Journal of Agricultural and Resource Economics 49(2):265–282 ISSN: 1068-5502 (Print); 2327-8285 (Online)

doi: 10.22004/ag.econ.338998

Empirical Challenges for Estimating Moral Hazard Effects of Crop Insurance on Pesticide Use

Hunter D. Biram, Jesse Tack, Richard Nehring, and Jisang Yu

The potential for moral hazard is an unforeseen outcome of achieving the dual agricultural policy goals of income stabilization and limited environmental impact. Here, we review key issues for identifying the moral hazard effects of crop insurance on pesticide use and include an empirical application that addresses both insurance endogeneity and quality adjustment of pesticides over time. Our results reveal no consistent linkage between insurance and pesticide use across four major crops. We discuss the differences in these effects across different specifications and crops and conclude by stressing that caution be used when looking to the academic literature for guidance on this key policy question.

Key words: agricultural policy, causal inference, producer behavior

Introduction

Among the many objectives of US agricultural policy, two notable goals include smoothing farm income fluctuations through risk management programs and reducing the environmental impact of chemical inputs (US Department of Agriculture, 2022a; 104th Congress of the United States, 1996). Crop insurance provides risk protection from adverse weather, volatile price movements, and risks associated with expected yield loss, while pesticides offer protection against yield losses specifically associated with pests. The potential usefulness of both tools in mitigating risk is well established, but their interaction is less clear and has been a topic of debate for decades both in the academic literature and in public policy arenas.

An important dimension driving the debate is the potential for moral hazard, in which producers alter their applications of chemical inputs (e.g., pesticides) upon obtaining crop insurance coverage to increase the probability of receiving an indemnity (Horowitz and Lichtenberg, 1993; Smith and Goodwin, 1996; Coble et al., 1997). However, identifying this effect is difficult because both crop insurance participation and pesticide demand have been influenced by significant changes driven by government policies and production efficiencies. While crop insurance enrollment has almost surely been impacted by changes in its program provisions regarding eligible crops and premium subsidies, pesticide applications have been impacted by changes in key quality characteristics such as potency and toxicity (Fernandez-Cornejo and Jans, 1995; Fernandez-Cornejo et al., 2014). At the farm level, these decisions are further impacted by crop choice since certain crops and regions face different risks, leading to differences in insurance premium rates faced by producers and differences in pesticide active ingredients needed to mitigate various pest pressures.

Hunter D. Biram (corresponding author, hdbiram@uark.edu) is an assistant professor in the Department of Agricultural Economics and Agribusiness at the University of Arkansas. Jesse Tack is a professor and Jisang Yu is an associate professor in the Department of Agricultural Economics at Kansas State University. Richard Nehring is an agricultural economist at the US Department of Agriculture Economic Research Service.
The authors thank Editor Christian Langpap and two anonymous reviewers for the helpful comments on earlier versions of this manuscript. This work was funded in whole or part by the US Government and is not subject to copyright protection within the United States

Review coordinated by Christian A. Langpap.

This raises the question of whether crop insurance participation affects pesticide use and, if so, whether the effect is heterogeneous across crops. Previous work on this topic can be classified into theoretical and empirical findings. The theoretical literature is well developed, with findings explained by risk aversion under expected utility theory and by the nature of pesticides themselves; therefore, we make no effort to develop a framework here. The empirical literature is beginning to develop with the introduction of novel econometric methods and forms of measurement for both pesticide use and crop insurance participation. Findings are largely mixed, with both the theoretical and empirical literature showing positive (Horowitz and Lichtenberg, 1993; Möhring, Dalhaus, et al., 2020; Regmi, Briggeman, and Featherstone, 2022), negative (Babcock and Hennessy, 1996; Smith and Goodwin, 1996; Möhring et al., 2020a), and null or mixed (Horowitz and Lichtenberg, 1994; Weber, Key, and O'Donoghue, 2016) effects of crop insurance participation on pesticide use.

The concerns that have emerged in the empirical literature primarily deal with the endogeneity of crop insurance decisions and the measurement of both pesticide use and crop insurance participation, with most work focusing on a single crop. The timing of the crop insurance and pesticide use decisions has been noted as a factor driving the endogeneity of the crop insurance decision, with some papers modeling the insurance decision as being made prior to the pesticide decision (Horowitz and Lichtenberg, 1993; Möhring, Dalhaus, et al., 2020) and others modeling the decisions as simultaneous and/or allowing for pesticide application choices to be made after the insurance decision (Smith and Goodwin, 1996; Weber, Key, and O'Donoghue, 2016).

In the context of crop insurance, measurement of pesticide use has generally been limited to expenditures per acre, but some studies have constructed alternative measures to account for changes in pesticide qualities (Fernandez-Cornejo and Jans, 1995; Fernandez-Cornejo et al., 2014; Möhring, Bozzola, et al., 2020). In the crop insurance literature, participation has been measured in multiple ways, with some studies utilizing a participation rate variable at the extensive margin (Smith and Goodwin, 1996; Connor and Katchova, 2020; Feng, Han, and Qiu, 2021) and others incorporating the intensive margin as well (Goodwin, Vandeveer, and Deal, 2004; Weber, Key, and O'Donoghue, 2016; Connor and Katchova, 2020). It is also common for studies to focus on a single crop, with only a few considering the moral hazard effect more generally across multiple crops (Roberts, Key, and O'Donoghue, 2006; Weber, Key, and O'Donoghue, 2016). The endogeneity of the insurance decision also provides empirical difficulties, with some studies tackling it directly (Smith and Goodwin, 1996; Wu, 1999; Roberts, Key, and O'Donoghue, 2006; Cornaggia, 2013; Weber, Key, and O'Donoghue, 2016; Yu, Smith, and Sumner, 2018; DeLay, 2019; Connor and Katchova, 2020; Möhring, Dalhaus, et al., 2020; Regmi, Briggeman, and Featherstone, 2022). Overall, no single study has comprehensively addressed all of these empirical challenges, leading to a fractured academic literature that has failed to deliver a consensus recommendation on this key policy question.

In this paper, we provide a topical overview of the inherent challenges associated with identifying the moral hazard effect of crop insurance on pesticide use, focusing on the aspects of econometric modeling and the measurement of key variables. To mitigate the bias from a possible correlation between crop insurance participation and unobservables, we first consider conventional two-way fixed effects approaches. A key concern for these estimators is the presence of any state-specific and time-varying unobservable factors that affect both pesticide use and crop insurance decisions; therefore, we also consider an alternative instrumental variable (IV) approach. Specifically, we construct a novel shift-share IV based on changes in insurance subsidy rates and exploit quasirandom variations in crop insurance participation. We also explore a difference-in-differences design combined with the shift-share IV based on two specific changes in subsidies, one in 1994 and the other in 2000. Regarding the measurement of key variables, we consider (i) insurance participation based on both the extensive (whether to insure) and intensive (how much to insure) margins and (ii) pesticide use based on the quality adjustment of active ingredients over time to account for changes in both potency and toxicity, among other quality variables, which we discuss later.

Our sample dataset is a state-level panel spanning 45 US states from 1965 to 2019. Our three identification strategies never provided a robust estimate, suggesting the feasibility of adequately

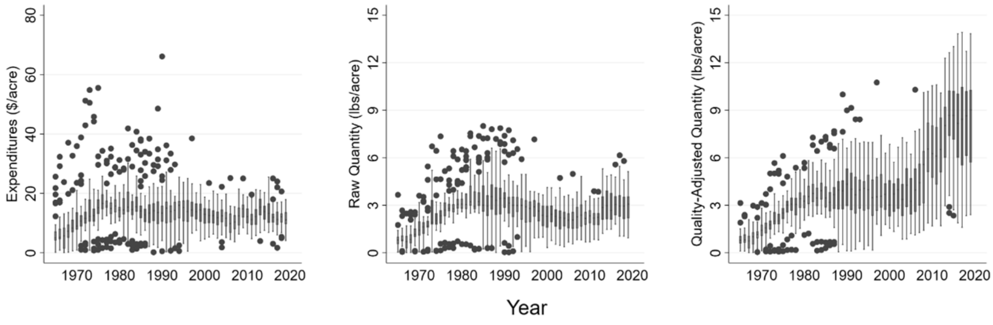

Figure 1. Spatial and Temporal Variation in Pesticide Variables, 1965–2019

Notes: Figure 1 plots expenditures per acre, raw pesticide quantity applied per acre, and quality-adjusted pesticide quantity per acre for corn. All three variables are constructed at the state level. Expenditures per acre are found by deflating total expenditures using the CPI reported by the Bureau of Labor Statistics and dividing this measure by planted acreage. The raw quantity is found by taking the total expenditures and dividing it by the average price received across active ingredients. The quality-adjusted quantity is found by dividing the total expenditures by active ingredient and dividing it by the quality-adjusted price received across active ingredients.

addressing endogeneity in reduced-form settings linking pesticides to insurance participation. We show that the way in which endogeneity in the crop insurance decision is approached may induce a sign flip for most major crops. We also show that while the instruments we constructed have solid theoretical support for meeting the exclusion restriction, the validity of the exclusion restriction and the relevance assumptions may vary across the specifications regarding the set of controls. We consider other controls that may influence pesticide use (e.g., GMO seed adoption, rainfall, and temperature) and find the same pattern of inconsistent estimates across measurement and identification approaches. Overall, these findings indicate that measuring the effect of crop insurance participation on pesticide use should be done with caution, and policies formed from empirical findings should consider the many nuances uncovered here before enacting them into public law.

Data and Variable Construction

For this analysis, we utilize measures for pesticide usage and crop insurance participation for four crops: corn, soybeans, wheat, and cotton. Data on pesticide usage come from the USDA Economic Research Service (ERS), while crop insurance participation variables are drawn from USDA National Agricultural Statistics Service (NASS) and USDA Risk Management Agency (RMA) data; futures prices are from Bloomberg.

Pesticide Use Measures

The pesticide use data consist of a state–year panel of annual pesticide expenditures and application rates (in pounds per acre) by active ingredient spanning 45 contiguous US states from 1965 to 2019. Table 1 breaks down the number of state–year observations by crop. These data are used to construct quality-adjusted and quality-unadjusted (i.e., raw) measures of pesticide application rates by leveraging the hedonic pricing methods outlined in Fernandez-Cornejo and Jans (1995).[1]

[1] We construct quality-adjusted pesticide use measures by following Fernandez-Cornejo and Jans (1995) and Fernandez-Cornejo et al. (2014). First, hedonic pricing models for pesticides are run regressing the logarithm of pesticide prices across many different pesticides on quality variables and year dummy variables using 1965 as the reference year. The quality variables used in these hedonic estimations are soil toxicity, potency, soil half-life, solubility, and whether the pesticide active ingredient is carcinogenic, mutagenic, or teratogenic (Kellogg et al., 2002). All quality measures are provided by proprietary sources. Code for replicating the quality adjustment may be provided upon request. Next, parameter estimates from all control variables in the hedonic estimation are used to calculate the quality-adjusted pesticide price. Finally, the quality-adjusted quantity for each state–year–crop is found by dividing the total quantity of pesticide active ingredient in pounds per acre by the quality-adjusted price.

Table 1. Summary Statistics for Pesticide Use and Crop Insurance Variables

	Corn			Soybeans			Wheat			Cotton		
	Mean	**Min.**	**Max.**	**Mean**	**Min.**	**Max.**	**Mean**	**Min.**	**Max.**	**Mean**	**Min.**	**Max.**
Pesticide use variables												
Expenditures ($/ac)	0.13	0.00	0.66	0.10	0.01	0.34	0.04	0.00	0.32	0.60	0.02	27.09
	(0.06)			(0.05)			(0.04)			(1.64)		
Raw quantity (lb/acre)	2.57	0.00	7.87	1.34	0.05	3.93	0.41	0.00	3.91	9.39	0.33	383.94
	(1.24)			(0.65)			(0.52)			(24.14)		
Adjusted quantity (lb/acre)	3.94	0.00	13.83	3.42	0.07	16.71	2.42	0.00	15.95	16.00	0.76	658.96
	(2.54)			(2.93)			(2.89)			(38.49)		
Crop insurance participation variables												
EBP	0.34	0.00	1.00	0.41	0.00	1.00	0.45	0.00	1.00	0.45	0.00	1.00
	(0.34)			(0.35)			(0.31)			(0.40)		
LBP	0.24	0.00	1.00	0.29	0.00	1.00	0.34	0.00	1.00	0.32	0.00	1.00
	(0.27)			(0.28)			(0.28)			(0.30)		
No. of obs.		1,988			1,408			1,045			771	
States		38			29			28			16	
Years		1965–2019			1965–2019			1970–2019			1965–2019	

Notes: Values in parentheses are standard deviations.
Source: US Department of Agriculture (2022a,b,c), Bloomberg.

Crop-specific expenditures per acre were calculated by summing total expenditures across all active ingredients and dividing them by the number of planted acres for a given state–year combination. Figure 1 illustrates the sources of variation among these three measures.

The quality-adjusted quantity is a measure of pesticide use that accounts for changes in pesticide potency and other quality variables over time and represents pesticide usage when potency and other quality variables remain constant (Fernandez-Cornejo and Jans, 1995). Therefore, we should see higher pesticide usage for quality-adjusted quantities relative to raw (i.e., quality-unadjusted) quantities using the base period of 1965. In other words, the quality-adjusted measure provides insight into producer behavior, assuming that pesticide quality remained constant relative to 1965. For example, if pesticide potency increased over time, we would expect farmers to have used less pesticides, *ceteris paribus*. This difference in pesticide use measures is highlighted by Figures 1b and 1c, with the quality-adjusted quantity in Figure 1c showing relatively more pesticide use over time relative to Figure 1b, which shows the raw, quality-unadjusted quantity.

Insurance Participation

We use data on insured acres and purchased liabilities from RMA State/County/Crop Summary of Business (SOB) data files,[2] NASS yields, marketing year average cash prices received, and planted acres to construct crop insurance participation variables. Daily harvest-month futures prices during planting months for all four crops were retrieved using a Bloomberg terminal, and a breakdown by crop of the years for which there were price data can be found in Table 1. Annual measures for futures prices, excluding wheat, were calculated by taking the average of the daily closing price for January and the months leading up to the sign-up deadline, as in Yu, Smith, and Sumner (2018). Since winter wheat is typically planted in the fall and thus has a different sign-up deadline, we take the average of the daily prices for July through September.

We utilize two measures for crop insurance participation in individual plans: enrollment-based participation (*EBP*) and liability-based participation (*LBP*). *EBP* is simply the ratio of insured acres to planted acres for a given state–year–crop combination and is an extensive margin measure of participation. *LBP* is the ratio of purchased liability to the maximum available liability and better represents the extensive and intensive margin decision-making components of the crop insurance participation decision as highlighted by Goodwin, Vandeveer, and Deal (2004) and Connor and Katchova (2020). *EBP* can easily be constructed using the raw data described above, but *LBP* must be constructed by using raw data combined with a calculation of the maximum available liability. Purchased liability is given by the SOB data, and the maximum available liability is calculated by taking the product of an expected price, yield, planted acreage, and the highest coverage level available. Figure 2 illustrates the differences in variation between these two measures.

