Addressing moral hazard and premium rate heterogeneity in crop insurance: applications in pesticides and hurricanes

by

Hunter Biram

B.S.A., Arkansas State University, 2016
M.S., Mississippi State University, 2019

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
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Abstract

Essay 1: Crop Insurance Participation has Heterogeneous Impacts on Pesticide Use

Two major goals of agricultural policy include smoothing farm income fluctuations through risk management programs and reducing the environmental impact of chemical inputs. An unforeseen outcome in achieving these goals is the potential for moral hazard in which producers alter applications of chemicals, such as pesticides, upon obtaining federally subsidized crop insurance. This raises the question of whether crop insurance participation effects pesticide use and if the effect is heterogeneous across crops. In this work, we utilize state-level panel data for 45 states in the U.S. over the span of 1965-2019 within a shift-share instrumental variables framework and find that participating in crop insurance results in heterogeneous treatment effects on pesticide use across six major crops. For corn, soybeans, and sorghum, the treatment effect is negative and robust to measurement and model specification, while wheat, cotton, and rice give more nuanced estimated treatment effects across measurement of the pesticide use decision. 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. Therefore, 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.

Essay 2: Hurricane Incidence Results in Significant Increases to Crop Damages: Evidence from the Mississippi Delta

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Dr. Jesse Tack

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Dedication

I dedicate this work to my ultimate source of strength, grace, and patience, my Lord Jesus Christ. I have never been so closely drawn to Him as I was during this tough season, and I am so grateful for the trials given to me that only grew me and shaped me into who I am today. I also dedicate this work to my loving wife, Annie. Annie, I may never have the words to truly express the love and support I felt from you as I wrote this. I am forever grateful for your servant's heart.

Chapter 1 - Crop Insurance Participation has Heterogeneous Impacts on Pesticide Use

1.1 Introduction

Two major goals of 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). In the U.S., crop insurance and pesticides are popular risk-reducing tools used in agricultural production. 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[1]. The potential usefulness of both tools in mitigating risk is clear, but the interaction of the two is less clear and has been a topic of debate for decades both in the literature and in the public policy arena.

An unforeseen outcome driving this 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 productivity of inputs. While crop insurance enrollment has almost surely been impacted by changes in its program provisions regarding eligible crops and premium subsidy rates, pesticide applications have been

[1] We define "pest" following Fernandez-Cornejo, et al. (2014), where examples include insects, weeds, plant pathogens, and rodents.

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.

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[2] 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

[2] We recognize the recent contributions of Cumulative Prospect Theory and Generalized Expected Utility Theory to the theoretical literature on crop insurance (Babcock, 2015; Feng, Du, and Hennessy, 2019; Dalhaus, Barnett, and Finger, 2020) but note there have been no studies to apply Cumulative Prospect Theory to the moral hazard problem in the context of pesticides and crop insurance.

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, 1996; Mohring et al., 2020a) and others modeling the decision as simultaneous 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 pesticides 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 to model the decision as one made at the extensive margin (Smith and Goodwin, 1996; Connor and Katchova, 2020; Feng, Han, and Qiu, 2021), while others model the decision as one made also at the intensive margin (Goodwin, Vandeveer, and Deal, 2004; Weber, Key, and O’Donoghue, 2016; Connor and Katchova, 2020). We also note most studies due to data limitations present main findings for a single crop with only a few considering the moral hazard effect more generally within multiple crops (Roberts, Key, and O’Donoghue, 2009) and more specifically with pesticides (Weber, Key, and O’Donoghue, 2016).

Here, we provide a synthesis of econometric methods, measurement of key variables, and a broader analysis across crops and regions in order to provide a basis for comparison, shed light on mixed findings, and explore the heterogeneous nature of the moral hazard effect. We use an instrumental variables approach to account for the endogeneity of the crop insurance decision following Yu, Smith, and Sumner (2017). We add to this approach results using an exposure-weighted shift-share instrumental variable design by weighting exogenous national-level changes in the crop insurance premium subsidy rate with exogenous shares of acres enrolled in the most popular coverage levels over time (i.e., 65% and 75%). We consider measurement of the pesticide use decision beyond per acre expenditures by providing results for raw quantities applied per acre, as well as a quality-adjusted measure of pesticide use to account for changes in pesticide potency and toxicity over time. We utilize state-level panel data for 45 states in the U.S. over the span of 1965-2019 and find that participating in crop insurance yields heterogeneous treatment effects on pesticide use across six major crops. For corn, soybeans, and sorghum, the treatment effect is negative and robust to measurement and model specification, while wheat, cotton, and rice give more nuanced estimated treatment effects across measurement of the pesticide use decision.

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 motivation for identifying treatment effects under the potential outcomes framework using 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 and includes results found from models which control for possible confounding factors such as GMO seed adoption and weather. The last section concludes and provides implications for the main findings.

1.2 Data and Variable Construction

For this analysis, we utilize measures for pesticide usage and crop insurance participation for six crops: corn, soybeans, cotton, wheat, rice, and sorghum. Data on pesticide usage comes from USDA Economic Research Service (ERS), while crop insurance participation variables draws on data from the USDA National Agricultural Statistics Service (NASS) and USDA Risk Management Agency (RMA), as well as futures prices from Bloomberg.

1.2.1 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 1.1 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 outlined in Fernandez-Cornejo and Jans (1995). The quality-adjusted measure can give us insight into behavior under a scenario where pesticide quality remained constant over time. Crop-specific per acre expenditures[3] 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.

Spatial and Temporal Variation in Pesticide Variables

[3] Expenditures were adjusted for inflation using historical national CPI (1982-1984 = 100) data from the Federal Reserve Economic Data from the Federal Reserve Bank of St. Louis.

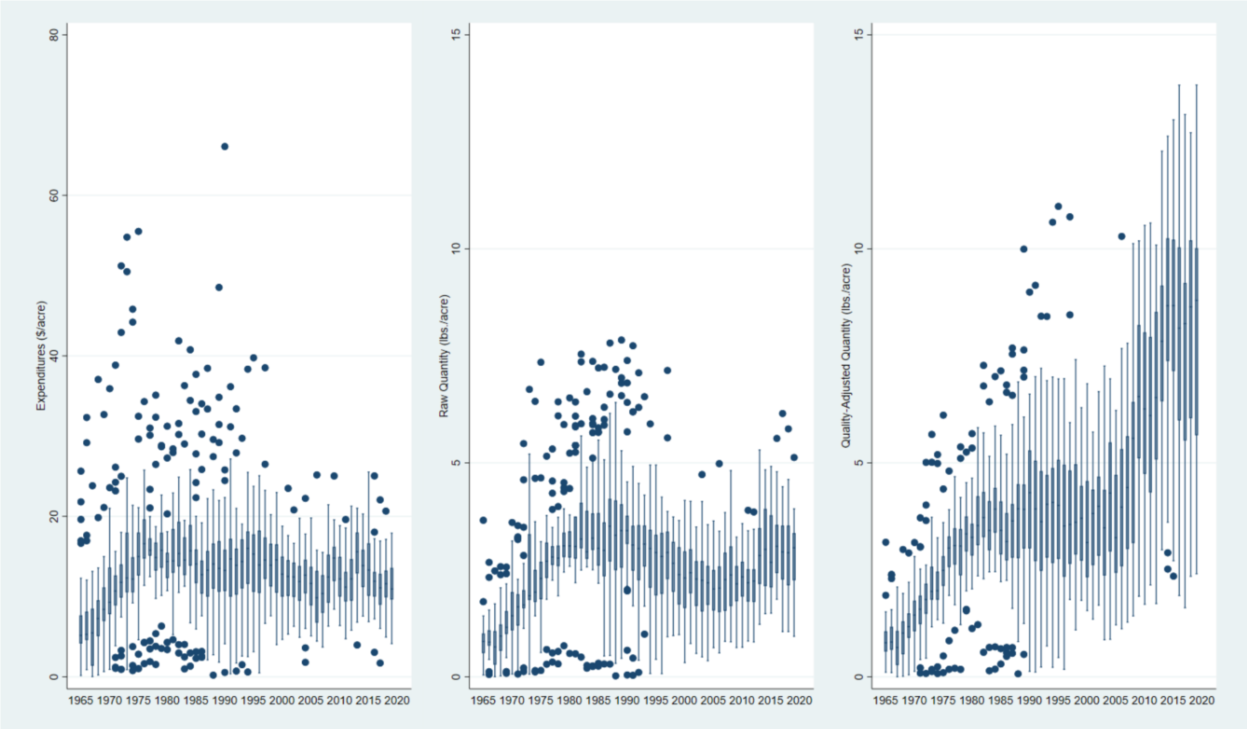

Figure 1.1 Spatial and Temporal Variation in Pesticide Variables The figure above plots expenditures per acre, raw pesticide quantity applied per acre, and quality-adjusted pesticide quantity per acre for corn.

1.2.2 Insurance Participation

We use data on insured acres and purchased liabilities from RMA Summary of Business (SOB), 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 six crops were retrieved using a Bloomberg terminal (Bloomberg, 2022), and a breakdown by-crop of the years for which there is price data can be found in Table 1.1. 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[4] plans of insurance: 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 and by calculating 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[5], yield, planted acreage, and the highest coverage level available. The differences in variation between these two measures can be seen in Figure 1.2.

[4] We only consider individual plans of insurance since the indemnity calculation is based on farm-level yields rather than county-, or area-, level yields, and the subsidy structure differs from that of area yield insurance plans.
[5] We calculate the expected price following RMA's practice outlined in Yu, Smith, and Sumner (2017).

