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

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An unforeseen outcome in achieving the dual agricultural policy goals of income stabilization with limited environmental impact is the potential for moral hazard. Here, we provide an overview of key issues for identifying 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 provide no consistent linkage between insurance and pesticide use across four major crops. We discuss the differences of 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, producer behavior, causal inference

Introduction

Two major goals of U.S. agricultural policy include smoothing farm income fluctuations through risk management programs and reducing the environmental impact of chemical inputs (USDA-RMA, 2022; P.L. 104-170, 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 loss more 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 public policy arenas.

An important dimension driving the debate is the potential for moral hazard in which producers alter applications of chemical inputs, such as pesticides, upon obtaining crop insurance coverage in order to increase the probability of receiving an indemnity (Horowitz and Lichtenberg, 1993; Smith and Goodwin, 1996; Coble, et al., 1997). However, it is difficult to identify this effect 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 the producer and differences in pesticide active ingredients needed to mitigate various pest pressures.

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This raises the question of whether crop insurance participation affects pesticide use, and if so, is the effect heterogeneous across crops? Previous work on this question 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, so we make no effort to develop a framework here. The empirical literature is beginning to become more developed 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; Mohring, et al., 2020a; Regmi, Briggeman, and Featherstone, 2022), negative (Smith and Goodwin, 1996; Babcock and Hennessy, 1996; Mohring, et al. 2020b) and null or mixed (Horowitz and Lichtenberg, 1994; Weber, Key, and O'Donoghue, 2016) effects of crop insurance participation on pesticide use.

The concerns which have emerged in the empirical literature primarily deal with the endogeneity of the crop insurance decision and measurement of both pesticide use and crop insurance participation with most works 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; Mohring et al., 2020a) and others modeling the decision 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 in the literature have constructed alternative measures to account for changes in pesticide qualities (Fernandez-Cornejo and Jans, 1995; Fernandez-Cornejo, et al, 2014; Mohring et al., 2020b). In the crop insurance literature, participation has been measured in different 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), while others incorporate 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, 2009; 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, 2017; DeLay, 2019; Connor and Katchova, 2020; Mohring et al., 2020a; Regmi, Briggeman, and Featherstone, 2022). Overall, any one study has failed to address all of these empirical challenges comprehensively, 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 for identifying the moral hazard effect of crop insurance on pesticide-use, focusing on the aspects of econometric modeling and measurement of key variables. To mitigate the bias from a possible correlation between the 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 approach. Specifically, we construct a novel shift-share instrumental variable based on changes in insurance subsidy-rates and exploit quasi-random variations in crop insurance participation. We also explore a difference-in-differences design combined with the shift-share IV based around two specific changes in subsidies, one in 1994 and the other in 2000. Regarding 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 we discuss later.

Our sample dataset is a state-level panel spanning 45 U.S. states from 1965-2019. 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. We show the way in which endogeneity of 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 to meet the exclusion restriction, how valid the exclusion restriction and the relevance assumptions may vary across the specifications regarding the set of controls. We consider other controls which may influence pesticide use, such as 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.

The remainder of the paper is organized as follows. The next section describes the various sources of data used to construct key pesticide and crop insurance measures and the variation exploited to identify the treatment effect of interest. A shift-share instrumental variables identification strategy is also discussed. The following section highlights the main findings from regressions of pesticide use on crop insurance participation. The last section concludes and provides implications for the main findings.

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 comes from USDA Economic Research Service (ERS), while crop insurance participation variables draw on data from the USDA National Agricultural Statistics Service (NASS) and USDA Risk Management Agency (RMA), as well as futures prices from Bloomberg.

Pesticide Use Measures

The pesticide use data consists of a state-year panel of annual pesticide expenditures and application rates (in pounds per acre) by active ingredient spanning 45 contiguous U.S. states from 1965-2019. See Table 1 for a breakdown of the number of state-year observations by crop. These data were used to construct quality-adjusted and quality-unadjusted (i.e., raw) measures of pesticide application rates by leveraging the hedonic pricing methods[1] outlined in Fernandez-Cornejo and Jans (1995). Crop-specific per acre expenditures 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. The different sources of variation among these three measures can be seen in Figure 1.

[1] The way in which we construct quality-adjusted pesticide use measure is 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 if the pesticide active ingredient is a 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 pounds of pesticide active ingredient per acre by the quality-adjusted price.

