Managing Heat Risk: Crop Insurance and Rural Economic Resilience*

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Abstract

This paper studies the economic impacts of the Federal Crop Insurance Program (FCIP), the largest individual government assistance program for agricultural production in the United States. We analyze the program's impacts on rural communities, focusing on both the agricultural sector and broader effects beyond direct benefits to farmers. Using a panel of U.S. counties from 1991 to 2019, we estimate the effects of weather extremes on FCIP enrollment and then link enrollment and indemnities to local employment and business establishments across industries. We exploit variation in extreme heat exposure and show how FCIP moderates its economic impacts. The findings show that extreme heat significantly dampens employment and establishment growth in rural communities, particularly in agricultural industries. However, FCIP enrollment substantially mitigates these adverse effects and generates positive spillovers to non-tradable sectors such as retail, hospitality, and healthcare. Back-of-the-envelope calculations suggest the FCIP preserves about 100,000 rural jobs annually, with growing impacts over time. These findings highlight how federal insurance in the agricultural sector supports rural labor markets and should be considered in 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 farmers in the United States. Established in 1938 and greatly expanded in size and scope in the 1990s and 2000s, the FCIP offers farmers financial protection against losses from drought, hail, wind, plant disease, and crop price fluctuations. The program, which is administered by the US Department of Agriculture's Risk Management Agency, is available for 134 different commodities. From 2000 through 2022, an average 293 million acres of farmland were enrolled in the program each year, comprising 81 percent of eligible acreage.

The FCIP is the single largest financial assistance program for agricultural producers and the cost of the program to the federal government has risen sharply over the past two decades. According to a 2023 Government Accountability Office (GAO) report, the program costs the US government 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 the subsidies' distortionary effects 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. In addition, advocates for the program, and for agricultural support programs more generally, often emphasize the purported broader economic benefits of the program, especially in sustaining local rural economies.

Existing research has largely focused on how crop insurance demand responds to prices, subsidies, or policy parameters, with less attention paid to dynamic responses following realized weather shocks and no analysis, to our knowledge, of the impacts the program has on local economic outcomes (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 there is uncertainty in 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 non-tradable industries through changes in farm income, employment, and consumption. By stabilizing farm revenues following 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 not only in agriculture but also in healthcare, entertainment, and food services (Executive Office of the President, 2013).

This paper addresses these research gaps by studying two related questions. First, we examine how farmers adjust their crop insurance decisions under the FCIP 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 enrollment in the FCIP affects outcomes in rural labor markets, distinguishing between direct effects on the agricultural sector and spillover effects on local non-tradable sectors. Our analysis focuses on counties in the eastern United States and relies on county-level measures constructed from granular underlying data whenever possible: extreme weather exposure is aggregated based on the spatial distribution of actual planted acreage, while employment and business outcomes are built up from establishment-level data, restricted to rural areas and disaggregated by industry.

Using insurance and yield data on corn and soybeans, we find that farmers respond to adverse weather and yield shocks by increasing participation in the FCIP, primarily along the extensive margin. Counties experiencing lower yields in the previous growing season enroll significantly more acres in FCIP in the subsequent year, with instrumental variables estimates implying that a 10 percent yield decline increases insured acreage by roughly 4.9 percent for corn and 3.4 percent for soy. In contrast, yield losses have negligible effects on average coverage levels, indicating that adjustment occurs mainly through acres enrolled rather than coverage intensity.

We further find that crop insurance plays an important protective role in insulating rural economies from the adverse effects of extreme heat. Extreme heat shocks significantly depress employment and establishment growth in agricultural industries and, to a lesser extent, in local non-tradable sectors that depend on agricultural activity and farm income. However, higher FCIP coverage substantially mitigates these effects and these protective effects operate both through insurance coverage and realized indemnity payments. The largest effects accrue to directly insured agricultural industries, with additional gains propagating to retail, accommodation, and other locally oriented sectors. Our estimates indicate that FCIP enrollment preserved approximately 100,000 jobs per year on average between 1991 and 2019, with spillover effects outside agriculture accounting for the bulk of these employment gains as these sectors employ a much larger share of the population.

This paper contributes to several strands of the literature. First, it relates to a large body of work examining the impacts of the FCIP, which has primarily focused on farmers' production decisions and farm-level outcomes. Existing 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), while 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) further show that crop insurance indemnities help farmers manage liquidity constraints and smooth financial outcomes following adverse shocks. Our findings complement this literature by highlighting that farmers actively update their insurance coverage in response to realized weather and yield shocks, underscoring the role of FCIP enrollment itself as a dynamic risk management decision rather than a fixed institutional feature.

In doing so, our paper also connects to an emerging literature on farmers' adaptation and learning behaviors in response to short-run weather shocks. While prior studies in this literature 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 extend this line of inquiry by documenting adaptive responses in financial risk management through crop insurance participation.

By examining the impacts of the FCIP on rural business establishments and labor market outcomes, this study provides a unique lens on the connection between agriculture and the broader rural economy. Despite frequent assertions of such linkages[1], there are relatively few empirical studies, with much of the existing evidence based 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 as an instrument to study the impacts of higher agricultural revenues on county economic outcomes in the U.S. heartland. They find that higher agricultural revenues raise farm income and employment but have little effect on nonfarm income or employment. Their county-level employment data from the Bureau of Economic Analysis do not distinguish between urban and rural employment within counties, however, which may attenuate

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

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 examining the role of insurance in supporting community financial resilience and economic recovery following 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 following 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), while cross-country evidence suggests that disasters in economies with higher insurance penetration experience smaller real economic losses (Von Peter et al., 2012; Melecky and Raddatz, 2015). More broadly, these findings echo evidence from labor market insurance programs, such as unemployment insurance, which generate 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 beyond insured producers 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.

2 Policy Background

The Federal Crop Insurance Program (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. While 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% of yield) for just an administrative fee and no premium cost. This provision dramatically increased participation. Subsequent 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% 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 shocks on local labor markets, input suppliers, and non-farm 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). In recent years, rising program costs, driven in part by greater exposure to climate extremes, have increased concerns over long-run fiscal sustainability. A 2022 Office of Management and Budget (OMB) analysis of climate risk exposure to the federal government projected a 3.5 to 22 % increase in premium subsidies by 2080 (OMB, 2022).

