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Climate, Insurance, and Crop Yield: Evidence from U.S. Agriculture

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Climate, Insurance, and Crop Yield: Evidence from U.S. Agriculture

Abstract: This paper investigates the impact of federal crop insurance program (FCIP) on corn and soybean yields in the United States, using a county-level large panel dataset spanning over 1950-2022. As extreme heat becomes a grand challenge in the U.S. agriculture, the focus of this article is on estimating the mediating role of FCIP on weather-yield relationship using different identification techniques. Results from fixed effect instrumental variable (FE-IV) approach suggest that the sensitivity of insured corn yield to overheating growing degree days (GDD) is 36%-104% higher than non-insured corn, depending upon the time frame under consideration. Similarly, results from staggered Difference-in-Difference (DiD) estimation technique suggest that the negative effect of FCIP on insured corn yield is pronounced in hot counties when compared to cool counties. Similar patterns are observed for soybean yields.

Keywords: Crop insurance, moral hazard, overheating growing degree day, sensitivity

JEL classification: G22, Q18

1. INTRODUCTION

Agriculture production is sensitive to extreme weather events (Walsh et al. 2020; Won, 2024). In U.S., highly subsidized Federal Crop Insurance Program (FCIP) is the primary policy protecting farmers from various risks associated with agriculture production. Initially introduced on a small scale, both geographically and commodity wise, FCIP now covers subsidized insurance premiums for more than 100 crops across the entire U.S. (Goodwin and Smith, 2012). As of 2024, about 539 million acres of agricultural land in the U.S. were under FCIP with government outlay of \$9.82 billion as premium subsidy (Risk Management Agency (RMA), 2024). The FCIP has long been scrutinized for its impact on farming practices and farm output. However, as extreme weather events have become the grand challenge for agriculture production, the role of FCIP in the weather-yield relationship is still unclear. Using rich county-level dataset (1950-2022) of corn and soybean yields, weather, and insurance, this paper attempts to fill this research gap by analyzing how crop insurance moderates the impact of extreme weather events on crop yields in the U.S. using different estimation techniques.

Previous research regarding the impact of crop insurance on crop production can be broadly classified into two categories. The first categories are related to the impact of crop insurance on production patterns, crop planting choice, and acreage under crops. Empirical results suggest that when farmers have choice to insure their crops against various risk, then they are incentivized to increase the acreage under crop (Young et al., 2001; Goodwin et al., 2004; Goodwin and Smith, 2012; Miao et al., 2016; Yu et al., 2018). However, quantitatively the impact of crop insurance on crop acreage is found to be modest. For instance, Young et al. (2001) estimated 0.4% higher total planted acreage of major crops under subsidized insurance programs compared to without the program.

The second categories of research are related to the moral hazard aspects of crop insurance, where researchers explore the relationship between crop insurance participation and input use. However, the results are inconclusive. For example, Horowitz and Lichtenberg (1993) find that farmers enrolled in the insurance program use more fertilizer and pesticides. Similarly, Ghosh et al. (2021) find that the increased premium subsidy has positive impact on the total freshwater withdrawals and fresh surface water withdrawals used for crop irrigation. Nevertheless, the positive relationship between insurance participation and input use has been questioned by Quiggin et al. (1993) and Smith and Goodwin (1996). They suggest that insurance provides moral hazard incentives to farmers. Therefore, insured farmers use fewer chemical inputs and do not adopt risk mitigation strategies in the period of extreme weather, making them more sensitive to extreme events. In line with this category of research, Annan and Schlenker (2015) and Wang et al., (2021) find that counties with higher crop insurance coverage are more sensitive to extreme heat in the U.S. Similarly, using farm-level data, Regmi et al. (2023) suggest that the impact of extreme heat on corn and wheat yield is negative and in larger magnitude in insured farms when compared to uninsured farms. Our research adds to the findings from Annan and Schlenker (2015), Wang et al., (2021), and Regmi et al. (2023). However, our study differs from previous studies in three aspects.

First, previous studies utilizing the U.S. county-level data to study the impact of FCIP on yield-weather relationship consider narrow time framework when compared to ours. To the best of our knowledge, this study is the first to utilize the comprehensive dataset as our data spans over 1950-2022. Second, we address the endogeneity issues of the econometric model which were ignored by previous studies and use different methods of estimation. Finally, we utilize two measures of insurance coverage which include (1) the fraction of land insured, defined as the

ratio of insured area to planted area as in Annan and Schlenker (2015) and (2) insurance intensity, defined as the ratio of total liability to net insured area. In the U.S., crop insurance program has increased both extensively (area) and intensively (coverage level). Therefore, utilizing a fraction of land insured in the county as a measure of insurance coverage may bias our estimation. However, use of insurance intensity can address this issue by incorporating change in both extensive margin and intensive margin of insurance coverage.

The subsequent sections of this article are organized as follows. Section 2 presents a background of the federal crop insurance program development in the U.S. Section 3 describes the data and variables. Section 4 describes the empirical models, and Section 5 presents the results. Section 6 concludes.

2. BACKGROUND

In the U.S., crop insurance has long history and was introduced in the staggered manner. Initially crop insurance was established by private company as an experiment in 1899 in Minneapolis, as “all-risk” crop insurance (Wantoch, 2021; Biram and Coble, 2023). Then after, the other two commercial attempts in 1919 and in 1922, designed to offer multiple-peril crop insurance (MPCI), were immediately terminated (Smith, 2012; Wantoch, 2021). The great depression and the dust bowl of 1930s and Roosevelt’s commitment in the presidential election campaign, geared Congress to authorize Federal Crop Insurance Program (FCIP). Furthermore, to expand and implement crop insurance program, Federal Crop Insurance Corporation (FCIC) was established in 1938 (USDA, 2024).

Despite FCIP and FCIC, the crop insurance coverage was not satisfactory. The crops and states under insurance program were limited. For example, in 1948, there were only 36 policies in 13 states (Figure 1). Even after 45 years of enactment, there was little progress in the federal crop

insurance participation as congress expected. Various factors were identified contributing to under-performance, including comparatively low institutional commitment to the program, lack of producer confidence in the program stemming from uninformed rate-determining procedure and novelty of product, insufficient insurance rates to incentivize producers to enroll, producer financial constraints, and availability of region-wide ad-hoc free disaster relief transfer payments or loan in the event of crop failure (Che et al., 2019). Furthermore, the insurance program was not actuarially based for two reasons. First, adverse selections of insurance plans because premiums calculation was behind schedule, and farmers who had good crops either cancelled their applications or did not respond to the premium contracts. Second, there was no adequate data regarding the farmers' information at farm-level and inexperienced estimators relied mainly on county averages in setting premiums (Kramer, 1983). Agricultural Appropriation Act in 1943 cancelled the agriculture insurance program, citing two reasons: *i.*) the significant underwriting loss each year, and *ii.*) low level of coverage and participation. However, two years later the insurance program resumed.