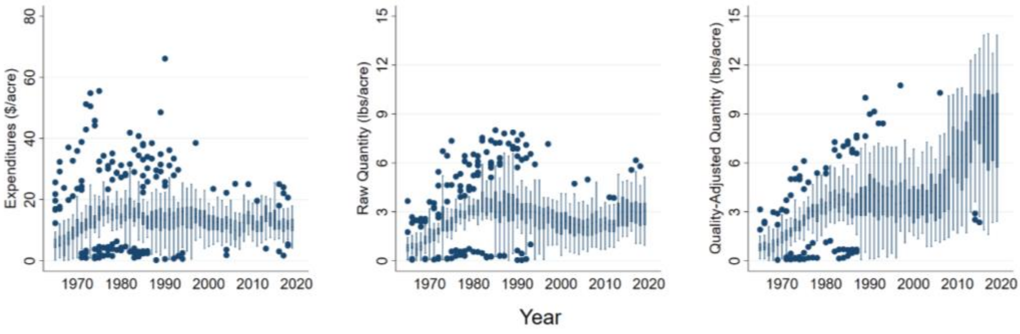

Figure 1. Spatial and Temporal Variation in Pesticide Variables (1965-2019)
The figure above plots expenditures per acre, raw pesticide quantity applied per acre, and quality-adjusted pesticide quantity per acre for corn. All three variables are constructed at the state-level. Expenditures per acre are found by deflating total expenditures using 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.

The quality-adjusted quantity is a measure of pesticide use which accounts for changes in pesticide potency and other quality variables over time and represents pesticide usage in the case where potency and other quality variables remain constant (Fernandez-Cornejo and Jans, 1995). Therefore, we should see higher pesticide usage for the quality-adjusted quantity relative to the raw (i.e., quality-unadjusted) quantity using the base period of 1965. In other words, the quality-adjusted measure provides insight into producer behavior assuming pesticide quality remained constant over time relative to the year 1965. For example, if pesticide potency increases over time, we would expect farmers to use less pesticides, all other things held constant. This difference in the pesticide use measures is highlighted by the second and third panels in Figure 1 with the quality-adjusted quantity in the third panel showing relatively more pesticide usage over time relative to panel 2 which shows raw, quality-unadjusted quantity.

Insurance Participation

We use data on insured acres and purchased liabilities from RMA State/County/Crop Summary of Business[2] (SOB) data files, 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 on all four crops were retrieved using a Bloomberg terminal, and a breakdown by crop of the years for which there is 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 (2017). 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 for individual plans of insurance: enrollment-based participation (*EBP*) and liability-based participation (*LBP*). *EBP* is simply the

[2] While most studies use the State/County/Crop/Coverage Level Summary of Business data files which span 1989-2023 from USDA-RMA, we also use the State/County/Crop Level Summary of Business data files which span 1948-1989 since we are only concerned with historical purchased liability and not county-level coverage level choices. Here is a link to the State/County/Crop Summary of Business Data Files.

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

	Corn			**Soybeans**			**Wheat**			**Cotton**			**All Crops**		
	Mean	**Min**	**Max**	**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	0.14	0.00	1.61
	(0.06)			(0.05)			(0.04)			(1.64)			(0.13)		
Raw Quantity (lbs./ac)	2.57	0.00	7.87	1.34	0.05	3.93	0.41	0.00	3.91	9.39	0.33	383.94	2.30	0.00	13.56
	(1.24)			(0.65)			(0.52)			(24.14)			(2.11)		
Adjusted Quantity (lbs./ac)	3.94	0.00	13.83	3.42	0.07	16.71	2.42	0.00	15.95	16.00	0.76	658.96	4.65	0.00	32.23
	(2.54)			(2.93)			(2.89)			(38.49)			(4.66)		
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	0.41	0.00	1.00
	(0.34)			(0.35)			(0.31)			(0.40)			(0.35)		
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	0.24	0.00	1.00
	(0.27)			(0.28)			(0.28)			(0.30)			(0.31)		
OBS		1,988			1,408			1,045			771			5,212	
States		38			29			28			16			45	
Years		1965-2019			1965-2019			1970-2019			1965-2019			1965-2019	

Note: Standard deviations are in parentheses.
Source: ERS (2022), NASS (2022), RMA (2022), Bloomberg (2022)