Model Specification and Endogeneity of Insurance Participation

We specify the dependent variable as either pesticide expenditures per acre or quantity applied per acre for a producer in state i and year t, Y_{it}, while the explanatory variable of interest is crop insurance participation, I_{it}, given either by *EBP* or *LBP*. Considering heterogeneity across crops, we estimate crop-specific regressions. Our main specification is

$$\ln(Y_{it}) = \alpha_0 + \tau I_{it} + \varepsilon_{it}, \tag{1}$$

where ε_{it} denotes random errors.

[2] While most studies use the State/County/Crop/Coverage Level Summary of Business data files spanning 1989–2023 from the USDA-RMA, we also use the State/County/Crop Level Summary of Business data files that span 1948–1989 since we are only concerned with historical purchased liability and not county-level coverage-level choices. The State/County/Crop Summary of Business Data Files can be found at https://www.rma.usda.gov/Information-Tools/Summary-of-Business/State-County-Crop-Summary-of-Business.

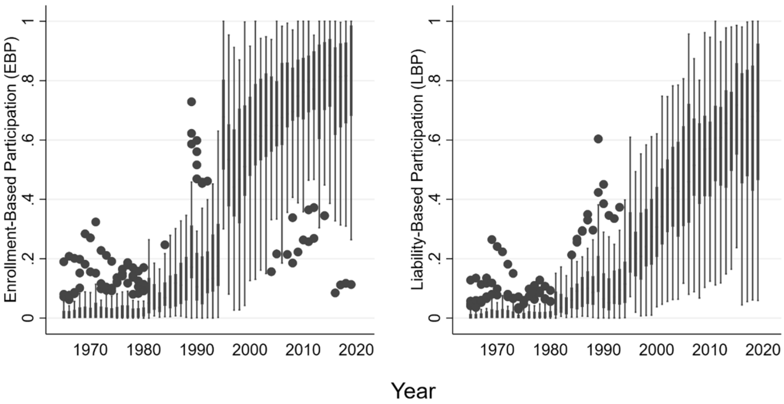

Figure 2. Spatial and Temporal Variation in Crop Insurance Participation Variables, 1965–2019

Notes: Figure 2 plots the ratio of insured acres to planted acres (*EBP*) and the ratio of purchased liability to the maximum amount of liability that can be purchased (*LBP*).

The identification issue in estimating equation (1) arises from the possible correlation between crop insurance participation, I_{it}, and the error term, ε_{it}. That is, any unobservable factors that affect production decisions—including input usage and the crop insurance decisions—are a threat to the identification of the effect of crop insurance participation on pesticide usage.

Several works have discussed the issue of endogeneity in estimating the effects of crop insurance participation measures on production decisions (e.g., Smith and Goodwin, 1996; Goodwin, Vandeveer, and Deal, 2004; O'Donoghue, Roberts, and Key, 2009; Yu, Smith, and Sumner, 2018). While recent studies (e.g., Weber, Key, and O'Donoghue, 2016; Yu, Smith, and Sumner, 2018; Ghosh, Miao, and Malikov, 2021; Connor, Rejesus, and Yasar, 2022) have attempted to tackle the endogeneity of insurance participation via different identification strategies, studying the role of crop insurance in input usage remains challenging.

Horowitz and Lichtenberg (1993) assume the crop insurance decision to be exogenous by not accounting for any of the possible sources of endogeneity. Several works have argued that the crop insurance and pesticide use decision are simultaneous or even overlap, where pesticide applications are made after the insurance decision within the growing season and should be accounted for via instrumental variables and systems of equations estimation (e.g., Smith and Goodwin, 1996; Weber, Key, and O'Donoghue, 2016; Möhring, Dalhaus, et al., 2020). Furthermore, Lichtenberg and Zilberman (1986) model pesticides as risk-reducing inputs, which suggests that pesticide usage should be greater for those who do not enroll in crop insurance since pesticides are arguably a form of insurance.

In the general crop insurance literature, a few recent works have that argued the endogeneity of the crop insurance decision should be accounted for via instrumental variables, where the instrument is exogenous changes in national-level subsidy rates across time (e.g., Yu, Smith, and Sumner, 2018; DeLay, 2019; Connor and Katchova, 2020). Additionally, Roberts, Key, and O'Donoghue (2006) account for the endogeneity of the crop insurance decision using a general fixed effects approach.

Identification Strategies

To mitigate the bias from a possible correlation between crop insurance participation, I_{it}, and the error term, ε_{it}, we first consider the so-called two-way fixed effects estimator (TWFE). In other words, we include state fixed effects, u_i, to capture the effects of time-invariant, unobserved heterogeneity across states (e.g., soil characteristics and climate) and year fixed effects,

ν_t, to control for time-varying shocks common to all states (e.g., pesticide policies, pesticide technologies, and price levels). Hence, we can rewrite the error term, ε_{it}, as $\varepsilon_{it} = u_i + \nu_t + \eta_{it}$, where η_{it} is an error term. Equation (1) becomes

$$\ln(Y_{it}) = \alpha_0 + \tau I_{it} + u_i + \nu_t + \eta_{it}. \tag{2}$$

However, the identification fails if crop insurance participation is correlated with the new error term, η_{it}. That is, if there are any state-specific and time-varying unobservable factors that affect both pesticide use and crop insurance decisions, the TWFE no longer provides the identification of the effect, τ.

Therefore, we also consider an alternative identification strategy that uses an instrumental variable.[3] We construct a shift-share instrumental variable (SSIV) and exploit quasirandom variations in crop insurance participation to tackle possible endogeneity of the crop insurance participation variable. We build on the instrument introduced by Yu, Smith, and Sumner (2018) by taking a weighted sum of the time-varying exogenous changes to the national premium subsidy rate (i.e., shifts), where the weight is the percentage of acres enrolled in crop insurance devoted to the most popular coverage levels across the presubsidy period of our sample (i.e., shares). This gives us exogenous variation in both the time series and cross-sectional components of our instrument, which is necessary in our panel setting to properly instrument an endogenous variable that varies across space and time. This so-called shift-share design goes back to Bartik (1991), who defines a less aggregated local employment rate as the product of the more aggregated national-level employment growth rate with the local industry employment shares; recent studies (e.g., Goldsmith-Pinkham, Sorkin, and Swift, 2020; Borusyak, Hull, and Jaravel, 2022) have formalized the shift-share design and provide conditions under which the design can provide well-identified estimates.

We construct the SSIV for our crop insurance participation measures as

$$Z_{it} = \boldsymbol{S}_{i0}\boldsymbol{R}_t = s_{i,0.65,0}r_{t,0.65} + s_{i,0.75,0}r_{t,0.75}, \tag{3}$$

where Z_{it} is the SSIV, $\boldsymbol{S}_{i0}$ is the vector of average shares planted to the 65% and 75% coverage levels for state i in a base period, and $\boldsymbol{R}_t$ is the vector of premium subsidy rates for the 65% and 75% coverage levels.[4] We choose the 65% and 75% coverage levels because they have been offered since the inception of the crop insurance program in 1938 (75th Congress of the United States, 1980) and they are the most popular coverage levels across the time series in our sample. We use the period 1989–1994 as the base period, as the year 1994 is when the first large change in subsidy rates occurred. In other words, we take the average state-specific shares of acreage enrolled in the 65% and 75% coverage levels over the years 1989-1994. We do not do this for the years prior to the first premium subsidy rate introduction in 1980 because the RMA SOB data do not include participation specific to coverage levels until 1989.

We use the instrument, Z_{it}, for the crop insurance variable, I_{it}, to estimate equation (1). The identification relies on the assumptions that (i) Z_{it} is strongly correlated with I_{it} (relevance of the instrument) and (ii) Z_{it} is uncorrelated with the error term (exclusion restriction). With the inclusion of fixed effects or other covariates, the assumptions need to be satisfied conditional on

[3] We recognize an instrumental variable approach that leverages heteroskedastic errors to construct an instrument for the endogenous variable of interest (Lewbel, 2012) and an application of this instrument in the crop insurance context (Won et al., 2024). We acknowledge that this approach could be useful when there is no external instrument, but there is a concern about whether it can satisfy the exclusion restriction in practice. While our shift-share design-based instrument still may face a similar exclusion restriction issue, we have more theoretical ground on why this instrument can meet the exclusion restriction as we explore the economic mechanism of government policy to explain crop insurance participation. Therefore, we do not consider the heteroskedasticity-based instrument.

[4] We used the stated subsidy rates given by Glauber (2004), the FCIA of 1980 (96th Congress of the United States, 1980), the Federal Crop Insurance Reform Act of 1994 (103rd Congress of the United States, 1994), the Agriculture Risk Protection Act of 2000 (106th Congress of the United States, 2000), the Food, Conservation, and Energy Act of 2008 (110th Congress of the United States, 2008), and the Agricultural Act of 2014 (113th Congress of the United States, 2014).

the fixed effects or the other covariates. We first consider the TWFE (TWFE-SSIV) and explore a fixed-effects estimator without time fixed effects (FE-SSIV).

We multiway cluster standard errors by state and year. We cluster at the state level to allow for the most flexible form of autocorrelation in the errors and cluster at the year level to allow for unmeasured shocks common to all states in a given year, such as price shocks and numerous agricultural policies that impact pesticide use (Fernandez-Cornejo et al., 2014). Additionally, we cluster only if the number of clusters in a specific dimension is greater than 20, following Bertrand, Duflo, and Mullainathan (2004). We report first-stage F-statistics using the Kleibergen–Paap test statistic (Baum, Schaffer, and Stillman, 2010), which accounts for the adjustment in calculating standard errors.[5]

We also explore a difference-in-differences design combined with the SSIV (DID-SSIV). Two significant policy changes have affected subsidy rates: the Federal Crop Insurance Reform Act (FCIRA) of 1994 (103rd Congress of the United States, 1994) and the Agriculture Risk Protection Act (ARPA) of 2000 (106th Congress of the United States, 2000). We further investigate these policy changes separately to explore possible heterogeneous responses across the policy regimes. Consider the following estimation equation:

$$\Delta \ln \left(Y_{ip}\right) = \gamma + \tau \Delta I_{ip} + \Delta \varepsilon_{ip}, \tag{4}$$

where subscript p denotes a 3-year period and the difference operator Δ denotes the difference between two 3-year periods before and after the policy changes. For the 1994 FCIRA, we take the difference between period 1, 1992–1994, and period 2, 1995–1997, for the 2000 ARPA, we define period 1 as 1995–1997 and period 2 as 2001–2003.[6]

As the observed difference in the crop insurance participation variable can be correlated with the unobserved changes, $\Delta \varepsilon_{ip}$, we construct an SSIV. Under the difference-in-differences design, the SSIV is

$$\Delta Z_{ip} = \Delta \boldsymbol{S}_{i1} \boldsymbol{R}_p = s_{i,0.65,1} \Delta r_{p,0.65} + s_{i,0.75,1} \Delta r_{p,0.75}, \tag{5}$$

where subscript 1 denotes period 1, as defined above. Note that the base period now becomes the period before the policy (i.e., period 1) for each policy change. Note that the identification assumptions are parallel to those of panel SSIV approaches.

Results

Tables 2–5 present alternative estimated results for equation (1) by crop. Column 1 reports estimation results with naïve ordinary least squares (OLS) without controlling for any sources of endogeneity. Column 2 provides results obtained using a TWFE estimator with state and year fixed effects to control for unobserved confounders. Columns 3–5 report estimation results using the SSIV approach but with different ways to control for unobserved heterogeneity across time, where column 3 gives results using a TWFE and SSIV approach (TWFE-SSIV) and columns 4–5 give results using an SSIV approach with state fixed effects (FE-SSIV) and different time trend specifications.

We first discuss the results for corn and soybeans (Tables 2–3), which show similar patterns. In general, OLS gives positive estimates of the crop insurance participation variables, while using a TWFE estimator yields relatively smaller estimates in magnitude. Under TWFE-SSIV, the estimated effect is found to be positive and greater in magnitude than that of OLS. Using linear and quadratic time trends instead of year fixed effects leads to negative estimates of the effect of the crop insurance participation variables.

[5] We use *ivreg2* in Stata to implement all IV estimations.

[6] Because there have been ad hoc subsidies in 1998 and 1999 and the 2000 ARPA codified these ad hoc subsidies, we exclude the period 1998–2000 to have a clear assessment of the policy change.

Table 2. Effect of Crop Insurance Participation on Pesticide Usage (Corn) (N = 1988)

	OLS	TWFE	TWFE-SSIV	FE-SSIV	FE-SSIV
Covariates	**1**	**2**	**3**	**4**	**5**
Dependent variable: ln of expenditures per acre					
Enrollment-based participation	0.16	0.18	2.00*	−1.18	−1.88***
	(0.15)	(0.51)	(1.11)	(0.80)	(0.61)
Liability-based participation	0.21	0.35	4.19*	−7.18	−3.98***
	(0.17)	(0.49)	(2.44)	(7.55)	(1.45)
Dependent variable: ln of quality-unadjusted (raw) quantity per acre					
Enrollment-based participation	0.33*	0.07	1.89*	−1.78**	−2.70***
	(0.20)	(0.46)	(1.02)	(0.91)	(0.67)
Liability-based participation	0.42*	−0.04	3.95	−10.80	−5.69***
	(0.23)	(0.43)	(2.45)	(10.97)	(1.72)
Dependent variable: ln of quality-adjusted quantity per acre					
Enrollment-based participation	1.20***	−0.08	1.61	−2.26***	−2.51***
	(0.23)	(0.48)	(1.08)	(0.76)	(0.66)
Liability-based participation	1.53***	0.18	3.37	−13.68	−5.29***
	(0.27)	(0.47)	(2.39)	(15.70)	(1.69)
State fixed effects	no	yes	yes	yes	yes
Year fixed effects	no	yes	yes	no	no
Crop-specific linear trend	no	no	no	yes	yes
Crop-specific quadratic trend	no	no	no	no	yes
First-stage F-statistic (*EBP*)	n/a	n/a	4.16	10.20	22.21
First-stage F-statistic (*LBP*)	n/a	n/a	2.99	0.53	24.17
States	38	38	38	38	38
Years	55	55	55	55	55

Notes: Values in parentheses are multiway-clustered (by state and year) standard errors. Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Kleibergen–Paap F-statistics, which account for adjustments in standard error calculations, are reported.

Columns 3–5 provide estimates that generate an interesting discussion. The first-stage F-statistics vary across the columns, indicating that the strength of the instrument changes depending on how we specify the role of the time-specific effects. Year fixed effects seem to capture most of the variations in the instrument, as we see small F-statistics in column 3. The inclusion of linear or quadratic time trends instead of year fixed effects leads to larger first-stage F-statistics. In column 5, we observe that the F-statistics are larger than the rule-of-thumb threshold of 10 (Stock and Yogo, 2002).[7]

The specification on how to capture time-specific unobservable factors leads to mixed results. In the context of the two identification assumptions, the use of year fixed effects violates the relevance

[7] Recently, a growing literature on the inference with potentially weak instruments (e.g., Andrews, Stock, and Sun, 2019; Lee et al., 2022; Keane and Neal, 2023) indicates the possibility of incorrect inference even when the first-stage F-statistics exceed the rule-of-thumb threshold of 10. This growing literature provides more robust ways to conduct statistical inferences (e.g., Anderson and Rubin, 1949, p-value), and we recommend conducting robustness tests when exploring the proposed instruments in different contexts. In our context, however, we refrain from providing alternative inferences because we do not find stable estimates that indicate a clear causal direction and we do not claim to find causal effects.

