ²			0.00000*** (0.00000)			-0.00000 (0.000)	-0.00002*** (0.00000)
ln(PlantAcres)	0.941*** (0.026)	0.942*** (0.027)	0.943*** (0.027)	0.006 (0.004)	0.005 (0.004)	0.005 (0.004)	0.659* (0.361)
Mean dep. var.	-	-	-	66.001	66.509	66.509	37.758
Observations	39,659	39,659	39,659	38,778	38,778	38,778	39,659
Adjusted R ²	0.929	0.929	0.930	0.821	0.820	0.821	0.771

Notes: This table reports estimates of the effects of lagged weather and yield shocks on FCIP take-up for soybeans. Columns (1) and (3) present OLS estimates based on Equation (3); Columns (2) and (4) report the corresponding 2SLS estimates. Columns (5) and (6) present reduced-form regressions as specified in Equation (1), and Column (7) reports the first-stage regression from Equation (2). Dependent variables are indicated in the top panel. Standard errors are clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

Overall, these results indicate that, in response to adverse weather and yield shocks, farmers primarily adjust along the extensive margin (acres enrolled) rather than the intensive margin (coverage level). Yield losses induce substantial increases in insured acreage but have negligible effects on the coverage levels farmers choose.

5.2 Projected Increase in FCIP Take-Up due to Climate Change

Figure 1 presents our historical attribution and projections of temperature-driven FCIP uptake for corn and soy. The left panels show planted acres (black), realized FCIP coverage (dark blue), the counterfactual FCIP coverage under pre-2000 baseline temperatures (light blue), and the difference

between the two—the share of FCIP enrollment attributable to temperature (red). Solid lines show historical attribution, and dotted lines show future projections. The right panels show the corresponding national, acreage-weighted *GDD* and *KDD* series, alongside their pre-2000 baselines.

Over the historical period, the temperature-driven increase in FCIP uptake has been modest: averaging across 2016–2020, warming accounts for roughly 0.17 million additional acres of corn enrolled (0.27 percent of total corn enrollment) and 1.54 million additional acres of soy (2.55 percent of total soy enrollment).

Under future climate scenario RCP 4.5, both *GDD* and *KDD* rise steadily through 2050, and the temperature-driven contribution to FCIP enrollment grows substantially: by the end of the projection period (2046–2050), warming is projected to raise corn enrollment by 2.72 million acres on average (3.51 percent) and soy enrollment by 5.93 million acres (8.43 percent). The implied effect of climate change on FCIP uptake by midcentury is therefore roughly an order of magnitude larger than the temperature-driven changes already observed in the historical record, with soy showing a larger absolute and proportional response than corn.

This increase in enrollment will have implications for the federal budget. In 2000–2025, mean net losses to the FCIP for corn and soy were \$15.29 (25–75th percentile = 1.95–19.46) and \$6.42 (25–75th percentile = 1.77–10.56) per acre, respectively. We define net loss as the difference between the indemnity amount and the premium payment received by the government (premium less subsidy). Net losses are highly variable over time (Figure A2) due to different indemnities.

With an additional 2.72 and 5.93 million acres of corn and soy, respectively, projected to be enrolled per year over 2046–2050, we expect annual losses to increase by \$41.6 and \$38.1 million. Compared to the 2000–2025 period, program losses increase by 3.7 and 9.0 percent for corn and soy, respectively.

These projections capture only the cost implications of additional acres entering the program in response to warming; they hold per-acre net loss rates fixed at their 2000–2025 historical averages and therefore do not incorporate any direct effect of climate change on weather-related losses on already-enrolled acres. To the extent that warming increases the frequency or severity of drought, heat, and extreme precipitation events beyond what is reflected in the historical loss distribution, our estimates are conservative lower bounds on the climate-attributable increase in FCIP costs. However, holding per-acre loss rates fixed implicitly assumes no offsetting adaptation—no shifts in crop mix, planting date, geographic distribution, irrigation, or management practices that would reduce per-acre risk. The two assumptions push in opposite directions but together align our

estimates most closely with the no-adaptation scenarios in [Crane-Droesch et al. \(2019\)](#), which project a 10 percent increase in FCIP premium subsidy costs under RCP4.5 by 2080 across corn, soybeans, and winter wheat. Our midcentury estimates of 3.7 percent and 9.0 percent for corn and soy, respectively, are similar in magnitude despite reaching that level three decades earlier and operating through a different mechanism: in [Crane-Droesch et al. \(2019\)](#), cost increases are driven primarily by higher liabilities (from climate-induced price increases on inelastic demand) and secondarily by greater yield risk, whereas our estimates isolate the extensive margin. The similarities in these estimates across different mechanisms suggest that enrollment growth alone may account for a substantial share of the total climate-driven cost increases and that estimates incorporating both channels jointly would likely exceed either taken in isolation.

5.3 The Protective Effect of Crop Insurance on Rural Economies

The preceding section shows that farmers respond to adverse weather and yield shocks by increasing FCIP participation. These findings raise a natural next question: whether this increased insurance uptake meaningfully alters the way local economies respond to extreme heat shocks. Crop insurance is designed to not only stabilize farm income but also smooth cash flows and reduce financial distress after production losses, with potential spillovers to the broader rural economy. If FCIP uptake mitigates income volatility in the farm sector, it may also dampen negative effects of extreme heat on related nonfarm, nontradable industries that depend on agricultural activity and local demand. In the following sections, we examine whether and to what extent FCIP uptake attenuates the adverse impacts of extreme heat on rural employment and business outcomes.

We start by examining the effect of extreme heat on aggregate employment and establishment growth at the county level, without considering insurance mechanisms and heterogeneity across industries. Using county-by-year data on total employment and establishments, we regress growth rates (in pp) on KDDs, weather controls, log planted acres, and fixed effects. Table 4 reports estimates under two fixed-effects specifications: county and year (Columns (1)–(2)) and county and state-by-year (Columns (3)–(4)).

Across specifications, the estimated coefficients on KDDs are uniformly negative but generally statistically insignificant. The only exception is Column (4), where the coefficient is statistically significant at the 5 percent level, indicating that one additional KDD during the growing season reduces establishment growth by 0.004 pp. A one-standard-deviation increase in KDDs therefore