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 how past heat shocks affect crop insurance uptake, we construct two measures of

[2]Accessed at https://www.rma.usda.gov/tools-reports/summary-of-business.

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 crops in the United States in terms of acreage and revenues.

To analyze the effects of crop insurance enrollment on rural business and employment outcomes, we develop a county-level measure of overall FCIP protection as the share of each county's cropland enrolled in FCIP across all crops for each year. To measure total cropland, we use the maximum cropped area observed during 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 4 km spatial resolution. 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. The estimated threshold is 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 killing degree days (KDD), a measure of cumulative heat exposure above the physiological tolerance point where additional temperature no longer contributes to growth and instead reduces yield, and growing degree days (GDD), which captures beneficial heat accumulation below the threshold. By combining fine spatial and temporal granularity with empirically derived biological cutoffs, these heat exposure measures more closely align with crop response mechanisms and improve the ability to

[3] Accessed at https://www.nass.usda.gov/Research_and_Science/Cropland/Release/index.php.

detect the impacts of heat 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 KDD 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 (NASS) County Agricultural Production Survey for the period 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

To measure rural economic outcomes, we use the National Establishment Time Series (NETS) Database, which contains establishment-level data on every establishment (private and government) in the U.S. during 1990-2022. This dataset allows us to observe the emergence of new establishments during the sample period and whether existing establishments continue their operation each year. The data provides industry classification at the 6-digit NASICS code level, number of employees in each year, and the precise estabishment 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 the context of the proposed project. First, the LBD covers non-farm private establishments only, whereas NETS covers the universe of establishments, including those in the agricultural industry, public, and non-profit sectors. This is crucial for studying the direct impacts of CRP and 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).

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 Non-Tradable 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

To represent rural economies, 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] Our classification mostly follows the standard two-digit NAICS sector, but with more granularity in the agriculture sector (see Table 1 for the classification scheme). Using this classification, we calculate total employment and the number of establishments with at least two employees[6] 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

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

[5]The 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.

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

hypothesized treatment effect. The first group includes the agriculture and adjacent industries that we hypothesize directly benefit from the protective effect of FCIP enrollment. In the second group are industries in the local non-tradable sector, including retail, accommodation and food services, health care, education, and others, which could be affected by spillover effects from FCIP enrollment. The third group incorporates industries for which FCIP should have no effect, including mining, manufacturing, and public administration; this third group of industries serves as a control group in our analysis.

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 subsequently 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:

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

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 growing degree day ($GDD_{c,t-1}$), killing degree day ($KDD_{c,t-1}$), a quadratic function of total precipitation ($Prcp_{ct}$), 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:

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

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

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

Essentially, we use lagged weather variables to instrument for lagged crop yield and estimate its effect on crop insurance uptake decision in the following 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). Note that 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 exclusion restriction, that weather shocks do not affect uptake through channels other than their impacts on crop yields.

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 more than 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 killing degree days (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. The coefficient β_4, which corresponds to the interaction between KDD and the direct treatment group, captures the primary effect of extreme heat on agriculture and adjacent industries. The coefficient β_6 captures the protective effect of crop insurance by further interacting this term with the share of cropland insured under FCIP. Note that these coefficients represent effects relative to the control industries, which is treated as the reference group in this regression.

Both the effect of extreme heat and that of crop insurance might affect the disposable income and consumption decisions of agricultural workers, which, in turn, might spill over to the non-tradable sector in the local economy. To allow for the spillover effects to differ from the direct effects, we include a parallel set of interactions which 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, the inclusion of $Cover_{ct}$ 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 a number of 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}) controls for cross-sectional variation between economic growth and industry composition, the state-by-year fixed effects (θ_{st}) controls for macroeconomic trends at the state level, and the industry-by-year fixed effects (δ_{it}) controls for national trends in each industry.

As our main outcomes are growth rates, they might be subject to extreme values where 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.

Table 2: Variable Weather, Yield, and FCIP Take-Up for Corn

	Dependent variable:						
	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^{**}	-0.004^{***}		0.00002	0.0003^{**}		
	(0.0005)	(0.001)		(0.0001)	(0.0001)		
GDD_{t-1}			0.00000			0.0001^{***}	0.041^{***}
			(0.0002)			(0.00003)	(0.010)
KDD_{t-1}			0.001^{***}			0.00004^{*}	-0.181^{***}
			(0.0003)			(0.00002)	(0.018)
Prcp_{t-1}			-0.001^{***}			-0.00002	0.042^{***}
			(0.0002)			(0.00002)	(0.015)
Prcp^2_{t-1}			0.00000^{***}			0.000	-0.00003^{***}
			(0.00000)			(0.000)	(0.00001)
ln(PlantAcres)	0.927^{***}	0.932^{***}	0.931^{***}	0.008	0.007	0.008	0.844
	(0.038)	(0.042)	(0.036)	(0.006)	(0.006)	(0.006)	(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 take-up for corn. Columns (1) and (3) present OLS estimates based on Equation (3), while 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

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 (i.e. KDD, GDD, and precipitation). Both estimates are negative and statistically significant, indicating that lower yields in the prior year lead to greater insurance enrollment. The 2SLS estimate is roughly four times larger than the OLS estimate, suggesting that the latter 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, GDD significantly increases yields, while KDD reduces them, and precipitation exhibits a significant nonlinear relationship with yield. Notably, one degree day of KDD has more than four times the marginal effect of one degree day of 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 KDD and adverse precipitation conditions, while showing no response to GDD.

Columns (4)–(6) shift the focus to the average coverage level chosen within a county. While 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–percentage-point increase in average coverage. 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 intensive margin (Column 5) to estimate the total impact of yield on insurance coverage.[7] We

[7] We define total insurance coverage as I, covered acres A, and coverage level as C. $I \equiv A \times C$. We are interested in $\frac{\partial I}{\partial Y} = A \times \frac{\partial I}{\partial C} + C \times \frac{\partial I}{\partial A}$. Defining β_A as the effect of yield on ln(Covered Acres) from Column (2) and β_C as the effect of yield on Coverage level from Column (3), we can write $\frac{\partial I}{\partial Y} = (A \times \beta_C) + (C \times \beta_A \times A)$. Note that here, $\frac{\partial I}{\partial C} = \beta_L$, while $\frac{\partial I}{\partial A} = \beta_A \times A$, since the latter coefficient is estimated in a log-linear regression. Thus, $\frac{\partial I}{\partial Y} = A \times (\beta_C + (C \times \beta_A))$. The mean coverage level is 66%, so $\bar{C} = 0.66$.

estimate that a a one-bushel-per-acre decline in yield increases total FCIP coverage by $(0.4\% \times 66\%) - 0.03\% = 0.23\%$, corresponding to a 2.8% increase in FCIP coverage for a 10% yield decline for the average county. Similarly, one additional killing degree day increases FCIP coverage by 0.07%, such that a 10% increase in killing degree days increases FCIP coverage by 0.9% in the average county. In both cases, the extensive margin dominates the intensive margin.