Table 3. Effect of Crop Insurance Participation on Pesticide Usage (Soybeans) (N = 1,408)

Covariates	OLS 1	TWFE 2	TWFE-SSIV 3	FE-SSIV 4	FE-SSIV 5
Dependent variable: ln of expenditures per acre					
Enrollment-based participation	0.15	−0.24	0.95	−2.01***	−2.61***
	(0.15)	(0.32)	(4.06)	(0.49)	(0.40)
Liability-based participation	0.11	−0.27	1.17	−6.57**	−4.54***
	(0.16)	(0.31)	(4.77)	(2.69)	(0.77)
Dependent variable: ln of quality-unadjusted (raw) quantity per acre					
Enrollment-based participation	0.77***	0.01	−0.46	−2.21***	−2.42***
	(0.19)	(0.33)	(3.49)	(0.57)	(0.55)
Liability-based participation	0.95***	−0.04	−0.56	−7.22**	−4.20***
	(0.21)	(0.35)	(4.39)	(3.61)	(1.15)
Dependent variable: ln of quality-adjusted quantity per acre					
Enrollment-based participation	1.56***	−0.24	2.38	−1.93***	−2.24***
	(0.23)	(0.33)	(6.06)	(0.53)	(0.47)
Liability-based participation	1.92***	−0.15	2.92	−6.32**	−3.89***
	(0.27)	(0.30)	(6.76)	(3.09)	(1.00)
State fixed effects	no	yes	yes	yes	yes
Year fixed effects	no	yes	yes	no	no
Crop-specific linear trend	no	no	no	yes	yes
Crop-specific quadratic trend	no	no	no	no	yes
First-stage F-statistic (*EBP*)	n/a	n/a	1.17	16.21	27.22
First-stage F-statistic (*LBP*)	n/a	n/a	1.71	3.00	39.63
States	29	29	29	29	29
Years	55	55	55	55	55

Notes: Values in parentheses are multiway-clustered (by state and year) standard errors. Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Kleibergen–Paap F-statistics, which account for adjustments in standard error calculations, are reported.

assumption (i.e., the instrument no longer explains crop insurance participation). Using linear or quadratic time trends seems to provide statistical power to the instrument. However, one needs to be careful with the exclusion restriction when using these specifications. The assumption now becomes that the instrument is uncorrelated with the error term conditional on either linear or quadratic time trends. Assuming this exclusion restriction to be valid, one can conclude that crop insurance participation leads to a reduction in pesticide use in corn and soybeans (columns 4–5).

While none of the SSIV specifications leads to large enough F-statistics for wheat (Table 4), patterns similar to those observed for corn and soybeans occur: The estimated effects tend to be positive and then switch to negative. However, the first-stage F-statistics are low and indicate a weak first stage, and standard errors are too large to draw conclusive inferences, therefore, we cannot draw any definitive conclusions from wheat. The first-stage F-statistic indicates a strong instrument for cotton in column 5 of Table 5, and we observe what appears to be the opposite pattern of results compared to the other crops considered. Interestingly, for cotton, we find that

Table 4. Effect of Crop Insurance Participation on Pesticide Usage (Wheat) (N = 1,045)

Covariates	OLS 1	TWFE 2	TWFE-SSIV 3	FE-SSIV 4	FE-SSIV 5
Dependent variable: ln of expenditures per acre					
Enrollment-based participation	1.96***	1.40*	3.92	−9.04	−4.90
	(0.37)	(0.71)	(4.28)	(9.11)	(4.39)
Liability-based participation	2.23***	1.21	7.54	5.30*	−12.65
	(0.38)	(0.77)	(8.64)	(2.81)	(16.40)
Dependent variable: ln of quality-unadjusted (raw) quantity per acre					
Enrollment-based participation	0.97**	1.60***	2.35	−17.23	−6.72
	(0.38)	(0.52)	(1.94)	(16.10)	(5.44)
Liability-based participation	1.18***	1.24**	4.52	10.09***	−17.32
	(0.40)	(0.58)	(3.93)	(4.07)	(22.92)
Dependent variable: ln of quality-adjusted quantity per acre					
Enrollment-based participation	1.61***	0.60	5.84	−15.18	0.66
	(0.38)	(0.67)	(3.90)	(14.00)	(4.55)
Liability-based participation	2.17***	0.29	11.25	8.89**	1.70
	(0.39)	(0.72)	(8.81)	(4.29)	(11.53)
State fixed effects	no	yes	yes	yes	yes
Year fixed effects	no	yes	yes	no	no
Crop-specific linear trend	no	no	no	yes	yes
Crop-specific quadratic trend	no	no	no	no	yes
First-stage F-statistic (*EBP*)	n/a	n/a	3.11	1.23	1.63
First-stage F-statistic (*LBP*)	n/a	n/a	1.49	4.07	0.74
States	28	28	28	28	28
Years	50	50	50	50	50

Notes: Values in parentheses are multiway-clustered (by state and year) standard errors. Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Kleibergen–Paap F-statistics, which account for adjustments in standard error calculations, are reported.

the estimated coefficients in column 5 are positive and statistically significant for the dependent variables that measure pesticide use in per acre expenditure and in per acre quality-adjusted quantity. The positive sign suggests that cotton producers apply more pesticides when they insure more acreage or purchase more crop insurance coverage. This could be because cotton incurs greater per acre expenses (see Table 1) by requiring more insecticides and less herbicides than corn and soybeans (Fernandez-Cornejo et al., 2014). Again, this assumes that the instrument meets the exclusion restriction conditional on quadratic time trends.

Finally, we assess the two policy changes, the 1994 FCIRA and the 2000 ARPA, separately. We estimate equation (4) using the instrument constructed by equation (5). Table 6 reports these results. A noticeable finding is the positive and significant effects of the crop insurance participation for corn using the 1994 FCIRA as an experiment (column 1). This is the only crop-by-policy pair that yields first-stage F-statistics larger than 10. None of the other crops or the 2000 ARPA have enough statistical powers in their first stage.

While we note that the estimates in Table 6 based on the difference-in-differences design suffer from small sample sizes, the estimates lead to an interesting discussion when we compare the

Table 5. Effect of Crop Insurance Participation on Pesticide Usage (Cotton) (N = 709)

Covariates	OLS 1	TWFE 2	TWFE-SSIV 3	FE-SSIV 4	FE-SSIV 5
Dependent variable: ln of expenditures per acre					
Enrollment-based participation	0.00	−0.06	−5.32	0.94***	0.68***
	(0.06)	(0.30)	(12.37)	(0.35)	(0.27)
Liability-based participation	−0.15**	−0.40**	22.57	9.62	1.45***
	(0.07)	(0.19)	(120.03)	(16.51)	(0.57)
Dependent variable: ln of quality-unadjusted (raw) quantity per acre					
Enrollment-based participation	−0.00	−0.22	−21.04	−1.08**	−0.31
	(0.06)	(0.33)	(37.31)	(0.53)	(0.33)
Liability-based participation	−0.00	0.08	89.29	−10.99	−0.66
	(0.08)	(0.18)	(435.96)	(20.44)	(0.71)
Dependent variable: ln of quality-adjusted quantity per acre					
Enrollment-based participation	0.95***	−0.20	−8.98	0.82***	0.68***
	(0.07)	(0.31)	(16.47)	(0.32)	(0.25)
Liability-based participation	1.18***	−0.37**	38.14	8.32	1.46***
	(0.08)	(0.19)	(193.29)	(14.37)	(0.49)
State fixed effects	no	yes	yes	yes	yes
Year fixed effects	no	yes	yes	no	no
Crop-specific linear trend	no	no	no	yes	yes
Crop-specific quadratic trend	no	no	no	no	yes
First-stage F-statistic (*EBP*)	n/a	n/a	0.26	11.38	15.25
First-stage F-statistic (*LBP*)	n/a	n/a	0.04	0.34	15.33
States	16	16	16	16	16
Years	55	55	55	55	55

Notes: Values in parentheses are multiway-clustered (by state and year) standard errors. Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Kleibergen–Paap F-statistics, which account for adjustments in standard error calculations, are reported.

results with those in Tables 2–5. In Table 6, assuming the exclusion restriction is valid, we find positive effects of crop insurance participation for corn. In Table 2, we find positive effects in column 3, which controls for year fixed effects, but negative effects in columns 4 and 5, which include linear or quadratic time trends. While the positive effects are based on the weak instrument, the comparison with Table 6 may imply that the exclusion restriction assumption in column 3 is more reasonable and reliable than those in columns 4 and 5.

We consider the potential influence of GMO seed adoption and weather on pesticide use to test the robustness of the inconsistency in parameter estimates for crop insurance participation (Chen and McCarl, 2001; Osteen and Fernandez-Cornejo, 2013; Fernandez-Cornejo et al., 2014; Perry et al., 2016). We find that controlling for these possibly confounding factors continues to provide a similar pattern of nonrobust estimates regarding the relationship between crop insurance participation and pesticide use for soybeans (Tables S3–S4), and wheat (Tables S5–S6). However, when we control for weather and GMO adoption, we find relatively consistent negative estimates

Table 6. Treatment Effects Estimated Using Difference-in-Differences with Shift-Share Instrument

	Corn		Soybeans		Wheat		Cotton	
	FCIRA (1994)	ARPA (2000)	FCIRA (1994)	ARPA (2000)	FCIRA (1994)	ARPA (2000)	FCIRA (1994)	ARPA (2000)
Covariates	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Dependent variable: ln of expenditures per acre								
Enrollment-based participation	2.61***	−9.35	2.26	−1.04	0.13	5.97	−559.17	6.16
	(1.02)	(10.50)	(3.21)	(3.74)	(4.30)	(3.92)	(106,592)	(12.24)
Liability-based participation	4.01**	5.51	13.25	−0.51	0.33	9.14	7.84	−32.54
	(1.81)	(7.46)	(39.63)	(1.73)	(10.47)	(6.90)	(9.99)	(148.23)
Dependent variable: ln of quality-unadjusted (raw) quantity per acre								
Enrollment-based participation	3.11**	−10.23	1.35	−1.97	1.19	4.98**	−262.02	14.60
	(1.41)	(13.73)	(2.26)	(4.63)	(1.50)	(2.29)	(49,808)	(21.64)
Liability-based participation	4.77*	6.03	7.92	−0.97	2.90	7.62**	3.68	−77.14
	(2.64)	(6.35)	(27.70)	(1.47)	(3.63)	(3.86)	(7.17)	(373.91)
Dependent variable: ln of quality-adjusted quantity per acre								
Enrollment-based participation	2.48*	−9.46	1.12	−4.26	0.76	5.59	−626.14	4.63
	(1.36)	(11.91)	(2.50)	(11.30)	(3.37)	(3.88)	(119,362)	(8.87)
Liability-based participation	3.81	5.57	6.54	−2.09	1.85	8.56	8.78	−24.46
	(2.44)	(7.15)	(25.18)	(1.50)	(8.33)	(6.58)	(10.95)	(115.08)
First-stage F-statistic (EBP)	12.02	0.26	1.10	0.10	5.45	2.90	0.00	0.27
First-stage F-statistic (LBP)	14.43	0.39	0.12	2.08	7.71	2.53	0.70	0.04
No. of obs.	37	39	28	28	18	28	15	16
States	37	39	28	28	18	28	15	16
Years	6	6	6	6	6	6	6	6

Notes: Values in parentheses are multiway-clustered (by state and year) standard errors. Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Kleibergen–Paap F-statistics, which account for adjustments in standard error calculations, are reported.

in corn across all five specifications using the *EBP* measure of crop insurance participation (Tables S1–S2). Additionally, we find mostly consistent positive estimates in cotton using FE-IV (Tables S7–S8) and DID-IV (Tables S9–S11). It should be noted that the first-stage *F*-statistics for the FE-SSIV (Tables S7–S8) and DID-IV (Tables S9–S11) estimators in cotton vary from somewhat strong when using FE-SSIV (i.e., 16.45 to 127.90) to very weak when using DID-IV (i.e., 4.22 to 4.33). Additionally, we find that the effects of Bt-resistant and herbicide-tolerant seed adoption tend to be negative and positive, respectively, for corn and cotton, in line with previous studies (Qaim et al., 2006; Perry et al., 2016). For a full set of results accounting for GMO seed adoption and weather, see Tables S1–S11 in the online supplement (available at www.jareonline.org).

Conclusion

We have addressed the empirical challenges of estimating the moral hazard effects of crop insurance participation by providing a comprehensive empirical analysis using methods and measures of key variables that are on the frontiers of the literature. Hedonic pricing methods are used to adjust measures of pesticide application rates to account for quality differences across time; two measures of insurance participation that differ by their inclusion of the intensity of coverage are considered. We also consider three distinct identification approaches: conventional two-way fixed effects estimators, a shift-share instrumental variable, and difference-in-differences design combined with SSIV.

Crop insurance participation affects pesticide use, but policies based on empirical findings need to consider many nuances uncovered in this article. We show that the way in which endogeneity in the crop insurance decision is approached may affect the findings on the effect of crop insurance on pesticide use. Our three identification strategies never provided a robust estimate, bringing into focus the feasibility of adequately addressing endogeneity in reduced-form settings linking pesticides to insurance participation. The specification of temporal trends and how they interact with policy changes is a key challenge of identification. More rigid assumptions using continuous trend variables enhance instrument strength in the first stage but are prone to specification errors compared to the more general year fixed effects approach. We also show that our findings are sensitive to the measure of the pesticide use variable, but the sensitivity is not as pronounced with alternative measures of crop insurance participation. This implies the importance of the underlying quality characteristics of pesticides, not just the raw quantities themselves, in the context of policy discussion.

Our work faces important limitations, which primarily revolve around the pesticide and insurance data used. Although our work uses state-level data with the longest span of time considered for any work in this vein of literature, highly aggregated data in the spatial dimension can eliminate important variation across counties and farms that could provide more external validity to the analysis. This data aggregation issue makes it difficult to control for unobserved heterogeneity across time in an instrumental variables framework and restricts the flexibility of the model by the inability to use fixed effects to achieve a strong first stage. Finally, the SOB data do not include data by coverage levels prior to 1989, which limits the number of years for which we can fix the shares used to construct the SSIV and prevents us from constructing the shares in a true prepolicy period (i.e., 1965–1980).