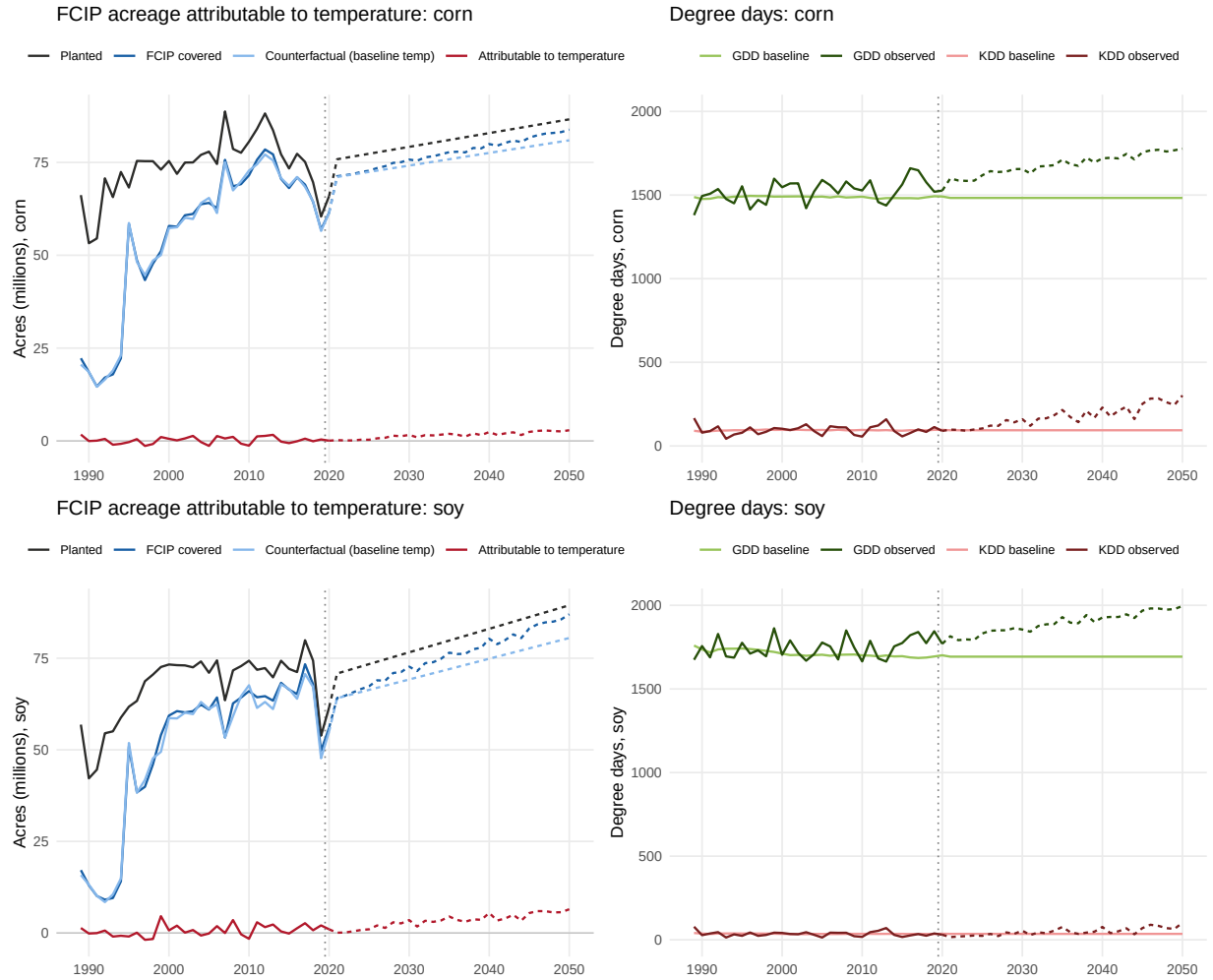


Figure 1: **Historical Attribution and Climate Projections of Federal Crop Insurance Program (FCIP) Enrollment Attributable to Temperature** Top row shows corn, bottom row shows soybeans. Left panels show national planted acres, predicted FCIP-covered acres under realized temperature, counterfactual predicted FCIP-covered acres under the county-specific pre-2000 baseline temperature, and the difference between the two (acres attributable to temperature). Right panels show national acreage-weighted growing degree days (GDDs) and killing degree days (KDDs), both observed and projected, alongside their pre-2000 baselines. Solid lines denote observed values; dashed lines denote projections for 2020–2050 under RCP 4.5, drawn from a probability-weighted ensemble of the 21 CMIP5 climate projections in the NASA Earth Exchange Global Daily Downscaled Projections dataset. The vertical dotted line at 2019.5 marks the historical–projection boundary. The sample is restricted to counties planting either corn or soybeans in the last 10 years of the estimation sample.

Table 4: The Effect of Extreme Heat on Employment and Establishment Growth

	<i>Dependent variable:</i>			
	Emp. growth (1)	Estab. growth (2)	Emp. growth (3)	Estab. growth (4)
KDD	−0.004 (0.003)	−0.002 (0.002)	−0.003 (0.004)	−0.004** (0.002)
FIPS	Y	Y	Y	Y
Year	Y	Y		
State × Year			Y	Y
Outcome mean	1.72	2.60	1.72	2.60
Observations	59,433	59,433	59,433	59,433
Adjusted R ²	0.124	0.696	0.178	0.862

Notes: This table reports estimates of the effects of extreme heat shocks on rural economies. Each observation is a county-year. As indicated in the top panel, the dependent variable in Columns (1) and (3) is overall employment growth associated with rural establishments; Columns (2) and (4) report estimates for the corresponding growth in establishment numbers. Standard errors are clustered by county. *p<0.1; **p<0.05; ***p<0.01

lowers establishment growth by 0.41 pp, or roughly 13 percent of the sample mean growth rate.⁸

Although these estimates appear to suggest that extreme heat has little effect on rural economic activity, they reflect net effects that already incorporate existing adaptation and risk-management responses, including protection provided by the FCIP. To the extent that insurance mitigates downstream employment and establishment losses after heat-induced yield shocks, the residual impact of heat on aggregate outcomes may appear muted and imprecisely estimated. Next, we explicitly disentangle the protective effects from the main effects of heat shocks by examining FCIP enrollment as a mediation factor in the impacts of heat shocks on local labor-market outcomes.

We estimate Equation (4) using data at the industry–county–year level (see Table A3 for summary statistics). This identifies the differential effects of heat shocks and crop insurance on agricultural industries and local nontradable sectors, relative to a set of control industries that are less directly exposed to agricultural climate risk.

Table 5 reports selected coefficients associated with KDDs. Columns (1) and (2) examine employment and establishment growth rates, respectively, under a parsimonious structure with county and state-by-year fixed effects. Columns (3) and (4) repeat the analysis using our preferred, more saturated specification with industry-by-county, state-by-year, and industry-by-year fixed

⁸The standard deviation of KDDs is 103.2, and the county-level sample mean establishment growth rate is 2.60, yielding $103.2 \times (-0.004)/2.60 \approx 0.16$.

Table 5: The Effect of FCIP Enrollment on Establishments and Employment

	<i>Dependent variable:</i>			
	Emp. growth (1)	Estab. growth (2)	Emp. growth (3)	Estab. growth (4)
KDD $\times$ Direct	−0.013*** (0.002)	−0.013*** (0.001)	−0.022*** (0.004)	−0.024*** (0.003)
KDD $\times$ Spillover	−0.008*** (0.002)	−0.007*** (0.001)	−0.014*** (0.004)	−0.001 (0.002)
KDD $\times$ Covered share $\times$ Direct	0.023*** (0.004)	0.037*** (0.003)	0.029*** (0.005)	0.039*** (0.004)
KDD $\times$ Covered share $\times$ Spillover	0.013*** (0.003)	0.012*** (0.002)	0.018*** (0.004)	0.008*** (0.002)
County	Y	Y		
NAICS $\times$ County			Y	Y
State $\times$ Year	Y	Y	Y	Y
NAICS $\times$ Year			Y	Y
Outcome mean	3.371	3.258	3.371	3.258
Observations	982,095	982,095	982,095	982,095
Adjusted R ²	0.041	0.290	0.071	0.436

Notes: This table reports estimates of the effects of extreme heat shocks on different rural economic sectors and their interaction with FCIP uptake, following Equation (4). Each observation is a county-industry-year, where industries are classified by their 2-digit NAICS code. As indicated in the top panel, the dependent variable in Columns (1) and (3) is employment growth associated with each industry; Columns (2) and (4) report estimates for the corresponding growth in establishment numbers. Standard errors are clustered by county. *p<0.1; **p<0.05; ***p<0.01

effects. The results are qualitatively similar, suggesting that differences in industrial composition across counties and industry-specific trends are unlikely to be the primary drivers of the estimated effects.

The coefficients on the triple interaction terms allow us to isolate how crop insurance coverage moderates the impact of extreme heat. We find that it has a statistically significant and positive protective effect, particularly for the agricultural sector. In Column (3), a 10 percent increase in the share of cropland covered by crop insurance is associated with a 0.3-basis-point (bp) increase of the heat penalty per KDD. Valuated at the sample mean coverage share of 0.41, insurance offsets about 55 percent of the effect of extreme heat on agricultural employment growth⁹; a complete offset would require a coverage share of roughly 0.76, near the top of the observed distribution.

⁹The calculation is $-0.022 + 0.029 \times 0.41 = -0.010$.

A similar but attenuated pattern emerges for local nontradable industries: because these sectors are less directly exposed to heat shocks, the associated insurance-mediated effects are smaller, but the offset at mean coverage is comparable at about 53 percent. Column (4) shows comparable patterns for establishment growth, reinforcing the conclusion that crop insurance dampens the adverse effects of extreme heat across both employment and firm dynamics.

Crop insurance coverage protects farms from extreme weather by compensating for realized losses. To more directly capture this transfer channel, we replace the coverage-share measure with the log of FCIP indemnity payments in the regression specification to reflect not only the extent of insurance participation but also the severity of realized losses and magnitude of financial transfers triggered by heat shocks. As shown in Table A4, the results point to similar offsetting effects from insurance payments, suggesting that the ex post income replacement dampens downstream contractions in labor demand and local economic activity after adverse weather shocks.

5.4 Disaggregating the Effect of Crop Insurance by Industry

To further examine heterogeneity in the effects of crop insurance across industries, we estimate regressions in which each industry within a given treatment group is represented by its own indicator and separately interacted with KDDs and FCIP coverage share. Figure 2 plots the resulting industry-specific estimates and 95 percent confidence intervals for the protective effects of FCIP on employment growth. The upper panel focuses on agriculture and adjacent industries and shows that crop and animal production and support activities¹⁰ experience the largest protective effects. In contrast, the remaining two industries in this group do not appear to benefit in the same way: the effect for agricultural wholesale is positive but smaller, and the effect for fishing and hunting is negative; both are statistically insignificant. This pattern is consistent with how FCIP does not insure economic losses in these industries. The bottom panel presents results for the local nontradable sector, where the estimated effects are positive and statistically significant across all industries. The magnitudes are broadly similar, with somewhat larger effects for retail and accommodation and food services and smaller effects for finance and insurance and educational services.

In Figure 3, we turn to the growth rate of establishments with at least two employees. The estimates for agricultural industries mirror the earlier pattern, with crop and animal production experiencing the largest increases, followed by support activities, and negligible effects for agricul-

¹⁰Support activities include cotton ginning, soil preparation, planting and cultivating, cotton harvesting, and farm labor contracting and management services.