Having realized the underperformance of FCIP, the government promulgated the disaster payment program in 1974. This payment program overlapped with the FCIP and was a matter of discussion for three main reasons: First, inefficient use of the nations' resources by incentivizing producers to produce in high-risk areas (Gardner, 1979). Second, associated moral hazards and adverse selectivity, and finally, inequitable program because of consideration of some selective crops (Miller and Walter, 1977). Therefore, the ad hoc disaster program was terminated in 1981 with the promulgation of the Federal Crop Insurance Act in 1980.

The Federal Crop Insurance Act of the 1980s was considered a paradigm shift to increase crop insurance coverage and participation. Private companies were encouraged to participate in

the sales and service of FCIP (Smith, 2020). One motive of the Federal Crop Insurance Act 1980 was to replace the ad hoc disaster payment programs. However, low insurance participation demanded that Congress pass four ad hoc disaster assistance programs in 1988, 1989, 1992, and 1993 (USDA, 2024; Smith, 2020). The expectation of ad hoc disaster assistance in the event of adverse yields disincentivized producers from enrolling in the federal crop insurance program. For this reason, annual disaster bills were supposed to compete with federal crop insurance programs. In response to this issue of competition, congress enacted the Federal Crop Insurance Reform Act in 1994, making farmers mandatory to be enrolled in crop insurance programs to be eligible for deficiency payments under price support programs and other benefits. This compulsion participation created catastrophic coverage (CAT). In 1996, congress eliminated compulsory enrollment program and establish crop revenue-based insurance products to protect against loss due to yield, price, or both (Coble and Barnett, 2013; Shields, 2015; Glauber and Collins, 2002).

In 2000, with the promulgation of the Agricultural Risk Protection Act (ARPA), congress further increased the subsidies for crop insurance programs. Participation in the CAT level has decreased after ARPA, as the subsidies to buy-up levels were increased. Furthermore, this ARPA has increased emphasis on the insurance needs of the specialty crop. Similarly, the Food, Conservation and Energy Act of 2008 also changed subsidy rates in the 2009 crop year. The 2014 Farm Bill, through the whole-Farm Revenue Protection scheme, started insuring all a farm's commodities under a single policy. The Agricultural Act of 2014 expanded existing coverage and authorized reimbursement of 'shallow losses' beginning in the 2015 crop year (Ghosh et al., 2021).

We present the status of crop insurance in different years in Figure 2 and 3. Specially, in Figure 4, we present the status of crop insurance of year 2023. As presented in Figure 4, the total insured value under crop insurance is 362.658 billion U.S. dollar. Similarly, the total premium for

this insured value is 36.18 billion dollars. Among the total insured dollars, the subsidized premium is 22.64 billion, indicating that around 63 percent of the total premium is paid by the government as subsidy. The loss ratio is 0.87, suggesting that annual indemnities of year 2023 total about 87% of total premium. Prior to mid-1990s, loss ratio was often greater than 1, indicating that the total premium collected was unable to pay the total losses. For example, in 1993 and 1995, the loss ratio was 2.19 and 1.016, respectively.

3. DATA AND VARIABLES

Our analysis focuses on corn and soybean producing counties in the United States, with a temporal framework over 1950-2023. In the remaining part of this section, we describe the key variables in detail. The summary statistics of the variables are presented in Tables 1 and Table 2.

Yield data: We obtained the county-level corn and soybean yield from 1950 to 2022 from the National Agricultural Statistics Services (NASS) of the U.S. Department of Agriculture (USDA). The range of corn yield is from 4.5 to 246 bushels per acre, whereas that of soybean is 0.7 to 69.3 bushels per acre.

Insurance data: We obtain crop insurance related data from the Risk Management Agency (RMA) of USDA. We follow Annan and Schlenker (2015) to construct the fraction of land being insured (extensive margin of insurance) as,

$$Fraction\ Insured_{it} = \frac{Insured\ acreage_{it}}{Maximum\ planted\ acreage\ in\ the\ county\ from\ 1950-2023_{it}} \quad (1)$$

In the U.S., the insurance policy has been extended both in terms of extensive coverage and intensive coverage. Using a fraction of land insured as a variable to represent the insurance coverage may bias our estimates. Therefore, we also constructed an additional variable as follows to represent both extensive and intensive margin of insurance coverage in US.

$$Insurance\ Intensity_{it} = \frac{Total\ Liability\ (in\ dollars)_{it}}{Total\ net\ reported\ insured\ quantity\ (acres)_{it}} \quad (2)$$

We used these two different variables in separate regression to see how the conclusion drawn in one model changes when the explanatory variable is being changed.

Weather data: The data for temperature and precipitation are obtained from the Terrestrial Hydrology Research Group at Princeton University. Existing literature suggests that the relationship between temperature and yield is non-linear (Schlenker and Roberts, 2009; Wang et al., 2021). To capture such a nonlinear relationship, we use the concept of growing degree days (GDD), reflecting the amount of time that the temperature falls in an interval on a specific day. Following Schlenker and Roberts (2009), we define the growing season as March to August and obtain growing degrees days (GDD) based on the data for daily maximum and minimum temperatures. The lower and upper thresholds of the GDD for corn are set to be 8°C and 29°C, respectively. For soybeans, these two thresholds are 8°C and 30°C, respectively. Furthermore, we define the GDD between the two thresholds as normal GDD, and GDD above the upper threshold as overheating GDD. Precipitation is measured as the total accumulation over the growing season. Following Schlenker and Roberts (2009), we include both linear and quadratic terms of precipitation.