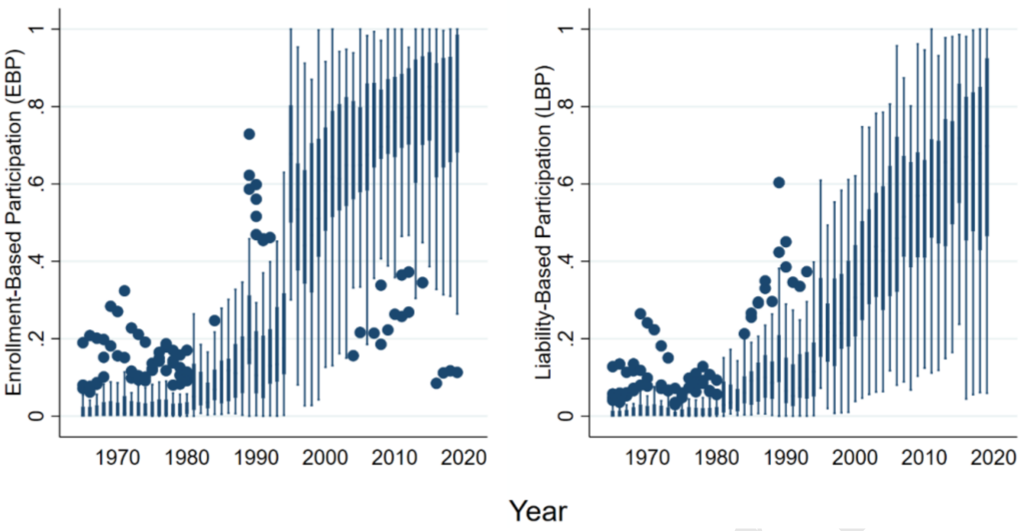

Figure 2. Spatial and Temporal Variation in Crop Insurance Participation Variables (1965-2019)

The figure above plots *EBP* and *LBP* for corn across time for all states in our sample. *EBP* is the ratio of insured acres to planted acres while *LBP* is the ratio of purchased liability to the maximum amount of liability which can be purchased.

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. The differences in variation between these two measures can be seen in Figure 2.

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:

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

where ε_{it} denotes random errors.

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 the production decisions including input usage and the crop insurance decisions are a threat to the identification of the effect of the 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, 2017). While recent studies (e.g., Weber, Key, and O'Donoghue, 2016; Yu, Smith, and

Sumner, 2017; Ghosh, Miao, and Malikov 2021; Connor, Roderick, and Mahmut, 2022) attempt to tackle the endogeneity of insurance participation via different identification strategies, it remains as a challenge in studying the role of crop insurance in input usage.

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 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; and Mohring, et al., 2020a). Furthermore, Lichtenberg and Zilberman (1986) model pesticides as risk-reducing inputs, which suggests that pesticide usage to be greater for those who do not enroll in crop insurance since pesticides have been argued to be a form of insurance.

In the general crop insurance literature, a few recent works have argued the endogeneity of the crop insurance decision should be accounted for via instrumental variables where the instrument is the exogenous changes in national-level subsidy rates across time (e.g., Yu, Smith, and Sumner, 2017; 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 the 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 such as soil characteristics and climate, and year fixed effects, v_t, to control for time-varying shocks common to all states such as pesticide policies, pesticide technologies, and price levels. Hence, we can rewrite the error term, ε_{it}, as $\varepsilon_{it} = u_i + v_t + \eta_{it}$ where η_{it} is an error term. Equation (1) becomes

(1') $$ln\,(Y_{it}) = \alpha_0 + \tau I_{it} + u_i + v_t + \eta_{it}.$$

However, the identification fails if the 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, TWFE no longer provides the identification of the effect, τ.

Therefore, we also consider an alternative identification strategy that uses an instrumental variable[1]. We construct a shift-share instrumental variable (SSIV) and exploit quasi-random 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 (2017) 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 pre-subsidy period of our sample (i.e., shares). This gives us exogenous variation in both the time-series and cross-section components of our instrument, which is necessary in our panel setting to properly instrument an endogenous variable

[1] 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, 2023). We acknowledge that this approach could be useful when there is no external instrument, yet the concern exists on 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.

which varies across space and time. This so-called shift-share design goes back to Bartik (1991), where he 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, and recent studies such as Goldsmith-Pinkham, Sorkin, and Swift (2020) and 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:

$$Z_{it} = \boldsymbol{S_{i0}}\boldsymbol{R_t} = s_{i,0.65,0}r_{t,0.65} + s_{i,0.75,0}r_{t,0.75} \tag{2}$$