Effects on Employment Growth

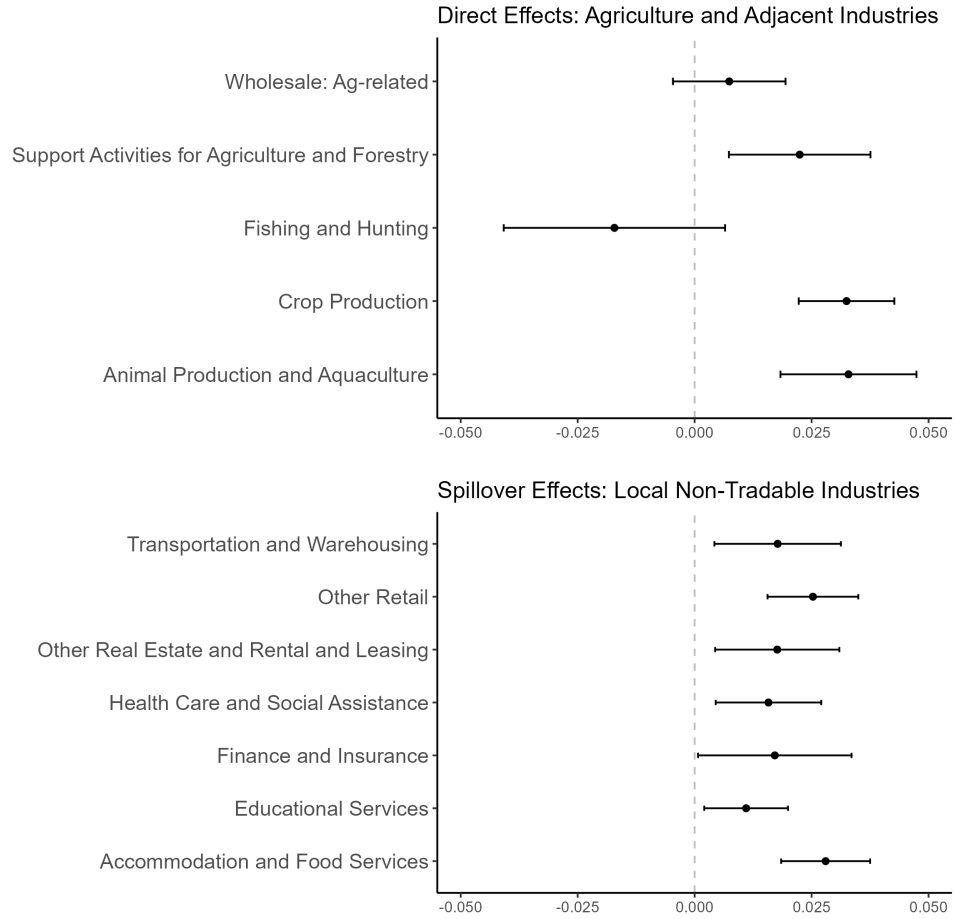


Figure 2: **Protective Effects on Employment Growth by Industry** This figure presents estimated protective effects, along with their 95 percent confidence intervals, separately for each industry in the direct treatment (top panel) and spillover (bottom panel) groups.

Effects on Establishment Growth

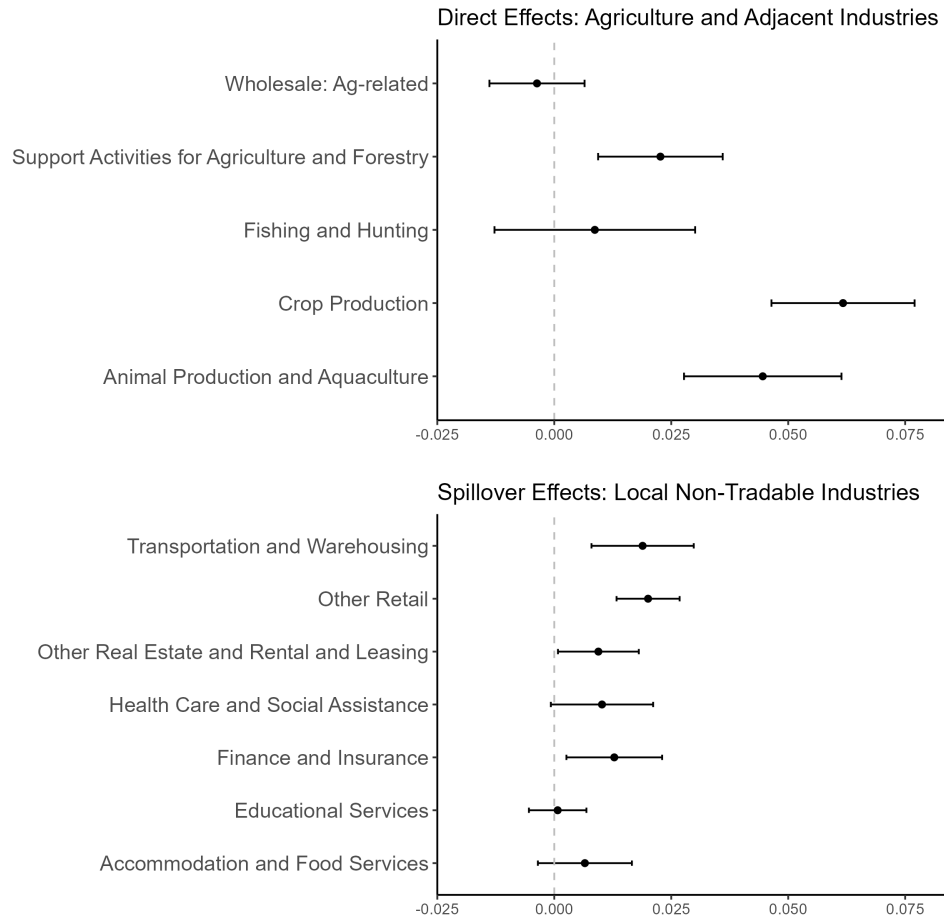


Figure 3: **Protective Effects on Establishment Growth by Industry** This figure presents estimated protective effects, along with their 95 percent confidence intervals, separately for each industry in the direct treatment (top panel) and spillover (bottom panel) groups.

tural wholesale and fishing and hunting. The results for the local nontradable sector are likewise similar to those reported earlier: establishment growth responds positively and significantly in all industries except educational services, with effect sizes that are broadly comparable across sectors.

Overall, these results indicate that FCIP enrollment plays an important role in mitigating the adverse effects of extreme heat on employment and establishment growth across a broad range of industries, though the magnitude of the response varies. Directly covered industries experience the largest gains, and the income support generated by FCIP also spills over to local providers of nontradable goods and services.

5.5 The Labor-Market Benefits of FCIP: Historical and Projected

The preceding section established that FCIP enrollment mitigates the effect of extreme heat on rural employment. We now quantify the magnitude of this protection in terms of how many jobs the program preserves and project how that benefit evolves as warming intensifies through midcentury under climate change.

We decompose the heat–FCIP relationship into two quantities, using the estimates from Column 3 of Table 5. The first, which we label the *gross heat effect*, is the employment loss that extreme heat would impose absent insurance, constructed from the KDD coefficients for the direct and spillover groups ($\hat{\beta}_4$, $\hat{\beta}_7$ in Equation 4) evaluated at observed (or projected) heat exposure. The second is the *protective effect* of FCIP, constructed from the triple-interaction coefficients ($\hat{\beta}_6$, $\hat{\beta}_9$ in Equation 4) and the county’s insured share. For each industry i , county c , and year t , we form the FCIP-induced change in the employment growth rate,

$$\Delta\text{Growth}_{ict} = \hat{\beta}_6 \cdot \text{KDD}_{ct} \cdot \text{Cover}_{ct} \cdot \text{Direct}_i + \hat{\beta}_9 \cdot \text{KDD}_{ct} \cdot \text{Cover}_{ct} \cdot \text{Spillover}_i, \quad (5)$$

and convert it to a job count using lagged employment, $\Delta\text{Jobs}_{ict} = \text{Jobs}_{ic,t-1} \times \Delta\text{Growth}_{ict}$. Aggregating to the national level yields an annual time series of jobs lost to heat and jobs preserved by insurance.

We restrict the exercise to counties in the eastern United States that planted corn or soybeans in the last 10 years of the sample so that the historical and projected series cover an identical population of counties. For the projection, we hold employment fixed at its 2019 level so that projected changes reflect climate and temperature-driven enrollment alone.

Figure 4 plots the resulting series from 1990 through 2050. Over the historical period, FCIP

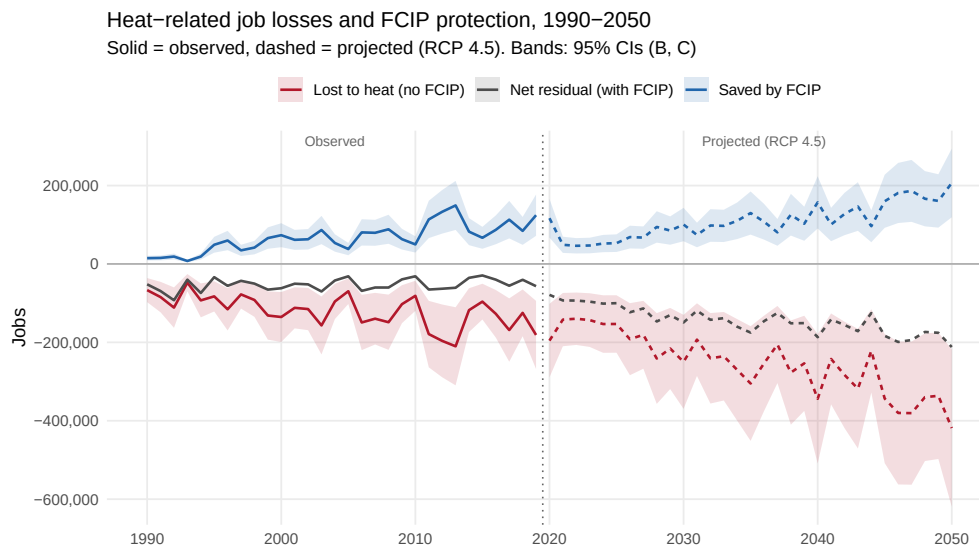


Figure 4: Heat-Related Job Losses and FCIP Protection in Eastern Corn- and Soybean-Producing Counties, 1990–2050 The red series (*lost to heat*) is the gross employment loss extreme heat would impose absent insurance; the blue series (*saved by FCIP*) is the offsetting protective effect of enrollment; the grey series is the net residual. Solid lines show the historical attribution; dashed lines show projections under RCP 4.5, which hold employment fixed at 2019 levels and feed in projected heat exposure and enrollment. Shaded bands are 95 percent confidence intervals derived from the labor-market coefficients via the delta method and understate total projection uncertainty. The vertical dotted line marks the 2019/2020 boundary between observed and projected periods.