We note that the best empirical approach to identifying causal effects in this context is any approach that accounts for the endogeneity of crop insurance participation given the major consensus of confounding factors that impact both the decision to enroll in any level of crop insurance and the decision to apply pesticides. Given the panel nature of the data, accounting for endogeneity via the so-called TWFE or through the SSIV approach would be appropriate since the TWFE accounts for confounding factors across states and years and because the SSIV uses exogenous variation in subsidy rates across states and years. However, the high level of spatial aggregation of the data in this context limits the use of year fixed effects to account for unobserved heterogeneity across time which limits the use of the so-called TWFE approach. Thus, we propose that the best estimation approach in this context is using a SSIV to account for the endogeneity of crop insurance participation and account for unobserved heterogeneity across time with a quadratic trend.

Previous studies have produced mixed findings for the estimated treatment effect, which can likely be attributed to various estimation approaches, measurements of key policy variables, and differences in management practices across crops. We also find treatment effects to be heterogeneous across multiple dimensions of empirical work, which underscores the fact that moral hazard effects are exceptionally difficult to untangle. Future work should consider finding the impact of crop insurance participation on less aggregated measures of pesticide use, such as a measure based on the type of pesticide used (e.g., herbicides and fungicides) or on measures that are specific to quality characteristic, such as toxicity. Additionally, the validity of the crop insurance SSIV constructed here should further be examined using county- or farm-level data and applied to other data on pesticides or other inputs utilized in the production process.

[First submitted June 2023; accepted for publication October 2023.]

References

103rd Congress of the United States. 1994. “Federal Crop Insurance Reform and Department of Agriculture Reorganization Act.” Pub. L. No. 103-354, 108 Stat. 3178. Available online at https://www.govinfo.gov/app/details/statute-108/statute-108-Pg3178.

104th Congress of the United States. 1996. “Food Quality Protection Act.” Pub. L. No. 104-170, 110 Stat. 1489-1538. Available online at https://www.govinfo.gov/app/details/PLAW-104publ170.

106th Congress of the United States. 2000. “Agricultural Risk Protection Act.” Pub. L. No. 106-224, 114 Stat. 358-456. Available online at https://www.govinfo.gov/app/details/PLAW-106publ224.

110th Congress of the United States. 2008. “Food, Conservation, and Energy Act.” Pub. L. No. 110-234, 122 Stat. 923-1551. Available online at https://www.govinfo.gov/app/details/PLAW-110publ234.

113th Congress of the United States. 2014. “Agricultural Act.” Pub. L. No. 113-79, 128 Stat. 649-1005. Available online at https://www.govinfo.gov/app/details/PLAW-113publ79.

75th Congress of the United States. 1980. “Agricultural Adjustment Act.” Pub. L. No. 75-430, 52 Stat. 31. Available online at https://uscode.house.gov/view.xhtml?path=/prelim@title7/chapter35&edition=prelim.

96th Congress of the United States. 1980. “Federal Crop Insurance Act.” Pub. L. No. 96-365, 94 Stat. 1312. Available online at https://www.govinfo.gov/app/details/statute-94/statute-94-Pg1312.

Anderson, T. W., and H. Rubin. 1949. “Estimation of the Parameters of a Single Equation in a Complete System of Stochastic Equations.” *Annals of Mathematical Statistics* 20(1):46–63. doi: 10.1214/aoms/1177730090.

Andrews, I., J. H. Stock, and L. Sun. 2019. “Weak Instruments in Instrumental Variables Regression: Theory and Practice.” *Annual Review of Economics* 11(1):727–753. doi: 10.1146/annurev-economics-080218-025643.

Babcock, B. A., and D. A. Hennessy. 1996. “Input Demand under Yield and Revenue Insurance.” *American Journal of Agricultural Economics* 78(2):416–427. doi: 10.2307/1243713.

Bartik, T. 1991. *Who Benefits from State and Local Economic Development Policies?* Kalamazoo, MI: W.E. Upjohn Institute. doi: 10.17848/9780585223940.

Baum, C. F., M. E. Schaffer, and S. Stillman. 2010. “IVREG2: Stata Module for Extended Instrumental Variables/2SLS and GMM Estimation.” Boston, MA: Boston College Department of Economics.

Bertrand, M., E. Duflo, and S. Mullainathan. 2004. “How Much Should We Trust Differences-in-Differences Estimates?” *Quarterly Journal of Economics* 119(1):249–275. doi: 10.1162/003355304772839588.

Borusyak, K., P. Hull, and X. Jaravel. 2022. “Quasi-Experimental Shift-Share Research Designs.” *Review of Economic Studies* 89(1):181–213. doi: 10.1093/restud/rdab030.

Chen, C.-C., and B. A. McCarl. 2001. “An Investigation of the Relationship between Pesticide Usage and Climate Change.” *Climatic Change* 50(4):475–487. doi: 10.1023/A:1010655503471.

Coble, K. H., T. O. Knight, R. D. Pope, and J. R. Williams. 1997. “An Expected-Indemnity Approach to the Measurement of Moral Hazard in Crop Insurance.” *American Journal of Agricultural Economics* 79(1):216–226. doi: 10.2307/1243955.

Connor, L., and A. L. Katchova. 2020. “Crop Insurance Participation Rates and Asymmetric Effects on U.S. Corn and Soybean Yield Risk.” *Journal of Agricultural and Resource Economics* 45(1):1–19. doi: 10.22004/ag.econ.298431.

Connor, L., R. M. Rejesus, and M. Yasar. 2022. “Crop Insurance Participation and Cover Crop Use: Evidence from Indiana County-Level Data.” *Applied Economic Perspectives and Policy* 44(4):2181–2208. doi: 10.1002/aepp.13206.

Cornaggia, J. 2013. "Does Risk Management Matter? Evidence from the U.S. Agricultural Industry." *Journal of Financial Economics* 109(2):419–440. doi: 10.1016/j.jfineco.2013.03.004.
DeLay, N. 2019. "The Impact of Federal Crop Insurance on the Conservation Reserve Program." *Agricultural and Resource Economics Review* 48(02):297–327. doi: 10.1017/age.2019.9.
Feng, S., Y. Han, and H. Qiu. 2021. "Does Crop Insurance Reduce Pesticide Usage? Evidence from China." *China Economic Review* 69:101679. doi: 10.1016/j.chieco.2021.101679.
Fernandez-Cornejo, J., and S. Jans. 1995. "Quality-Adjusted Price and Quantity Indices for Pesticides." *American Journal of Agricultural Economics* 77(3):645–659. doi: 10.2307/1243232.
Fernandez-Cornejo, J., R. F. Nehring, C. Osteen, S. Wechsler, A. Martin, and A. Vialou. 2014. *Pesticide Use in U.S. Agriculture: 21 Selected Crops, 1960-2008*. Economic Information Bulletin EIB-124. Washington, DC: USDA Economic Research Service. doi: 10.2139/ssrn.2502986.
Ghosh, P. N., R. Miao, and E. Malikov. 2021. "Crop Insurance Premium Subsidy and Irrigation Water Withdrawals in the Western United States." *Geneva Papers on Risk and Insurance - Issues and Practice* 48(4):968–992. doi: 10.1057/s41288-021-00252-4.
Glauber, J. W. 2004. "Crop Insurance Reconsidered." *American Journal of Agricultural Economics* 86(5):1179–1195. doi: 10.1111/j.0002-9092.2004.00663.x.
Goldsmith-Pinkham, P., I. Sorkin, and H. Swift. 2020. "Bartik Instruments: What, When, Why, and How." *American Economic Review* 110(8):2586–2624. doi: 10.1257/aer.20181047.
Goodwin, B. K., M. L. Vandeveer, and J. L. Deal. 2004. "An Empirical Analysis of Acreage Effects of Participation in the Federal Crop Insurance Program." *American Journal of Agricultural Economics* 86(4):1058–1077. doi: 10.1111/j.0002-9092.2004.00653.x.
Horowitz, J. K., and E. Lichtenberg. 1993. "Insurance, Moral Hazard, and Chemical Use in Agriculture." *American Journal of Agricultural Economics* 75(4):926–935. doi: 10.2307/1243980.
———. 1994. "Risk-Reducing and Risk-Increasing Effects of Pesticides." *Journal of Agricultural Economics* 45(1):82–89. doi: 10.1111/j.1477-9552.1994.tb00379.x.
Keane, M., and T. Neal. 2023. "Instrument Strength in IV Estimation and Inference: A Guide to Theory and Practice." *Journal of Econometrics* 235(2):1625–1653. doi: 10.1016/j.jeconom.2022.12.009.
Kellogg, R. L., R. F. Nehring, A. Grube, D. W. Goss, and S. Plotkin. 2002. "Environmental Indicators of Pesticide Leaching and Runoff from Farm Fields." In V. E. Ball and G. W. Norton, eds., *Agricultural Productivity,* Boston, MA: Springer US, 213–256. doi: 10.1007/978-1-4615- 0851-9_9.
Lee, D. S., J. McCrary, M. J. Moreira, and J. Porter. 2022. "Valid *t*-Ratio Inference for IV." *American Economic Review* 112(10):3260–3290. doi: 10.1257/aer.20211063.
Lewbel, A. 2012. "Using Heteroscedasticity to Identify and Estimate Mismeasured and Endogenous Regressor Models." *Journal of Business & Economic Statistics* 30(1):67–80. doi: 10.1080/07350015.2012.643126.
Lichtenberg, E., and D. Zilberman. 1986. "The Econometrics of Damage Control: Why Specification Matters." *American Journal of Agricultural Economics* 68(2):261. doi: 10.2307/1241427.
Möhring, N., M. Bozzola, S. Hirsch, and R. Finger. 2020a. "Are Pesticides Risk Decreasing? The Relevance of Pesticide Indicator Choice in Empirical Analysis." *Agricultural Economics* 51(3):429–444. doi: 10.1111/agec.12563.
Möhring, N., T. Dalhaus, G. Enjolras, and R. Finger. 2020b. "Crop Insurance and Pesticide Use in European Agriculture." *Agricultural Systems* 184:102902. doi: 10.1016/j.agsy.2020.102902.
O'Donoghue, E. J., M. J. Roberts, and N. Key. 2009. "Did the Federal Crop Insurance Reform Act Alter Farm Enterprise Diversification?" *Journal of Agricultural Economics* 60(1):80–104. doi: 10.1111/j.1477-9552.2008.00166.x.

Osteen, C. D., and J. Fernandez-Cornejo. 2013. "Economic and Policy Issues of U.s. Agricultural Pesticide Use Trends." *Pest Management Science* 69(9):1001–1025. doi: 10.1002/ps.3529.

Perry, E. D., F. Ciliberto, D. A. Hennessy, and G. Moschini. 2016. "Genetically Engineered Crops and Pesticide Use in U.s. Maize and Soybeans." *Science Advances* 2(8):e1600850. doi: 10.1126/ sciadv.1600850.

Qaim, M., A. Subramanian, G. Naik, and D. Zilberman. 2006. "Adoption of Bt Cotton and Impact Variability: Insights from India." *Review of Agricultural Economics* 28(1):48–58. doi: 10.1111/ j.1467-9353.2006.00272.x.

Regmi, M., B. C. Briggeman, and A. M. Featherstone. 2022. "Effects of Crop Insurance on Farm Input Use: Evidence from Kansas Farm Data." *Agricultural and Resource Economics Review* 51(2):361–379. doi: 10.1017/age.2022.5.

Roberts, M. J., N. Key, and E. O'Donoghue. 2006. "Estimating the Extent of Moral Hazard in Crop Insurance Using Administrative Data." *Review of Agricultural Economics* 28(3):381–390. doi: 10.1111/j.1467-9353.2006.00303.x.

Smith, V. H., and B. K. Goodwin. 1996. "Crop Insurance, Moral Hazard, and Agricultural Chemical Use." *American Journal of Agricultural Economics* 78(2):428–438. doi: 10.2307/ 1243714.

Stock, J., and M. Yogo. 2002. *Testing for Weak Instruments in Linear IV Regression*. Technical Working Paper 284. Cambridge, MA: National Bureau of Economic Research. doi: 10.3386/ t0284.

US Department of Agriculture. 2022a. "About the Risk Management Agency: Overview." Available online at https://www.rma.usda.gov/About-RMA.

———. 2022b. "Agricultural Productivity in the U.S." Available online at https://www.ers.usda.gov/data-products/agricultural-productivity-in-the-us.aspx.

———. 2022c. "Quick Stats: Chemical Use Surveys, 1990 to 2019." Available online at https://quickstats.nass.usda.gov/.

Weber, J. G., N. Key, and E. O'Donoghue. 2016. "Does Federal Crop Insurance Make Environmental Externalities from Agriculture Worse?" *Journal of the Association of Environmental and Resource Economists* 3(3):707–742. doi: 10.1086/687549.

Won, S., R. M. Rejesus, B. K. Goodwin, and S. Aglasan. 2024. "Understanding the Effect of Cover Crop Use on Prevented Planting Losses." *American Journal of Agricultural Economics* 106(2): 659–683. doi: 10.1111/ajae.12396.

Wu, J. 1999. "Crop Insurance, Acreage Decisions, and Nonpoint-Source Pollution." *American Journal of Agricultural Economics* 81(2):305–320. doi: 10.2307/1244583.

Yu, J., A. Smith, and D. A. Sumner. 2018. "Effects of Crop Insurance Premium Subsidies on Crop Acreage." *American Journal of Agricultural Economics* 100(1):91–114. doi: 10.1093/ajae/ aax058.

Journal of Agricultural and Resource Economics 49(1):S1–S17 ISSN: 1068-5502 (Print); 2327-8285 (Online)

doi: 10.22004/ag.econ.338998

Online Supplement: Online Supplement for Empirical Challenges for Estimating Moral Hazard Effects of Crop Insurance on Pesticide Use

Hunter D. Biram, Jesse Tack, Richard Nehring, and Jisang Yu

Model Robustness to GMO Seed Adoption and Weather

This section provides results testing model robustness referenced in the Results section of the main text. We consider the robustness of our results to possible confounding factors using measures for GMO seed adoption constructed using state-level planted acreage data on insect-resistant (i.e., Bt-resistant) and herbicide tolerant seed from USDA-ERS and weather data from the Parameter-Elevation Regressions on Independent Slopes Model (PRISM). The tables are organized by crop and crop insurance participation measures where we give results for EBP first then LBP for corn (tables S1-S2), soybeans (tables S3-S4), wheat (tables S5-S6), and cotton (tables S7-S8). We design tables S1-S8 in this appendix by taking the table for each crop in the main text (i.e., tables 2-5) and creating a larger three-panel version which now contains *F*-statistics for joint tests of statistical significance for weather variables, as well as parameter estimates for the effects of different measures of GMO seed adoption on pesticide usage. Each panel contains results for the three different pesticide use measures we construct with all regressions in a table using the same measure of crop insurance participation.

The main finding from these regressions is that the inconsistency of parameter estimates across the five main model specifications considered remains in most cases despite controlling for GMO seed adoption and weather. Corn estimates appear to be consistently negative in all estimation approaches using EBP and mostly negative using LBP except for a few special cases (columns (2), (3), and (13) in table S2). We also consider robustness to including these additional controls of the DID-IV estimator where we isolate changes in the premium subsidy rate put in place by the FCIRA of 1994 and the ARPA of 2000. We find that across both the FCIRA and ARPA estimations, the DID-IV estimates are largely unchanged. Cotton is the notable exception as we note the estimated effects become consistently positive. Results from these regressions may be found in tables S9-S11.