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[2] for the 65% and 75% coverage levels. We choose the 65% and 75% coverage levels because they have been offered since the inception of the crop insurance program in 1938 (P.L. 74-430), and they are the most popular coverage levels across the time series in our sample. We use the period 1989 – 1994 as a 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 years prior to the first premium subsidy rate introduction in 1980 because the RMA Summary of Business data do not have 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) the instrument, Z_{it}, is strongly correlated with the crop insurance variable, I_{it} (relevance of the instrument), and ii) the instrument, 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 the fixed effects or the other covariates. We first consider TWFE (TWFE-SSIV) and also 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 in order to allow for the most flexible form of autocorrelation in the errors and cluster at the year level in order to allow for unmeasured shocks common to all states in a given year such as price shocks and numerous agricultural policies which impact pesticide use (Fernandez-Cornejo, et al, 2014). Additionally, we only cluster if the number of clusters in a specific dimension are greater than 20, following Bertrand, Duflo, and Mullainathan (2004). We report first-stage F-statistics[3] using the Kleibergen-Paap test statistic (Baum, Schaffer, and Stillman, 2010) which accounts for the adjustment in calculating standard errors.

We also explore a difference-in-differences design combined with SSIV (DID-SSIV). As there have been essentially two significant policy changes that affected subsidy rates, the Federal Crop Insurance Reform Act (FCIRA) of 1994 (P.L. 103-354) and the Agriculture Risk Protection Act (ARPA) of 2000 (P.L. 106-224), we further investigate these policy changes separately to explore possible heterogeneous responses across the policy regimes. Consider the following estimation equation:

$$\Delta ln\ (Y_{ip}) = \gamma + \tau \Delta I_{ip} + \Delta \varepsilon_{\mathrm{ip}} \tag{3}$$

where subscript p denotes a three-year period and the difference operator Δ denotes the difference between two three-year periods before and after the policy changes. For the 1994 FCIRA, we take

[2] We used the stated subsidy rates given by Glauber (2004), the FCIA of 1980 (P.L. 96-365), the Federal Crop Insurance Reform Act of 1994 (P.L. 103-354), the Agriculture Risk Protection Act of 2000 (P.L. 106-224), the Food, Conservation, and Energy Act of 2008 (P.L. 110-246), and the Agricultural Act of 2014 (P.L. 113-79).
[3] We use *ivreg2* in Stata to implement all IV estimations.

the difference between period 1, 1992-1994, and period 2, 1995-1997, and for the 2000 ARPA, we define period 1 as 1995-1997 and period 2 as 2001-2003.[4]

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

$$\Delta Z_{ip} = \Delta \boldsymbol{S_{i1} R_p} = s_{i,0.65,1}\Delta r_{p,0.65} + s_{i,0.75,1}\Delta r_{p,0.75} \tag{4}$$

where subscript 1 denotes period 1, which is 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 OLS without controlling for any sources of endogeneity. Column (2) provides results using a two-way fixed effects (TWFE) estimator using 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 begin by first discussing results for corn and soybeans (Tables 2-3). Both crops 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 relative to 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.

Columns (3) – (5) provide estimates that generate an interesting discussion. The first stage F-statistics vary across the columns, which indicate 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).[5]

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 assumption. That is, the instrument no longer explains crop insurance participation. Using linear or quadratic time trends seems to provide statistical power to the instrument. Yet, 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

[4] 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.

[5] Recently, a growing literature on the inference with potentially weak instruments (e.g., Andrews, Stock, and Sun (2019), Lee et al. (2022) and Keane and Neal (2023)) indicate 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-Rubin p-value (Anderson and Rubin, 1949), and we recommend conducting robustness tests when one is exploring the proposed instruments in different contexts. In our context, however, as we do not find stable estimates that indicate a clear causal direction and we do not claim to find causal effects, we refrain ourselves from providing alternative inferences.