enrollment preserved an average of approximately 67,000 jobs per year against an average gross heat-related loss of about 120,000 jobs. That is, it offset more than half of the losses that extreme heat would otherwise have caused. The protective effect operates overwhelmingly through spillovers: of the jobs preserved, about 59,100 accrue to spillover industries and 8,200 to directly agricultural industries, reflecting the far larger employment base of the former.¹¹ This suggests that the bulk of the program’s labor-market value flows through demand linkages to the broader rural economy rather than through agriculture alone.

Although the annual estimates fluctuate, they show a pronounced upward trend, rising from roughly 15,000 jobs in the early 1990s to nearly 125,000 by 2019. This increase is primarily driven by the expansion of FCIP participation after a series of policy reforms that substantially raised premium subsidy rates.

Figure 5 illustrates the geographic distribution of FCIP’s protective effects on employment in 2019. The upper panel presents the absolute number of jobs added by county; the lower panel

¹¹All figures are averages over the indicated periods. The full decomposition by sector, period, and margin (all heat versus climate driven), with standard errors, appears in Appendix Table A5.

reports the corresponding percentage increase in employment. In absolute terms, rural economies near metropolitan areas experience the largest number of jobs added, with clusters scattered across the study area. In percentage terms, a clear north–south gradient emerges, with the largest employment gains concentrated in southern regions and declining with latitude. This pattern mirrors the spatial distribution of extreme heat exposure, as measured by KDDs, shown in the upper panel of Figure A1, where southern counties experience more frequent and intense heat shocks.

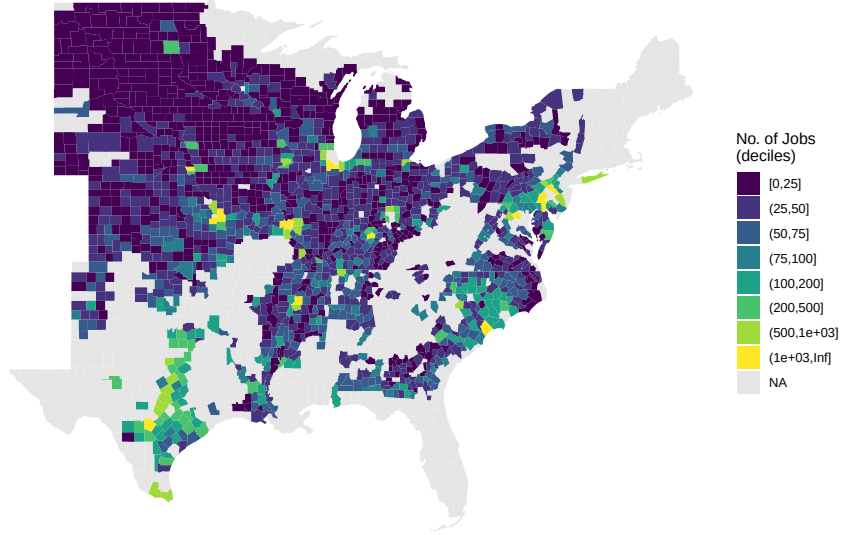
This north–south gradient reflects the spatial pattern of extreme heat shocks and corresponding protective role of crop insurance against heat-related yield losses. The geographic distribution of FCIP’s protective effects could differ for other insured risks, such as pests or disease, which follow distinct geographic and ecological patterns. In both absolute and percentage terms, the Coastal Plain region in eastern Texas stands out as benefiting most; it combines high exposure to extreme heat with high FCIP participation rates, amplifying the stabilizing effects of insurance on local employment (see Figure A1).

To gauge the economic significance of this benefit, we compare it to the cost of the program: for corn and soy in the last five years of our sample (2015–2019), including premium subsidies and administrative costs, this was approximately \$5.06 billion per year in the counties we study.¹² Set against the estimated 95,149 jobs preserved per year over this same period, this implies an average program cost of approximately \$53,230 per job. For comparison, the Council of Economic Advisers estimated that the American Recovery and Reinvestment Act of 2009 created jobs at a cost of roughly \$92,000 per job-year (Council of Economic Advisers, 2009). By this benchmark, FCIP appears relatively efficient in supporting rural labor market outcomes. At the same time, program costs have risen sharply since 2019, reaching \$17 billion in 2022, raising concerns about the program’s cost-effectiveness going forward.

The projections indicate that both the heat threat and FCIP’s protective role grow substantially by mid-century. Over 2020–2050, projected gross heat-related losses average roughly 253,000 jobs per year—more than double the historical figure—and FCIP enrollment is projected to preserve about 110,000 jobs per year, again concentrated in spillover sectors (approximately 100,000 of the total). The program’s protective benefit thus increases by 63 percent as warming raises the stakes, and the share of heat losses it offsets remains near one-half.

¹²We calculate subsidy costs (65 percent of total program costs) directly from the policy-level data. Underwriting and delivery costs are available at the program level from <https://www.ers.usda.gov/topics/farm-practices-management/risk-management/crop-insurance-at-a-glance>. We downscale these to the subset of crops and covered counties studied in our analysis using the share of FCIP policies.

No. of Jobs Preserved in 2019



%Jobs Preserved in 2019

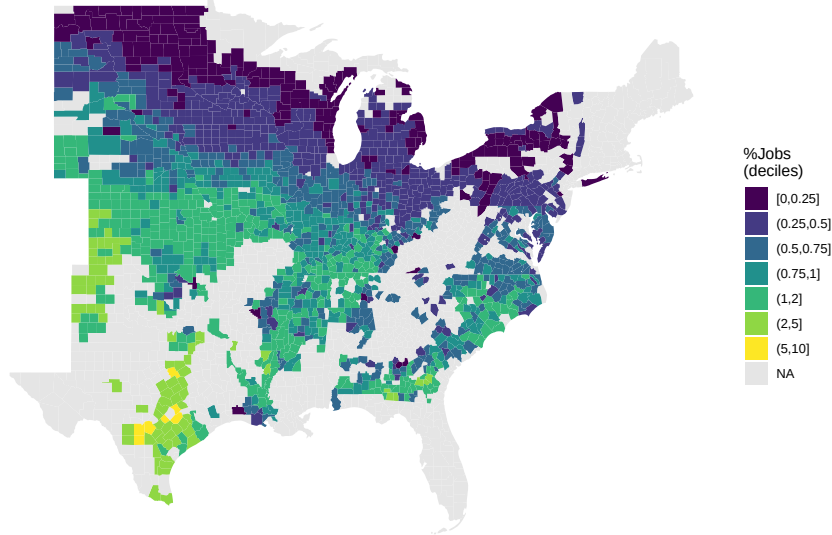


Figure 5: Jobs Preserved by the Federal Crop Insurance Program in 2019, by County

The top panel shows the estimated absolute number of jobs preserved; the bottom panel shows jobs preserved as a percentage of total county employment in agriculture-direct, agriculture-indirect, and control NAICS sectors. County-level estimates are constructed from the triple-interaction coefficients on covered acreage and killing degree days (KDDs) ($\hat{\beta}_6$ for agriculture-direct sectors and $\hat{\beta}_9$ for agriculture-indirect spillover sectors), evaluated at each county's realized 2019 KDDs, coverage ratio, and lagged sector employment and summed across NAICS groups within the county. The sample is restricted to eastern US counties planting corn or soybeans within its last 10 years. Bins follow the legend cutoffs shown at right; counties in grey are outside the estimation sample.

Isolating the component attributable to warming since the pre-2000 baseline clarifies how much of this growth is driven by climate change. Holding heat exposure at each county’s historical baseline, the temperature-driven increment to FCIP’s protective benefit rises from roughly 5,400 jobs per year to about 50,000 over 2046–2050, an order-of-magnitude increase that mirrors the climate-driven enrollment growth documented in Section 5.2. A growing share of the program’s labor-market value thus derives specifically from the additional heat that climate change imposes.

Several caveats apply. The calculation is conditioned on the subset of eastern counties with corn or soy production in the last 10 years of our sample ($N = 1,757$); it is not a program-wide accounting and excludes both western production and counties without recent acreage. The projections hold employment, industrial composition, and the estimated coefficients fixed and propagate uncertainty from the labor-market coefficients, not the climate or enrollment projections that feed them, so the confidence bands in Figure 4 should be read as lower bounds on total projection uncertainty.