4. EMPIRICAL MODEL

4.1 Fixed Effects (FE) and Fixed-Effect Instrumental Variable (FE-IV)

First, we utilize linear panel Fixed Effect (FE) model to address the unobserved heterogeneity at county level such as soil characteristics, which affect crop yield and the farmers' decision to enroll in the FCIP. The regression model for each crop yield and insurance participation measure is specified as follows:

$$y_{it}^c = \beta_{i1}C_{it} + \beta_{i2}I_{it} + \beta_{i3}C_{it} \times I_{it} + \beta_{i4}\psi_{it} + s_i + u_{it} . \quad (3)$$

where y represents crop yield per acre, c is either corn or soybean, C is a vector of weather variables and includes two-growing degree days variables to capture two different temperature thresholds (suitable and overheat) in addition to quadratic terms in precipitation, I can be either a fraction of cropland being insured or insurance intensity, ψ_{it} time trends to capture some other factors that may change over time such as overall technology progress and to absorb the common upward trend of crop insurance take-up rate, s_i control for time-invariant heterogeneity at the county level. β_{i2} and β_{i3} are the parameter of interest. Following Annan and Schlenker (2015), our regression model includes the potentially endogenous crop insurance variable (I) and its interaction with exogenous weather variables C_{it} , as shown in equation (3).¹

However, it is likely that crop insurance variable is endogenous in model (3) and FE alone cannot control the potential presence of residual endogeneity. For example, unobserved liquidity status and farmers learning by doing behavior varies over time and across counties and may affect farmers' decision to participate in crop insurance program (Goodwin and Rejesus, 2008). Therefore, we also employed a fixed-effect instrumental (FE-IV) approach to address the abovementioned endogeneity issues. The FE-IV approach is appropriate because it can address the endogeneity issues of explanatory variables by removing the fixed effects such as the county-level geographical and soil characteristics that may be correlated with some explanatory variables as well as by instrumenting endogenous variables using instrumental variables. Che et al., (2019) suggest that indemnity payouts increase participation in FCIP in the year following loss. We use the one-year lagged value of indemnity payment as an IV for the current period insurance participation measure. The lagged indemnity payment affects the current year's insurance

¹ We refer readers to read paper by Annan and Schlenker (2015).

participation decision of farmers but is unlikely to directly affect the current-year crop yield after we control weather, time trend, and year fixed effects.

4.2 Staggered Difference-in-Difference (DID)

To compare the results from FE and FE-IV with results from DID, we also employ the staggered DID approach. In traditional DID setting, the treatment for the treatment groups is at the same point of time. Specifically, there are two time periods (pre vs post) and two groups (treated vs control) in which treatment group receive the treatment simultaneously. Then, from these settings we can estimate the average treatment effects on the treated (ATETs). However, in the U.S. the crop insurance enrollment years differs across counties. Recent advancement in DID suggests that traditional DID can be biased when the treatment is staggered and the treatment effect varies across the subjects (Callaway and Sant's Anna, 2020; Goodman-Bacon, 2021). Therefore, to address this empirical challenge, we use Callaway and Sants's Annan (2020) approach to estimate the ATET. We use a binary indicator which takes value one for all the years after first crop insurance enrollment. By utilizing Callaway and Sants' approach, we estimate the overall ATETs across time and cohorts. Each cohort represents the start time of treatment. We categorize our sample as full sample (covering all the counties), sample that covers cool counties (Overheat GDD is below median value of samples overheat GDD), and hot counties (overheat GDD above median value of samples overheat GDD). For each category, the aggregated ATET is the weighted mean of all ATETs across time and cohorts given by,

$$\beta_{f,h,c} = \sum_{g \in G} \sum_{t=2}^T W(g, t) ATET(g, t), \quad (4)$$

where, β represents the overall average treatment effect, f represents model for full sample, h for samples with hot counties only, and c with sample with cool counties only. Each cohort g is the subset of G and is defined by the time it first receives treatment. Similarly, $t=2$ is the time periods

after the first treatment. The weight $W(g, t)$ is assigned to the group-time-specific treatment effect ATET (g, t) in the overall average β for each category.

5. RESULT

To start our analysis, we begin by replicating the climate-yield relationship of Schlenker and Roberts (2009) for each crop in Table 3. The sign and statistical significance level of the estimates of climate variables are robust across all regressions, and the results are consistent with previous studies focused on climate-crop relationships (Lobell and Field, 2007; Schlenker and Roberts, 2009; Miao et al., 2016; Malikov et al., 2020). In Table 4, we present the results after adding the fraction of land insured as an additional covariate in Schlenker and Roberts (2009) climate-yield relationship. Results from Table 4 show that the coefficients of fraction of land insured are negative and statistically significant in all the regression, except for soybean yield in column (d), suggesting that fraction of land under FCIP coverage and crop yields (corn and soybean) are negatively associated.

In Table 5-8, we estimate two different models for each crop (i.e., corn and soybean): the fixed effect (FE) model and the FE-IV model, after adding the interaction terms. Each weather variable is interacted with the insurance variable (fraction of land insured in Table 5 and Table 6, and insurance intensity in Table 7 and Table 8 for corn and soybean, respectively). We include FE models along with our preferred models (FE-IV) to show how the results differ between these two methods.

We use Kleibergne and Paap (2006) rk statistics to test for under identification for our models with FE-IV. The test results show that all our preferred models are identified. We use two tests for weak identification: Cragg-Donald F Wald statistic and Kleibergen-Paap Wald rk F statistic. Our results show that regression models with instrumental variables pass the weak

identification test, indicating that instrumental variables are strongly correlated with the endogenous variables. The overidentification test does not apply here because we have the same number of instruments as the number of endogenous variables.

From Tables 5-8, for both corn and soybean yields regression, we can see that in most of the regression results the coefficients of suitable GDD and interaction term between suitable GDD and insurance variables are positive and statistically significant. In contrast, the coefficient of overheating GDD and coefficient of interaction between overheating GDD and insurance variable are both negative and statistically significant. However, the magnitude of coefficients in FE and FE-IV models differs. From results we reconfirm that in the presence of insurance the farmers are reluctant to adopt the extreme heat effect mitigation strategies (Annan and Schlenker, 2015). In case of precipitation, the interaction term between square of precipitation and fraction of land insured (Table 5 and Table 7) and the interaction term between square of precipitation and insurance intensity are positive and statistically significant in most of the yield regression.

When analyzed at the sample means, models from 1(a), 2(a), and 3(a) of Table 5 suggest that 10% increase in insurance coverage in a county is associated with 0.5 to 1.3 percent decrease in the average corn yield. Similarly, results from models 1(b), 2(b), and 3(b) suggest that when there is 10% increase in insurance coverage, it decreases corn yield by 1.16%-4.56%. In Table 6, we present the results for soybean regression. Results from models 4(a), 5(a), and 6(a) suggest that 10% increase in insurance coverage decreases the soybean yield by 0.26%-0.27%. Similar results are obtained from model 4(b) and 5(b), which suggest that 10% increase in insurance coverage decrease the soybean yield by 0.86%-1.25%. However, the result from model 6(b) suggests that the impact of crop insurance on soybean yield is negative but statistically insignificant, when analyzed at sample means.

In Table 7, we present the corn yield regression results when we consider insurance intensity as the measure of insurance participation. When analyzed at the sample means, the result from model 7(a) and model 8(a) suggest that insurance intensity has a negative impact on crop yield whereas the result from 9(a) suggest that the impact of insurance is positive and statistically significant. Similarly, when analyzed at the sample means, results from models 7(b), 8(b), and 9(b) suggest that when there is a 1% increase in the insurance intensity, then there is 0.002%-0.03% decrease in the corn yield.