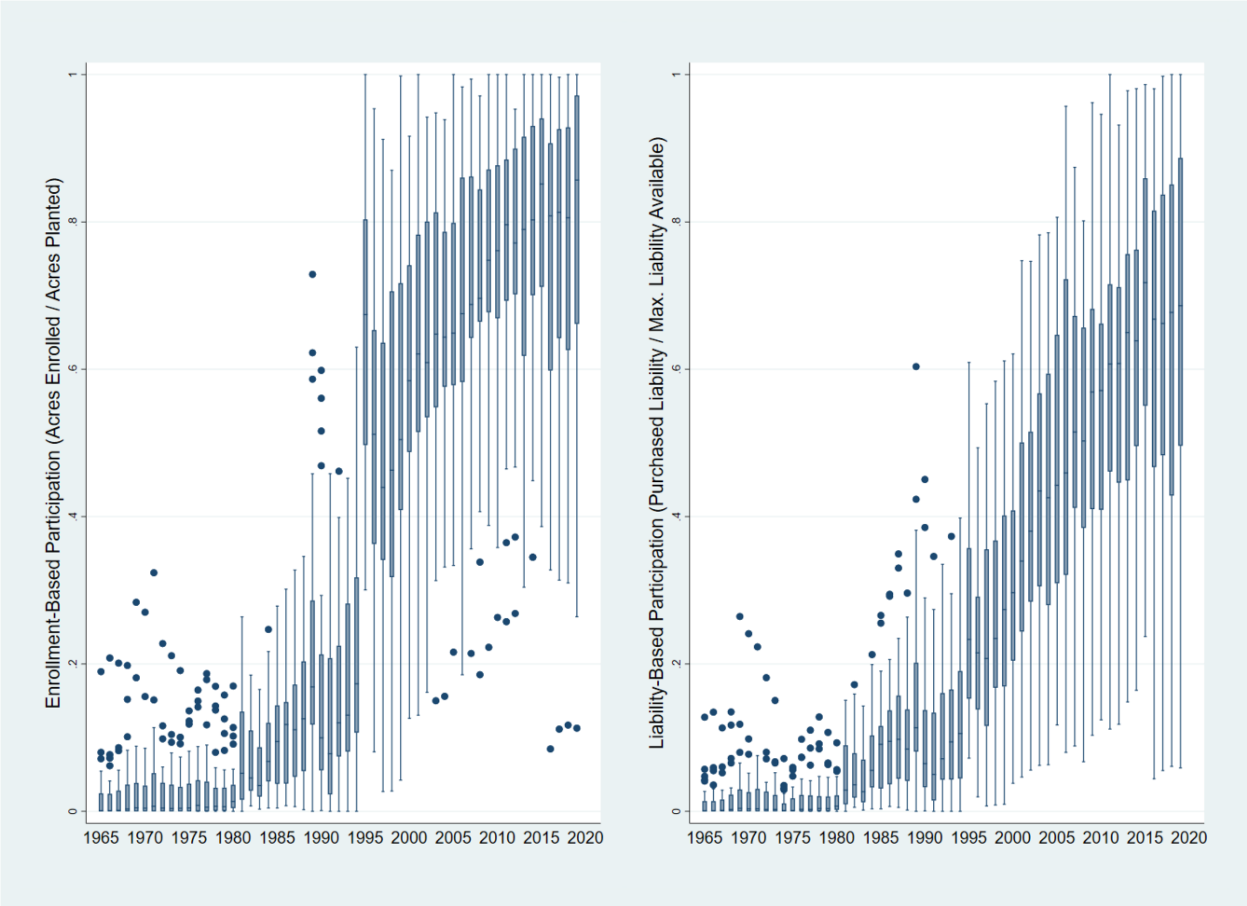

Figure 1.2 Spatial and Temporal Variation in Crop Insurance Participation Variables
The figure above plots EBP and LBP for corn across time for all states in our sample.

1.2.3 Additional Controls

To test the robustness of our model to possible confounding factors, we use measures for GMO seed adoption, weather, and market prices. We use state-level planted acreage data with Insect-resistant (i.e., Bt-resistant) and Herbicide-tolerant seed from ERS to construct GMO seed adoption rates, which are the ratio of acres planted with Bt-resistant and Herbicide-tolerant seed to planted acres. Following Lusk, Tack, and Hendricks (2018), we use an interpolation procedure for missing values of GMO acreage and back-fill all observations prior to 1996, the first year GMO seed was introduced commercially (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-crop-year combination.

We use daily grid-cell-level weather data from the Parameter-elevation Regressions on Independent Slopes Model (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 10ºC and 30ºC, while extreme heat days are defined to be days above 30ºC. Lastly, we construct a measure for relative output and input prices by taking the ratio of the calculated expected output price to the national-level producer price index given by NASS. Summary statistics for these additional controls can be found in Table 1.2.

Table 1.1 Summary Statistics for Pesticide Use and Crop Insurance Variables

	Corn			*Soybeans*			*Wheat*			*Cotton*			*Rice*			*Sorghum*			*All Crops*		
	Mean	Min	Max	Mean	Min	Max	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	0.31	0.09	0.67	0.07	0.00	0.33	0.14	0.00	1.61
	(0.06)			(0.05)			(0.04)			(1.64)			(0.11)			(0.05)			(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	4.15	1.48	8.79	2.24	0.17	8.12	2.30	0.00	13.56
	(1.24)			(0.65)			(0.52)			(24.14)			(1.67)			(1.34)			(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	9.73	2.62	22.97	3.15	0.24	10.80	4.65	0.00	32.23
	(2.54)			(2.93)			(2.89)			(38.49)			(5.00)			(2.12)			(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	0.73	0.01	1.00	0.61	0.07	0.96	0.41	0.00	1.00
	(0.34)			(0.35)			(0.31)			(0.40)			(0.28)			(0.20)			(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	0.43	0.00	1.00	0.37	0.03	0.64	0.24	0.00	1.00
	(0.27)			(0.28)			(0.28)			(0.30)			(0.24)			(0.15)			(0.31)		
OBS		1,988			1,408			1,045			771			148			206			5,709	
States		38			29			28			16			5			10			45	
Years		1965-2019			1965-2019			1970-2019			1965-2019			1990-2019			1997-2017			1965-2019	

Note: Standard deviations are in parentheses.

Source: ERS (2022), NASS (2022), RMA (2022), Bloomberg (2022)

Table 1.2 Summary Statistics for Additional Controls

GMO Adoption (%)	Mean	Min	Max
Bt-Resistance			
Corn	0.17	0	0.89
	(0.27)		
Cotton	0.22	0	0.97
	(0.32)		
Herbicide-Resistance			
Corn	0.15	0	0.89
	(0.27)		
Cotton	0.24	0	0.97
	(0.32)		
Soybeans	0.33	0	0.99
	(0.42)		
Weather Variables			
Growing Season Precipitation (mm)	606.65	94.13	1418.23
	(247.47)		
Optimal Growing Degree Days (hours between 10-30ºC)	1,847.98	926.06	3,191.48
	(563.02)		
Extreme Heat Growing Degree Days (hours greater than 30ºC)	36.29	0.09	293.43
	(39.64)		
Output/Input Price Ratio	0.97	0.07	3.61
	(0.65)		

Note: Standard deviations are in parentheses.

Source: ERS (2022), NASS (2022), RMA (2022), Bloomberg (2022), and PRISM (2022)

1.3 Treatment Effect Estimation Strategy

This section describes the motivation for estimating the treatment effect of crop insurance participation on pesticide use. We begin by briefly outlining the Potential Outcomes Framework as described in Rubin (1974) and how we can use this framework to identify the treatment effect of interest. Next, we present the econometric model specification. Then, we address the endogeneity of the crop insurance participation decision by first giving a brief history of how this endogeneity has been addressed in the literature and discuss our identification strategy using a shift-share instrumental variables approach.

1.3.1 Potential Outcomes Framework

There is a rapidly growing literature on the concept of estimating treatment effects under the potential outcomes framework, which is attributed to Rubin (1974). Rubin (1974) defines a causal effect as a comparison of two states of the world, where one state of the world is observed and can be captured by observable data, while the second state of the world, the counterfactual state of the world, is never actually observed. In the context of crop insurance, we are primarily interested in the question of whether participation alters producer behavior and can represent this question mathematically by using a switching equation. Under the Rubin Causal Model, the producer's switching equation is given as:

$$Y_i = I_i Y_i^1 + (1 - I_i) Y_i^0 \tag{1}$$

where Y_i is an observed outcome, in our case pesticide usage, for producer i. Y_i^1 and Y_i^0 are possible outcomes under two states of the world for the same producer i, one where a producer enrolls in crop insurance and one where he does not enroll in crop insurance. In this equation, I_i represents the decision of producer *i* to purchase crop insurance and takes a value of 1 when a producer is enrolled in crop insurance and value of 0 when they are not.

Producer *i*'s treatment effect can be calculated with the following equation:

$$\tau_i = Y_i^1 - Y_i^0 \tag{2}$$

Unfortunately, we only observe one outcome since the same producer can only exist in either a world where he has enrolled in insurance or world where he has not. This introduces the fundamental missing data problem of causal inference which makes calculating a treatment effect impossible. However, we can estimate the treatment effect using regression methods and now present our regression equation and model specification.

1.3.2 Model Specification

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. To evaluate robustness, we include a vector of covariates, $\boldsymbol{X_{it}}$,which include state fixed-effects to capture the effects of time-invariant unobserved heterogeneity across states such as soil characteristics and climate, and year fixed-effects to control for time-varying shocks common to all states such as pesticide policies and price levels. The vector of covariates also includes linear and quadratic time trends to account for changes in pesticide technology over time. To allow for treatment effect heterogeneity across crops, we run crop-specific regressions. The regression equation is:

$$\ln{(Y_{it})} = \alpha_0 + \tau I_{it} + \boldsymbol{\beta X_{it}} + \varepsilon_{it} \tag{3}$$

where ε_{it} are random errors. We note when aggregating many pesticide active ingredients to the state-level, using the current measure in levels does not provide a straightforward interpretation.

Therefore, we utilize a logarithmic transformation of the pesticide use variable in order to provide a standardized interpretation[6] of the treatment effect.

1.3.3 Endogeneity of Insurance Participation

According to Wooldridge (2010), there are three primary sources of endogeneity: omitted variables, measurement error, and simultaneity. Several works have argued crop insurance participation measures are plagued with these sources of endogeneity (Smith and Goodwin, 1994; Goodwin, Vandeveer, and Deal, 2004; O'Donoghue, Roberts, and Key, 2009; Yu, Smith, and Sumner, 2017). There is well-developed literature on estimating the treatment effect of crop insurance participation on pesticide usage in production agriculture where some works explicitly address either none, some, or all of these sources of endogeneity inherent in the insurance participation decision.

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 (Smith and Goodwin, 1996; Weber, Key, and O'Donoghue, 2016; and Mohring, et al., 2020). In the more general crop insurance space, 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 (Yu, Smith, and Sumner, 2017; Delay, 2019; Connor and Katchova, 2020). Additionally, Roberts, Key, and O'Donoghue (2006)

[6] Interpreting coefficients under this specification requires a transformation of the parameter estimate on insurance participation. Specifically, $\widehat{\tau_{ATT}} = 100 * \{\exp(\hat{\tau}) - 1\}$.

account for the endogeneity of the crop insurance decision using a general fixed effects approach.

Measurement of the crop insurance participation variable has also evolved a great deal across the literature. Several works have modeled crop insurance as a discrete [0,1] extensive margin decision (Horowitz and Lichtenberg, 1993; Smith and Goodwin, 1996; Wu, 1999; and Feng, Han, and Qiu, 2021), while others have proposed a measure to capture the extensive and intensive margin decision-making components (Goodwin, Vandeveer, and Deal, 2004; Weber, Key, and O'Donoghue, 2016; Connor and Katchova, 2020).

1.3.4 Identification Strategy: Shift-Share Instrumental Variable

As noted by Angrist and Pischke (2009) and Cunningham (2021), there are usually three parameters of interest to practitioners estimating treatment effects: the average treatment effect (ATE), the average treatment effect on the treated (ATT), and the average treatment effect on the untreated (ATU). Essentially, interest in each parameter varies based on which subpopulation you are interested in measuring treatment effects on. In this paper, we are interested in estimating the ATT, which is the treatment effect on the subpopulation of producers who participated in crop insurance which can be written as:

$$\begin{aligned} ATT &= E[\tau_i | I_i = 1] \\ &= E[Y_i^1 - Y_i^0 | I_i = 1] \\ &= E[Y_i^1 \big| I_i = 1] - E[Y_i^0 \big| I_i = 1] \end{aligned} \tag{4}$$

Unfortunately, we face a missing data problem in that we do not have observable data on counterfactual outcomes embodied by the second term in the ATT expression. Under certain conditions, however, we can still estimate the ATT with the data we do have (i.e., Y_{it} and I_{it}).