Construction of GMO Seed Adoption Measure

We construct state-level GMO seed adoption rates, which are the ratio of acres planted with Bt-resistant and herbicide-tolerant seed to state-level planted acreage following Lusk, Tack, and Hendricks (2018) by using an interpolation procedure for missing values of GMO acreage. Additionally, we back-fill all observations prior to the first year of commercial GMO seed introduction (Fernandez-Cornejo, et al., 2014) with zeroes to represent the period with no GMO adoption. The GMO adoption data differentiate between adoption of a single variety and stacked varieties so to avoid double-counting we take the greater of the adoption rates between single and stacked varieties adoption for a given state-year-crop combination. Box plots for GMO seed adoption variables are found in figures S1-S5.

The material contained herein is supplementary to the article named in the title and published in the *Journal of Agricultural and Resource Economics* (*JARE*).

Construction of Weather Variables

We use daily grid-cell-level weather data from PRISM and aggregate observations within the growing season to the state level to obtain measures for growing season rainfall, optimal growing degree-days, and extreme heat growing degree days (Schlenker and Roberts, 2009). We define a growing season for all crops except wheat to be the months of March through October, while the growing season for wheat is from September to March. We define optimal degree days to be temperatures between 10C and 30C, while extreme heat days are defined to be above 30C. Box plots for the additional weather variables are found in figures S6-S8.

References

Fernandez-Cornejo, J., Nehring, R. F., Osteen, C., Wechsler, S., Martin, A., & Vialou, A. (2014). Pesticide use in US agriculture: 21 selected crops, 1960-2008. *USDA-ERS Economic Information Bulletin*, (124).

Lusk, J. L., Tack, J., & Hendricks, N. P. (2018). Heterogeneous yield impacts from adoption of genetically engineered corn and the importance of controlling for weather. In *Agricultural productivity and producer behavior* (pp. 11-39). University of Chicago Press.

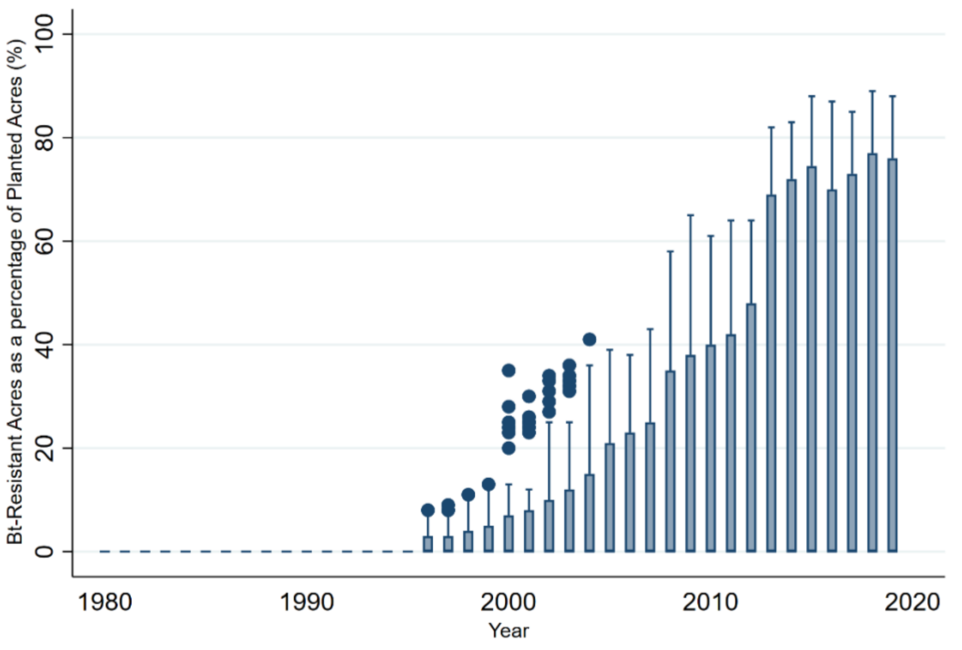

Figure S1. Variation in State-Level Bt-Resistant Seed Adoption in Corn (1980-2019)
Source: USDA-ERS (2022)

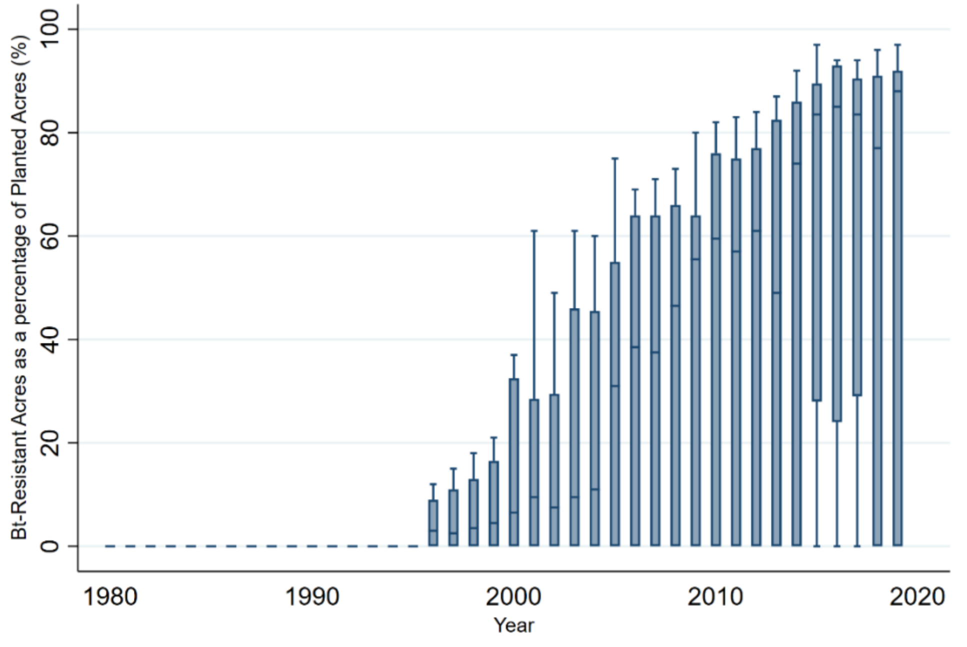

Figure S2. Variation in State-Level Bt-Resistant Seed Adoption in Cotton (1980-2019)
Source: USDA-ERS (2022)

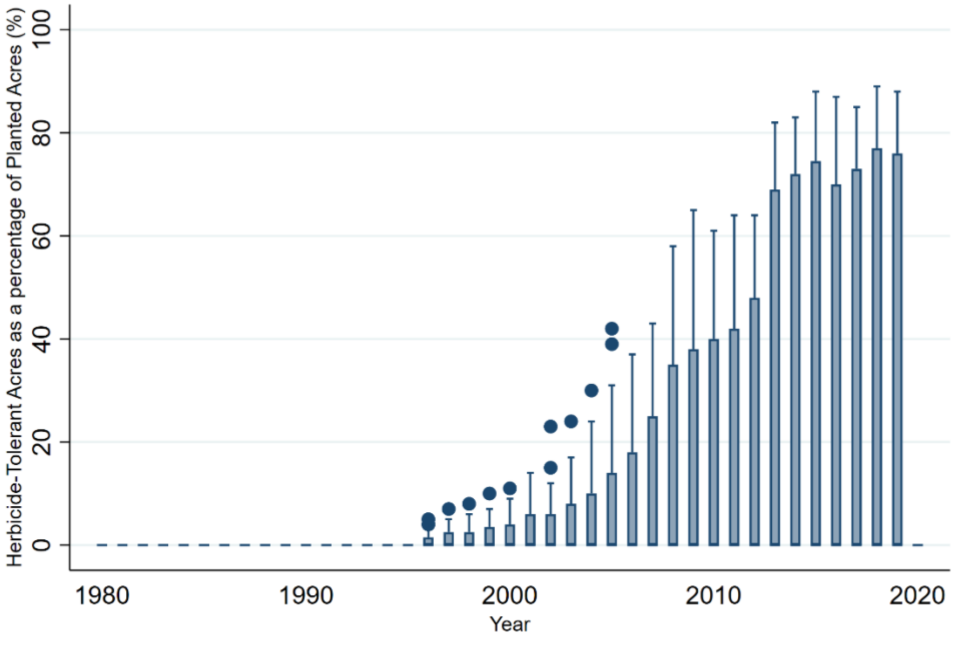

Figure S3. Variation in State-Level Herbicide-Tolerant Seed Adoption in Corn (1980-2019)
Source: USDA-ERS (2022)

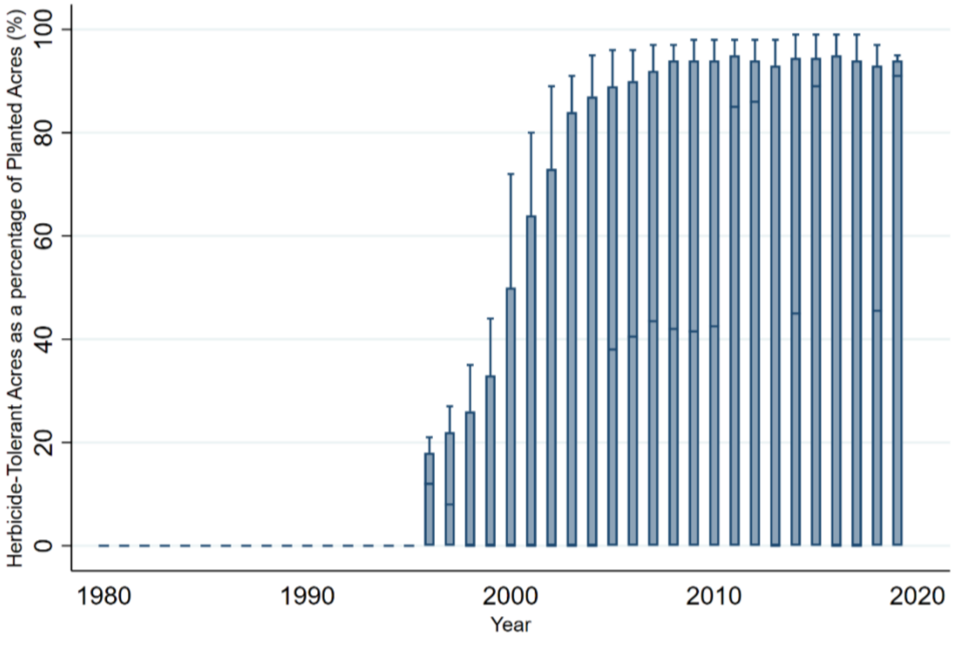

Figure S4. Variation in State-Level Herbicide-Tolerant Seed Adoption in Soybeans (1980-2019)
Source: USDA-ERS (2022)

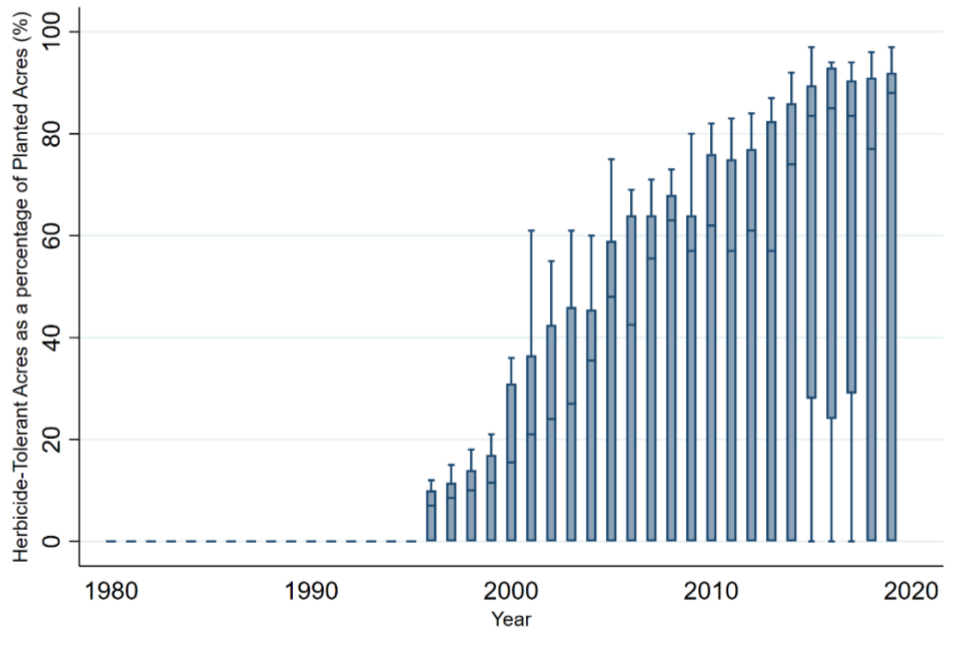

Figure S5. Variation in State-Level Herbicide-Tolerant Seed Adoption in Cotton (1980-2019)
Source: USDA-ERS (2022)

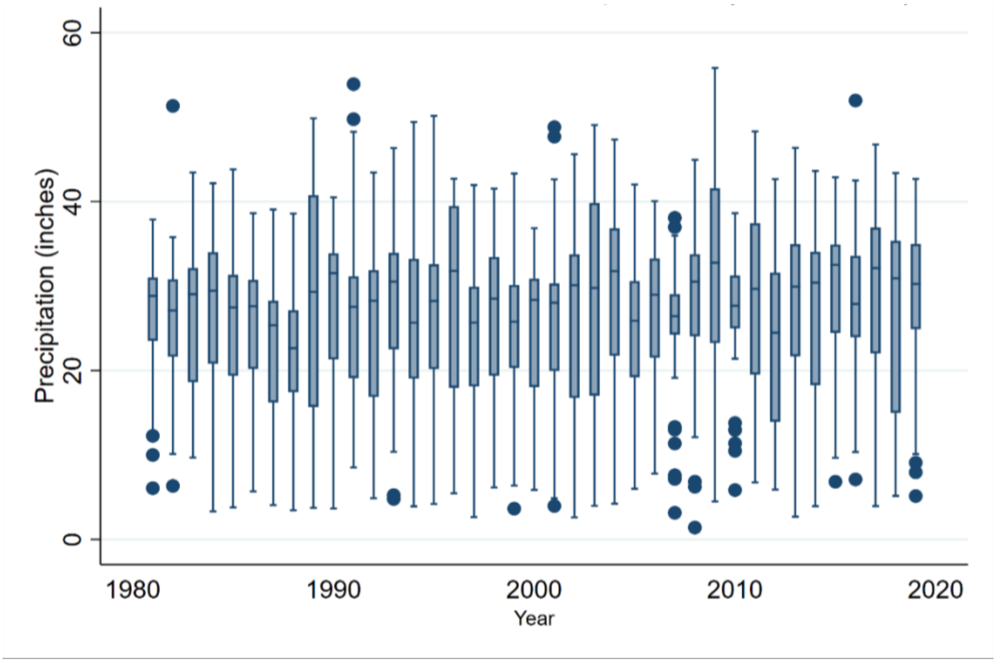

Figure S6. Variation in State-Level Precipitation (1980-2019)
Source: PRISM (2022)