Similarly, Table 8 presents the soybean yield regression results when we consider insurance intensity as the measure of insurance participation. The results from 10(a) and 11(a) suggest that 1% increase in insurance intensity is responsible for 0.003% and 0.0018% increase in soybean yield, respectively. However, model 12(a) suggests that the impact of insurance intensity is negative (-0.002) and statistically significant. Results from models 10(b) and 11(b) suggest that the insurance intensity has a negative impact on soybean yield when analyzed at the sample mean whereas result form 12(b) suggest positive but insignificant impact of insurance intensity on soybean yield.

From the above results, we conclude that when we do not address the endogeneity issue of our explanatory variables the results using a fraction of land insured and results using insurance intensity are not consistent. For example, in all the fixed effects models in table 5 we estimate that the impact of crop insurance on corn yield is negative. However, the fixed effects models from model 9(a) in table 7 suggest that the impact of crop insurance intensity is positive. In contrast, when we address the endogeneity issue of our explanatory variables, whether we use a fraction of land insured or insurance intensity as measures of insurance participation, we find

consistent results that the insurance has negative impact on corn and soybean yield in all crop yield models.

From our preferred models (FE-IV) in Table 5, we find that the sensitivity of insured corn to overhear GDD is 35%-105% larger than non-insured corn, depending upon the time frame of our considerations. Whereas the sensitivity of insured soybeans to overhear GDD is 78%-138% compared to non-insured soybeans. In Table 9, we present the preliminary results from the staggered DID estimation approach. From the table we can see that crop insurance participation has a negative and statistically significant impact on corn yield (on average 29% decrease in corn yield relative to untreated counties). This negative impact is profound in hot counties. For instance, the treated cool counties have on average 7% less corn yield relative to untreated cool counties. However, treated hot counties have on average 37% less corn yields relative to untreated hot counties. Similar heterogenous impact of crop insurance is observed in soybean yield. The impact of crop insurance on soybean yield across treated cool counties and untreated cool counties is statistically not significant. Whereas treated hot counties have 34.22% lower soybean yield when compared to untreated hot counties.

6. CONCLUSION

In this paper, we reexamine the role of federal crop insurance on corn and soybean yields in the U.S. Particularly, we focus on how crop insurance participation moderates the sensitivity of corn and soybean yields to overhear GDD. We use county-level data on corn and soybean yields and different measures of insurance participation with different estimation methods to examine the impact of FCIP on weather-crop yield relationship.

We find that insured corn and soybean crops are more sensitive to extreme heat compared to non-insured. Our findings using staggered DID suggest that the insured corn (soybean) yield

in hot counties is 47% (112%) lower compared to non-insured corn (soybean). However, in the case of cool counties the insured corn (soybean) yield is 7% (not significant difference) lower compared to non-insured. These findings shed light on the differential impact of crop insurance corn yield based on extreme GDD.

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List of figures

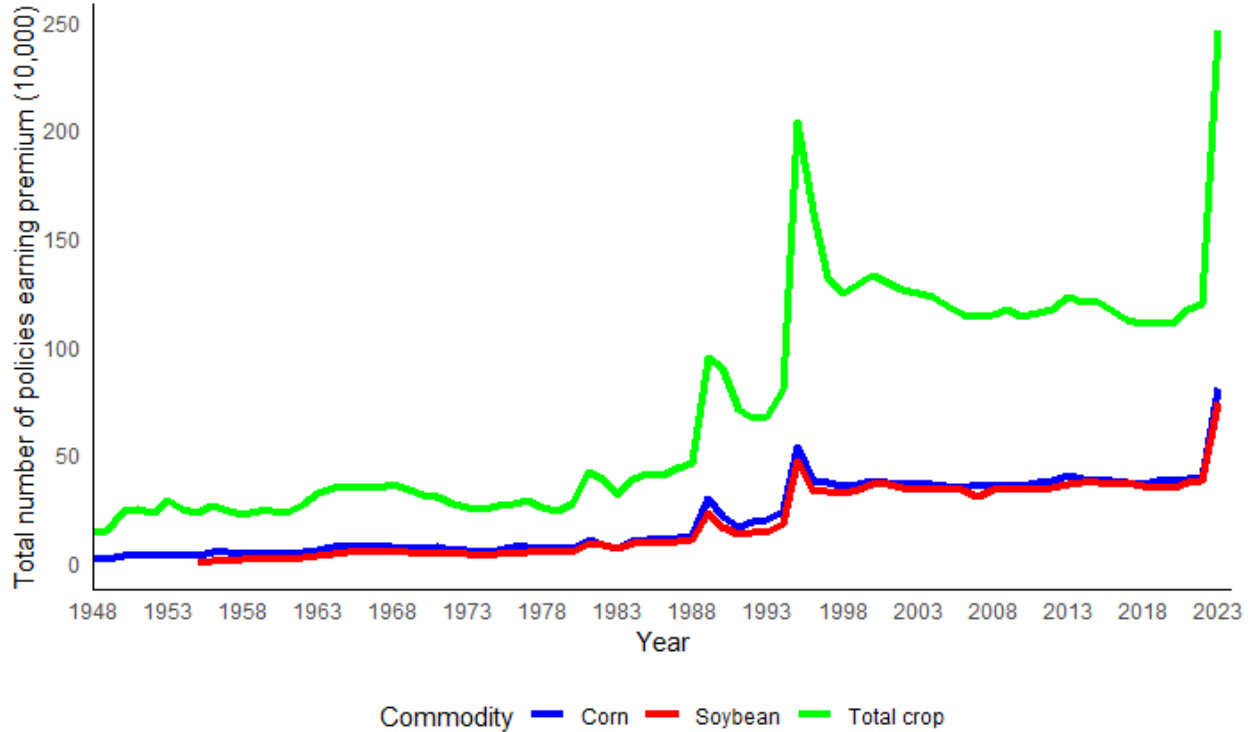
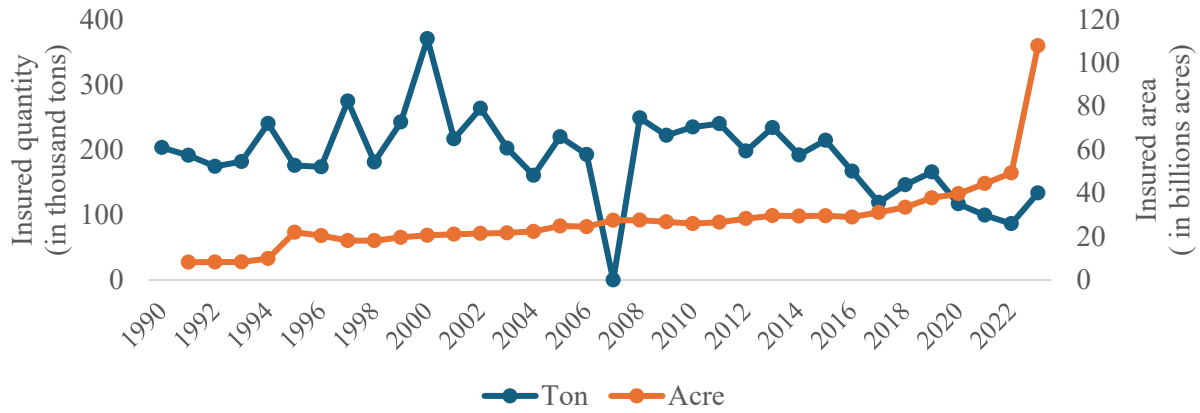
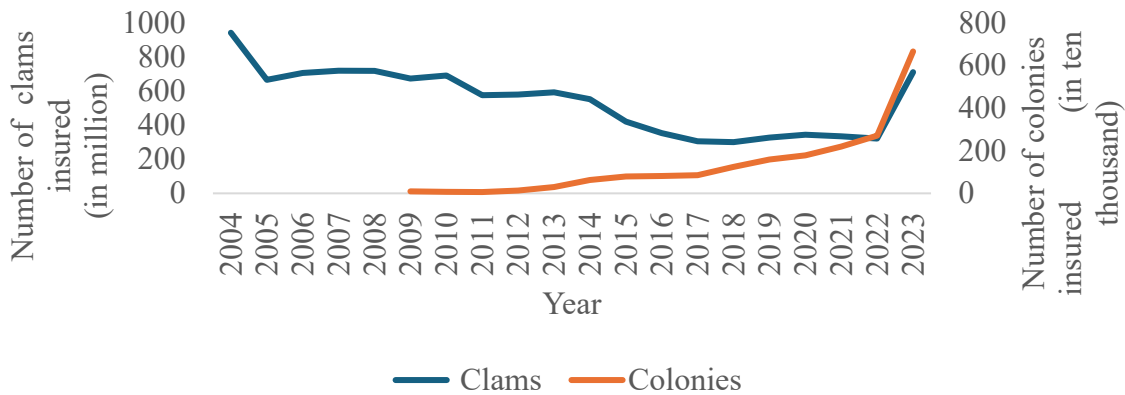