Angrist and Pischke (2009) show we can re-write the ATT as the difference in two terms:

$$E[Y_i^1 | I_i = 1] - E[Y_i^0 | I_i = 1] = E[Y_i | I_i = 1] - E[Y_i | I_i = 0] + E[Y_i^0 | I_i = 0] - E[Y_i^0 | I_i = 1] \quad (5)$$

where the first two terms represent the observed differences in average outcomes, and the latter two terms represent selection bias[7]. We expect selection bias to be present since producers who are more risk-averse tend to select into participating in crop insurance. Further, pesticides are risk-reducing inputs (Lichtenberg and Zilberman, 1986), we would expect 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[8]. Thus, the selection bias here would produce an upward bias in the treatment effect if not accounted for (i.e., $E[Y_i^0 | I_i = 0] > E[Y_i^0 | I_i = 1]$).

We use a shift-share instrumental variables (SSIV) estimator and exploit quasi-random variation in crop insurance participation to eliminate the selection bias. We build on the instrument introduced by Yu, Smith, and Sumner (2017) by weighting the time-varying exogenous changes to the national premium subsidy rate (i.e., shifts) with 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 which varies across space and time (Cameron and Trivedi, 2005).

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[7] In their hospitalization example, Angrist and Pischke (2009) also note that the selection bias can be so large in absolute value that a negative selection bias can mask a positive treatment effect. In our context, Smith and Goodwin (1996) took note of this masking effect and used it to argue this is why Horowitz and Lichtenberg (1993) found a positive treatment effect of crop insurance participation rather than a negative treatment effect.

[8] There is an extensive literature on this concept dating back to Hillebrandt (1960). Other works which consider the theoretical and empirical evidence of this are Norgaard (1976), Feder (1979), Just and Quiggin (1991), Horowitz and Lichtenberg (1994), Smith and Goodwin (1996), Babcock and Hennessy (1996).

The concept of exposure-weighting a time-varying shock common to all units has been attributed 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. Other works have more-or-less formalized the instrument (Blanchard and Katz, 1992; Goldsmith-Pinkham, Sorkin, and Swift, 2019; and Borusyak, Hull, and Jaravel, 2022), and a few works have utilized it in one form or another in the crop insurance context (O'Donoghue, Roberts, and Key, 2009; and DeLay, 2019). The intuition is that we can take a variable with only exogenous variation in the time dimension and interact it with exogenous unit-level shares to arrive at a single variable with exogenous variation in the time series and cross-sectional dimensions.

In our setting, we can formally write this as:

$$Z_{it} = \boldsymbol{S_{i0}} \boldsymbol{R_t} = \sum_{c=0.65}^{0.75} s_{ic0} r_{tc} \tag{6}$$

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 the pre-subsidy period[9] for our sample, and $\boldsymbol{R_t}$ is the vector of premium subsidy rates[10] 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. In the summation operator, s_{ic0} is the average share of the c^{th} coverage level for state *i* in the

[9] Ideally, the pre-subsidy rate period for our sample would be 1965-1980. However, the SOB data does not report coverage level-specific data until 1989. Therefore, we can only calculate shares by coverage level for the period 1989-1994. Since this period is prior to the legislation which provided the largest jump in subsidy rates, we do not think this greatly affects identification.

[10] 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).

baseline period, and r_{tc} is the national premium subsidy rate for the c^{th} coverage level. The SSIV components plotted separately, as well as the SSIV itself, can be seen in Figure 1.3.

As noted by Goldsmith-Pinkham, Sorkin, and Swift (2019), we fix the coverage level shares to an initial period because this allows the design to exploit variation in a single cross-section ensuring the time-invariant portion of the SSIV is indeed exogenous. Further, the reason shares are fixed to the baseline period is because this allows us to draw a parallel to Difference-in-Differences, where we exploit variation in the exogenous subsidy rate changes to explain variation in the crop insurance participation measures before and after the rate changes are implemented. The first-stage regression equation is:

$$I_{it} = \mu_0 + \rho Z_{it} + \boldsymbol{\beta X_{it}} + \vartheta_{it} \tag{7}$$

One may question other confounding factors impacting crop insurance participation and the pesticide use decision such as GMO seed adoption, weather, and price levels. As a robustness check, we provide estimation results from models which include these variables in a vector of covariates in the regression equations above. We note the results are largely unchanged.

We cluster standard errors at the state and year levels. 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 is a specific dimension are greater than 20, following Bertrand, Duflo, and Mullainathan (2004). All standard error calculations are robust to heteroskedasticity. We report first-stage F-statistics using the Kleibergen-Paap test statistic reported in the Stata output given by the *ivreg2* command (Baum, Schaffer, and Stillman, 2010), as this accounts for the adjustment in calculating standard errors.

1.3.5 Interpretation of the ATT

Since we are using a participation rate measure, as opposed to a discrete binary measure for crop insurance, we must be careful in how we interpret the ATT. Substituting the log-transformed pesticide use variable for the outcome into the expectations operator of equation (5) would yield a difference in conditional means between two logarithms. Since "true zeroes" only appear in the earlier years of our panel, and "true ones" only appear in the nearby years of our panel, we must think of the ATT as a difference in growth rates of pesticide usage across time between fully insured and uninsured producers. Therefore, parameter estimates may yield relatively large[11] treatment effects.

[11] To put the interpretation into perspective, average pesticide use growth rates by crop range anywhere from 13% to 80 times that of average usage in 1965. To see the growth in use by crop, see Appendix A Section 1.

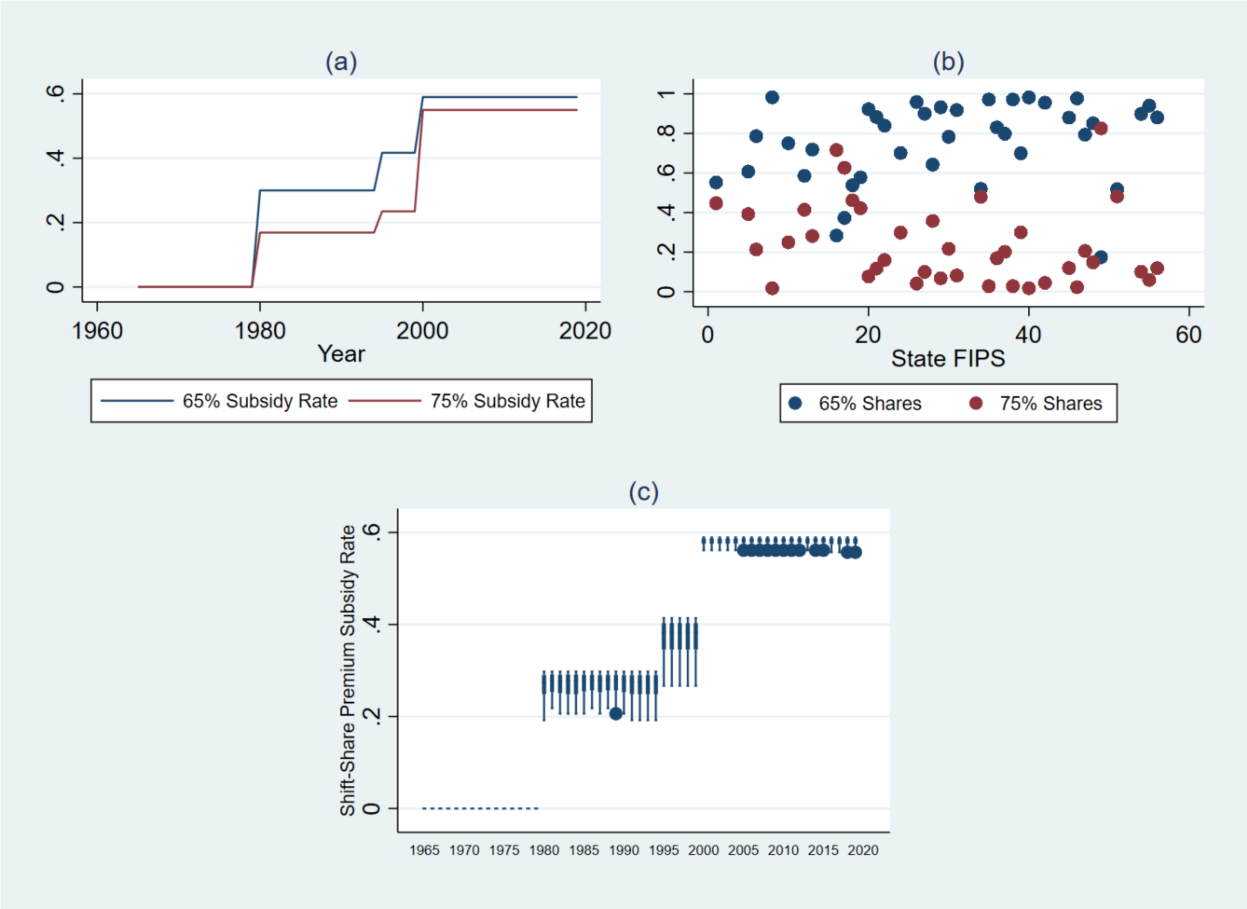

Figure 1.3 Components of the Shift-Share Instrumental Variable for Corn

1.4 Results

This section highlights two main findings from the treatment effects estimation of crop insurance participation on pesticide use. First, we find the ATT of crop insurance participation on pesticide use is heterogeneous across the six crops considered. Second, we find the selection bias appears to be positive as indicated by the ATT estimated via OLS and that the SSIV eliminates this bias. We present results across five model specifications to give insight on the direction of the selection bias and show the pattern of results across various strengths of the first-stage F-statistic. Findings are robust to controlling for the possible confounders mentioned above.

Tables 1.3-1.8 show alternative estimated results for equation (3) by crop. Column (1) reports estimation results with naïve OLS without controlling for any sources of endogeneity. Column (2) gives 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-IV) and columns (4) – (5) give results using an SSIV approach with state fixed-effects (FE-IV) and different time trend specifications. For results using SSIV, we will focus our discussion on those estimates for which the first-stage F-statistics are greater than 10[12].

1.4.1 Heterogeneous Treatment Effects

We begin by first discussing results for corn, soybeans, and sorghum. Holding measurement and model specification constant, results for corn, soybeans, and sorghum follow a similar pattern (Tables 1.3-1.5). In general, OLS gives positive ATT estimates, while using a TWFE estimator with state and time fixed effects to control for unobservable confounders yields a relatively smaller estimate in magnitude. Under TWFE-IV, the ATT is found to be positive and greater in magnitude relative to that of OLS. Lastly, using linear and quadratic time trends to account for unobserved heterogeneity across time and the SSIV, we find the ATT to be negative.

[12] Staiger and Stock (2010) argue in their paper than even though one may be able to reject the null of all coefficients being zero, this may not be strong enough evidence to indicate a strong first stage estimation in any IV setting. Thus, they suggest using the rule of an F-statistic greater than or equal to 10 to conclude if the first stage is strong enough to give consistent sample estimates.