6 Conclusion

This paper documents two central findings about the FCIP. First, farmers respond to negative weather and yield shocks by increasing participation, primarily along the extensive margin: adverse heat exposure and lower yields in one year lead to substantially greater acreage enrolled in the next year. This pattern indicates that FCIP enrollment itself functions as an adaptive response to climate risk. Second, crop insurance plays a critical role in protecting rural economies against extreme heat. We show that heat shocks significantly reduce employment and establishment growth in agricultural industries and, to a lesser extent, local nontradable sectors. Higher FCIP coverage and indemnity payments substantially mitigate these effects, preserving jobs in agriculture and generating meaningful spillovers to retail, hospitality, health care, and other industries that depend on demand from the farm sector.

The policy implications are twofold. First, evaluations of FCIP should account for not only farm-level risk management benefits but also its broader role in stabilizing rural labor markets through demand spillovers. Focusing narrowly on agricultural outcomes risks understating the program’s contribution to rural economic resilience, particularly as climate change intensifies extreme heat exposure. Second, rising fiscal costs underscore the importance of designing crop insurance in ways that preserve these stabilizing benefits while improving efficiency and long-run sustainability. Policymakers face the challenge of maintaining protection against increasingly frequent climate

shocks while aligning incentives for adaptation and fiscal responsibility in a changing climate. As with the National Flood Insurance Program, which has transferred catastrophic tail risk to private reinsurers and capital markets since 2016 and faces ongoing proposals to expand private-market participation in flood risk and create a dedicated federal reinsurance mechanism, options such as reinsurance placement or expanded private risk-sharing arrangements may help the FCIP better absorb climate-driven losses without placing the full cost of tail risk directly on the federal budget (US Congress, Senate, 2025; FEMA Review Council, 2026).

References

- Ahmed, M. H., W. M. Tesfaye, and F. Gassmann (2023). Early Growing Season Weather Variation, Expectation Formation and Agricultural Land Allocation Decisions in Ethiopia. *Journal of Agricultural Economics* 74(1), 255–72.
- Annan, F. (2024). Adapting the U.S. Federal Crop Insurance Program for Climate Change: Critical Lessons for Policy Design. Technical report, University of California Giannini Foundation of Agricultural Economics.
- Annan, F. and W. Schlenker (2015). Federal Crop Insurance and the Disincentive to Adapt to Extreme Heat. *American Economic Review* 105(5), 262–6.
- Azzam, A., C. Walters, and T. Kaus (2021). Does Subsidized Crop Insurance Affect Farm Industry Structure? Lessons From the US. *Journal of Policy Modeling* 43(6), 1167–80.
- Biram, H., J. Tack, R. Nehring, and J. Yu (2024). Empirical Challenges for Estimating Moral Hazard Effects of Crop Insurance on Pesticide Use. *Journal of Agricultural and Resource Economics* 49(2), 265–82.
- Burke, M. and K. Emerick (2016). Adaptation to Climate Change: Evidence From US Agriculture. *American Economic Journal: Economic Policy* 8(3), 106–40.
- Butler, E. E. and P. Huybers (2013). Adaptation of US Maize to Temperature Variations. *Nature Climate Change* 3(1), 68–72.
- Butler, E. E., N. D. Mueller, and P. Huybers (2018). Peculiarly Pleasant Weather for US Maize. *Proceedings of the National Academy of Sciences* 115(47), 11935–40.
- Claassen, R., C. Langpap, and J. Wu (2017). Impacts of Federal Crop Insurance on Land Use and Environmental Quality. *American Journal of Agricultural Economics* 99(3), 592–613.
- Congressional Budget Office (2026, February). USDA Mandatory Farm Programs: CBO’s February 2026 Baseline. Technical report, Congressional Budget Office.
- Council of Economic Advisers (2009). *Estimates of Job Creation From the American Recovery and Reinvestment Act of 2009*. Executive Office of the President, Council of Economic Advisers.

- Crane-Droesch, A., E. Marshall, S. Rosch, A. Riddle, J. Cooper, and S. Wallander (2019). Climate Change and Agricultural Risk Management Into the 21st Century. Technical Report ERR-266, U.S. Department of Agriculture, Economic Research Service.
- Cui, X. and Q. Tang (2024). Extreme Heat and Rural Household Adaptation: Evidence From Northeast China. *Journal of Development Economics* 167, 103243.
- DeLay, N. D., B. Brewer, A. Featherstone, and D. Boussios (2023). The Impact of Crop Insurance on Farm Financial Outcomes. *Applied Economic Perspectives and Policy* 45(1), 579–601.
- Deryugina, T. and M. Konar (2017). Impacts of Crop Insurance on Water Withdrawals for Irrigation. *Advances in Water Resources* 110, 437–44.
- Di Maggio, M. and A. Kermani (2016). The Importance of Unemployment Insurance as an Automatic Stabilizer. Technical report, National Bureau of Economic Research.
- Ding, Y., K. Schoengold, and T. Tadesse (2009). The Impact of Weather Extremes on Agricultural Production Methods: Does Drought Increase Adoption of Conservation Tillage Practices? *Journal of Agricultural and Resource Economics* 34(3), 395–411.
- Duan, N. (1983). Smearing Estimate: A Nonparametric Retransformation Method. *Journal of the American Statistical Association* 78(383), 605–10.
- Executive Office of the President (2013). The Economic Importance of Passing a Comprehensive Food, Farm, and Jobs Bill. Technical report, Executive Office of the President of the United States.
- FEMA Review Council (2026, May). FEMA Review Council Final Report. Technical report, U.S. Department of Homeland Security.
- Gallagher, J. and D. Hartley (2017). Household Finance After a Natural Disaster: The Case of Hurricane Katrina. *American Economic Journal: Economic Policy* 9(3), 199–228.
- Goodwin, B. K. (1993). An Empirical Analysis of the Demand for Multiple Peril Crop Insurance. *American journal of agricultural economics* 75(2), 425–34.
- Harrison, L. (1993). The Impact of the Agricultural Industry on the Rural Economy—Tracking the Spatial Distribution of the Farm Inputs and Outputs. *Journal of Rural Studies* 9(1), 81–8.

- Hellwig, K.-P. (2021, 3). Supply and Demand Effects of Unemployment Insurance Benefit Extensions: Evidence from U.S. Counties. *IMF Working Papers 2021*(070), 1.
- Horowitz, J. K. and E. Lichtenberg (1993). Insurance, Moral Hazard, and Chemical Use in Agriculture. *American Journal of Agricultural Economics* 75(4), 926–35.
- Hsiang, S. (2016). Climate Econometrics. *Annual Review of Resource Economics* 8, 43–75.
- Huang, H.-H. and M. R. Moore (2018). Farming Under Weather Risk: Adaptation, Moral Hazard, and Selection on Moral Hazard. In *Agricultural Productivity and Producer Behavior*, pp. 77–124. University of Chicago Press.
- Ji, X. and K. M. Cobourn (2021). Weather Fluctuations, Expectation Formation, and Short-Run Behavioral Responses to Climate Change. *Environmental and Resource Economics* 78(1), 77–119.
- Kousky, C., M. Palim, and Y. Pan (2020). Flood Damage and Mortgage Credit Risk: A Case Study of Hurricane Harvey. *Journal of Housing Research* 29(sup1), S86–S120.
- Leatham, D. J., L. L. Jones, and L. M. Crane (1997). Economic Impact of Crop Insurance on the North Dakota State Economy.
- Lusk, J. L. (2017). Distributional Effects of Crop Insurance Subsidies. *Applied Economic Perspectives and Policy* 39(1), 1–15.
- Melear, C. and J. Theodorou (2024). Crop Insurance Reform. Technical report, R Street Institute.
- Melecky, M. and C. Raddatz (2015). Fiscal Responses After Catastrophes and the Enabling Role of Financial Development. *The World Bank Economic Review* 29(1), 129–49.
- Mieno, T., C. G. Walters, and L. E. Fulginiti (2018). Input Use Under Crop Insurance: The Role of Actual Production History. *American Journal of Agricultural Economics* 100(5), 1469–85.
- Morris, S. and S. Kaczmarek (2023). Crop Insurance: Update on Opportunities to Reduce Program Costs. Technical report, U.S. Government Accountability Office.
- Neumark, D., J. Zhang, and B. Wall (2007). Employment Dynamics and Business Relocation: New Evidence From the National Establishment Time Series. In *Aspects of worker well-being*, Volume 26, pp. 39–83. Emerald Group Publishing Limited.