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

	Dependent variable:						
	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^{***}	-0.009^{***}		-0.0001	0.0004		
	(0.001)	(0.002)		(0.0001)	(0.0003)		
GDD_{t-1}			0.001^{***}			0.00000	0.016^{***}
			(0.0001)			(0.00002)	(0.003)
KDD_{t-1}			0.003^{***}			-0.00003	-0.078^{***}
			(0.0004)			(0.00004)	(0.008)
Prcp_{t-1}			-0.001^{***}			0.00002	0.032^{***}
			(0.0002)			(0.00002)	(0.003)
Prcp^2_{t-1}			0.00000^{***}			-0.00000	-0.00002^{***}
			(0.00000)			(0.000)	(0.00000)
ln(PlantAcres)	0.941^{***}	0.942^{***}	0.943^{***}	0.006	0.005	0.005	0.659^{*}
	(0.026)	(0.027)	(0.027)	(0.004)	(0.004)	(0.004)	(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 soybean. Columns (1) and (3) present OLS estimates based on Equation (3), while 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

Table 3 reports analogous results for soybeans. The qualitative patterns closely mirror those observed for corn. Yield increases with GDD, decreases with KDD, 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: both OLS (Column (1)) and 2SLS (Column (2)) estimates suggest that a 10% decline in yield is associated with a 3.4 percent increase in insured acreage. In contrast, there is no statistically or economically meaningful change in the average coverage level (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. While our baseline analysis focuses on responses to the most recent growing season, farmers' 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 additional lags does not change the estimated coefficients on shorter lags, suggesting that omission of earlier yield realizations does not introduce meaningful omitted variable bias. Second, the coefficient on the most recent yield remains the largest in magnitude and the most statistically significant across specifications. Together, these findings indicate that farmers' 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.

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

5.2 The Protective Effect of Crop Insurance on Rural Economies

The preceding section shows that farmers respond to adverse weather and yield shocks by increasing their participation in the FCIP. 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 not only to stabilize farm income but also to smooth cash flows and reduce financial distress following 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 non-farm, non-tradable 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

Table 4: The effect of extreme heat on employment and establishment growth

	Dependent variable:			
	Emp. growth	Estab. growth	Emp. growth	Estab. growth
	(1)	(2)	(3)	(4)
KDD	−0.004	−0.002	−0.001	−0.006**
	(0.003)	(0.002)	(0.003)	(0.003)
FIPS	Y	Y	Y	Y
Year	Y	Y		
State × Year			Y	Y
Outcome mean	1.76	2.68	1.76	2.68
Observations	69,685	69,685	69,685	69,685
Adjusted R^2	0.137	0.687	0.196	0.862
Note:				*p<0.1; **p<0.05; ***p<0.01

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 percentage points) on killing degree days (KDD), weather controls, log planted acres, and fixed effects. Table 4 reports estimates under two fixed-effects specifications: columns (1)–(2) include county and year fixed effects, while columns (3)–(4) include county and state-by-year fixed effects.

Across specifications, the estimated coefficients on KDD are uniformly negative but generally statistically insignificant. The only exception is column (4), where the coefficient is statistically significant at the 5% level, indicating that one additional killing degree day during the growing season reduces establishment growth by 0.006 percentage points (pp). A one-standard-deviation increase in KDD therefore lowers establishment growth by 0.64 pp, or roughly 19% of the sample mean growth rate.[8]

While these estimates appear to suggest that extreme heat has little effect on rural economic activity, it is important to note that 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 following heat-induced yield shocks, the residual impact of heat on aggregate outcomes may appear muted and

[8]The standard deviation of KDD is 107 and the sample mean establishment growth rate is 3.38, yielding $107 \times (-0.006)/3.38 \approx 0.19$.

Table 5: The effect of FCIP enrollment on establishments and employment

	Dependent variable:			
	Emp. growth	Estab. growth	Emp. growth	Estab. growth
	(1)	(2)	(3)	(4)
KDD × Direct	−0.014***	−0.012***	−0.025***	−0.022***
	(0.002)	(0.001)	(0.005)	(0.002)
KDD × Spillover	−0.006***	−0.006***	−0.015***	−0.002
	(0.001)	(0.001)	(0.005)	(0.002)
KDD × Covered share × Direct	0.023***	0.037***	0.029***	0.036***
	(0.004)	(0.003)	(0.005)	(0.003)
KDD × Covered share × Spillover	0.011***	0.011***	0.017***	0.008***
	(0.003)	(0.002)	(0.004)	(0.002)
County	Y	Y		
NAICS × County			Y	Y
State × Year	Y	Y	Y	Y
NAICS × Year			Y	Y
Outcome mean	3.476	3.380	3.476	3.380
Observations	1,145,088	1,145,088	1,145,088	1,145,088
Adjusted R^2	0.041	0.296	0.070	0.437
Note:				*p<0.1; **p<0.05; ***p<0.01

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.

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

Table 5 reports selected coefficients associated with killing degree days (KDD). Columns (1) and (2) examine employment and establishment growth rates, respectively, under a parsimonious fixed-effects structure that includes 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 effects. The results are qualitatively similar across specifications, suggesting that differences in industrial composition across counties and industry-specific trends

are unlikely to be the primary drivers of the estimated effects.

The interaction terms between KDD and indicators for industries with direct and spillover exposure identify the differential effects of extreme heat on these sectors relative to the control industries. We find that KDD has negative effects on both groups, with substantially larger impacts on agricultural industries than on local non-tradable sectors. Under our preferred specifications in columns (3) and (4), one additional killing degree day reduces employment growth in the agricultural sector by approximately 0.025 pp and establishment growth by 0.022 pp. In the local non-tradable sector, the corresponding effect on employment growth is smaller—about a 0.015 pp decline—while the effect on establishment growth is close to zero. Evaluated at the standard deviation of KDD of 106.6, these magnitudes are economically meaningful, corresponding to roughly one-half to two-thirds of the average growth rate in the sample. Taken together, these results align with our expectations and indicate that extreme heat affects industries unevenly: it directly depresses activity in agriculture and, to a lesser extent, propagates through demand-side spillovers that influence employment in related local industries, with minimal effects on establishment entry or exit.