Table 1.3 The Effect of Crop Insurance Participation on Pesticide Usage (Corn)

Covariates	(1) (OLS)	(2) (TWFE)	(3) (TWFE-IV)	(4) (FE-IV)	(5) (FE-IV)
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	1988	1988	1988	1988	1988
States	38	38	38	38	38
Years	55	55	55	55	55

*Parameter estimates are robust to heteroskedasticity and are clustered at the state-year level. Standard errors reported in parentheses. *,**,*** indicate statistical significance at the 10%, 5%, 1% levels, respectively Kleibergen-Paap F-statistics, which account for adjustments in standard error calculations, are reported.*

Table 1.4. The Effect of Crop Insurance Participation on Pesticide Usage (Soybeans)

Covariates	(1) (OLS)	(2) (TWFE)	(3) (TWFE-IV)	(4) (FE-IV)	(5) (FE-IV)
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	1408	1408	1408	1408	1408
States	29	29	29	29	29
Years	55	55	55	55	55

*Parameter estimates are robust to heteroskedasticity and are clustered at the state-year level. Standard errors 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 1.5. The Effect of Crop Insurance Participation on Pesticide Usage (Sorghum)

Covariates	(1) (OLS)	(2) (TWFE)	(3) (TWFE-IV)	(4) (FE-IV)	(5) (FE-IV)
Dependent Variable: Ln of Expenditures per acre					
Enrollment-Based Participation	0.50**	-0.23	15.84	-3.09	-5.04
	(0.28)	(0.37)	(13.85)	(2.12)	(3.43)
Liability-Based Participation	1.08***	0.18	9.57**	-4.10	-8.30
	(0.30)	(0.40)	(4.04)	(2.75)	(6.36)
Dependent Variable: Ln of Quality-Unadjusted (Raw) Quantity per acre					
Enrollment-Based Participation	0.42*	-0.17	11.32	-3.22*	-4.42
	(0.24)	(0.32)	(8.56)	(1.83)	(3.07)
Liability-Based Participation	1.11***	-0.07	6.84***	-4.27	-7.27
	(0.30)	(0.48)	(2.37)	(2.86)	(6.79)
Dependent Variable: Ln of Quality-Adjusted Quantity per acre					
Enrollment-Based Participation	1.63***	-0.57	16.35	-3.72*	-3.75
	(0.25)	(0.45)	(14.14)	(2.18)	(3.01)
Liability-Based Participation	2.92***	-0.07	9.88**	-4.93*	-6.18
	(0.28)	(0.47)	(4.21)	(2.75)	(5.11)
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	1.50	6.27	3.73
First-Stage F-Statistic (LBP)	NA	NA	11.10	5.02	1.36
Observations	206	206	206	206	206
States	10	10	10	10	10
Years	21	21	21	21	21

*Parameter estimates are robust to heteroskedasticity and are clustered at the year level. Standard errors 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.*

We now turn to results for wheat, cotton, and rice (Tables 1.6-1.8). We find the estimated ATT for wheat is positive across nearly all measurements and model specifications. However, the first-stage F-statistics for wheat using alternative SSIV estimation approaches are all less than 10, so conclusions drawn from these results should be made with caution. Using the SSIV approach, we find statistically significant estimated ATTs of crop insurance participation for cotton and rice to be positive using the expenditures measure of pesticide use and observe a divergence in the signs of the treatment effects across the other pesticide use measures. Comparing estimates across SSIV specifications with F-statistics greater than 10, the sign of the ATT flips for rice using the quality-adjusted measure, while the sign of the ATT for cotton is positive across insurance participation measures using the raw measure of pesticide use.

1.4.2 Model Performance: SSIV Appears to Eliminate Selection Bias

Results for corn, soybeans, and sorghum are largely robust across all measures of pesticide use and crop insurance participation, but it is important to note is the differences across estimation approaches and model specifications. For example, using OLS with no additional covariates gives positive ATT estimates. Although statistical significance varies for corn, the ATT ranges from around 17% to 362% which means that since 1965, pesticide usage grew over three times more for a producer with full coverage crop insurance relative to a producer who did not have any insurance (Table 1.3). We find a statistically significant treatment effect for soybeans under OLS between 12% and 582% indicating fully insured producers used nearly six times more pesticides than their uninsured counterparts (Table 1.4), and sorghum results under OLS would indicate being enrolled in full coverage insurance causes pesticide use to grow by up to 18 times that of the 1965 level (Table 1.5).

Table 1.6. The Effect of Crop Insurance Participation on Pesticide Usage (Wheat)

Covariates	(1) (OLS)	(2) (TWFE)	(3) (TWFE-IV)	(4) (FE-IV)	(5) (FE-IV)
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	1045	1045	1045	1045	1045
States	28	28	28	28	28
Years	50	50	50	50	50

*Parameter estimates are robust to heteroskedasticity and are clustered at the state-year level. Standard errors 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 1.7. The Effect of Crop Insurance Participation on Pesticide Usage (Cotton)

Covariates	(1) (OLS)	(2) (TWFE)	(3) (TWFE-IV)	(4) (FE-IV)	(5) (FE-IV)
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

*Parameter estimates are robust to heteroskedasticity and are clustered at the year level. Standard errors 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 1.8. The Effect of Crop Insurance Participation on Pesticide Usage (Rice)

Covariates	(1) (OLS)	(2) (TWFE)	(3) (TWFE-IV)	(4) (FE-IV)	(5) (FE-IV)
Dependent Variable: Ln of Expenditures per acre					
Enrollment-Based Participation	0.78***	0.78***	-0.45	0.53**	-4.23
	(0.10)	(0.26)	(1.29)	(0.22)	(44.36)
Liability-Based Participation	0.96***	1.18***	1.96	-5.94	-3.60
	(0.09)	(0.30)	(3.40)	(15.82)	(30.96)
Dependent Variable: Ln of Quality-Unadjusted (Raw) Quantity per acre					
Enrollment-Based Participation	-0.33***	1.38***	3.29**	1.17**	-17.88
	(0.09)	(0.35)	(1.59)	(0.53)	(174.88)
Liability-Based Participation	-0.38***	1.26***	-14.31	13.16	-15.21
	(0.13)	(0.31)	(32.78)	(30.78)	(118.92)
Dependent Variable: Ln of Quality-Adjusted Quantity per acre					
Enrollment-Based Participation	1.11***	0.54**	-0.68	-0.54	-21.96
	(0.17)	(0.23)	(1.33)	(0.40)	(203.92)
Liability-Based Participation	1.62***	0.59	2.95	6.10	-18.67
	(0.11)	(0.36)	(4.37)	(14.57)	(136.49)
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	2.64	14.19	0.01
First-Stage F-Statistic (LBP)	NA	NA	0.17	0.15	0.02
Observations	148	148	148	148	148
States	5	5	5	5	5
Years	30	30	30	30	30

*Parameter estimates are robust to heteroskedasticity and are clustered at the year level. Standard errors 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.*

Using TWFE, results for corn, soybeans, and sorghum tend to show a decrease relative to the OLS estimate which could be indicative that there are possibly confounding factors we need to control for. Adding further complexity by using SSIV to achieve randomization of treatment with TWFE, we find that the model "breaks down" and ATT estimates blow up due to weak first-stage estimations indicated by F-statistics less than 10. Sorghum is the exception to this with an F-statistic of 11.10 using LBP as the crop insurance participation variable. However, since its estimated ATT is comparable in magnitude and sign to the EBP measure, which has an F-statistic of 1.50, we interpret these parameter estimates with caution and do not draw any firm conclusions from them.

We find a negative and statistically significant ATT under FE-IV with quadratic trends for corn ranging between -85% and -100% which under this specification means that fully insured producers used 85-100% less pesticides than their uninsured peers between 1965 and 2019 (Table 1.3). Soybeans results are nearly identical to corn and are statistically significant at the 1% across both SSIV approaches. We find fully insured soybeans producers to use between 89-99% less pesticides than their uninsured counterparts (Table 1.4). We caution against drawing conclusions from the models using sorghum since most first-stage F-statistics are less than 10 (Table 1.5).

Findings for wheat, cotton, and rice are not as clear as those above. Estimation results for wheat indicate a positive and statistically significant ATT for LBP, but with first-stage F-statistics less than 10, we do not consider these estimates conclusive (Table 1.6). The only reliable estimation result using SSIV for rice is the FE-IV linear trend specification using EPB, where results using expenditures per acre and raw quantity per acre indicate a positive ATT, and results using the quality-adjusted quantity give a negative ATT (Table 1.8).

For cotton, we highlight SSIV results using EBP and FE-IV using the LBP measure for crop insurance participation where findings vary by pesticide use measure considered. Using expenditures per acre, the ATT of crop insurance participation shows an increase in pesticide usage between 97-326% (Table 1.7), which is nearly identical to the ATT using the quality-adjusted measure of pesticide use quantity. Using the raw measure of pesticide quantity, we find a negative ATT between -27% an -48%. Using the LBP measure of participation for cotton, the signs are the same as those of EBP but tend to be greater in absolute value.

1.4.3 Model Robustness to Additional Controls

Here, we focus on the models with all controls and discuss their effects on pesticide usage. Results are reported in Appendix A Section 2 and are broken down by crop insurance participation measure. We note results across all crops are surprisingly robust to additional controls that most likely impact the pesticide use and crop insurance participation decision and are robust to the pesticide use and crop insurance measures considered. The adoption of GMO seed and the futures prices relative to the producer input price index appear to be the most statistically significant drivers of pesticide use, but weather does not appear to be a significant driver of use (Tables A.14 and A.15 in Appendix A).

GMO seed adoption appears to have given mixed impacts on pesticide use depending on the type of seed that was adopted. The adoption of Bt-resistant seed in corn and cotton appear to have induced a decrease in pesticide use (Tables A.2 and A.6 in Appendix A), which falls in line with the intuition that producing a crop with a germ that kills insects almost eliminates the need to apply pesticides and also follows the trends outlined in Fernandez-Cornejo, et al. (2014). Planting herbicide-tolerant seed in corn and cotton appears to encourage herbicide applications (Tables A.2 and A.6 in Appendix A) while appearing to cause a decline in herbicide usage in soybeans (Table A.3 in Appendix A). Output and input price levels drive pesticide use in corn, soybeans, cotton under EBP, and rice under LBP (Tables A.14 and A.15 in Appendix A), where an increase in the futures price relative to the input price index results in an increase in pesticide usage for corn soybeans, and rice but induces a reduction in pesticide applications for cotton.

1.5 Conclusion

In this work, we have addressed the question of whether crop insurance participation effects pesticide use and if the effect is heterogeneous across crops by providing the most comprehensive empirical analysis using methods and measures of key variables that are on the frontiers of this vein of literature. Using state-level panel data for 45 states in the U.S. over the span of 1965-2019 within a shift-share instrumental variables framework, we find that participating in crop insurance yields heterogeneous treatment effects on pesticide use across six major crops. For corn, soybeans, and sorghum, the treatment effect is negative and robust to measurement and model specification, while wheat, cotton, and rice give more nuanced estimated treatment effects across measurement of the pesticide use decision. Additionally, among the drivers of pesticide use considered, we find GMO seed adoption appears to impact the pesticide use decision in soybeans and cotton but with different statistically significant effects using alternative measures of pesticide use.