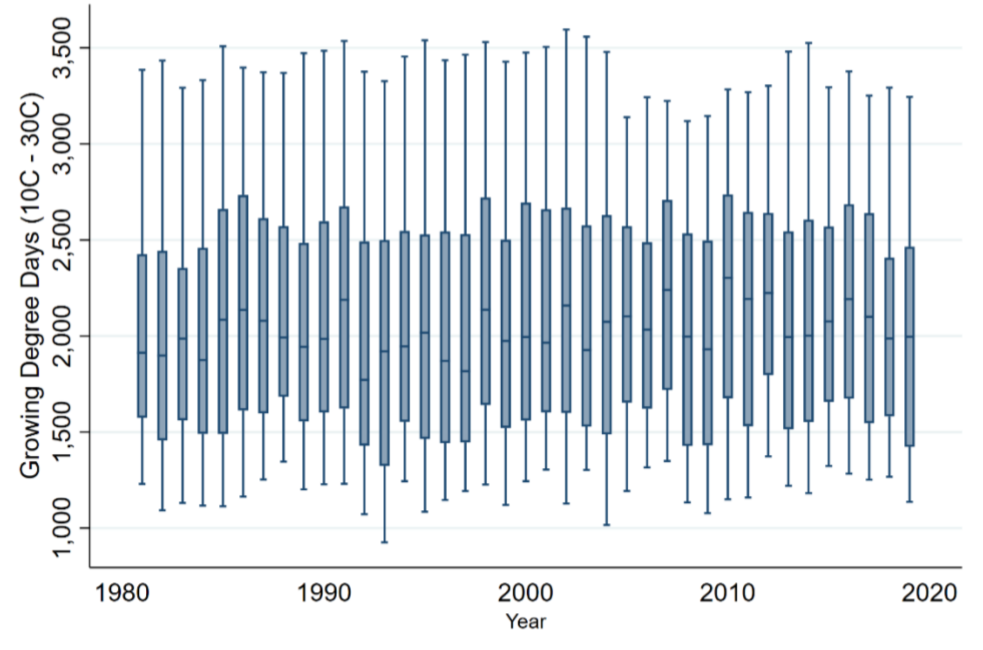

Figure S7. Variation in State-Level Optimal Growing Degree Days (1980-2019)
Source: PRISM (2022)

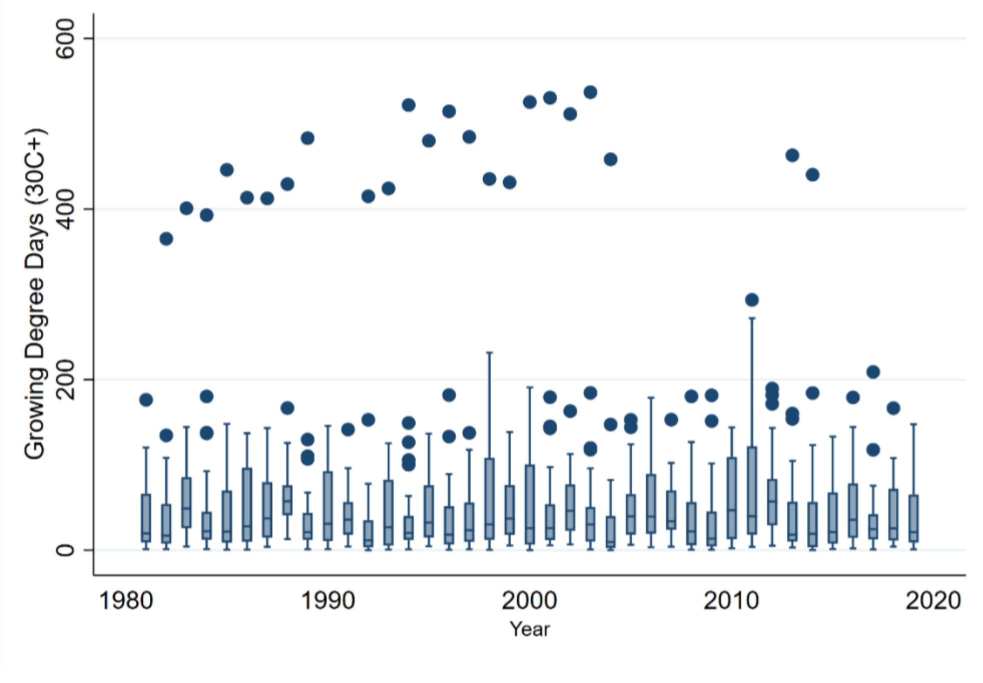

Figure S8. Variation in State-Level Extreme Growing Degree Days (1980-2019)
Source: PRISM (2022)

Table S1. Robustness of EBP Crop Insurance on Pesticide Use Controlling for GMO-Adoption and Weather (Corn)

	Dependent Variable: Ln of Expenditures per Acre					Dependent Variable: Ln of Quality-Unadjusted (Raw) Quantity per Acre					Dependent Variable: Ln of Quality-Adjusted Quantity per Acre				
	(1) (OLS)	(2) (TWFE)	(3) (TWFE-SSIV)	(4) (FE-SSIV)	(5) (FE-SSIV)	(6) (OLS)	(7) (TWFE)	(8) (TWFE-SSIV)	(9) (FE-SSIV)	(10) (FE-SSIV)	(11) (OLS)	(12) (TWFE)	(13) (TWFE-SSIV)	(14) (FE-SSIV)	(15) (FE-SSIV)
Enrollment-based participation	-0.11	-0.25*	-7.92	-0.42	-0.47	-0.57***	-0.63***	0.02	-2.22***	-2.27***	-0.05	-0.53***	-3.25	-1.65***	-2.51***
	(0.08)	(0.14)	(10.51)	(0.35)	(0.41)	(0.09)	(0.16)	(2.10)	(0.59)	(0.73)	(0.09)	(0.20)	(4.50)	(0.61)	-0.66
Bt-adoption	0.22	0.02	-0.74	-0.13	-0.13	-0.23	-0.11	-0.05	-0.37	-0.36	-0.88**	-0.57***	-0.84*	-1.16***	-1.17***
	(0.22)	(0.14)	(1.22)	(0.20)	(0.21)	(0.30)	(0.17)	(0.25)	(0.38)	(0.38)	(0.37)	(0.17)	(0.48)	(0.37)	(0.36)
HT-adoption	-0.41**	-0.35**	-0.23	-0.15	-0.07	0.42*	-0.24	-0.25	-0.21	-0.14	1.73***	0.00	0.05	0.93**	0.79**
	(0.18)	(0.17)	(0.46)	(0.26)	(0.23)	(0.24)	(0.19)	(0.20)	(0.32)	(0.30)	(0.33)	(0.20)	(0.18)	(0.42)	(0.35)
Precipitation *F*-statistic	12.52	0.82	0.52	2.92	2.83	3.79	1.64	2.95	3.26	3.37	6.02	0.18	0.48	0.29	0.23
	(0.00)***	(0.45)	(0.77)	(0.23)	(0.24)	(0.03)**	(0.21)	(0.23)	(0.20)	(0.19)	(0.01)***	(0.84)	(0.79)	(0.87)	(0.89)
Temperature *F*-statistic	0.31	1.18	0.45	7.01	6.23	16.33	1.17	2.04	1.19	1.09	15.70	0.09	0.44	0.44	0.86
	(0.74)	(0.32)	(0.80)	(0.03)**	(0.05)**	(0.00)	(0.32)	(0.36)	(0.55)	(0.58)	(0.00)***	(0.92)	(0.80)	(0.80)	(0.65)
State fixed effects	no	yes	yes	yes	yes	no	yes	yes	yes	yes	no	yes	yes	yes	yes
Year fixed effects	no	yes	yes	no	no	no	yes	yes	no	no	no	yes	yes	no	no
Crop-specific linear trend	no	no	no	yes	yes	no	no	no	yes	yes	no	no	no	yes	yes
Crop-specific quadratic trend	no	no	no	no	yes	no	no	no	no	yes	no	no	no	no	yes
First-stage *F*-statistic	N/A	N/A	0.42	23.35	11.96	N/A	N/A	0.42	23.35	11.96	N/A	N/A	0.42	23.35	11.96
Observations	467	467	467	467	467	467	467	467	467	467	467	467	467	467	467
States	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12
Years	39	39	39	39	39	39	39	39	39	39	39	39	39	39	39

Notes: Parameter estimates are robust to heteroskedasticity and are clustered by year. Standard errors are reported in parentheses for insurance participation and GMO seed adoption variables. Chi-square statistics for *F*-statistics of joint significance for weather variables are reported in parentheses for each set of weather variables considered. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Kleibergen-Paap *F*-statistics, which account for adjustments in standard error calculations, are reported.

Table S2. Robustness of LBP Crop Insurance on Pesticide Use Controlling for GMO-Adoption and Weather (Corn)

	Dependent Variable: Ln of Expenditures per Acre					Dependent Variable: Ln of Quality-Unadjusted (Raw) Quantity per Acre					Dependent Variable: Ln of Quality-Adjusted Quantity per Acre				
	(1) (OLS)	**(2)** (TWFE)	**(3)** (TWFE-SSIV)	**(4)** (FE-SSIV)	**(5)** (FE-SSIV)	**(6)** (OLS)	**(7)** (TWFE)	**(8)** (TWFE-SSIV)	**(9)** (FE-SSIV)	**(10)** (FE-SSIV)	**(11)** (OLS)	**(12)** (TWFE)	**(13)** (TWFE-SSIV)	**(14)** (FE-SSIV)	**(15)** (FE-SSIV)
Liability-based participation	-0.11	0.18	2.89***	-0.40	-0.40	-0.77***	-0.44**	-0.01	-2.12***	-1.95***	-0.05	-0.52**	1.18	-1.57***	-1.35***
	(0.09)	(0.21)	(1.17)	(0.29)	(0.30)	(0.09)	(0.20)	(0.76)	(0.42)	(0.35)	(0.11)	(0.24)	(1.06)	(0.50)	(0.41)
Bt-adoption	0.24	0.05	0.14	-0.11	-0.11	-0.15	-0.07	-0.05	-0.26	-0.29	-0.90**	-0.53***	-0.47**	-1.08***	-1.12***
	(0.21)	(0.15)	(0.31)	(0.18)	(0.18)	(0.27)	(0.18)	(0.19)	(0.22)	(0.20)	(0.38)	(0.18)	(0.23)	(0.30)	(0.26)
HT-adoption	-0.36**	-0.38**	-0.78**	0.02	0.03	0.59***	-0.18	-0.25	0.68***	0.32*	1.75***	0.07	-0.18	1.59***	1.10***
	(0.17)	(0.18)	(0.39)	(0.15)	(0.18)	(0.23)	(0.20)	(0.26)	(0.19)	(0.19)	(0.32)	(0.20)	(0.33)	(0.26)	(0.26)
Precipitation F-statistic	14.05	0.51	1.10	2.06	2.01	4.53	1.19	2.81	0.63	2.13	6.02	0.09	0.90	0.74	0.21
	(0.00)***	(0.61)	(0.58)	(0.26)	(0.37)	(0.02)**	(0.32)	(0.25)	(0.73)	(0.35)	(0.01)***	(0.91)	(0.64)	(0.69)	(0.90)
Temperature F-statistic	0.38	2.00	3.67	7.45	6.99	18.20	1.59	3.36	2.23	1.98	15.82	0.01	0.37	0.58	0.47
	(0.69)	(0.15)	(0.16)	(0.02)**	(0.03)**	(0.00)***	(0.22)	(0.19)	(0.33)	(0.37)	(0.00)***	(0.99)	(0.83)	(0.75)	(0.79)
State fixed effects	no	yes	yes	yes	yes	no	yes	yes	yes	yes	no	yes	yes	yes	yes
Year fixed effects	no	yes	yes	no	no	no	yes	yes	no	no	no	yes	yes	no	no
Crop-specific linear trend	no	no	no	yes	yes	no	no	no	yes	yes	no	no	no	yes	yes
Crop-specific quadratic trend	no	no	no	no	yes	no	no	no	no	yes	no	no	no	no	yes
First-stage F-statistic	N/A	N/A	9.78	42.80	39.61	N/A	N/A	9.78	42.80	39.61	N/A	N/A	9.78	42.80	39.61
Observations	467	467	467	467	467	467	467	467	467	467	467	467	467	467	467
States	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12
Years	39	39	39	39	39	39	39	39	39	39	39	39	39	39	39

Notes: Parameter estimates are robust to heteroskedasticity and are clustered by year. Standard errors are reported in parentheses for insurance participation and GMO seed adoption variables. Chi-square statistics for *F*-statistics of joint significance for weather variables are reported in parentheses for each set of weather variables considered. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Kleibergen-Paap *F*-statistics, which account for adjustments in standard error calculations, are reported.

Table S3. Robustness of EBP Crop Insurance on Pesticide Use Controlling for GMO-Adoption and Weather (Soybeans)

	Dependent Variable: Ln of Expenditures per Acre					Dependent Variable: Ln of Quality-Unadjusted (Raw) Quantity per Acre					Dependent Variable: Ln of Quality-Adjusted Quantity per Acre				
	(1) (OLS)	**(2)** (TWFE)	**(3)** (TWFE-SSIV)	**(4)** (FE-SSIV)	**(5)** (FE-SSIV)	**(6)** (OLS)	**(7)** (TWFE)	**(8)** (TWFE-SSIV)	**(9)** (FE-SSIV)	**(10)** (FE-SSIV)	**(11)** (OLS)	**(12)** (TWFE)	**(13)** (TWFE-SSIV)	**(14)** (FE-SSIV)	**(15)** (FE-SSIV)
Enrollment-based participation	0.45	-0.25	-13.15	-0.11	0.01	-0.07	0.13	-16.13	-1.10***	-0.53***	0.04	0.19	5.68	-0.98***	-0.17
	(0.07)	(0.21)	(22.20)	(0.13)	(0.21)	(0.07)	(0.17)	(29.26)	(0.22)	(0.15)	(0.13)	(0.28)	(10.38)	(0.32)	(0.27)
HT-adoption	-0.56***	-0.65***	-2.48	-0.98***	-0.99***	0.41***	0.09	-2.22	0.03	-0.04	0.84***	-0.51	0.28	-0.22	-0.32***
	(0.08)	(0.25)	(2.75)	(0.12)	(0.12)	(0.07)	(0.22)	(3.64)	(0.15)	(0.07)	(0.13)	(0.32)	(1.42)	(0.20)	(0.11)
Precipitation *F*-statistic	11.02	0.11	0.34	3.85	4.27	0.60	0.47	0.36	3.66	0.49	4.69	0.12	0.38	1.09	2.10
	(0.00)***	(0.89)	(0.84)	(0.15)	(0.12)	(0.55)	(0.63)	(0.83)	(0.16)	(0.78)	(0.02)**	(0.88)	(0.83)	(0.58)	(0.35)
Temperature *F*-statistic	2.04	0.10	0.32	6.93	7.77	3.90	0.80	0.35	0.43	0.29	12.82	0.04	0.34	0.52	1.51
	(0.15)	(0.91)	(0.85)	(0.03)**	(0.02)**	(0.03)	(0.46)	(0.84)	(0.81)	(0.86)	(0.00)***	(0.97)	(0.84)	(0.77)	(0.47)
State fixed effects	no	yes	yes	yes	yes	no	yes	yes	yes	yes	no	yes	yes	yes	yes
Year fixed effects	no	yes	yes	no	no	no	yes	yes	no	no	no	yes	yes	no	no
Crop-specific linear trend	no	no	no	yes	yes	no	no	no	yes	yes	no	no	no	yes	yes
Crop-specific quadratic trend	no	no	no	no	yes	no	no	no	no	yes	no	no	no	no	yes
First-stage *F*-statistic	n/a	n/a	0.33	15.85	8.76	n/a	n/a	0.33	15.85	8.76	n/a	n/a	0.33	15.85	8.76
Observations	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498
States	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13
Years	39	39	39	39	39	39	39	39	39	39	39	39	39	39	39

Notes: Parameter estimates are robust to heteroskedasticity and are clustered by year. Standard errors are reported in parentheses for insurance participation and GMO seed adoption variables. Chi-square statistics for *F*-statistics of joint significance for weather variables are reported in parentheses for each set of weather variables considered. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Kleibergen-Paap *F*-statistics, which account for adjustments in standard error calculations, are reported.