- Nguyen, C. N. and I. Noy (2020). Measuring the Impact of Insurance on Urban Earthquake Recovery Using Nightlights. *Journal of Economic Geography* 20(3), 857–77.
- Obolensky, M. (2024). Protect or Prepare? Crop Insurance and Adaptation in a Changing Climate. Technical report, Working Paper.
- O’Donoghue, E. (2014). The Effects of Premium Subsidies on Demand for Crop Insurance. *USDA-ERS economic research report* (169).
- OMB (2022). Climate Risk Exposure: An Assessment of the Federal Government’s Financial Risks to Climate Change. Technical report, Office of the President of the United States.
- Paggi, M. S., C. P. Rosson III, F. J. Adcock, and D. Hanselka (2011). National and Regional Impacts of US Agricultural Exports. *Choices* 26(1).
- PRISM Climate Group (2023). PRISM Climate Data. <https://prism.oregonstate.edu>. Data accessed April 25, 2023.
- Rasmussen, D., M. Meinshausen, and R. E. Kopp (2016). Probability-Weighted Ensembles of US County-Level Climate Projections for Climate Risk Analysis. *Journal of Applied Meteorology and Climatology* 55(10), 2301–22.
- Rosch, S. (2021). Federal Crop Insurance: A Primer (No. R46686). *Congressional Research Service*.
- Santangelo, G. (2019). Firms and Farms: The Local Effects of Farm Income on Firms’ Demand. Technical Report 1924, Faculty of Economics, University of Cambridge, Cambridge, UK.
- Schauberger, B., S. Archontoulis, A. Arneth, J. Balkovic, P. Ciais, D. Deryng, J. Elliott, C. Folberth, N. Khabarov, C. Müller, et al. (2017). Consistent Negative Response of US Crops to High Temperatures in Observations and Crop Models. *Nature Communications* 8(1), 13931.
- Schlenker, W. and M. J. Roberts (2009). Nonlinear Temperature Effects Indicate Severe Damages to US Crop Yields Under Climate Change. *Proceedings of the National Academy of sciences* 106(37), 15594–98.
- Serra, T., B. K. Goodwin, and A. M. Featherstone (2003). Modeling Changes in the US Demand for Crop Insurance During the 1990s. *Agricultural Finance Review* 63(2), 109–25.

- Shi, J., J. Wu, and B. Olen (2020). Assessing Effects of Federal Crop Insurance Supply on Acreage and Yield of Specialty Crops. *Canadian Journal of Agricultural Economics* 68(1), 65–82.
- Smith, V. H. and B. K. Goodwin (1996). Crop Insurance, Moral Hazard, and Agricultural Chemical Use. *American Journal of Agricultural Economics* 78(2), 428–38.
- Tsiboe, F. and D. Turner (2023). The Crop Insurance Demand Response to Premium Subsidies: Evidence From US Agriculture. *Food Policy* 119, 102505.
- US Congress, Senate (2025). S. 2349 — Incorporating National Support for Unprecedented Risks and Emergencies (INSURE) Act. 119th Congress, 1st Session.
- USDA National Agricultural Statistics Service (2022). Cropland Data Layer.
- USDA National Agricultural Statistics Service (2023). USDA National Agricultural Statistics Service NASS - Quick Stats.
- von Peter, G., S. von Dahlen, and S. C. Saxena (2012, December). Unmitigated Disasters? New Evidence on the Macroeconomic Cost of Natural Catastrophes. BIS Working Paper 394, Bank for International Settlements. Available at SSRN: <https://ssrn.com/abstract=2195975>.
- Walls, M., P. Lee, and M. Ashenfarb (2020). National Monuments and Economic Growth in the American West. *Science Advances* 6(12), eaay8523.
- Weber, J. G., C. Wall, J. Brown, and T. Hertz (2014). Crop Prices, Agricultural Revenues, and the Rural Economy. *Applied Economic Perspectives and Policy* 37(3), 459–76.
- Welch, K. L., D. M. Lambert, L. H. Lambert, and A. Hagerman (2024). The Effects of Disaster Relief Insurance on Drought Impacts: A Case Study of Southwest Oklahoma. *Review of Regional Studies* 54(3), 215–40.
- Wu, S., B. K. Goodwin, and K. Coble (2020). Moral Hazard and Subsidized Crop Insurance. *Agricultural Economics* 51(1), 131–42.
- You, X. and C. Kousky (2024). Improving Household and Community Disaster Recovery: Evidence on the Role of Insurance. *Journal of Risk and Insurance* 91(2), 299–338.
- Yu, J., A. Smith, and D. A. Sumner (2018). Effects of Crop Insurance Premium Subsidies on Crop Acreage. *American Journal of Agricultural Economics* 100(1), 91–114.

Zalom, F. G., P. B. Goodell, L. T. Wilson, W. W. Barnett, and W. J. Bentley (1983). Degree-Days:
The Calculation and Use of Heat Units in Pest Management. *UC DANR Leaflet 21373*.

A Additional Tables and Figures

Table A1: Summary Statistics: Yield and FCIP Uptake

Statistic	N	Mean	St. Dev.	Min	Max
A. Corn					
Covered acres	44,252	39,286.490	49,077.000	0	367,545
Coverage level	43,279	66.001	8.357	35.000	89.677
Planted acres	44,252	53,390.670	57,531.860	200	397,000
Yield	44,252	122.993	39.672	0.000	246.700
KDD	44,252	133.600	103.530	0.923	861.652
GDD	44,252	1,603.241	219.168	925.684	2,329.130
Precipitation	44,252	741.577	213.714	104.432	1,920.459
B. Soybean					
Covered acres	39,659	39,697.130	46,519.930	0	539,359
Coverage level	38,778	66.509	8.363	32.425	89.274
Planted acres	39,659	54,323.410	53,058.690	70	541,000
Yield	39,659	37.758	10.971	0.700	80.400
KDD	39,659	44.141	42.033	0.000	362.021
GDD	39,659	1,789.053	234.654	936.684	2,581.295
Precipitation	39,659	597.081	170.435	122.677	1,627.266

Table A2: Distributed Lag Model of Yield and FCIP Take-Up for Corn

	<i>Dependent variable:</i>					
	ln(CoveredAcres)			Coverage level		
	(1)	(2)	(3)	(4)	(5)	(6)
Yield _{t-1}	-0.001** (0.0005)	-0.001** (0.0004)	-0.001** (0.0003)	0.00002 (0.0001)	-0.00000 (0.0001)	-0.00001 (0.0001)
Yield _{t-2}		-0.0004 (0.0002)	-0.0004** (0.0002)		-0.00001 (0.00005)	-0.00003 (0.00004)
Yield _{t-3}			0.00000 (0.0002)			0.00000 (0.00003)
ln(PlantedAcres)	0.927*** (0.038)	0.907*** (0.031)	0.897*** (0.024)	0.008 (0.006)	0.009 (0.006)	0.009 (0.005)
Observations	44,252	42,349	40,500	43,279	41,388	39,552
Adjusted R ²	0.940	0.946	0.952	0.816	0.828	0.837

Notes: This table reports estimates of the effects of lagged yields on FCIP take-up for corn using a distributed lag model. Columns (1)–(3) include one, two, and three lags of yield as regressors and log covered acres as the outcome; Columns (4)–(6) present the parallel estimates for coverage level as the outcome. Dependent variables are indicated in the top panel. Standard errors are clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

Table A3: Summary Statistics: Industry Sample

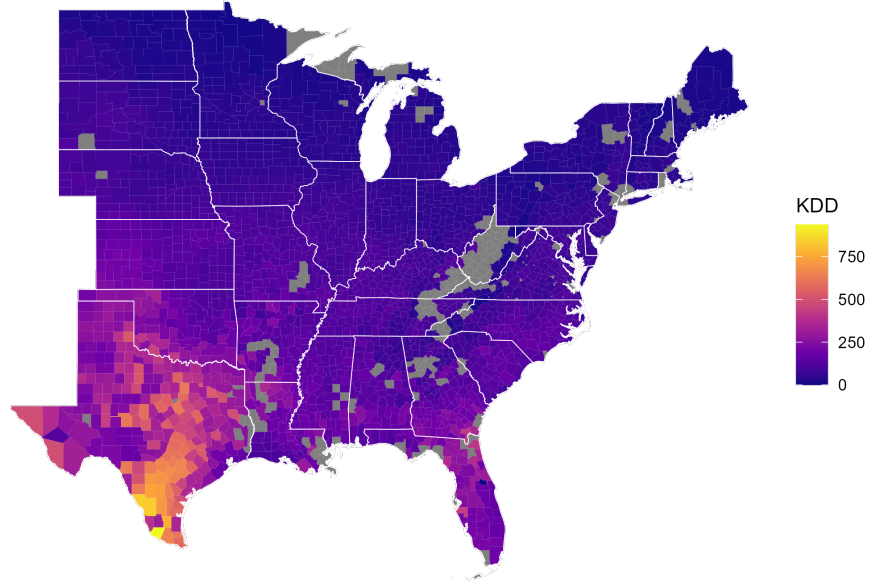
Statistic	N	Mean	St. Dev.	Min	Max
Covered acres	982,135	89,917.050	110,754.100	0	948,921
Planted acres	982,135	134,003.900	162,223.500	0.000	1,585,787.000
Covered share	982,135	0.414	0.193	0.000	0.900
Total indemnities (\$)	961,647	1,887,034.000	5,077,825.000	0.000	153,953,905.000
Direct	982,135	0.266	0.442	0	1
Spillover	982,135	0.422	0.494	0	1
Employment	982,135	704.719	5,255.953	2	436,178
Estab. (> 1 employees)	982,135	44.858	293.201	1	31,799
Employment growth (%)	982,135	3.371	28.845	-99.889	1,000.000
Establishment growth (%)	982,135	3.258	21.226	-99.346	700.000
KDD	982,095	101.157	103.168	0.466	1,141.403
Precipitation	982,095	688.912	206.774	66.168	2,453.785