The coefficients associated with the triple interaction terms allow us to further separate how crop insurance coverage interact with the effect of extreme heat. Across the board, we find that insurance coverage creates a statistically significant and positive effect on the agriculture sector. Specifically, the coefficients in column (3) suggest that a 10% increase in the share of cropland covered by crop insurance is associated with a 0.3-basis-point (bp) increase in employment growth rate. Equivalently, if 85% of cropland in a county is covered by crop insurance, then it will almost entirely eliminate the negative effect of extreme heat on agricultural industries. We observe a similar pattern for industries in local non-tradable sector, but as the effect of extreme heat is smaller, the protective effects of crop insurance is also smaller but still economically meaningful. A 10% increase in the share of cropland covered by crop insurance is associated with a 0.17-basis-point increase in employment growth rate. We also observe these same patterns for establishment growth in column (4).

The coefficients on the triple interaction terms allow us to isolate how crop insurance coverage moderates the impact of extreme heat. We find that insurance coverage has a statistically significant and positive protective effect, particularly for the agricultural sector. In column (3), a 10% increase in the share of cropland covered by crop insurance is associated with a 0.3-basis-point (bp) increase in the employment growth rate. Where roughly 85% of cropland is insured, this effect

is large enough to nearly offset the negative impact of extreme heat on agricultural industries. A similar but attenuated pattern emerges for local non-tradable industries. Because these sectors are less directly exposed to heat shocks, the associated insurance-mediated effects are smaller but remain economically meaningful: a 10% increase in insurance coverage raises employment growth by about 0.17 bp. 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 producers 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. This alternative measure reflects not only the extent of insurance participation but also the severity of realized losses and the magnitude of financial transfers triggered by heat shocks. As shown in Table A4, the results point to similar offsetting effects from insurance payments. This finding suggests that the ex post income replacement through crop insurance dampens downstream contractions in labor demand and local economic activity following adverse weather shocks.

5.3 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 (i.e., direct or spillover) is represented by its own indicator and separately interacted with KDD and FCIP coverage share. Figure 1 plots the resulting industry-specific estimates and 95% confidence intervals for the protective effects of FCIP enrollment on employment growth. The upper panel focuses on agriculture and adjacent industries and shows that crop and animal production, as well as support activities,[9] experience the largest protective effects from FCIP enrollment. 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 statistically insignificant, while the effect for fishing and hunting is negative and also insignificant. This pattern is consistent with the fact that FCIP does not insure economic losses in these industries. The bottom panel presents results for the local non-tradable 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