Figure 1. Number of policies earning premium: 1948-2023.

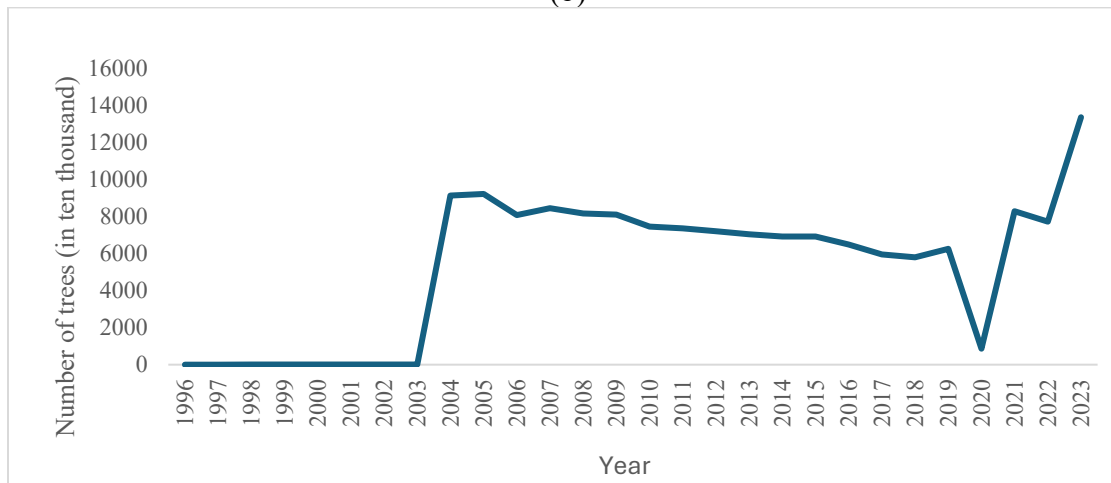
Source: Compiled by the authors using RMA's Summary of Business Reports data. This figure includes the policies totals earning premium for crops insured in tons, colonies, and tress.



(a)



(b)



(c)

Figure 2. Insured quantity in tons, acres, clams, colonies, and trees in year 1990-2023. Graph (a) represents the total amount of insured quantities in tons and in acre. Graph (b) represents the number of insured clams and number of insured colonies. Finally, Graph (c) represents the number of trees being insured.

Source: Compiled by the authors using RMA's Summary of Business Reports data.

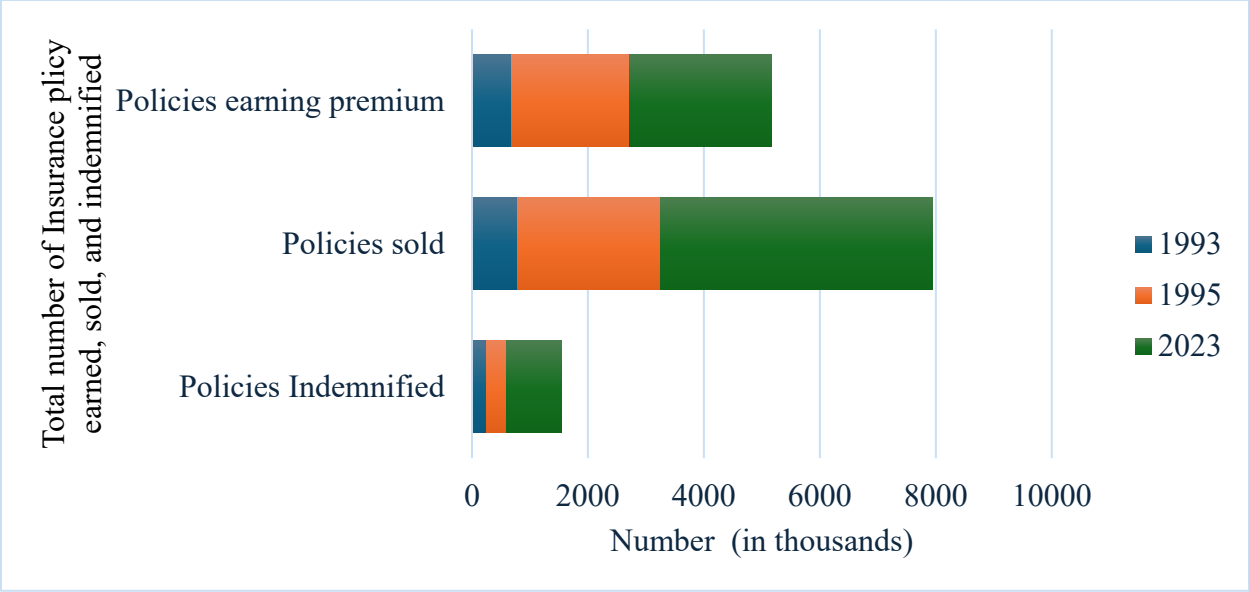


Figure 3. Total number of policies sold, policies earning premium, and policies indemnified in three different years.