Table S4. Robustness of LBP Crop Insurance on Pesticide Use Controlling for GMO-Adoption and Weather (Soybeans)

	Dependent Variable: Ln of Expenditures per Acre					**Dependent Variable: Ln of Quality-Unadjusted (Raw) Quantity per Acre**					**Dependent Variable: Ln of Quality-Adjusted Quantity per Acre**				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**
	(OLS)	**(TWFE)**	**(TWFE-SSIV)**	**(FE-SSIV)**	**(FE-SSIV)**	**(OLS)**	**(TWFE)**	**(TWFE-SSIV)**	**(FE-SSIV)**	**(FE-SSIV)**	**(OLS)**	**(TWFE)**	**(TWFE-SSIV)**	**(FE-SSIV)**	**(FE-SSIV)**
Liability-based participation	0.53***	-0.37***	-1.52***	-0.29	0.02	0.33*	-0.29***	-1.86***	-3.06***	-0.92***	0.76***	-0.06	0.66	-2.73***	-0.30
	(0.11)	(0.14)	(0.53)	(0.37)	(0.37)	(0.17)	(0.10)	(0.63)	(0.71)	(0.24)	(0.22)	(0.14)	(0.61)	(1.03)	(0.48)
HT-adoption	-0.59***	-0.71**	1.02***	-0.94***	-0.99***	0.18	-0.00	-0.42	0.42*	0.05	0.42***	-0.55*	-0.36	0.13	-0.29**
	(0.10)	(0.24)	(0.32)	(0.14)	(0.13)	(0.11)	(0.19)	(0.34)	(0.24)	(0.07)	(0.15)	(0.32)	(0.36)	(0.32)	(0.14)
Precipitation *F*-statistic	10.80	0.08	0.75	3.03	4.06	1.19	0.85	4.38	5.50	0.67	7.01	0.09	0.53	3.08	1.93
	(0.00)***	(0.92)	(0.69)	(0.22)	(0.13)	(0.31)	(0.43)	(0.11)	(0.06)*	(0.71)	(0.00)***	(0.91)	(0.77)	(0.22)	(0.38)
Temperature *F*-statistic	4.61	0.11	0.15	6.33	7.68	6.66	1.58	3.62	1.20	0.07	16.76	0.14	0.13	0.60	1.30
	(0.02)**	(0.90)	(0.93)	(0.04)**	(0.02)**	(0.03)**	(0.22)	(0.16)	(0.55)	(0.97)	(0.00)***	(0.87)	(0.94)	(0.74)	(0.52)
State fixed effects	no	yes	yes	yes	yes	no	yes	yes	yes	yes	no	yes	yes	yes	yes
Year fixed effects	no	yes	yes	no	no	no	yes	yes	no	no	no	yes	yes	no	no
Crop-specific linear trend	no	no	no	yes	yes	no	no	no	yes	yes	no	no	no	yes	yes
Crop-specific quadratic trend	no	no	no	no	yes	no	no	no	no	yes	no	no	no	no	yes
First-stage *F*-statistic	n/a	n/a	38.33	11.34	12.03	n/a	n/a	38.33	11.34	12.03	n/a	n/a	38.33	11.34	12.03
Observations	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498
States	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13
Years	39	39	39	39	39	39	39	39	39	39	39	39	39	39	39

Notes: Parameter estimates are robust to heteroskedasticity and are clustered by year. Standard errors are reported in parentheses for insurance participation and GMO seed adoption variables. Chi-square statistics for *F*-statistics of joint significance for weather variables are reported in parentheses for each set of weather variables considered. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Kleibergen-Paap *F*-statistics, which account for adjustments in standard error calculations, are reported.

Table S5. Robustness of EBP Crop Insurance on Pesticide Use Controlling for Weather (Wheat)

	Dependent Variable: Ln of Expenditures per Acre					Dependent Variable: Ln of Quality-Unadjusted (Raw) Quantity per Acre					Dependent Variable: Ln of Quality-Adjusted Quantity per Acre				
	(1) (OLS)	(2) (TWFE)	(3) (TWFE-SSIV)	(4) (FE-SSIV)	(5) (FE-SSIV)	(6) (OLS)	(7) (TWFE)	(8) (TWFE-SSIV)	(9) (FE-SSIV)	(10) (FE-SSIV)	(11) (OLS)	(12) (TWFE)	(13) (TWFE-SSIV)	(14) (FE-SSIV)	(15) (FE-SSIV)
Liability-based participation	1.95***	0.75	1.04	-4.46	-22.38	1.17***	1.12***	7.13	-10.71	-38.79	1.57***	0.26	-6.93	-5.00	5.53
	(0.33)	(0.71)	(10.36)	(3.69)	(85.92)	(0.32)	(0.54)	(10.42)	(6.67)	(154.98)	(0.33)	(0.66)	(14.45)	(4.73)	(31.86)
Precipitation *F*-statistic	7.74	2.70	5.67	9.05	0.33	7.71	1.45	1.38	1.88	0.10	3.69	2.01	2.42	7.17	1.42
	(0.00)***	(0.09)*	(0.06)*	(0.01)***	(0.85)	(0.00)***	(0.25)	(0.50)	(0.39)	(0.95)	(0.04)**	(0.15)	(0.30)	(0.03)**	(0.49)
Temperature *F*-statistic	4.03	0.50	0.12	3.22	0.12	2.15	0.69	1.28	3.23	0.09	1.55	0.83	0.43	2.65	0.10
	(0.03)**	(0.61)	(0.94)	(0.20)	(0.94)	(0.14)	(0.51)	(0.53)	(0.20)	(0.96)	(0.23)	(0.45)	(0.80)	(0.27)	(0.95)
State fixed effects	no	yes	yes	yes	yes	no	yes	yes	yes	yes	no	yes	yes	yes	yes
Year fixed effects	no	yes	yes	no	no	no	yes	yes	no	no	no	yes	yes	no	no
Crop-specific linear trend	no	no	no	yes	yes	no	no	no	yes	yes	no	no	no	yes	yes
Crop-specific quadratic trend	no	no	no	no	yes	no	no	no	no	yes	no	no	no	no	yes
First-stage *F*-statistic	n/a	n/a	0.42	3.05	0.06	n/a	n/a	0.42	3.05	0.06	n/a	n/a	0.42	3.05	0.06
Observations	855	855	855	855	855	855	855	855	855	855	855	855	855	855	855
States	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28
Years	39	39	39	39	39	39	39	39	39	39	39	39	39	39	39

Notes: Parameter estimates are robust to heteroskedasticity and are multiway clustered by state and year. Standard errors are reported in parentheses for insurance participation and GMO seed adoption variables. Chi-square statistics for *F*-statistics of joint significance for weather variables are reported in parentheses for each set of weather variables considered. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Kleibergen-Paap *F*-statistics, which account for adjustments in standard error calculations, are reported.

Table S6. Robustness of LBP Crop Insurance on Pesticide Use Controlling for Weather (Wheat)

	Dependent Variable: Ln of Expenditures per acre					Dependent Variable: Ln of Quality-Unadjusted (Raw) Quantity per acre					Dependent Variable: Ln of Quality-Adjusted Quantity per acre				
	(1) (OLS)	(2) (TWFE)	(3) (TWFE-SSIV)	(4) (FE-SSIV)	(5) (FE-SSIV)	(6) (OLS)	(7) (TWFE)	(8) (TWFE-SSIV)	(9) (FE-SSIV)	(10) (FE-SSIV)	(11) (OLS)	(12) (TWFE)	(13) (TWFE-SSIV)	(14) (FE-SSIV)	(15) (FE-SSIV)
Liability-based participation	2.15***	0.44	0.87	9.70	28.44	1.39***	0.67	5.93	23.26	49.31	2.16***	-0.09	-5.77	10.86	-7.03
	(0.34)	(0.71)	(8.81)	(13.11)	(91.30)	(0.33)	(0.55)	(8.78)	(23.62)	(140.99)	(0.36)	(0.67)	(10.20)	(13.51)	(32.82)
Precipitation *F*-statistic	6.80	2.72	5.10	0.67	0.10	7.80	1.58	2.22	0.35	0.09	3.43	2.10	3.77	0.72	1.02
	(0.00)***	(0.08)*	(0.08)*	(0.72)	(0.95)	(0.00)***	(0.22)	(0.33)	(0.84)	(0.96)	(0.05)**	(0.14)	(0.15)	(0.70)	(0.60)
Temperature *F*-statistic	2.84	0.67	0.57	0.43	0.06	1.41	0.86	1.26	0.29	0.09	1.04	1.02	0.90	0.16	0.26
	(0.08)*	(0.52)	(0.75)	(0.81)	(0.97)	(0.26)	(0.44)	(0.53)	(0.87)	(0.96)	(0.37)	(0.37)	(0.64)	(0.92)	(0.88)
State fixed effects	no	yes	yes	yes	yes	no	yes	yes	yes	yes	no	yes	yes	yes	yes
Year fixed effects	no	yes	yes	no	no	no	yes	yes	no	no	no	yes	yes	no	no
Crop-specific linear trend	no	no	no	yes	yes	no	no	no	yes	yes	no	no	no	yes	yes
Crop-specific quadratic trend	no	no	no	no	yes	no	no	no	no	yes	no	no	no	no	yes
First-stage *F*-statistic	n/a	n/a	0.61	0.76	0.11	n/a	n/a	0.61	0.76	0.11	n/a	n/a	0.61	0.76	0.11
Observations	855	855	855	855	855	855	855	855	855	855	855	855	855	855	855
States	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28
Years	39	39	39	39	39	39	39	39	39	39	39	39	39	39	39

Notes: Parameter estimates are robust to heteroskedasticity and are multiway clustered by state and year. Standard errors are reported in parentheses for insurance participation and GMO seed adoption variables. Chi-square statistics for *F*-statistics of joint significance for weather variables are reported in parentheses for each set of weather variables considered. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Kleibergen-Paap *F*-statistics, which account for adjustments in standard error calculations, are reported.

Table S7. Robustness of EBP Crop Insurance on Pesticide Use Controlling for GMO-Adoption and Weather (Cotton)

	Dependent Variable: Ln of Expenditures per acre					**Dependent Variable: Ln of Quality-Unadjusted (Raw) Quantity per acre**					**Dependent Variable: Ln of Quality-Adjusted Quantity per acre**				
	(1) (OLS)	**(2) (TWFE)**	**(3) (TWFE-SSIV)**	**(4) (FE-SSIV)**	**(5) (FE-SSIV)**	**(6) (OLS)**	**(7) (TWFE)**	**(8) (TWFE-SSIV)**	**(9) (FE-SSIV)**	**(10) (FE-SSIV)**	**(11) (OLS)**	**(12) (TWFE)**	**(13) (TWFE-SSIV)**	**(14) (FE-SSIV)**	**(15) (FE-SSIV)**
Enrollment-based participation	0.03	0.28	-2.42	0.96***	1.36***	-0.22*	-0.09	1.04	-0.12	0.35**	0.07	0.03	-2.61	0.65***	1.13***
	(0.14)	(0.26)	(1.70)	(0.14)	(0.29)	(0.12)	(0.18)	(1.04)	(0.11)	(0.17)	(0.12)	(0.25)	(1.65)	(0.12)	(0.27)
Bt-adoption	-0.87*	-1.22**	0.07	-1.37**	-1.75***	0.52**	-0.33	-0.87*	0.01	-0.44*	-0.62	-1.08**	0.18	-1.16**	-1.63***
	(0.49)	(0.50)	(0.79)	(0.58)	(0.55)	(0.23)	(0.25)	(0.50)	(0.21)	(0.24)	(0.47)	(0.44)	(0.78)	(0.49)	(0.47)
HT-adoption	0.85	0.21	-0.13	1.14*	1.00	-0.10	-0.20	-0.06	-0.13	-0.30	1.50***	0.15	-0.18	1.19**	1.02*
	(0.56)	(0.51)	(0.42)	(0.69)	(0.72)	(0.28)	(0.33)	(0.36)	(0.31)	(0.26)	(0.53)	(0.45)	(0.38)	(0.59)	(0.61)
Precipitation *F*-statistic	5.48	0.34	1.85	0.21	1.03	2.75	0.50	0.35	4.62	2.67	5.43	0.46	2.38	0.10	1.13
	(0.01)***	(0.71)	(0.40)	(0.90)	(0.60)	(0.08)*	(0.61)	(0.84)	(0.10)*	(0.26)	(0.01)***	(0.63)	(0.31)	(0.95)	(0.57)
Temperature *F*-statistic	7.52	1.35	1.45	1.76	0.75	4.73	1.29	3.14	1.44	4.32	4.30	1.64	1.74	3.25	1.72
	(0.00)***	(0.27)	(0.49)	(0.42)	(0.69)	(0.02)**	(0.29)	(0.21)	(0.49)	(0.12)	(0.02)**	(0.21)	(0.42)	(0.20)	(0.42)
State fixed effects	no	yes	yes	yes	yes	no	yes	yes	yes	yes	no	yes	yes	yes	yes
Year fixed effects	no	yes	yes	no	no	no	yes	yes	no	no	no	yes	yes	no	no
Crop-specific linear trend	no	no	no	yes	yes	no	no	no	yes	yes	no	no	no	yes	yes
Crop-specific quadratic trend	no	no	no	no	yes	no	no	no	no	yes	no	no	no	no	yes
First-stage *F*-statistic	n/a	n/a	9.56	127.90	32.15	n/a	n/a	9.56	127.90	32.15	n/a	n/a	9.56	127.90	32.15
Observations	385	385	385	385	385	385	385	385	385	385	385	385	385	385	385
States	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
Years	39	39	39	39	39	39	39	39	39	39	39	39	39	39	39

Notes: Parameter estimates are robust to heteroskedasticity and are clustered by year. Standard errors are reported in parentheses for insurance participation and GMO seed adoption variables. Chi-square statistics for *F*-statistics of joint significance for weather variables are reported in parentheses for each set of weather variables considered. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Kleibergen-Paap *F*-statistics, which account for adjustments in standard error calculations, are reported.