Table A4: The Effect of FCIP Indemnities

	<i>Dependent variable:</i>			
	Emp. growth (1)	Estab. growth (2)	Emp. growth (3)	Estab. growth (4)
KDD × Direct	-0.030*** (0.006)	-0.026*** (0.004)	-0.066*** (0.009)	-0.065*** (0.007)
KDD × Spillover	-0.018*** (0.005)	-0.018*** (0.004)	-0.047*** (0.008)	-0.014*** (0.005)
KDD × Log indemn. × Direct	0.002*** (0.0004)	0.002*** (0.0003)	0.004*** (0.001)	0.004*** (0.0004)
KDD × Log indemn. × Spillover	0.001*** (0.0004)	0.001*** (0.0003)	0.003*** (0.001)	0.001*** (0.0003)
FIPS	Y	Y		
NAICS × FIPS			Y	Y
State × Year	Y	Y	Y	Y
NAICS × Year			Y	Y
Observations	961,621	961,621	961,621	961,621
Adjusted R ²	0.041	0.289	0.071	0.437

Notes: This table reports estimates of the effects of extreme heat shocks on different rural economic sectors and their interaction with FCIP indemnities. Each observation is a county-industry-year, where industries are classified by their 2-digit NAICS code. As indicated in the top panel, the dependent variable in Columns (1) and (3) is employment growth associated with each industry; Columns (2) and (4) report estimates for the corresponding growth in establishment numbers. Standard errors are clustered by county. *p<0.1; **p<0.05; ***p<0.01

KDD in 2019



FCIP cover share in 2019

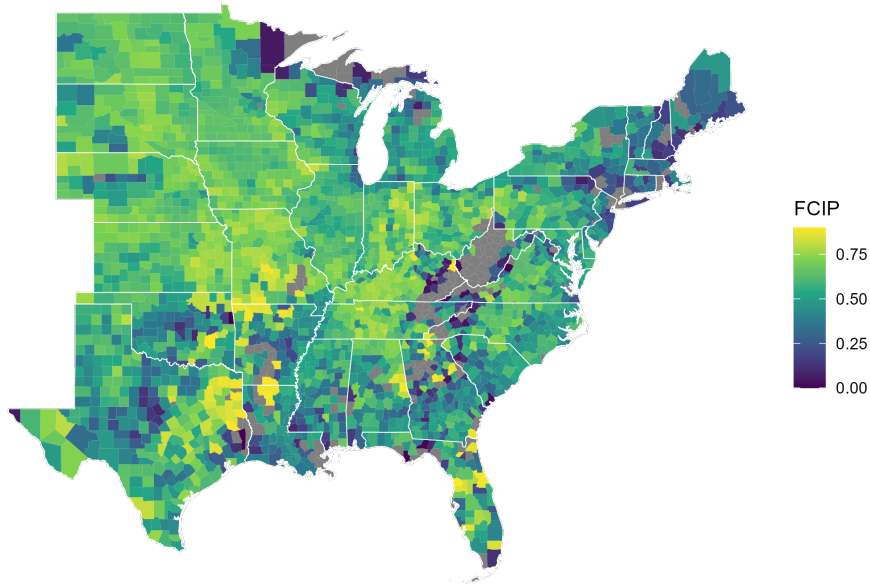


Figure A1: **Killing Degree Days (KDDs) and Federal Crop Insurance Program (FCIP) Cover Share in 2019** The top panel shows a map of county-level KDDs in 2019, and the bottom panel shows the share of cropland covered by FCIP across counties in 2019. The sample is restricted to eastern US counties planting corn or soybeans. Counties in grey are not included in the sample.

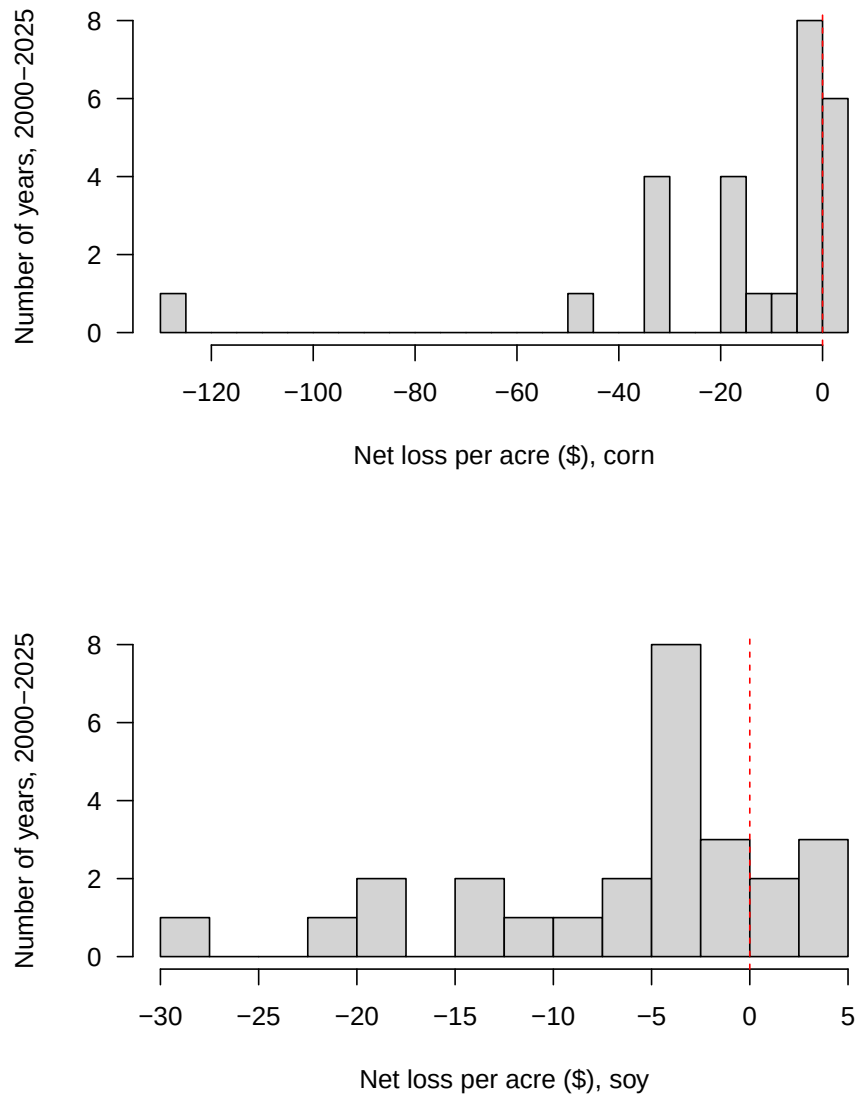


Figure A2: **Distribution of Annual Net Federal Losses per Acre Covered by Federal Crop Insurance Program, 2000–2025** Corn is shown on the top row, soybeans on the bottom. Net loss is defined as the government’s per-acre premium subsidy plus indemnity payout minus total premium collected, computed from the USDA Risk Management Agency’s Summary of Business county-crop files. Negative values (left of the red dashed line) indicate years in which the government paid out more in subsidies and indemnities than it collected in premiums; positive values indicate net revenue. Each bar shows the number of years, out of 26, in which per-acre net losses fell within the indicated range.

		Jobs preserved by FCIP	Gross heat loss (no FCIP)
Margin	Sector	(jobs/yr)	(jobs/yr)
<i>Panel A. Historical (1991–2019)</i>			
All heat	Direct	8,189	−14,757
		(1,449)	(2,755)
	Spillover	59,099	−105,536
		(13,222)	(26,825)
	Both	67,288	−120,293
		(14,350)	(28,952)
Climate-driven	Direct	686	−937
		(121)	(175)
	Spillover	4,731	−6,676
		(1,058)	(1,697)
	Both	5,417	−7,613
		(1,153)	(1,832)
<i>Panel B. Projected (2020–2050), RCP 4.5</i>			
All heat	Direct	9,337	−21,605
		(1,652)	(4,034)
	Spillover	100,211	−231,563
		(22,420)	(58,858)
	Both	109,548	−253,168
		(23,695)	(61,946)
Climate-driven	Direct	4,220	−9,568
		(746)	(1,786)
	Spillover	45,465	−100,897
		(10,172)	(25,645)
	Both	49,685	−110,464
		(10,748)	(27,013)

Table A5: Federal Crop Insurance Program (FCIP) Labor-Market Effects The table shows jobs preserved and gross heat losses by period, sector, and margin. Cells report average jobs per year over the indicated period within eastern counties planting corn or soybeans in the last five years of the sample; delta-method standard errors in parentheses. “Jobs preserved by FCIP” is the protective effect from the triple-interaction coefficients ($\hat{\beta}_6, \hat{\beta}_9$); “gross heat loss” is the employment loss extreme heat would impose absent insurance ($\hat{\beta}_4, \hat{\beta}_7$). “All heat” evaluates effects at realized (or projected) killing degree days; “climate-driven” evaluates only the increment of heat exposure above each county’s pre-2000 baseline. “Both” is the sum of the direct and spillover sectors. Standard errors propagate uncertainty in the estimated labor-market coefficients only.