Notes: policies earning premium denotes the number of insurance policies for which acreage has been reported to RMA, policies sold represent the total number of policies reported to RMA as being sold, and policies indemnified represent the number of policies for which losses have been reported to RMA for respective year. *Source* Compiled by the authors using RMA’s Summary of Business Reports data.

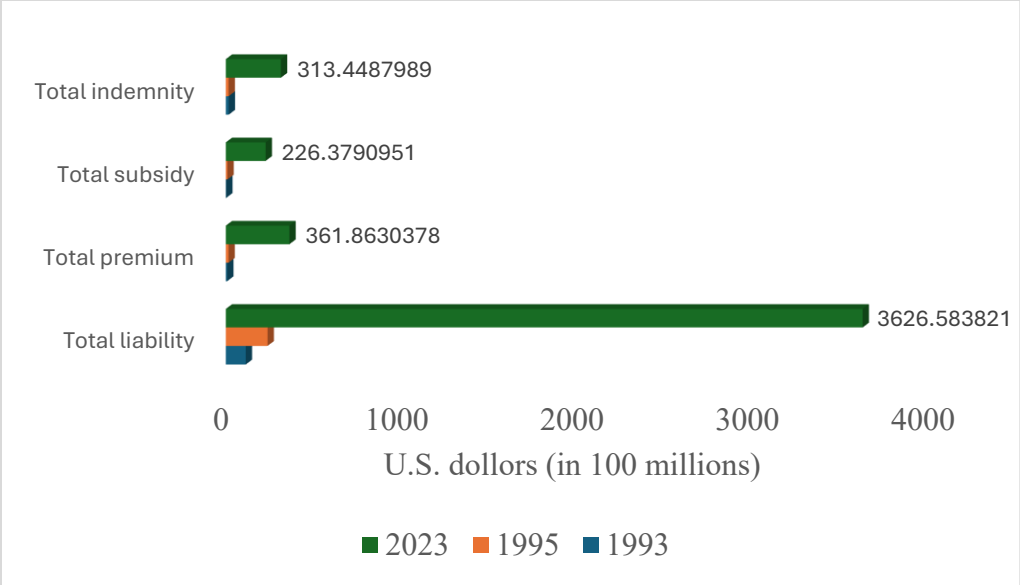


Figure 4. The amount of total liability, premium, subsidy and indemnity of FCIP in the U.S. for year 1993, 1995, and 2023. Note: Total Liability is the maximum dollar amount of insurance for all the crops, total premium is the premium amount before subsidy, total subsidy is the amount of subsidized premium, and total indemnity is the amount of loss. *Source:* Compiled by the authors using RMA’s Summary of Business Reports data.

Table 1. Summary Statistics for corn regression

Variable	Number of observations	Mean	Std. dev.	Min	Max
Corn yield (bu./acre)	148,121	89	45.81575	0.3	277.1
Suitable GDD (1,000)	148,121	2	0.609824	0.879779	4.452479
Extreme GDD (100)	148,121	1	0.605827	0	7.797476
Precipitation	148,121	735	236.8946	5.422573	1839.645
Precipitation Square	148,121	596,655	352528.3	29.4043	3384294
Corn acreage insured (in fraction)	148,121	.1542648	0.250285	0	2.439298
Insurance intensity	148,121	115	177.3115	0	1372.2
Indemnity (in U.S. \$)	148,121	366373	2262307	-71034	140000000.0

Table 2. Summary statistics for soybean regression

Variable	Number of observations	Mean	Std. dev.	Min	Max
Soybean Yield (bu./acre)	108,623	30.56174	11.794	0.7	80.4
Suitable GDD (1,000)	108,623	2.546423	0.5765069	1.019183	4.5186
Extreme GDD (100)	108,623	0.3973438	0.3867513	0	3.696282
Precipitation aggregate	108,623	777.6316	205.0134	137.7985	1858.072
Precipitation square	108,623	646741	341218.5	18988.42	3452433
Insurance intensity (ratio)	108,623	100.6947	132.9845	0	977.4456
Soybean acreage insured (in fraction)	108,623	0.2011232	0.3509595	0	55.1
Indemnity (in U.S.\$)	108,623	234895.7	956684	0	36,900,000

Table 3. Weather- crop yield relationship

	Dependent variable: log of corn yield			Dependent variable: log of soybean yield		
	1950-2022 1(a)	1971-2022 2(a)	1981-2022 3(a)	1950-2022 4(a)	1971-2022 5(a)	1981-2022 6(a)
Suitable GDD	0.2406*** (0.0126)	0.1967*** (0.0128)	0.2079*** (0.0123)	0.2157*** (0.0128)	0.1871*** (0.0123)	0.1989*** (0.0134)
Overheat GDD	-0.4754** (0.0084)	-0.4431** (0.0092)	-0.4486*** (0.0091)	-0.5287*** (0.0081)	-0.5477** (0.0082)	-0.5665*** (0.0103)
Precipitation	0.0006*** (0.0000)	0.0006*** (0.0000)	0.0004*** (0.0000)	0.0009*** (0.0000)	0.0007*** (0.0000)	0.0007*** (0.0000)
Square precipitation	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)
Observations	147,623	104,841	80,334	108,623	83,720	66,073
R-squared	0.760	0.592	0.533	0.698	0.606	0.560
Number of counties	2,794	2,732	2,617	2,252	2,246	2,183

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses. All columns include county fixed effects, year fixed effects, and county specific quadratic time trends. Suitable GDD is in thousands and overheat GDD in hundred.