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

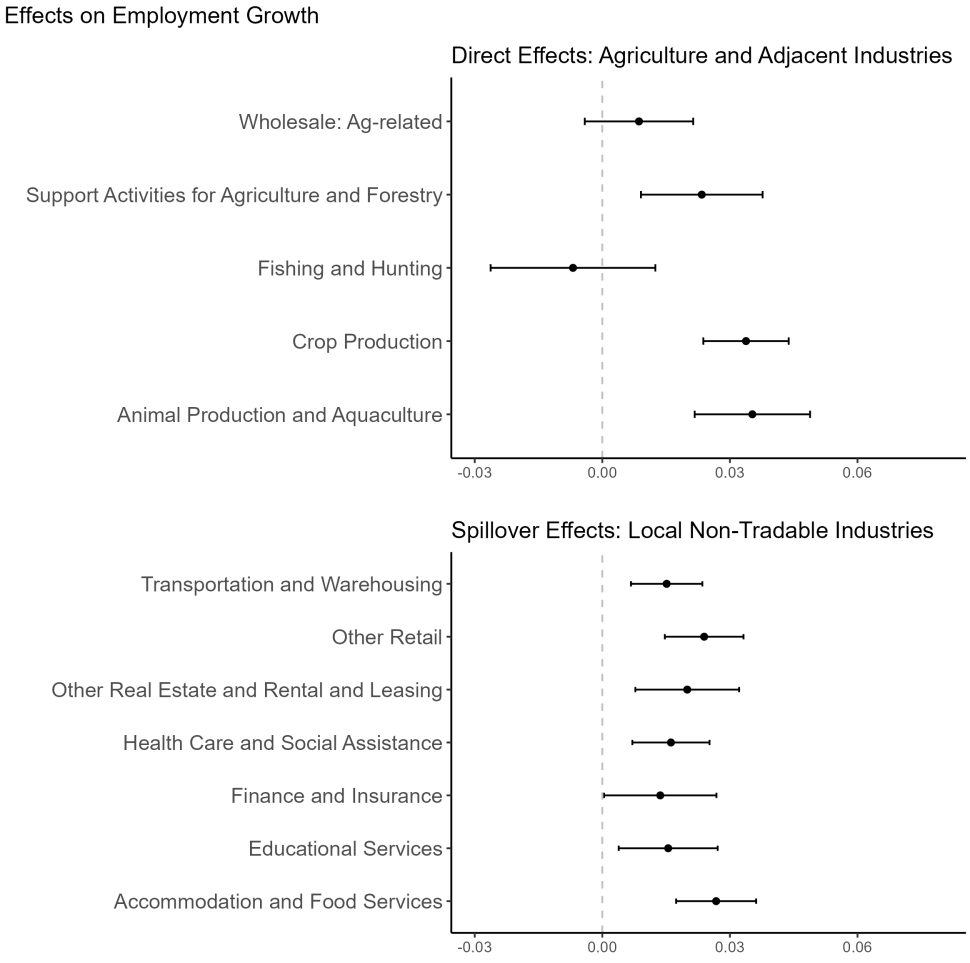


Figure 1: Employment Effect by Industry

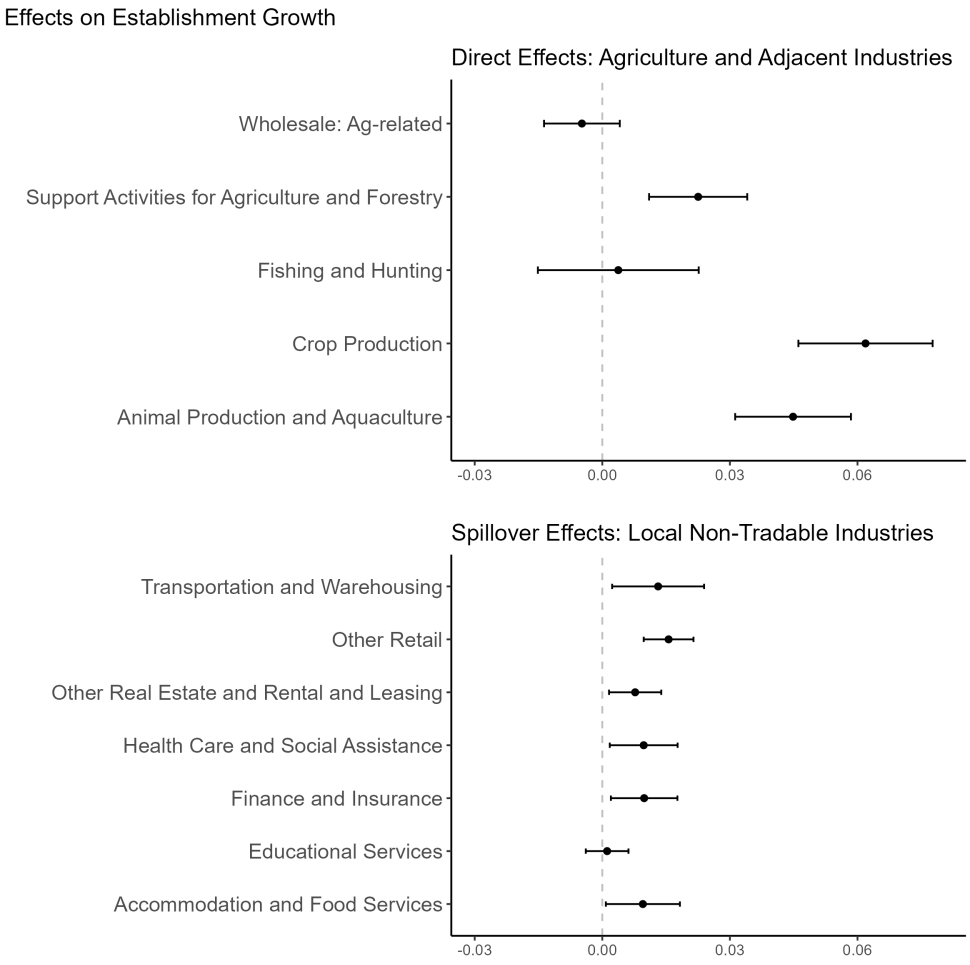


Figure 2: Establishment Effect by Industry

smaller effects for finance and insurance and educational services.

In Figure 2, 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, while effects for agricultural wholesale and fishing and hunting are negligible. The results for the local non-tradable sector are likewise similar to those reported above: 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. Industries that receive direct coverage under the program experience the largest gains, while the income support generated by FCIP also

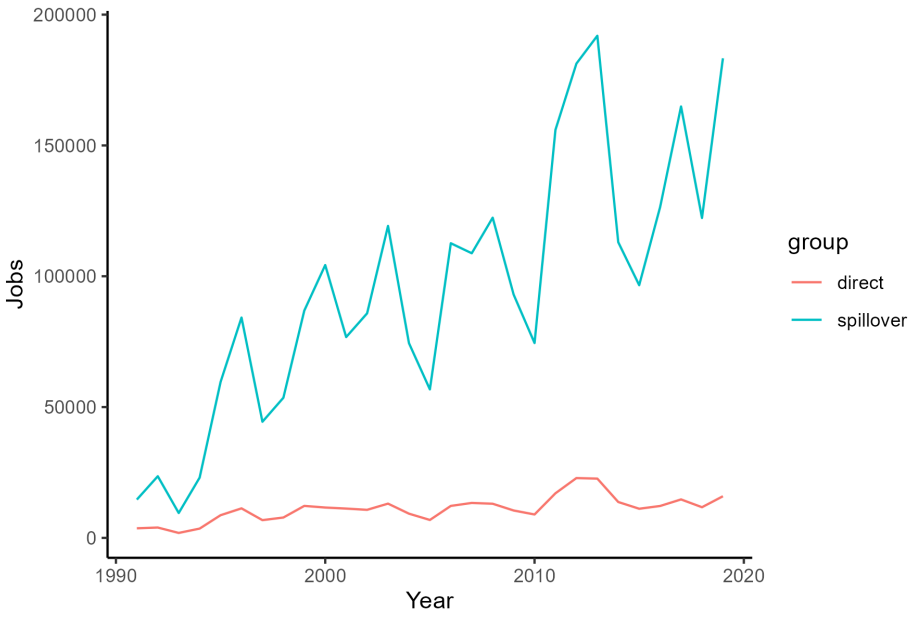


Figure 3: Effect on Jobs By Year

spills over to local providers of non-tradable goods and services.

5.4 Back-of-the-Envelope: Labor Market Benefits of FCIP

Our results in the previous section suggest that FCIP enrollment substantially mitigates the adverse effects of extreme heat on employment and establishment growth in the agricultural sector as well as in industries providing local goods and services. In this section, we assess the economic significance of these estimates by conducting a back-of-the-envelope calculation of the number of jobs preserved each year due to the FCIP.

We apply the following calculation to observations in the direct and spillover treatment groups in our regression sample, defined at the industry (i), county (c), and year (t) level:

$$\Delta Jobs_{ict} = Jobs_{ic,t-1} \times \Delta Growth_{ict} \tag{5}$$

where $Jobs_{ic,t-1}$ denotes employment in the previous year and $\Delta Growth_{ict}$ represents the FCIP-induced change in the employment growth rate. The latter is constructed using the estimated coefficients from column (3) of Table 5 as

$$\Delta Growth_{ict} = \hat{\beta}^{direct} \cdot KDD_{ct} \cdot Direct_i + \hat{\beta}^{spillover} \cdot KDD_{ct} \cdot Spillover_i. \tag{6}$$

According to this calculation, over the sample period from 1991 to 2019, FCIP enrollment contributed to the preservation or creation of an average of 102,871 jobs per year. Figure 3 plots the resulting time series of jobs supported in rural economies. Although the annual estimates fluctuate, there is a pronounced upward trend, rising from roughly 18,000 jobs in the early 1990s to just under 200,000 by 2019. This increase is primarily driven by the expansion of FCIP participation over time, following a series of policy reforms that substantially raised premium subsidy rates. Notably, the bulk of the jobs preserved are attributable to spillover effects, highlighting the importance of considering the program's impacts beyond the agricultural sector through multiplier channels that operate in broader rural economies.