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 induce a sign-flip for most major crops, and this effect particularly stands out in corn, soybeans, and sorghum. One implication stemming from this could be that future policy should consider the timing of pesticide applications relative to the crop insurance decision since the way in which this is modeled can result in a sign-flip of the treatment effect. Additionally, findings are sensitive to the measure of the pesticide use variable under the models we consider, but the sensitivity is not as pronounced with alternative measures of crop insurance participation with only small changes in the magnitude of the treatment effect. This implies the need for clear policy objectives which target the underlying quality characteristics of pesticides rather than only the raw quantities themselves as policies this general could result in negative externalities in the production of crops whose pesticides were not the intended target.

The heterogeneity in moral hazard effects could be largely driven by the differences among management practices and pest pressures across crops and regions. For example, cotton has primarily faced an insect pest problem driven by the boll weevil, which in the 1970s initiated a movement across the southeastern states to collectively eradicate the boll weevil population (Fernandez-Cornejo et al., 2014). Conversely, corn producers have tended to use pesticides less intensely than cotton producers given the relatively smaller pest threat attributed to insects. Further, corn and soybean producers were more quick to adopt HT which induced variation in usage in the early 2000s ultimately resulting in more herbicide applications.

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. While we attempt to control for confounding factors across time for all units by constructing measures for GMO seed adoption, weather, and price levels, we recognize data availability for some of these variables is usually highly aggregated as well. 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).

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.

Chapter 2 - Hurricane Incidence Results in Significant Increases in Crop Damages: Evidence from the Mississippi Delta

2.1 Introduction

Every year crop producers cope with many risks. While exposure to some risks is more universal, such as price volatility and global trade policies, exposure to others may be felt differently across regions, like extreme weather such as hurricanes (Hardaker, Lien, and Anderson, 2015). Hurricanes and tropical storms occur in the U.S. every year with multiple different hurricanes occasionally striking the same area (NOAA National Hurricane Center, 2022). In 2021 alone, hurricanes caused $145 billion in total damages to commercial and personal property making it the third most costly hurricane season on record and the seventh straight year in which 10 or more one-billion-dollar events occurred (NOAA Office for Coastal Management, 2022). Further, the association of increasing sea surface temperatures and hurricane incidence in the Atlantic Ocean basin has been well documented implying these catastrophic events are likely to increase in frequency and magnitude in the coming years due to climate change (Webster, et al., 2005; Trenberth, 2005; Emanuel, 2005).

An increased risk of hurricanes presents a potential threat to agricultural production systems in areas prone to this risk leading crop producers to adopt various risk management tools such as crop insurance which requires a producer to pay a subsidized premium. Crop insurance premium rates, the price of insurance per dollar of liability, are an indicator of riskiness in agricultural production and may impact participation in crop insurance across regions (Biram, et al., 2022). Heterogeneity in farm-level characteristics such as soil types, and region-specific risks including local climate and catastrophic weather events, may lead to differences in crop insurance premium rates across regions (Chen and Chang, 2005; Miller, Tack, and Bergtold, 2020; Tsiboe and Tack, 2021). Although it is popular to purchase crop insurance to mitigate losses resulting from hurricanes, there exists the potential for premium rate increases driven by more frequent hurricane incidence raising the costs to utilize the very tool providing risk protection. However, little attention has been given to measuring the regional riskiness driven by hurricane events and the implications for crop insurance premium rates (Chen and Chang, 2005).

This work aims to measure the impact of hurricane incidence on on-farm damages for crops grown in the Mississippi Delta region (i.e., Arkansas, Louisiana, and Mississippi), an area which has experienced 18 hurricanes and tropical storms in the past ten years. Previous works relevant to this question fall into two veins of literature which include the implications of climate change on increased tropical storm incidence and the impact of this incidence on crop yield variability. Prior research has measured the impacts of climate change on hurricane frequency and intensity through changes in maximum wind speeds and simulating storm tracks (Boose et al, 2004; Emanuel et al., 2005). Boose et al. (2004) estimate maximum sustained wind speeds and reconstruct hurricane storm tracks to model hurricane damages as a function of wind speeds. Emanuel et al. (2005) produce synthetic hurricane tracks to assess hurricane risk and damages using a power dissipation index based on a maximum wind speed. In regard to tropical storm incidence in the area we study, Jagger and Elsner (2006) show hurricanes with the greatest wind speeds are experienced in the Gulf of Mexico with category 4 and 5 hurricanes estimated to have strike at least once every 10 years.

Other relevant research considers the impacts of climate change and extreme weather on mean yields and yield variability. In general, warmer temperatures tend to be associated with decreased yields in corn, cotton, and soybeans (Schlenker and Roberts, 2009) and rice (Peng et al., 2004). It is also well-documented that climate change is associated with impacts to more than mean yields with increases also to yield variability (McCarl et al., 2008; Tack et al., 2012) and reductions in producer welfare (Chen and McCarl, 2009; Strobl, 2012; Fuss et al., 2015). A few works have considered the impacts of tropical storms on rice production in the Pacific Ocean basin and find rice production to be most susceptible to damages in the heading stage (Masutomi et al., 2012; Blanc and Strobl, 2016). To our knowledge, there is only one other paper which specifically explores the implications of increased hurricane incidence to crop insurance premia (Chen and Chang, 2005). Chen and Chang (2005) estimate a crop yield response function and show increases in air temperature and levels of precipitation have raised yield variability and have lowered yields of rice, corn, and adzuki beans grown in Taiwan and suggest weather index insurance, or even an extreme weather loading factor, has a role to play and could stabilize farm incomes.

We add to the growing literature on the impacts of climate change on yield variability by being the first to quantify the impact of hurricanes on on-farm damages in the Mississippi Delta. We do this by using a novel monthly data set on crop losses attributed to specific causes of loss which includes losses attributed to hurricane incidence. We leverage county-level panel data spanning 2002-2021 from the USDA-RMA Summary of Business and Cause of Loss, and daily data from the NOAA National Hurricane Center using a measure for hurricane treatment assignment under a Difference-in-Differences (DiD) identification strategy. We find on-farm damages conditional on a hurricane happening to result in up to 20 percentage points in loss-cost ratios (LCR) for yield and revenue insurances across all crops predominantly grown in the region. We also find that the components of a hurricane, wind and rain, give different magnitudes of effects with wind effects resulting in the most damages caused for rice, corn, and cotton and rain effects impacting soybeans the most.

The remainder of the paper is organized as follows. The next section describes the sources of data used to construct hurricane wind field measures and the measure we use to represent crop insurance rates by specific causes of loss associated with hurricane incidence. We motivate identification of hurricane treatment effects on crop damages using DiD, discuss the assumptions necessary to conduct valid inference, and present a regression specification using a two-way fixed effects (TWFE) estimator. The fourth section highlights main findings from hurricane event-specific regressions. The last section concludes and provides implications of the estimated treatment effects of hurricane incidence on premium rates.

2.2 Data and Variable Construction

We use data spanning 2002-2021 on county-level indemnities and liabilities from RMA to construct crop insurance loss-cost ratios (LCR) and use daily historical hurricane tracker data from NOAA spanning the same period to construct a measure to assign hurricane treatment. We use the RMA Summary of Business (SOB) to obtain data on liabilities which will provide the information needed to form the sample by which we assign hurricane treatment. Data on cause specific indemnities from the RMA Cause of Loss (COL) are used to construct cause specific LCRs which is the ratio of indemnities to liabilities. NOAA's HURDAT-2 and Wind Field Advisory hurricane tracker data provide variables which contain the latitudes and longitudes of hurricane centroids on the path of a hurricane every six-hours. These data sets also include information on the length of wind field radii of maximum one-minute sustained wind speeds of 34-knots per hour for a given wind field quadrant (i.e., NE, SE, SW, or NW), which is used in the construction of the hurricane treatment measure.

We form our sample of hurricane treatment assignment variables by first considering only hurricanes and tropical storms which made landfall in Louisiana or Mississippi across years in which wind field data are available. We further filter our sample based on if a hurricane had at least one recorded six-hour time stamp in Louisiana or Mississippi in order to guarantee we have at least one hurricane centroid to construct a wind field treatment measure. For a list of hurricanes by name and year included in the sample, see Table 2.1. Using liabilities from the SOB, we form the sample from which we construct LCRs by only preserving counties for which there is liability recorded in a given year. From here, we combine[13] the SOB and COL data to form cause[14] specific LCRs at the county and month level by summing together indemnities across listed causes of loss that are associated with hurricane incidence.

2.2.1 Hurricane Wind Field Treatment Assignment

We construct a polygon wind field measure to assign county-level hurricane treatment using the wind field radii variables from the HURDAT-2 data. First, we calculate latitudes and longitudes for the corners of each quadrant of the wind field polygon by using the six-hour time stamps of latitudes and longitudes of the hurricane centroids and the rules of a right triangle whose legs are the same length. The longitude of each corner point in a quadrant is found by:

$$LON_{tsq}^{j} = LON_{t}^{j} + \frac{R_{tsq}^{j}}{\sqrt{2}}\left(\frac{1}{111.32*\cos\left(LAT_{t}^{j}*\frac{\pi}{180}\right)}\right) \tag{1}$$

where LON_{tsq}^{j} is the longitude of a wind field corner point of hurricane event j at six-hour time stamp t and wind speed s for wind field quadrant q, where $q\epsilon[NE, SE, SW, NW]$. R_{tsq}^{j} is the

[13]Importantly, if a county did not report a cause of loss associated with hurricane incidence, we would record the associated LCR as a zero rather than drop the observation since this may provide information which is needed for a counterfactual in our treatment effect estimation.
[14]For this work we consider wind, excess precipitation, flood, and hurricane/tropical depression causes of loss to construct cause specific LCRs. For a full list of the covered causes of loss see the RMA Loss Adjustment Manual (USDA-RMA, 2006).

length of a wind field radius in kilometers, and LON_t^j and LAT_t^j is the longitude and latitude of the hurricane centroid.

The second term gives us the degrees longitude, moving west or east, that is required to arrive at the corner point of a given wind field quadrant. The fraction $\frac{R_{tsq}^j}{\sqrt{2}}$ gives us the distance between the hurricane centroid and the new point of longitude, while the term in parentheses converts the distance to degrees longitude. The latitude of a corner point of a wind field quadrant can similarly be calculated as:

$$LAT_{tsq}^j = LAT_t^j + \frac{R_{tsq}^j}{\sqrt{2}}\left(\frac{1}{111.32}\right) \quad (2)$$

2.2.2 Rainfall Field Treatment Assignment

Since some hurricanes induce more damages from rainfall, some treatment effect estimations could be downward biased for a hurricane with heavy rain and little to no wind. We address this potential bias by creating a rainfall field treatment measure which is done using the wind field measure and the observed time stamps for hurricane centroids beyond the locations where wind speeds are recorded. We assume rainfall to be cast out as far as the wind field polygon with the largest area from the hurricane centroid and interpolate its path using the hurricane centroids which do not record any wind speeds of 34-knots per hour or greater. An example of the different types of hurricane effects considered can be seen in Figure 2.1.