Table 2. The Effect of Crop Insurance Participation on Pesticide Usage (Corn)

	(1) (OLS)	(2) (TWFE)	(3) (TWFE-SSIV)	(4) (FE-SSIV)	(5) (FE-SSIV)
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*)	NA	NA	4.16	10.20	22.21
First-Stage F-Statistic (*LBP*)	NA	NA	2.99	0.53	24.17
Observations	1,988	1,988	1,988	1,988	1,988
States	38	38	38	38	38
Years	55	55	55	55	55

*Multiway-clustered (by state and year) standard errors are reported in parentheses. *,**,*** 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 3. The Effect of Crop Insurance Participation on Pesticide Usage (Soybeans)

	(1) (OLS)	(2) (TWFE)	(3) (TWFE-SSIV)	(4) (FE-SSIV)	(5) (FE-SSIV)
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*)	NA	NA	1.17	16.21	27.22
First-Stage F-Statistic (*LBP*)	NA	NA	1.71	3.00	39.63
Observations	1,408	1,408	1,408	1,408	1,408
States	29	29	29	29	29
Years	55	55	55	55	55

Multiway-clustered (by state and year) standard errors are reported in parentheses. *,**,*** 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 4. The Effect of Crop Insurance Participation on Pesticide Usage (Wheat)

	(1) (OLS)	(2) (TWFE)	(3) (TWFE-SSIV)	(4) (FE-SSIV)	(5) (FE-SSIV)
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*)	NA	NA	3.11	1.23	1.63
First-Stage F-Statistic (*LBP*)	NA	NA	1.49	4.07	0.74
Observations	1,045	1,045	1,045	1,045	1,045
States	28	28	28	28	28
Years	50	50	50	50	50

Multiway-clustered (by state and year) standard errors are reported in parentheses. *,**,*** 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 5. The Effect of Crop Insurance Participation on Pesticide Usage (Cotton)

	(1) (OLS)	(2) (TWFE)	(3) (TWFE-SSIV)	(4) (FE-SSIV)	(5) (FE-SSIV)
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*)	NA	NA	0.26	11.38	15.25
First-Stage F-Statistic (*LBP*)	NA	NA	0.04	0.34	15.33
Observations	709	709	709	709	709
States	16	16	16	16	16
Years	55	55	55	55	55

Multiway-clustered (by state and year) standard errors are reported in parentheses.. *,**,*** 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 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)***
	(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
Observations	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

Multiway-clustered (by state and year) standard errors are reported in parentheses. *,**,*** 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.

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 SSIV specifications lead to large enough F-statistics for wheat (table 4), patterns similar to corn and soybeans occur where estimated effects tend to be positive 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 inference, so we draw no definitive conclusion from wheat. The first-stage F-statistic indicates a strong instrument for cotton in column 5 (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 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 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 relative to 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 (3) using the instrument constructed by equation (4). The results are reported in table 6. 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 the first-stage F-statistics larger than 10. All other crops and the 2000 ARPA do not 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 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 find 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 is more reasonable and reliable for column (3) than those of 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 controlling for these possibly confounding factors continues to provide a similar pattern of non-robust 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 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 (S9-S11). It should be noted that the first-stage F-statistics for the FE-SSIV (table S7-S8) and DID-IV (S9-S11) estimators in cotton vary from somewhat strong using FE-SSIV (i.e., 16.45 to 127.90) to very weak using DID-IV (i.e., 4.22 to 4.33). Additionally, we find the effects of Bt-resistant and herbicide-tolerant seed adoption tend to be negative and positive, respectively, for corn and cotton which falls 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.

Conclusion

Here we have addressed the empirical challenges of estimating 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, and two measures of insurance participation are considered that differ by their inclusion of the intensity of coverage. 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.

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. We show the way in which endogeneity of 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. A key challenge of identification is shown to be the specification of temporal trends and how they interact with policy changes, i.e. 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 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 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. Lastly, the SOB data do not have data by coverage levels prior to 1989 which limits the number of years we can fix the shares used to construct the SSIV and prevents us from constructing the shares in a true pre-policy period (i.e., 1965-1980).

We note the best empirical approach to identify causal effects in this context to be any approach which accounts for endogeneity of crop insurance participation given the major consensus of confounding factors which 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 TWFE accounts for confounding factors across states and years and using the SSIV uses exogenous variation in subsidy rates across states and years. However, the highly aggregated data in the spatial dimension in this context limits the use of year fixed effects to account for unobserved heterogeneity across time which limits the so-called TWFE approach. Thus, we propose the best estimation approach in this context to be to use a SSIV to account for endogeneity of crop insurance participation and account for unobserved heterogeneity across time with a quadratic trend.

Previous studies give 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 explore the impacts 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 quality characteristic-specific, 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.

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