Total FCIP outlays between 2012 and 2022—including premium subsidies and administrative costs—averaged approximately $10 billion per year, nearly twice the average annual spending in the previous decade and more than ten times that of the 1990s.[10] Based on these figures, the average program cost per job preserved in 2019 is approximately $50,798. For comparison, the Council of Economic Advisers estimated that the American Recovery and Reinvestment Act of 2009 spent roughly $92,000 per job-year created (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.

Figure 4 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, while the lower panel 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 KDD, shown in the upper panel of Figure A1, where southern counties experience more frequent and intense heat shocks.

Importantly, this north–south gradient reflects the spatial pattern of extreme heat shocks and the 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,

[10] Annual program costs are obtained from https://www.ers.usda.gov/topics/farm-practices-management/risk-management/crop-insurance-at-a-glance.

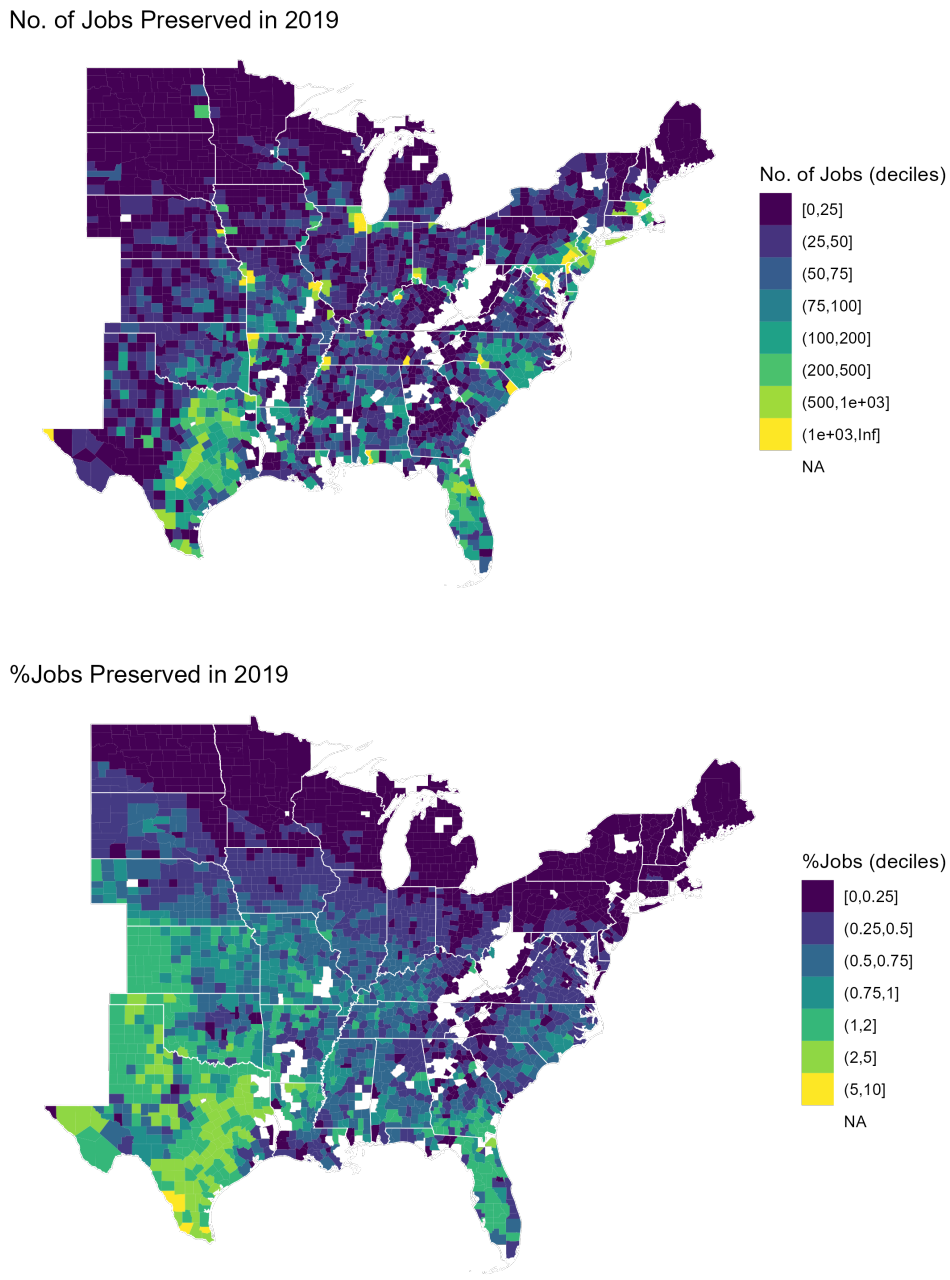


Figure 4: Employment Effect across Counties in 2019

the Coastal Plain region in eastern Texas and much of Florida stand out as areas benefiting most from the protective effects of crop insurance. These regions combine high exposure to extreme heat with high FCIP participation rates, amplifying the stabilizing effects of insurance on local employment (see Figure A1).

6 Conclusion

This paper documents two central findings about the Federal Crop Insurance Program (FCIP). First, farmers respond to negative weather and yield shocks by increasing insurance participation, primarily along the extensive margin: adverse heat exposure and lower yields in one year lead to substantially greater acreage enrolled in crop insurance in the following 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, in local non-tradable 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 not only for farm-level risk management benefits but also for 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.