Table 2.1. Hurricanes Which Made Landfall (2002-2021)

Year	Month	Name	Category
2002	August	Bertha	TS
2002	September	Isidore	2
2002	October	Lili*	3
2003	July	Bill	TS
2004	October	Matthew	TS
2005	July	Cindy	TS
2005	July	Dennis	4
2005	August	Katrina*	4
2005	September	Rita*	4
2007	September	Humberto*	1
2008	September	Gustav*	4
2008	September	Ike*	3
2010	August	Five	0
2011	September	Lee	TS
2012	August	Isaac*	1
2015	June	Bill	TS
2017	June	Cindy	TS
2017	August	Harvey	3
2017	September	Irma	4
2017	October	Nate	1
2018	September	Gordon	TS
2019	July	Barry*	1
2019	October	Olga	TS
2020	September	Beta	TS
2020	June	Cristobal	TS
2020	October	Delta*	3
2020	August	Laura*	4
2020	October	Zeta	2
2021	August	Ida	4
2021	June	Claudette	TS

*Indicates hurricane is in the sample used to estimate treatment effects

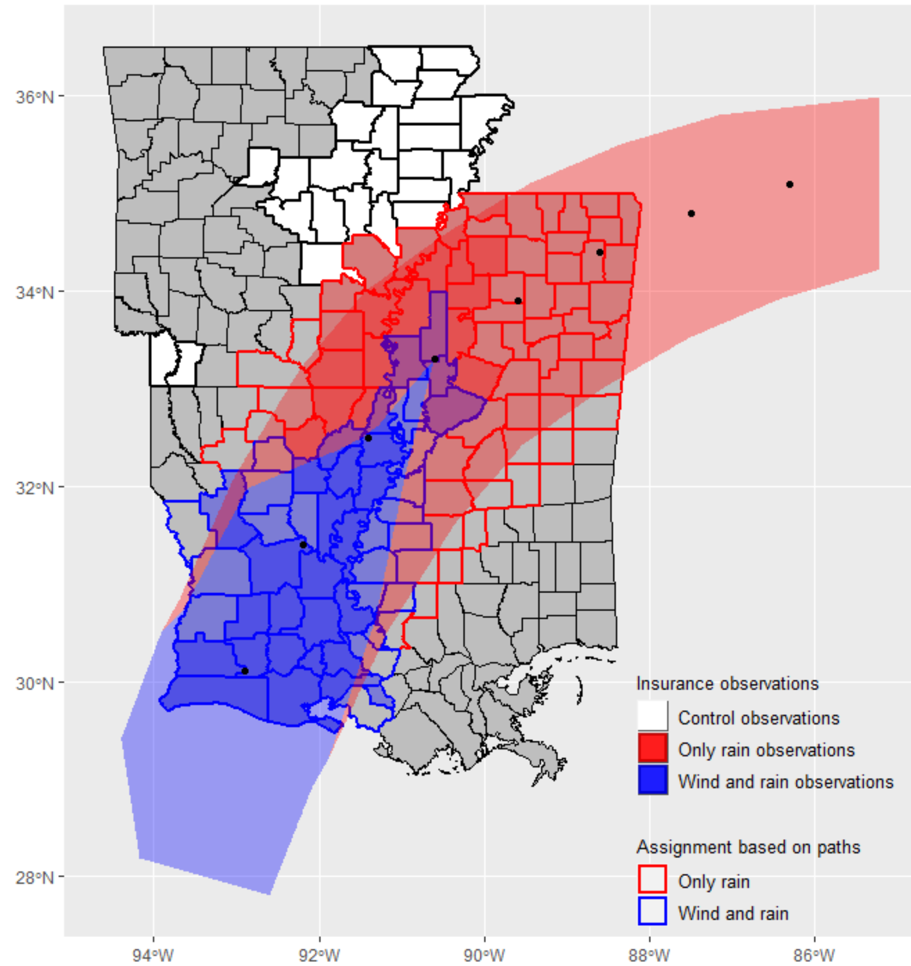

Figure 2.1 County-level treatment assignment based on wind and rain paths (Hurricane Delta, October 2020) The figure above gives a visual summary of the final polygons used to assign hurricane treatment effects. The counties which are in the sample but are untreated are given by the white fill color and bold borders. The counties which are in the sample for insurance data and are treated by wind and rain are given by the blue fill, while the counties which are only treated by rain are given by the red fill. Counties which have grey fill are outside the sample for which there is insurance data available.

2.2.3 Lost Cost Ratio Construction and Premium Rates

In order to evaluate the impact of hurricanes on on-farm damages we use insurance data and follow previous studies that follow the actuarial principal that the mean of the county-level LCR is the equivalent of an actuarially fair premium rate (Woodard, Sherrick, and Schnitkey, 2011; Rejesus, et al., 2015; Woodard and Verteramon-Chiu, 2017). Thus, when we run regressions with LCRs as the outcome variable we are estimating the impact of hurricanes on losses as a percentage of purchased liability. Using the data on losses associated with hurricane incidence in a given month, one can identify the impact of hurricanes on damages by measuring the impact of specific hurricanes on the portion of the LCR attributed to hurricane losses. This approach allows us to identify the potential impact of a specific catastrophic risk event on a premium rate and draw implications from our damage estimation.

We consider three different LCR measures which incorporate additional losses. First, we consider a hurricane-only cause LCR which consists of a sum of indemnities with the hurricane/tropical depression cause of loss code. Second, we consider an LCR which contains indemnities across hurricane/tropical depression and wind causes of loss. Third, we consider an LCR summed across hurricane/tropical depression, wind, excess moisture, and flood causes of loss. In order to isolate losses that are only associated with a hurricane event, we sum indemnities across all losses in the months prior to the month in which a hurricane struck to create the cumulative LCR in the pre-period. The cause-specific LCR is formed in the post-treatment period by summing the indemnities by causes of loss for the specific LCR measure we consider. Additionally, we consider the losses for a particular LCR measure in the month immediately following a month in which a hurricane event occurred to capture any claims which may have been filed late and consider this the treatment period (Joe Deeter, personal communication, 2022). For example, we would write the pre- and post-period hurricane cause specific LCRs for a hurricane in October as:

$$LCR_{i,PRE} = \sum_{C \in \{1,2,3\}} \sum_{m=3}^{9} LCR_m^C \tag{4}$$

$$LCR_{i,POST}^{1} = LCR_{PRE} + LCR_{10}^{1} + LCR_{11}^{1} \quad (5)$$

where *C* is the cause associated with an indemnity in the COL data, the values 1, 2, and 3 represent indemnities for hurricane/tropical depression and wind losses, excess moisture and flood losses, and all other losses, respectively, and *m* is the month in which the losses were recorded. LCR_{10}^{1} and LCR_{11}^{1} is the LCR summed across hurricane/tropical depression losses recorded in October and November, respectively. Lastly, we pair hurricane-associated causes of loss in a given month with the hurricane which made landfall in the same month to arrive at a final panel dataset which gives county-level LCRs by treatment period and estimate event-specific regressions (i.e., one for each hurricane event listed in Table 2.1 and denoted as being in the sample).

2.3 Identification Strategy

We use a Difference-in-Differences (DiD) identification strategy to isolate the treatment effects of hurricanes on on-farm damages. We allow for heterogeneous treatment effects across hurricanes and specify a hurricane-specific regression equation as:

$$LCR_{ip}^{C} = \gamma_p + \sigma_i + \beta W_{ip} + \varepsilon_{ip} \quad (6)$$

where LCR_{ip}^{C} is a cause-specific cumulative LCR for $C\epsilon[Hurricane/Wind, Rain, Both]$, county i, and period p. γ_p is a period fixed-effect equal to one in the treatment period of a hurricane event, W_{ip} is an indicator variable equal to one when an insured county is assigned hurricane treatment in the treatment period of a hurricane event, and σ_i is a county fixed-effect which controls for confounding factors which influence losses associated with a hurricane as well as the likelihood of being treated such as proximity to the coast and regional differences in climate.

Under DiD, two critical assumptions one must make in order to identify an average treatment effect on the treated (ATT) is the no anticipation effect and common trends (Wooldridge, 2021). The no anticipation assumption in this context implies producers do not alter their behavior in such a way as to increase their losses in anticipation of hurricane occurrence. The common trends assumption implies that losses would evolve the same throughout the growing season for treated and control counties in the absence of experiencing a hurricane.

Further, we recognize due to the difficulty in assigning consistent treatment, some hurricanes will either treat most all counties or very few. Thus, we provide another rule for preserving which hurricane events and crops will remain in the sample. That is, we drop all events for which wind field and rainfall field treatment is greater than 90 or less than 10 percent of the sample counties and estimate the treatment effect using equation (6) above. We provide a list of hurricanes included in the sample by crop and the percentage of treated and control observations in Tables B.1 – B.12 in Appendix B Section 1. We also recognize the possibility that years in which multiple hurricanes occur may result in a failure of the parallel trends assumption since the treatment and control groups are not the same for every hurricane event.

2.4 Results

This section gives results for event-specific regressions of hurricanes on three different LCRs and two different treatment measures. We first give an example of regression results for one hurricane, highlight differences between models, and provide an interpretation of the estimated ATTs (Table 2.2). We consider four different models across different combinations of LCRs and hurricane treatment effect measures which allows us to learn the effects of changing the hurricane damage measure or the hurricane treatment measure. We then present results for estimated treatment effects across all hurricanes in the sample.

2.4.1 Hurricanes Gustav and Ike: Effects of Hurricane Components

Gustav and Ike provide an example of what we can learn by modifying the hurricane damage and treatment measures and provide the unique case where two hurricane events occur in the same month and year. In this case, we hold the LCR measure constant across hurricane events since they occur in the same month and modify the hurricane treatment measure by allowing for the same treated counties across both hurricanes. Models (1) – (3) hold hurricane treatment constant using the wind field treatment assignment measure, and Model (4) includes the rainfall field measure of treatment. Model (1) contains an LCR which only includes losses with the hurricane/tropical depression cause of loss. Model (2) builds on Model (1) by adding in wind losses. Model (3) builds on Model (2) by adding in excess moisture and flood losses to give us an LCR measure which contains losses associated with both wind and rain produced by a hurricane. Regression results for hurricanes Gustav and Ike across all models and crops can be found in Table 2. Results for each hurricane event by crop can be found in Appendix B Section 2.

Columns (1) – (3) give the progression of including more losses in the LCR measure while holding the treatment assignment constant with treatment effects expected to increase with the inclusion of more losses. Adding wind and hurricane recorded losses in the LCR (Column 2) does not appear to change the treatment effect relative to the hurricane only LCR (Column 1) indicating that hurricane recorded losses in the wind field were mostly associated with wind. The model accounting for both the wind and rain weather effects of a hurricane provides the most robust parameter estimates with ATTs range between 1 percentage point for rice and 26 percentage points for cotton. More specifically, we interpret the ATT of a county being in the hurricane wind field for rice as experiencing damages which is four percentage points higher relative to a county which is not in the wind field and 1 percentage point higher for a county in the rainfall field.