B Constructing Agriculture Heat Exposure Measures

B.1 Crop-Specific Temperature and Precipitation Exposure

Our raw temperature data are from [PRISM Climate Group \(2023\)](#) and contain daily minimum and maximum temperature at $\sim 4\text{km}$ grid level. To capture the exposure of agriculture to temperature shocks, we calculate time spent during the growing seasons in increments of 1°C from $0\text{--}40^\circ\text{C}$. Temperatures below 0°C are binned together, as are temperatures above 40°C . We construct these measures using daily minimum and maximum temperature from PRISM and the sine method described in [Zalom et al. \(1983\)](#) which closely approximates the daily temperature cycle. This method models the temperature exposure over a day using a function:

$$y(t) = A \cdot \cos(2\pi(t - h)) + k \quad (\text{B1})$$

A is the amplitude of the cosine wave, defined as half the absolute difference between the daily maximum and minimum temperatures; h is the horizontal shift of the cosine function, set to 0.5; and k is the vertical shift of the cosine function, which is the average of the daily maximum and minimum temperatures. This shifts the cosine function to have its minimum values at the start and end of the day. We estimate the temperature for a series of time values t ranging from 0 to 1 in increments of 0.01, representing roughly 15-minute intervals:

$$t_i \in \{0, 0.01, 0.02, \dots, 1\} \quad (\text{B2})$$

We calculate the proportion of the day that the temperature remains within the bounds of the binned intervals $[\text{lower_temp}, \text{upper_temp}]$ using the equation

$$\text{portion_in} = \frac{\text{Number of } t_i \text{ where } \text{lower_temp} \leq y(t_i) \leq \text{upper_temp}}{\text{Total number of } t_i} \quad (\text{B3})$$

We also obtain daily precipitation estimates from PRISM to construct two measures of rainfall for each season: total precipitation and precipitation squared.

All weather variables are constructed at the native resolution of the data ($\sim 4\text{km}$) and then aggregated to the county by year by crop by season level. When spatially aggregating weather variables to the county level, we weight by crop-specific area from the USDA's Cropland Data Layer ([USDA National Agricultural Statistics Service, 2022](#)). In particular, we first assign each

4km weather grid cell to a county using its centroid. Then, we calculate the area of the grid cell covered by each crop. Weights are constructed as the cropped area of the grid cell divided by its county’s total cropped area. This process yielded a dataset with county-level, crop-specific weather measures for each growing season and year.

B.2 Estimating the Yield–Temperature Relationship

Using these weather data, we estimate local nonlinear effects of temperature on yields (Hsiang, 2016) and use this to inform the construction of our main measure of heat shock in our analysis of FCIP takeup and rural businesses. We conduct separate yield analyses for soybeans and corn, focusing on states in the Eastern United States.

We model yield in county c and year t as the following:

$$Yield_{ct} = \int_{\underline{h}}^{\bar{h}} g(h)\theta_{ct}(h)dh + \phi W_{ct} + \delta_c + \gamma_t + \varepsilon_{ct} \quad (\text{B4})$$

where $\theta_{ct}(h)$ represents the time distribution of temperature during the mid growing season in $1^\circ C$ intervals, and $g(h)$ denotes yield growth at temperature h . The term $g(h)$ describes the relationship between temperature and yield and is specified as a piecewise linear function:

$$g(h) = \begin{cases} \beta_1(h - h^*) & \text{if } h < h^* \\ \beta_2(h - h^*) & \text{if } h \geq h^* \end{cases} \quad (\text{B5})$$

where growth increases linearly up to a threshold h^* and then decreases linearly beyond it. The threshold can be interpreted as the optimal temperature for crop growth and will be inferred using a data-driven approach. We focus on midseason temperature because preliminary exploration shows that it has the most pronounced effects on crop yields, which significantly improves precision.

The specification also includes a vector of other weather variables (W_{ct}) that vary by county and year, which consists of planting and harvest season temperature represented in $5^\circ C$ bins and a quadratic function of each growing season’s precipitation. In addition, we also account for county fixed effects, which control for time-invariant county characteristics, such as soil type, and year fixed effects, which control for year-specific shocks that affect crop yields in all counties.

To find the threshold temperature for crop growth, we loop over all whole $^\circ C$ values and pick the one that generates the best-fitted regression: $27^\circ C$ for corn and $30^\circ C$ for soy. These estimates

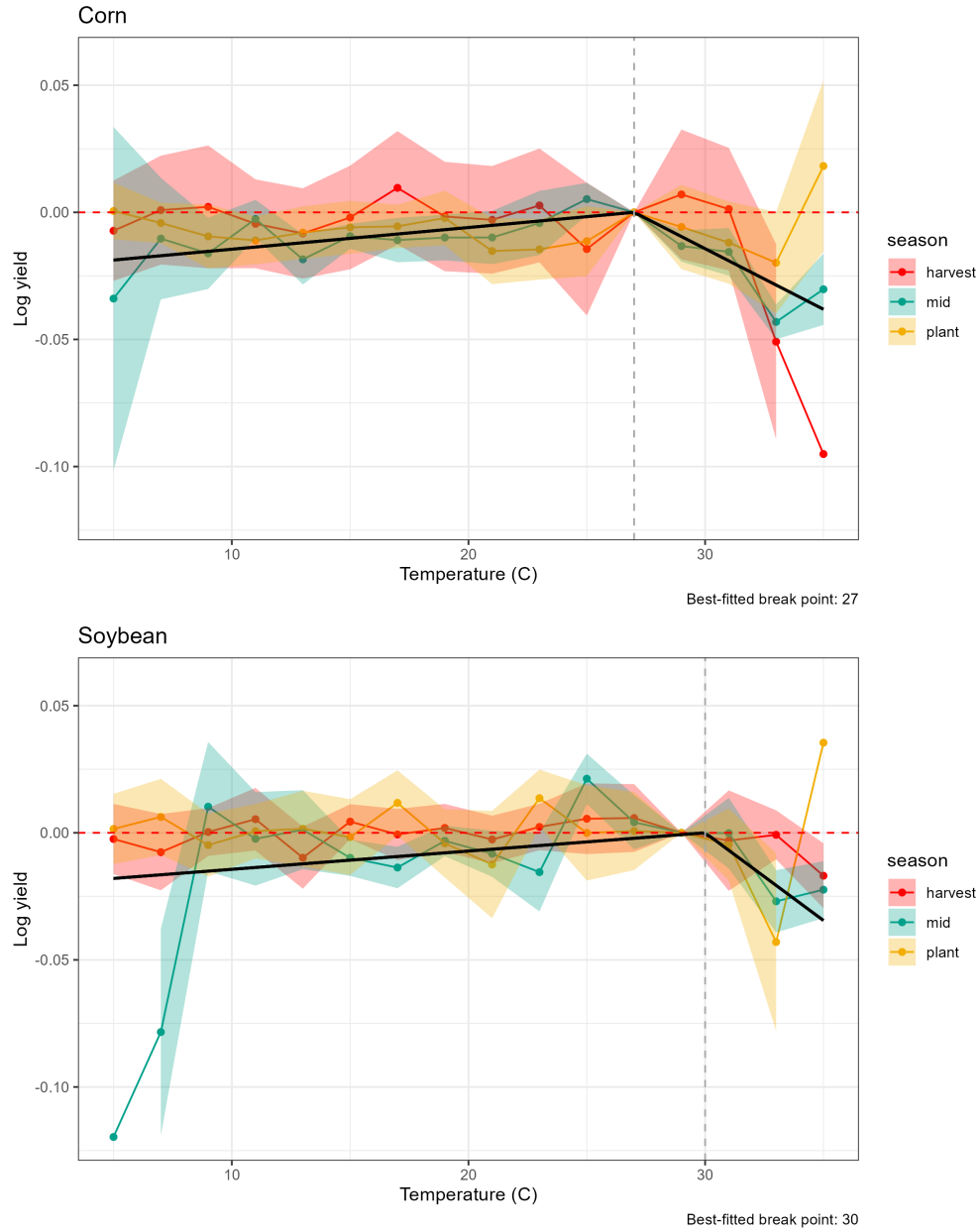


Figure A3: Estimated Relationship between Yield and Temperature. The colored bands show nonparametric estimates and their 95 percent confidence intervals of this relationship during the planting season (yellow), midseason (green), and harvest season (red), with temperature recorded in 2°C intervals. The black solid line represents the best-fit piecewise function following Equation (B4), and the vertical grey dashed line marks the best-fit heat threshold.

are in line with the literature (Schlenker and Roberts, 2009; Schaubberger et al., 2017). Figure A3 plots the estimated piecewise functions for corn (upper panel) and soy (lower panel) against nonparametric estimates of the relationship based on two-degree temperature intervals in each growing season segment.

B.3 Constructing the Killing Degree Day (KDD) Measure

Using the estimated thresholds, we calculate the daily KDDs for each crop as follows:

$$KDD = \begin{cases} 0 & \text{if } h < h^* \\ h - h^* & \text{if } h^* \leq h < 40 \\ 40 - h^* & \text{if } h \geq 40 \end{cases} \quad (\text{B6})$$

We then sum it over the entire growing season for each county to calculate the overall KDDs for that crop in that county. Similarly, we calculate the growing degree day (*GDD*) between 9°C and the estimated threshold.¹³ These measures are our main temperature variables in the analysis.

¹³The choice of the lower threshold of 9°C is consistent with the literature (Schlenker and Roberts, 2009; Butler and Huybers, 2013; Butler et al., 2018).