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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

	Dependent variable:					
	ln(CoveredAcres)			Coverage level		
	(1)	(2)	(3)	(4)	(5)	(6)
Yield_{t-1}	-0.001^{**}	-0.001^{**}	-0.001^{**}	0.00002	-0.00000	-0.00001
	(0.0005)	(0.0004)	(0.0003)	(0.0001)	(0.0001)	(0.0001)
Yield_{t-2}		-0.0004	-0.0004^{**}		-0.00001	-0.00003
		(0.0002)	(0.0002)		(0.00005)	(0.00004)
Yield_{t-3}			0.00000			0.00000
			(0.0002)			(0.00003)
ln(PlantedAcres)	0.927^{***}	0.907^{***}	0.897^{***}	0.008	0.009	0.009
	(0.038)	(0.031)	(0.024)	(0.006)	(0.006)	(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, while 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	1,145,296	80,818.630	112,287.300	0	2,154,806
Planted acres	1,145,296	120,149.700	162,687.900	0.000	2,905,025.000
Covered share	1,145,296	0.399	0.199	0.000	0.900
Total indemnities ($)	1,088,498	1,735,530.000	4,915,915.000	0.000	153,953,905.000
Direct	1,145,296	0.266	0.442	0	1
Spillover	1,145,296	0.423	0.494	0	1
Employment	1,145,296	724.185	5,115.431	2	436,178
Estab. (>1 employees)	1,145,296	46.004	289.080	1	31,799
Employment growth (%)	1,145,296	3.476	29.165	−99.889	1,000.000
Establishment growth (%)	1,145,296	3.380	21.613	−99.346	800.000
KDD	1,145,088	107.579	106.617	0.000	1,142.018
Precipitation	1,145,088	697.861	227.682	0.000	2,628.272

Table A4: The Effect of FCIP Indemnities

	Dependent variable:			
	Emp. growth	Estab. growth	Emp. growth	Estab. growth
	(1)	(2)	(3)	(4)
KDD × Direct	-0.043^{***}	-0.021^{***}	-0.081^{***}	-0.056^{***}
	(0.009)	(0.003)	(0.013)	(0.005)
KDD × Spillover	-0.027^{***}	-0.013^{***}	-0.060^{***}	-0.013^{***}
	(0.010)	(0.003)	(0.014)	(0.003)
KDD × Log indemn. × Direct	0.003^{***}	0.002^{***}	0.005^{***}	0.004^{***}
	(0.001)	(0.0003)	(0.001)	(0.0003)
KDD × Log indemn. × Spillover	0.002^{**}	0.001^{***}	0.004^{***}	0.001^{***}
	(0.001)	(0.0002)	(0.001)	(0.0002)
FIPS	Y	Y		
NAICS × FIPS			Y	Y
State × Year	Y	Y	Y	Y
NAICS × Year			Y	Y
Observations	1,088,317	1,088,317	1,088,317	1,088,317
Adjusted R^2	0.042	0.294	0.071	0.439
Note:				*p<0.1; **p<0.05; ***p<0.01

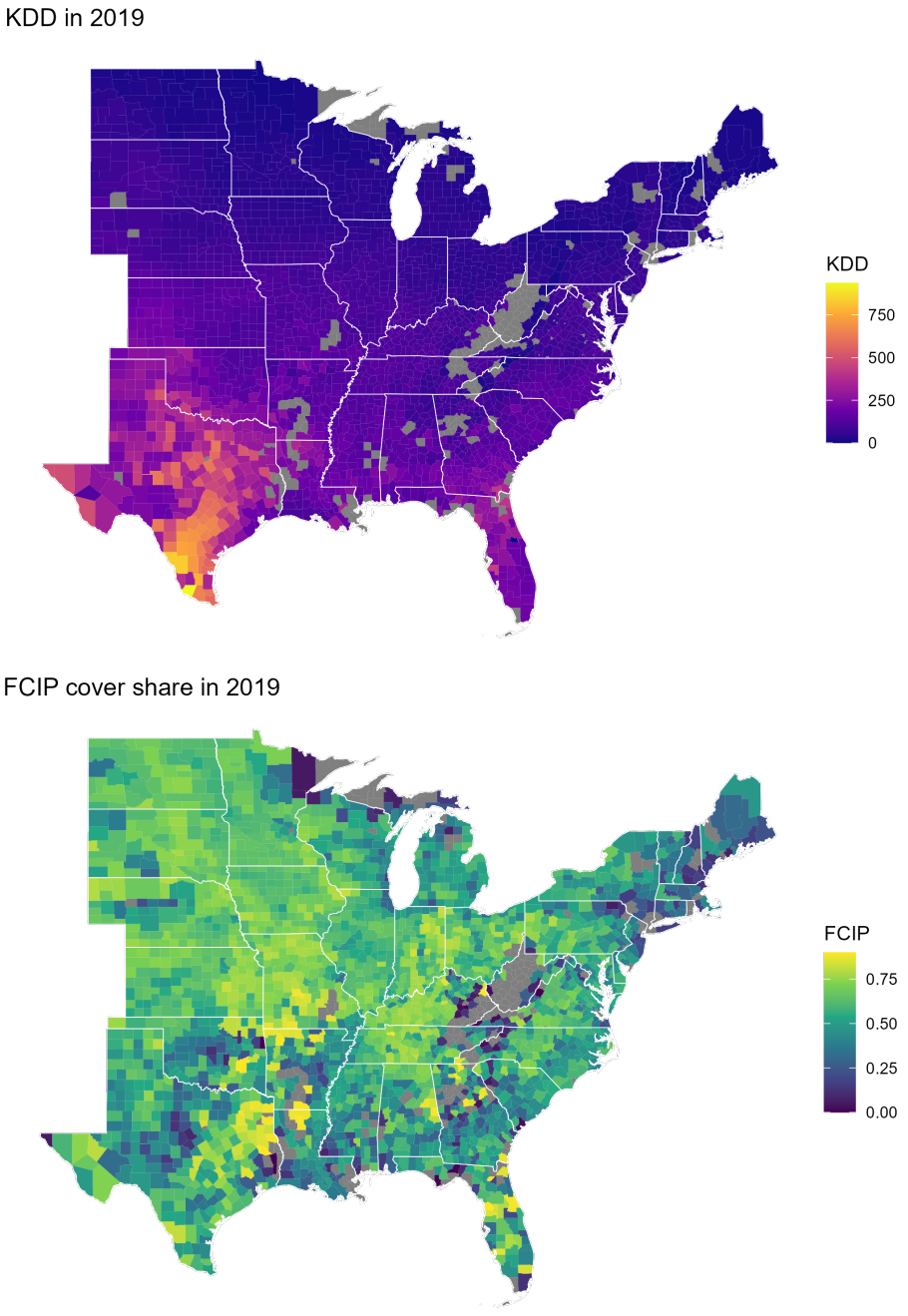


Figure A1: KDD and FCIP Cover Share in 2019

B Constructing Agriculture Heat Exposure Measures

B.1 Crop-Specific Temperature and Precipitation Exposure

Our raw temperature data from PRISM Climate Group (2023) and contains daily minimum and maximum temperature at ∼4km 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°C to 40°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:

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

In this formula, 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 from the start to the end of the day:

$$t_i \in \{0, 0.01, 0.02, \ldots, 1\} \tag{B2}$$

We calculate the proportion of the day that the temperature remains within the bounds of the binned intervals [lower_temp, upper_temp] using the equation:

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

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 (∼4km) 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 the weather data described above, we estimate local non-linear effects of temperature on yields (Hsiang, 2016). The estimated relationship is then used to inform the construction of our main measure of heat shock in our analysis of FCIP take-up 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:

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

where $\theta_{ct}(h)$ represents the time distribution of temperature during the mid growing season in $1°C$ 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:

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

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 mid season temperature here because preliminary exploration shows that mid season temperature has the most pronounced effects on crop yields, which significantly improves the precision of this procedure.

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 $5°C$ bins and a quadratic function of each growing season's precipitation. In addition, we also account for county fixed effects, which controls for time-invariant county characteristics such as soil type, and year fixed effects, which controls for year-specific shocks that affect crop yields in all counties.

To find the threshold temperature for crop growth, we loop over all whole $°C$ values and pick

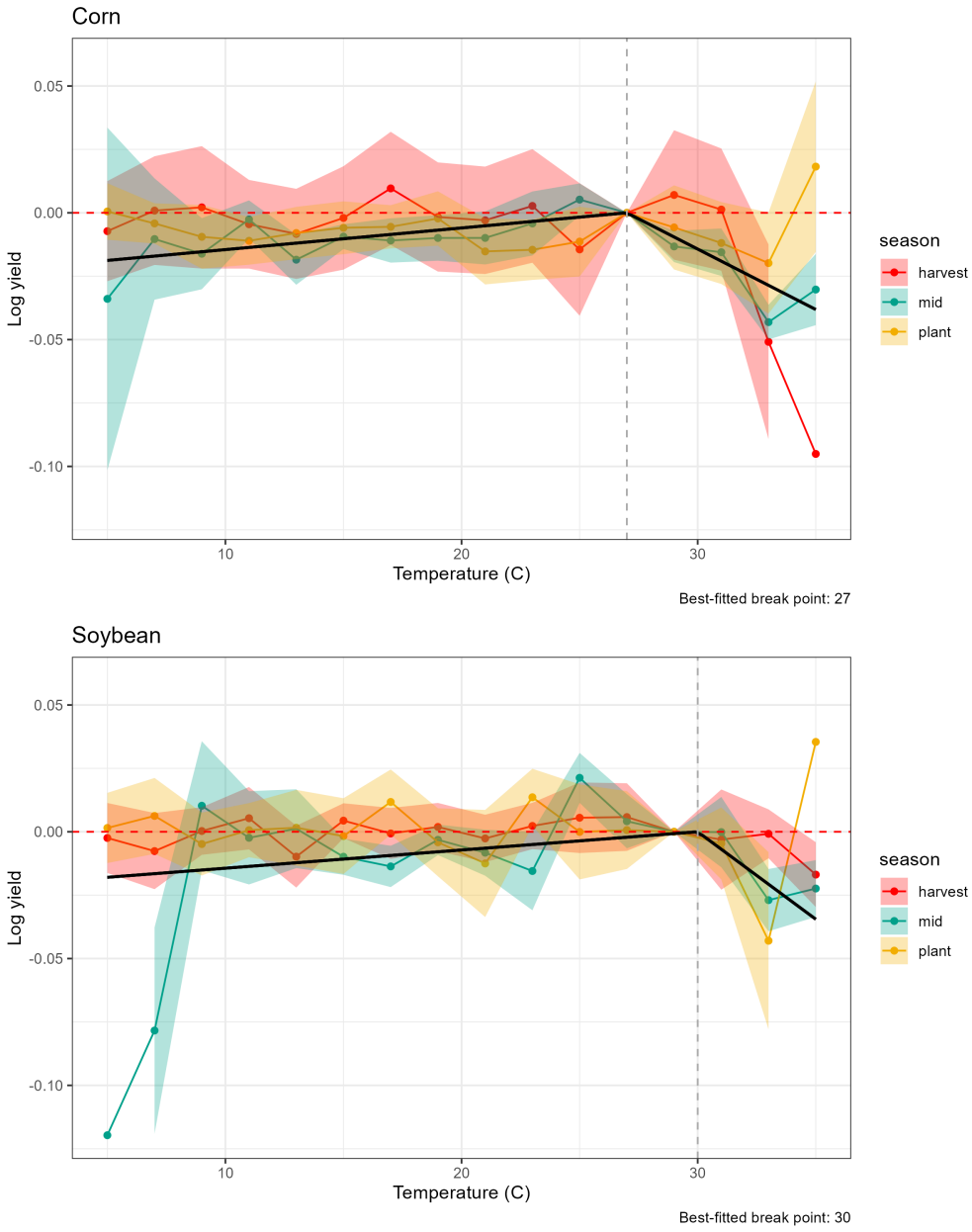


Figure A2: Nonparametric Relationship between Yield and Temperature

the one that generated the best fitted regression. We find that the best fitted threshold temperature is 27 °C for corn and 30 °C for soy. These estimates are in line with the literature (Schlenker and Roberts, 2009; Schauberger et al., 2017). Figure A2 plots the estimated piecewise functions for corn (upper panel) and soy (lower panel) against nonparametric estimates of the relationship based on 2-degree temperature intervals in each growing season segments.

B.3 Constructing the Killing Degree Day Measure

Using the estimated thresholds above, we calculate the daily killing degree day (KDD) for each crop as follows:

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

We then sum it over the entire growing season for each county to calculate the overall KDD for that crop in that county. Similarly, we calculate the growing degree day (GDD) between $9°C$ and the estimated threshold.[11] These measures will be our main temperature variables in the analysis below.

[11] The choice of the lower threhold of $9°C$ is consistent with the literature (Schlenker and Roberts, 2009; Butler and Huybers, 2013; Butler et al., 2018).