Table 4. Weather-crop yield relationship (including fraction of land insured as additional covariate)

	Dependent variable: log of corn yield			Dependent variable: log of soybean yield		
	1950-2022 1(a)	1971-2022 2(a)	1981-2022 3(a)	1950-2022 4(a)	1971-2022 5(a)	1981-2022 6(a)
Suitable GDD	0.2239*** (0.0124)	0.1784*** (0.0124)	0.1958*** (0.0122)	0.2171*** (0.0128)	0.1829*** (0.0123)	0.1945*** (0.0135)
Overheat GDD	-0.4748*** (0.0084)	-0.4431*** (0.0093)	-0.4483*** (0.0091)	-0.5289*** (0.0081)	-0.5481*** (0.0082)	-0.5670*** (0.0103)
Precipitation	0.0006*** (0.0000)	0.0006*** (0.0000)	0.0004*** (0.0000)	0.0009*** (0.0000)	0.0007*** (0.0000)	0.0007*** (0.0000)
Square precipitation	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)
Fraction insured	-0.0916*** (0.0143)	-0.0877*** (0.0130)	-0.0701*** (0.0118)	0.0082* (0.0047)	-0.0229*** (0.0066)	-0.0337*** (0.0072)
Observations	147,623	104,841	80,334	108,509	83,698	66,067
R-squared	0.760	0.593	0.534	0.698	0.607	0.560
Number of Groups	2,794	2,732	2,617	2,236	2,235	2,180

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses. All columns include county fixed effects, year fixed effects, and county specific quadratic time trends. Suitable GDD is in thousands and overheat GDD in hundreds.

Table 5. Weather-corn yield relationship (including interaction between weather variables and fraction of land insured)

	Dependent variable: log of corn yield					
	1950-2022		1971-2022		1981-2022	
	FE 1(a)	FE-IV 1(b)	FE 2(a)	FE-IV 2(b)	FE 3(a)	FE-IV 3(b)
Suitable GDD	0.2081*** (0.0132)	0.1995*** (0.0124)	0.1487*** (0.0139)	0.1138*** (0.0142)	0.1775*** (0.0143)	0.1289*** (0.0171)
Fraction insured × Suitable GDD	0.0894*** (0.0248)	0.1740*** (0.0315)	0.1310*** (0.0253)	0.2655*** (0.0323)	0.0794*** (0.0245)	0.2307*** (0.0362)
Overheat GDD	-0.4883*** (0.0090)	-0.4534*** (0.0084)	-0.4326*** (0.0102)	-0.3766*** (0.0109)	-0.4103*** (0.0105)	-0.3470*** (0.0156)
Fraction insured × Overheat GDD	0.0483* (0.0247)	-0.1668*** (0.0426)	-0.0752*** (0.0279)	-0.3329*** (0.0440)	-0.1338*** (0.0283)	-0.3638*** (0.0505)
Precipitation	0.0009*** (0.0000)	0.0010*** (0.0000)	0.0008*** (0.0001)	0.0009*** (0.0001)	0.0004*** (0.0001)	0.0006*** (0.0001)
Fraction insured × precipitation	-0.0011*** (0.0002)	-0.0018*** (0.0002)	-0.0006*** (0.0001)	-0.0012*** (0.0002)	-0.0001 (0.0001)	-0.0007*** (0.0002)
Square precipitation	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)
Fraction insured × square precipitation	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	-0.0000 (0.0000)	0.0000* (0.0000)
Fraction insured	0.1318 (0.0847)	0.3758*** (0.0802)	-0.1222 (0.0796)	-0.0303 (0.0834)	-0.1164 (0.0733)	-0.1113 (0.0927)
Observations	147,623	146,182	104,841	107,160	80,334	80,268
R-squared	0.762	0.755	0.594	0.602	0.536	0.529
Number of Groups	2,794	2,755	2,732	2,685	2,617	2,551
Kleibergen-Paap <i>rk</i> LM statistic		1991 (<i>p</i> <0.001)		1752 (<i>p</i> <0.001)		1385.42 (<i>p</i> <0.001)
Cragg-Donald Wald <i>F</i> statistic)		1082.90		619.4		338.14
Kleibergen-Paap <i>rk</i> Wald <i>F</i> statistic		56.877		53.92		50.54

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. All columns include county fixed effects, year fixed effects, and county specific quadratic time trends. Models 1(a), 2(a), and 3(a) treat all the explanatory variables as exogenous whereas models

1(b), 2(b), and 3(b) address the endogeneity issue of the explanatory variables. The instrumental variable use is the one-year lag of the indemnity payment. Suitable GDD is in thousands and overheat GDD in hundreds.

Table 6. Weather-soybean yield relationship (including interaction between weather variables and insurance fraction)

	Dependent variable: log of soybean yield					
	1950-2022		1971-2022		1981-2022	
	FE 4(a)	FE-IV 4(b)	FE 5(a)	FE-IV 5(b)	FE 6(a)	FE-IV 6(b)
Suitable GDD	0.2326** (0.0138)	0.1861** (0.0132)	0.1634** (0.0132)	0.0859** (0.0159)	0.1432** (0.0160)	0.0417** (0.0202)
Fraction insured × Suitable GDD	-0.041** (0.0145)	0.1841** (0.0245)	0.0992** (0.0150)	0.3712** (0.0282)	0.1559** (0.0204)	0.4854** (0.0371)
Overheat GDD	-0.5183** (0.0087)	-0.4846** (0.0092)	-0.5100** (0.0096)	-0.4595** (0.0128)	-0.5121** (0.0132)	-0.4297** (0.0209)
Fraction insured × Overheat GDD	-0.0883** (0.0285)	-0.3820** (0.0574)	-0.1902** (0.0307)	-0.4964** (0.0655)	-0.2018** (0.0339)	-0.5642** (0.0786)
Precipitation	0.0010** (0.0000)	0.0016** (0.0001)	0.0009** (0.0000)	0.0016** (0.0001)	0.0009** (0.0001)	0.0020** (0.0003)
Fraction insured × precipitation	-0.0002 (0.0002)	-0.0033** (0.0005)	-0.0006** (0.0001)	-0.0033** (0.0006)	-0.0006** (0.0001)	-0.0039** (0.0010)
Square precipitation	-0.0000** (0.0000)	-0.0000** (0.0000)	-0.0000** (0.0000)	-0.0000** (0.0000)	-0.0000** (0.0000)	-0.0000** (0.0000)
Fraction insured × square precipitation	0.0000 (0.0000)	0.0000** (0.0000)	0.0000** (0.0000)	0.0000** (0.0000)	0.0000** (0.0000)	0.0000** (0.0000)
Fraction insured	0.2042** (0.0871)	0.9552** (0.1466)	0.0833* (0.0498)	0.5856** (0.1704)	-0.0503 (0.0518)	0.5746** (0.2615)
Observations	108,509	102,038	83,698	79,178	66,067	62,367
R-squared	0.700	0.692	0.608	0.596	0.563	0.544
Number of Groups	2,236	2,131	2,235	2,121	2,180	2,045
Kleibergen-Paap <i>rk</i> LM statistic		364.13 (<i>p</i> <0.001)		275.38 (<i>p</i> <0.001)		138.42 (<i>p</i> <0.001)
Cragg-Donald Wald <i>F</i> statistic)		144.08		76.43		28.4
Kleibergen-Paap <i>rk</i> Wald <i>F</i> statistic		40.15		37.16		25.89

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. All columns include county fixed effects, year fixed effects, and county specific quadratic time trends. Models 4(a), 5(a), and 6(a) treat all the explanatory variables as exogenous whereas models 4(b), 5(b), and 6(b) address the endogeneity issue of the explanatory variables. The instrumental variable use is the one-year lag of the indemnity payment. Suitable GDD is in thousands and overheat GDD in hundreds.