Adding in losses associated with rain and holding wind field treatment constant (Column 3) tends to result in larger treatment effects for cotton and only marginally smaller for rice, corn, and soybeans. We would expect treatment effects to only increase assuming we have correct treatment assignment, so the decrease in ATTs may point to failure of the parallel trends assumption where rainfall-related losses in the counterfactual counties increased by more than the treated counties. However, when we add controls for wind and rain effects and hold the LCR measure constant (Column 4), we see more variation in losses attributed to being in the wind field compared to only measuring treatment from the wind field (Column 3) with increases in ATTs across all crops. We can also gain insight as to which weather effect drives losses by crop with rice, corn, and cotton experiencing most losses from wind and soybeans from rainfall.

2.4.2 Impacts Across All Hurricane Events

Having provided an example ATT estimation, we now provide main findings across all hurricane events. Findings for ATTs of hurricanes on on-farm damages across all plans of insurance are shown in the histograms of Figure 2.2, while results for yield and revenue insurance products are reported separately in Figures 2.3 and 2.4, respectively. We chose to report results in the form of histograms to best show the average effect of hurricane incidence while preserving the variability in hurricane treatment across hurricanes. We find that hurricanes on the average may cause on-farm damages across the Mississippi Delta to increase by up to more than 20 percentage points and that treatment effects are heterogeneous across hurricanes with most hurricanes causing increases in damages of about 2 percentage points. We also find treatment effects to be heterogeneous across crops with cotton facing the greatest impact from hurricanes. Treatment effects also vary across yield and revenue insurance products with revenue insurance products facing the greatest losses resulting from hurricane incidence.

Table 2.2. Estimated Treatment Effects of Hurricanes Gustav and Ike on On-Farm Damages (September 2008)

	(1)	(2)	(3)	(4)	
Treatment Measure	(Wind)	(Wind)	(Wind)	(Wind)	(Rainfall)
Rice	0.0363*	0.0361*	0.0348*	0.0429**	0.0100
	(0.0199)	(0.0199)	(0.0210)	(0.0204)	(0.0095)
Corn	0.0135	0.0135	0.0121	0.0263	0.0246*
	(0.0177)	(0.0177)	(0.0194)	(0.0179)	(0.0139)
Soybeans	0.0277***	0.0280***	0.0260**	0.0330***	0.0132
	(0.0103)	(0.0102)	(0.0105)	(0.0109)	(0.0090)
Cotton	0.2122***	0.2122***	0.2491***	0.2588***	0.0169
	(0.0497)	(0.0497)	(0.0601)	(0.0632)	(0.0300)

*,**,*** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county level.

The different approaches to measurement provide interesting patterns in the distribution of ATTs across hurricanes. Not only does including more losses tend to increase the treatment effects but this also allows for analysis of more hurricanes since there may be crop insurance adjusters in counties further north who are uncomfortable reporting a hurricane cause of loss. Perhaps a hurricane system became weaker and became a tropical storm by the time the system made it to their counties. Soybeans provide a nice example of this with the distribution of ATTs remaining constant across Models (1) and (2) but with a greater number of hurricanes. We see a similar pattern across the rice, corn, and cotton ATTs. Additionally, the symmetry of the distribution of treatment effects for rice tends to become more left skewed with the inclusion of more losses and the addition of a rainfall field treatment measure which points to the possible bias inherent in the estimated ATTs which do not account for rainfall treatment.

2.4.3 Heterogeneous Effects Across Crops

On the average, soybeans and cotton appear to consistently experience the greatest effects of hurricane incidence with cotton experiencing between 5 and 20 percentage point increase in on-farm damages and soybeans experiencing ATTs between 1 and 5 percentage points. Corn and rice follow with estimated ATTs of up to 5 and 4 percentage points, respectively. While ATTs across crops and models tend to have values around zero, we note that there are hurricane events with outlier ATTs for corn and cotton which result in an increase in the impact across time. For example, while most estimated damage impacts for cotton tend to zero under Model (4), there are a few hurricanes with ATTs falling between 5 and 20 percentage points which provides implications for the impacts of more destructive low probability hurricane events. Lastly, we note the negative ATTs as being a product of the failure of the parallel trends assumption conditional on county fixed effects where losses increased more for counterfactual counties compared to the treatment counties. Most of these effects are statistically insignificant with standard errors clustered at the county level and results can be found in Appendix B Section 2.

2.4.4 Impacts on Yield and Revenue Products

While results using an LCR measure which aggregates across all plans of insurance allows us to learn about the overall effects of hurricanes by crop, we now consider the impacts by yield and revenue products[15] separately to consider heterogeneous impacts across products.

[15] The yield products we consider are Actual Production History (APH) and Yield Protection (YP), and the revenue products we consider are Crop Revenue Coverage (CRC), Revenue Assurance (RA), Revenue Protection (RP), and Revenue Protection with Harvest Price Exclusion (RP-HPE).

While these findings will generally be driven by enrollment where products with more enrollment tending to experience greater treatment effects, a breakdown by product will allow us to gain insight which may provide implications for premium rating by product. Overall, ATTs appear to be largely the same across yield and revenue plans of insurance in Models (1) – (3) with large differences in treatment effects appearing in Model (4). ATTs under Models (1) – (3) for rice, corn, and soybeans tend to be between zero and 6 percentage points across both yield and revenue insurance. Under Model (4) we see differences in ATTs emerge across crops and insurance plans with rice, corn, and soybeans under revenue products experiencing greater ATTs than their yield counterparts, and cotton experiencing greater ATTs under the yield plans of insurance. We note the same pattern of adding losses to increase the hurricane sample size holds by considering the distribution of ATTs across Models (1) and (2) for both yield and revenue products. Additionally, much like in the aggregated case, we see a progressive shift in left skewness in the distribution of ATTs for rice and soybeans under yield products while the shift is most pronounced for cotton insured under revenue products lending to the possible bias produced by not including rainfall treatment.

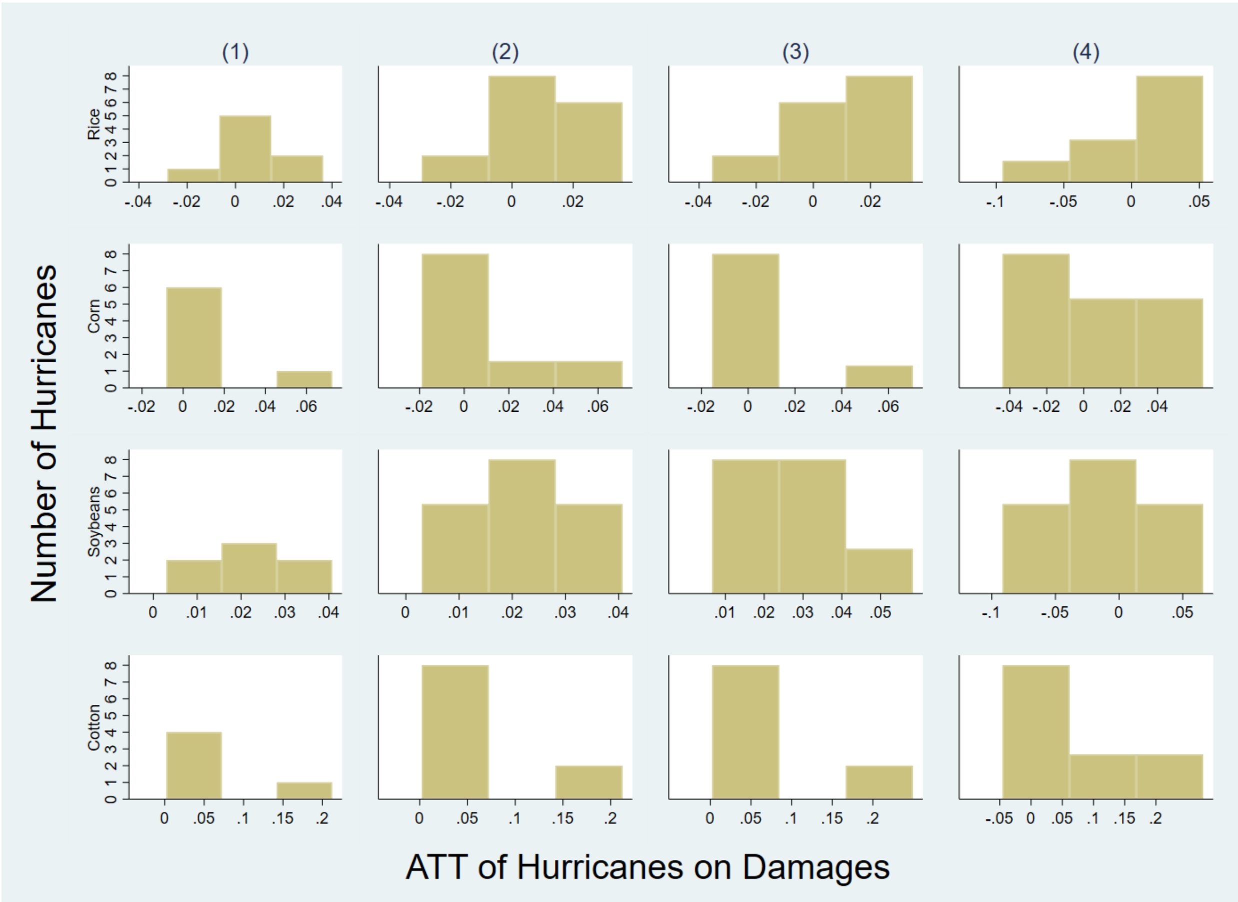

Figure 2.2 Histograms of Treatment Effects Across All Insurance Products Results for estimated treatment effects using equation (4) across hurricanes from the 2002-2021 are reported above in the form of histograms. This allows us to capture the overall effects of hurricanes and their components, while preserving the heterogeneous treatment effects of the hurricanes in our sample. We report results for rice, corn, soybeans, and cotton and a breakdown of treatment effects by the four models outlined in the results section above.