Table S8. Robustness of LBP Crop Insurance on Pesticide Use Controlling for GMO-Adoption and Weather (Cotton)

	Dependent Variable: Ln of Expenditures per Acre					**Dependent Variable: Ln of Quality-Unadjusted (Raw) Quantity per Acre**					**Dependent Variable: Ln of Quality-Adjusted Quantity per Acre**				
	(1) (OLS)	**(2)** (TWFE)	**(3)** (TWFE-SSIV)	**(4)** (FE-SSIV)	**(5)** (FE-SSIV)	**(6)** (OLS)	**(7)** (TWFE)	**(8)** (TWFE-SSIV)	**(9)** (FE-SSIV)	**(10)** (FE-SSIV)	**(11)** (OLS)	**(12)** (TWFE)	**(13)** (TWFE-SSIV)	**(14)** (FE-SSIV)	**(15)** (FE-SSIV)
Liability-based participation	-0.89***	-0.33	-1.57*	3.17***	3.53***	-0.76***	-0.14	0.68	-0.41	0.90*	-0.62***	-0.46**	-1.70**	2.13***	2.95***
	(0.18)	(0.23)	(0.88)	(0.95)	(1.11)	(0.13)	(0.15)	(0.67)	(0.37)	(0.51)	(0.15)	(0.21)	(0.81)	(0.71)	(1.00)
Bt-adoption	-0.79	-0.94**	-0.38	-2.65***	-2.91***	0.72***	-0.31	-0.68**	0.18	-0.74**	-0.59	-0.86**	-0.30	-2.02***	-2.60***
	(0.52)	(0.46)	(0.45)	(0.70)	(0.70)	(0.19)	(0.25)	(0.32)	(0.30)	(0.34)	(0.48)	(0.41)	(0.42)	(0.56)	(0.62)
HT-adoption	1.40**	0.17	0.16	1.46**	1.45**	0.05	-0.19	-0.18	-0.17	-0.18	1.95***	0.15	0.13	1.40**	1.40**
	(0.61)	(0.49)	(0.45)	(0.71)	(0.73)	(0.23)	(0.33)	(0.30)	(0.34)	(0.27)	(0.55)	(0.44)	(0.40)	(0.60)	(0.62)
Precipitation *F*-statistic	3.17	0.47	1.76	1.93	2.17	1.83	0.51	0.67	4.79	3.96	3.41	0.61	2.25	0.97	1.84
	(0.05)**	(0.63)	(0.42)	(0.38)	(0.34)	(0.17)	(0.60)	(0.71)	(0.09)*	(0.14)	(0.04)**	(0.55)	(0.32)	(0.62)	(0.40)
Temperature *F*-statistic	1.36	1.27	2.74	0.83	0.66	1.09	1.27	3.49	1.23	4.64	1.15	1.59	3.33	2.16	1.37
	(0.27)	(0.29)	(0.25)	(0.66)	(0.72)	(0.35)	(0.29)	(0.17)	(0.54)	(0.10)*	(0.33)	(0.22)	(0.19)	(0.34)	(0.50)
State fixed effects	no	yes	yes	yes	yes	no	yes	yes	yes	yes	no	yes	yes	yes	yes
Year fixed effects	no	yes	yes	no	no	no	yes	yes	no	no	no	yes	yes	no	no
Crop-specific linear trend	no	no	no	yes	yes	no	no	no	yes	yes	no	no	no	yes	yes
Crop-specific quadratic trend	no	no	no	no	yes	no	no	no	no	yes	no	no	no	no	yes
First-stage *F*-statistic	n/a	n/a	24.78	19.49	16.45	n/a	n/a	24.78	19.49	16.45	n/a	n/a	24.78	19.49	16.45
Observations	385	385	385	385	385	385	385	385	385	385	385	385	385	385	385
States	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
Years	39	39	39	39	39	39	39	39	39	39	39	39	39	39	39

Notes: Parameter estimates are robust to heteroskedasticity and are clustered by year. Standard errors are reported in parentheses for insurance participation and GMO seed adoption variables. Chi-square statistics for *F*-statistics of joint significance for weather variables are reported in parentheses for each set of weather variables considered. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respecttively. Kleibergen-Paap *F*-statistics, which account for adjustments in standard error calculations, are reported.

Table S9. Treatment Effects Estimated Using Difference-in-Differences with Shift-Share Instrument

	Enrollment-Base Participation (EBP)								Liability-Based Participation (LBP)							
	Corn		Soybeans		Wheat		Cotton		Corn		Soybeans		Wheat		Cotton	
	FCIRA (1994)	***ARPA (2000)***	***FCIRA (1994)***	***ARPA (2000)***	***FCIRA (1994)***	***ARPA (2000)***	***FCIRA (1994)***	***ARPA (2000)***	***FCIRA (1994)***	***ARPA (2000)***	***FCIRA (1994)***	***ARPA (2000)***	***FCIRA (1994)***	***ARPA (2000)***	***FCIRA (1994)***	***ARPA (2000)***
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Dependent variable: Ln of expenditures per acre																
Crop insurance participation	2.82*	-10.65	1.36	-5.37	1.22	2.96	3.30	2.34***	4.18*	13.13	2.55	1.15	4.23	3.92	5.78	6.55**
	(1.71)	(22.51)	(2.94)	(18.95)	(3.00)	(4.16)	(2.67)	(0.73)	(2.25)	(23.93)	(5.41)	(1.45)	(10.31)	(5.61)	(4.59)	(3.01)
Bt-adoption	3.83	-1.25	n/a	n/a	n/a	n/a	-14.06	-1.68	-3.24	0.67	n/a	n/a	n/a	n/a	-5.00	-6.03
	(5.69)	(4.29)					(15.95)	(1.90)	(4.34)	(3.08)					(14.19)	(3.75)
HT-adoption	-11.23	-5.40	-1.92**	-1.52	n/a	n/a	5.18	4.50**	-12.89	-10.38	-3.23	0.29	n/a	n/a	2.80	8.06**
	(8.61)	(13.57)	(0.84)	(5.73)			(11.00)	(1.87)	(8.58)	(20.05)	(2.85)	(0.25)			(9.25)	(3.52)
Precipitation *F*-statistic	0.02	0.38	3.77	0.06	5.78	3.93	1.40	16.03	0.46	1.11	4.72	1.22	5.60	3.52	1.72	9.31
	(0.99)	(0.83)	(0.15)	(0.97)	(0.06)**	(0.14)	(0.50)	(0.00)***	(0.80)	(0.58)	(0.09)*	(0.54)	(0.06)*	(0.17)	(0.42)	(0.01)***
Temperature *F*-statistic	2.56	0.85	3.37	1.39	5.19	3.04	1.88	1.16	5.81	0.19	4.27	4.72	4.98	11.80	1.67	0.61
	(0.28)	(0.66)	(0.19)	(0.50)	(0.08)*	(0.22)	(0.39)	(0.56)	(0.06)*	(0.91)	(0.12)	(0.09)*	(0.08)*	(0.00)***	(0.43)	(0.74)
First-stage *F*-statistic	7.70	0.11	0.99	0.07	10.21	5.22	4.22	4.33	11.99	0.40	1.49	2.13	6.95	6.22	3.91	2.93
Observations	37	39	26	28	18	28	15	16	37	39	26	28	18	28	15	16
States	37	39	26	28	18	28	15	16	37	39	26	28	18	28	15	16
Years	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6

Notes: Parameter estimates are robust to heteroskedasticity. Standard errors are reported in parentheses for insurance participation and GMO seed adoption variables. Chi-square statistics for *F*-statistics of joint significance for weather variables are reported in parentheses for each set of weather variables considered. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Kleibergen-Paap *F*-statistics, which account for adjustments in standard error calculations, are reported.

Table S10. Treatment Effects Estimated Using Difference-in-Differences with Shift-Share Instrument

	Enrollment-Base Participation (EBP)								Liability-Based Participation (LBP)							
	Corn		**Soybeans**		**Wheat**		**Cotton**		**Corn**		**Soybeans**		**Wheat**		**Cotton**	
	FCIRA (1994)	***ARPA (2000)***	***FCIRA (1994)***	***ARPA (2000)***	***FCIRA (1994)***	***ARPA (2000)***	***FCIRA (1994)***	***ARPA (2000)***	***FCIRA (1994)***	***ARPA (2000)***	***FCIRA (1994)***	***ARPA (2000)***	***FCIRA (1994)***	***ARPA (2000)***	***FCIRA (1994)***	***ARPA (2000)***
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Dependent variable: Ln of quality-unadjusted (raw) quantity per acre																
Crop insurance participation	3.24**	-10.42	1.42	-5.38	0.03	5.48***	2.73	4.25***	4.80**	12.85	2.66	1.15	0.10	7.28***	4.80	11.88***
	(1.67)	(23.54)	(2.09)	(19.76)	(0.88)	(1.68)	(2.61)	(0.31)	(2.49)	(22.03)	(3.67)	(1.77)	(3.07)	(2.29)	(4.36)	(2.65)
Bt-adoption	7.39	-0.95	n/a	n/a	n/a	n/a	-13.38	-0.89	-0.73	0.93	n/a	n/a	n/a	n/a	-5.87	-8.78***
	(6.00)	(4.46)					(17.43)	(0.59)	(4.46)	(3.12)					(13.98)	(3.29)
HT-adoption	-19.32	-5.15	-1.87***	-1.11	n/a	n/a	4.28	2.19***	-21.23**	-10.03	-3.24	0.70**	n/a	n/a	2.31	8.65***
	(9.91)	(13.50)	(0.59)	(5.91)			(12.08)	(0.70)	(10.99)	(18.61)	(2.14)	(0.35)			(9.47)	(3.30)
Precipitation *F*-statistic	0.58	0.61	10.34	0.09	10.59	0.77	1.98	103.99	0.77	0.98	9.37	1.37	8.69	1.03	3.57	22.28
	(0.75)	(0.74)	(0.01)***	(0.96)	(0.01)***	(0.68)	(0.37)	(0.00)***	(0.68)	(0.61)	(0.01)***	(0.51)	(0.01)***	(0.60)	(0.17)	(0.00)***
Temperature *F*-statistic	4.08	1.65	1.73	0.22	1.31	4.20	1.33	7.17	6.04	1.49	1.24	0.67	0.94	6.05	1.14	1.56
	(0.13)	(0.44)	(0.42)	(0.89)	(0.52)	(0.12)	(0.52)	(0.03)**	(0.05)**	(0.47)	(0.54)	(0.72)	(0.63)	(0.05)*	(0.57)	(0.46)
First-stage *F*-statistic	7.70	0.11	0.99	0.07	10.21	5.22	4.22	4.33	11.99	0.40	1.49	2.13	6.95	6.22	3.91	2.92
Observations	37	39	26	28	18	28	15	16	37	39	26	28	18	28	15	16
States	37	39	26	28	18	28	15	16	37	39	26	28	18	28	15	16
Years	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6

Notes: Parameter estimates are robust to heteroskedasticity. Standard errors are reported in parentheses for insurance participation and GMO seed adoption variables. Chi-square statistics for *F*-statistics of joint significance for weather variables are reported in parentheses for each set of weather variables considered. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Kleibergen-Paap *F*-statistics, which account for adjustments in standard error calculations, are reported.

Table S11. Treatment Effects Estimated Using Difference-in-Differences with Shift-Share Instrument

	Enrollment-Base Participation (EBP)								**Liability-Based Participation (LBP)**							
	Corn		**Soybeans**		**Wheat**		**Cotton**		**Corn**		**Soybeans**		**Wheat**		**Cotton**	
	FCIRA (1994)	***ARPA (2000)***	***FCIRA (1994)***	***ARPA (2000)***	***FCIRA (1994)***	***ARPA (2000)***	***FCIRA (1994)***	***ARPA (2000)***	***FCIRA (1994)***	***ARPA (2000)***	***FCIRA (1994)***	***ARPA (2000)***	***FCIRA (1994)***	***ARPA (2000)***	***FCIRA (1994)***	***ARPA (2000)***
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**
Dependent variable: Ln of quality-adjusted quantity per acre																
Crop insurance participation	2.23	-12.70	0.17	3.63	3.14	4.28	3.43	2.44***	3.30	15.65	0.32	-0.77	10.91	5.68	6.01	6.81**
	(1.75)	(27.84)	(2.06)	(13.66)	(2.83)	(3.69)	(2.72)	(0.62)	(2.53)	(26.76)	(3.85)	(1.20)	(9.79)	(4.98)	(4.60)	(2.80)
Bt-adoption	6.26	-2.62	n/a	n/a	n/a	n/a	-15.89	-1.10	0.68	-0.33	n/a	n/a	n/a	n/a	-6.47	5.62
	(4.85)	(5.23)					(16.35)	(1.65)	(3.64)	(3.72)					(14.16)	(3.53)
HT-adoption	-15.53*	-5.46	-1.90***	1.38	n/a	n/a	6.41	3.84**	-16.84*	-11.40	-2.06	0.16	n/a	n/a	3.94	7.54**
	(8.33)	(16.02)	(0.75)	(4.16)			(11.56)	(1.59)	(9.43)	(22.88)	(1.96)	(0.24)			(9.57)	(3.23)
Precipitation F-statistic	0.21	0.63	19.31	0.18	3.07	1.83	1.29	23.22	0.15	1.43	8.17	0.02	3.83	1.86	1.60	11.45
	(0.90)	(0.73)	(0.00)***	(0.92)	(0.22)	(0.40)	(0.53)	(0.00)***	(0.93)	(0.49)	(0.02)**	(0.99)	(0.15)	(0.40)	(0.45)	(0.00)***
Temperature F-statistic	7.30	0.86	7.28	0.15	3.02	2.28	1.91	2.17	8.97	0.95	6.50	7.82	5.19	10.50	1.72	0.75
	(0.03)**	(0.65)	(0.03)**	(0.93)	(0.22)	(0.32)	(0.39)	(0.34)	(0.01)***	(0.62)	(0.04)**	(0.02)**	(0.08)*	(0.01)***	(0.42)	(0.69)
First-stage F-statistic	7.70	0.11	0.99	0.07	10.21	5.22	4.22	4.33	11.99	0.40	1.49	2.13	6.95	6.22	3.91	2.93
Observations	37	39	26	28	18	28	15	16	37	39	26	28	18	28	15	16
States	37	39	26	28	18	28	15	16	37	39	26	28	18	28	15	16
Years	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6

Notes: Parameter estimates are robust to heteroskedasticity. Standard errors are reported in parentheses for insurance participation and GMO seed adoption variables. Chi-square statistics for *F*-statistics of joint significance for weather variables are reported in parentheses for each set of weather variables considered. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Kleibergen-Paap *F*-statistics, which account for adjustments in standard error calculations, are reported.