Table 7. Weather-corn yield relationship (including interaction between weather variables and insurance intensity)

	Dependent variable: log of corn yield					
	1950-2022		1971-2022		1981-2022	
	FE 7(a)	FE-IV 7(b)	FE 8(a)	FE-IV 8(b)	FE 9(a)	FE-IV 9(b)
Suitable GDD	0.2064*** (0.0127)	0.2138*** (0.0120)	0.1224*** (0.0131)	0.1340*** (0.0135)	0.1606*** (0.0132)	0.1504*** (0.0166)
Insurance Intensity* Suitable GDD	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0004*** (0.0000)	0.0004*** (0.0000)	0.0003*** (0.0000)	0.0003*** (0.0001)
Overheat GDD	-0.4936*** (0.0091)	-0.4462*** (0.0090)	-0.4303*** (0.0102)	-0.3642*** (0.0121)	-0.4089*** (0.0103)	-0.3318*** (0.0177)
Insurance Intensity * Overheat GDD	0.0001*** (0.0000)	-0.0003*** (0.0001)	-0.0002*** (0.0000)	-0.0006*** (0.0001)	-0.0002*** (0.0000)	-0.0006*** (0.0001)
Precipitation	0.0009*** (0.0000)	0.0010*** (0.0000)	0.0008*** (0.0000)	0.0009*** (0.0001)	0.0006*** (0.0000)	0.0006*** (0.0001)
Insurance Intensity * precipitation	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)
Square precipitation	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)
Insurance Intensity * square precipitation	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000 (0.0000)
Insurance Intensity	0.0000 (0.0001)	0.0006*** (0.0001)	-0.0003*** (0.0001)	-0.0001 (0.0002)	-0.0001** (0.0001)	-0.0002 (0.0002)
Observations	147,623	146,182	107,218	107,160	80,334	80,268
R-squared	0.764	0.755	0.608	0.599	0.535	0.522
Number of Groups	2,794	2,755	2,743	2,685	2,617	2,551
Kleibergen-Paap <i>rk</i> LM statistic		983 (<i>p</i> <0.001)		888 (<i>p</i> <0.001)		800.79 (<i>p</i> <0.001)
Cragg-Donald Wald <i>F</i> statistic)		873.96		537		343.6
Kleibergen-Paap <i>rk</i> Wald <i>F</i> statistic		83.00		80.55		81.45

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. All columns include county fixed effects, year fixed effects, and county specific quadratic time trends. Models 7(a), 8(a), and 9(a) treat all the explanatory variables as exogenous whereas models 7(b), 8(b), and 9(b) address the endogeneity issue of the explanatory variables. The instrumental variable use is the one-year lag of the indemnity payment. Suitable GDD is in thousands and overheat GDD in hundreds.

Table 8. Weather-soybean yield relationship (including interaction between weather variables and insurance intensity)

	Dependent variable: log of soybean yield					
	1950-2022		1971-2022		1981-2022	
	FE 10(a)	FE-IV 10(b)	FE 11(a)	FE-IV 11(b)	FE 12(a)	FE-IV 12(b)
Suitable GDD	0.2488*** (0.0135)	0.2112*** (0.0117)	0.1507*** (0.0129)	0.1162*** (0.0135)	0.1109*** (0.0143)	0.0801*** (0.0159)
Insurance Intensity* Suitable GDD	-0.0001*** (0.0000)	0.0003*** (0.0001)	0.0003*** (0.0000)	0.0007*** (0.0001)	0.0005*** (0.0000)	0.0010*** (0.0001)
Overheat GDD	-0.5264*** (0.0088)	-0.4814*** (0.0099)	-0.5186*** (0.0097)	-0.4509*** (0.0140)	-0.5193*** (0.0129)	-0.4155*** (0.0219)
Insurance Intensity * Overheat GDD	0.0000 (0.0001)	-0.0008** (0.0001)	-0.0002*** (0.0001)	-0.0010** (0.0001)	-0.0003*** (0.0001)	-0.0012*** (0.0002)
Precipitation	0.0012*** (0.0000)	0.0013*** (0.0001)	0.0010*** (0.0000)	0.0012*** (0.0001)	0.0010*** (0.0001)	0.0016*** (0.0002)
Insurance Intensity * precipitation	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)
Square precipitation	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)
Insurance Intensity * square precipitation	0.0000*** (0.0000)	0.0000** (0.0000)	0.0000*** (0.0000)	0.0000* (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)
Insurance Intensity	0.0014*** (0.0001)	0.0009** (0.0004)	0.0002* (0.0001)	0.0001 (0.0004)	-0.0004*** (0.0001)	0.0005 (0.0005)
Observations	108,623	102,119	83,720	79,190	66,073	62,367
R-squared	0.701	0.694	0.609	0.603	0.567	0.557
Number of Groups	2,252	2,141	2,246	2,125	2,183	2,045
Kleibergen-Paap <i>rk</i> LM statistic		279.65 (<i>p</i> <0.001)		260.30 (<i>p</i> <0.001)		260.012 (<i>p</i> <0.001)
Cragg-Donald Wald <i>F</i> statistic		172.13		116.99		90.32
Kleibergen-Paap <i>rk</i> Wald <i>F</i> statistic		62.04		57.16		57.78

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. All columns include county fixed effects and year fixed effects. Models 10(a), 11(a), and 12(a) treat all the explanatory variables as exogenous whereas models 10(b), 11(b), and 12(b) address the endogeneity issue of the explanatory variables. The instrumental variable use is the one-year lag of the indemnity payment. Suitable GDD is in thousands and overheat GDD in hundreds.

Table 9. Overall average treatment effect of insurance on treated counties

	Average Treatment Effect on Treated (ATET) (1vs 0)	
	Corn	Soybean
Full sample	-0.35*** (0.0797)	-0.34*** (0.35)
Number of observations	130,085	102,161
Hot counties	-0.47*** (0.064)	-1.122*** (0.11)
Number of observations	65,368	35,136
Cool counties	-0.077* (0.04)	-0.075 (0.066)
Number of observations	63,081	65,552

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Model controls the weather variables.