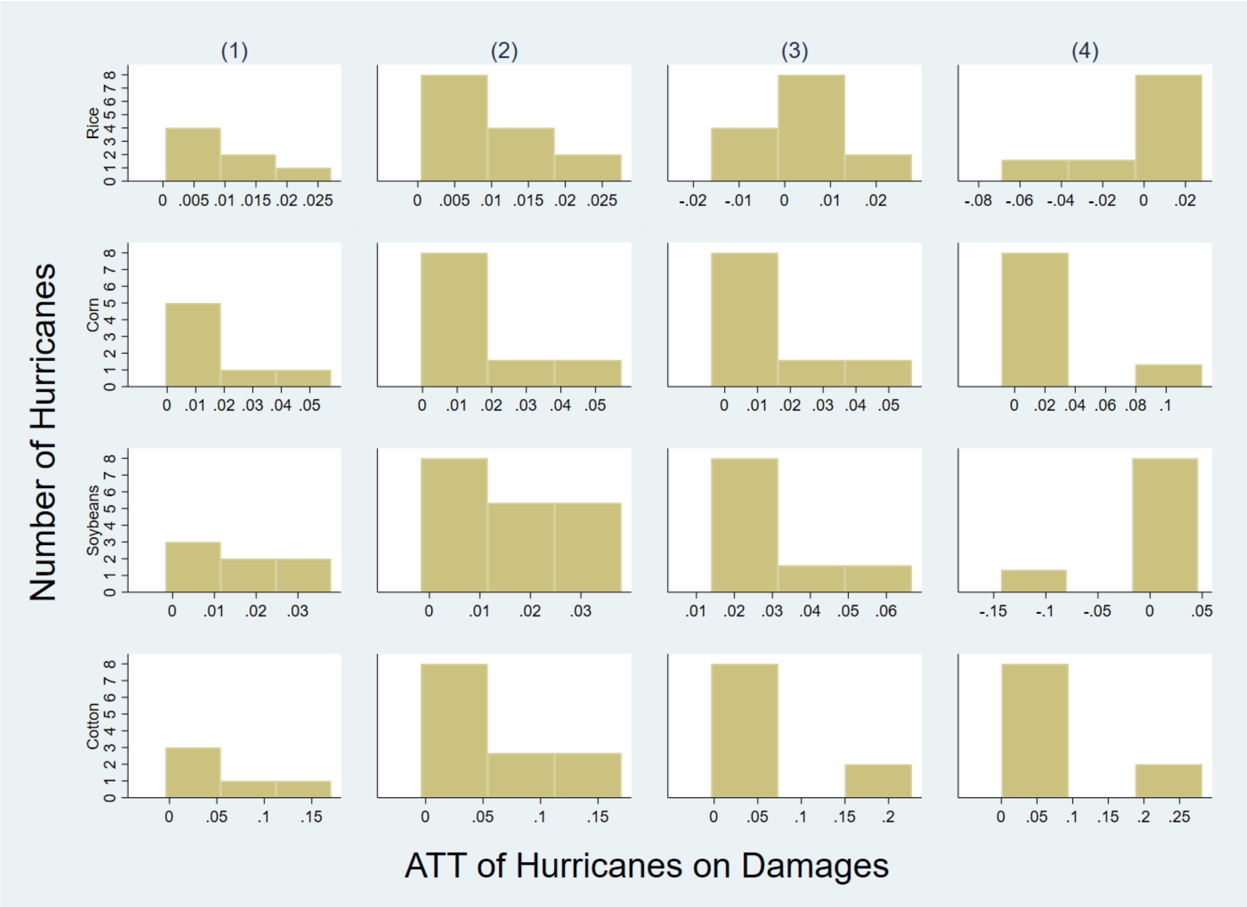

Figure 2.3 Histograms of Treatment Effects Across Yield Insurance Products Results for estimated treatment effects using equation (4) across indemnities triggered by individual plans of yield insurance (i.e., Yield Protection and Actual Production History) are given in the histograms above. This allows us to capture the overall effects of hurricanes and their components, while preserving the heterogeneous treatment effects of the hurricanes in our sample. We report results for rice, corn, soybeans, and cotton and a breakdown of treatment effects by the four models outlined in the results section above.

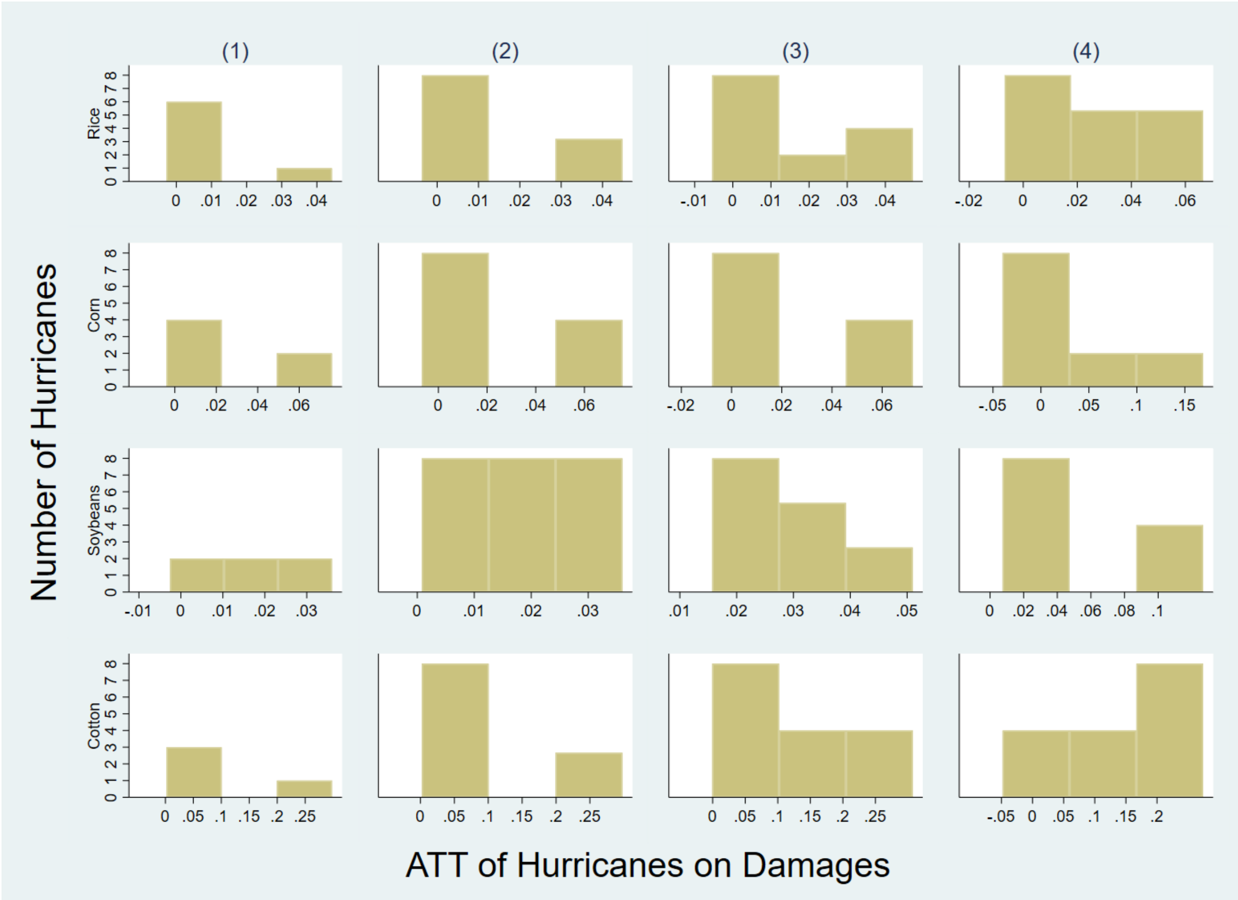

Figure 2.4 Histograms of Treatment Effects Across Revenue Insurance Products Results for estimated treatment effects using equation (4) across indemnities triggered by individual plans of revenue insurance (i.e., Revenue Protection, Revenue Protection with Harvest Price Exclusion, Crop Revenue Coverage, and Revenue Assurance) are given in the histograms above. This allows us to capture the overall effects of hurricanes and their components, while preserving the heterogeneous treatment effects of the hurricanes in our sample. We report results for rice, corn, soybeans, and cotton and a breakdown of treatment effects by the four models outlined in the results section above.

2.5 Conclusion

We have estimated the impact of hurricane and tropical storm incidence on damages for 21 tropical cyclones which made landfall in the Mississippi Delta in the last twenty years. We leverage county-level panel data on indemnities and liabilities by cause of loss in a given month spanning 2002-2021 from RMA and daily hurricane best track data from NOAA to construct a measure representative of crop insurance premium rates and a measure for hurricane treatment assignment. Under a Difference-in-Differences identification strategy, we find that hurricanes result in increases to crop insurance damages for yield and revenue insurances across all crops grown in the region. We consider the weather produced by a hurricane, high speed winds and excess rainfall, and find wind and rain give different magnitudes of effects with wind resulting in the most damages caused. The effects of being in a hurricane wind field tend to have the greatest impact on cotton and corn with estimated average increases in on-farm damages of 2 to 15 percentage points in indemnities as a percentage of liability.

Our findings align with previous studies which find increases in mean yields and yield variability caused by more frequent catastrophic weather events result in a fall in producer welfare and have implications for crop insurance premium rates. Since premium rates are based on a 10-year farm-level actual production history (APH), the increasing frequency of hurricanes and other catastrophic weather events will most likely lower the means of APH yield histories leading to increased premium rates. RMA has begun to address this increased risk with the introduction of the Hurricane Insurance Protection – Wind Index (HIP-WI) but introducing a new program may only create more confusion in the already complicated suite of plans available. For example, Stacked Income Protection (STAX) designed for cotton has high subsidy rates at 80% across all coverage levels yet few producers enroll in it. Rather than introducing new products, it may be worthwhile to consider including a separate catastrophic weather loading factor in the base premium rate calculation for the most popular plans of insurance available (i.e., Yield Protection and Revenue Protection).

One limitation of this work is primarily concerned with measurement of hurricane treatment. One way we could improve the treatment assignment measure would be to include wind speed and consider the climatology of hurricanes, and we currently ignore variables which comprise a hurricane wind profile such as wind pressure and vertical shear which drive the intensity and direction of a hurricane. This analysis could also be built upon by including empirical state catastrophic loading factors to allow for comparison with the hurricane impacts we consider here. It is possible the hurricane effects we measure here may be included in a state catastrophic loading factor, but since there is specified range for the loading factor as it stands, future work should consider the magnitude by which the estimated effects here compare to that of state loading factors. Since the state catastrophic loading factor is split evenly across counties within a state, there may be scope to use this model to identify counties which have more or less incidence uncovering crop insurance pricing differentials. With an ever-changing climate, measuring the impact of hurricanes and other extreme weather events, on agricultural production is of the utmost importance.

References

References for Crop Insurance Participation has Heterogeneous Impacts on Pesticide Usage

An act to amend the Federal Insecticide, Fungicide, and Rodenticide Act and the Federal Food, Drug, and Cosmetic Act, and for other purposes. Pub. L. No. 104-170, 142 (1996). https://www.govinfo.gov/app/details/PLAW-104publ170

Angrist, J. D., & Pischke, J. S. (2008). Mostly harmless econometrics. In *Mostly Harmless Econometrics*. Princeton university press.

Babcock, B. A., & Hennessy, D. A. (1996). Input demand under yield and revenue insurance. *American journal of agricultural economics*, *78*(2), 416-427.

Bartik, T. J. (1991). *Who benefits from state and local economic development policies? Kalamazoo, MI: WE Upjohn Institute for Employment Research*.

Baum, Christopher & Schaffer, Mark & Stillman, Steven. (2010). ivreg2: stata module for extended instrumental variables/2SLS, GMM and AC/HAC, LIML and k-class regression. Stata Package.

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates?. *The Quarterly journal of economics*, *119*(1), 249-275.

Blanchard, O. J., Katz, L. F., Hall, R. E., & Eichengreen, B. (1992). Regional evolutions. *Brookings papers on economic activity*, *1992*(1), 1-75.

Bloomberg L.P. (2022) Retrieved March 9, 2022 from Bloomberg terminal.

Borusyak, K., Hull, P., & Jaravel, X. (2022). Quasi-experimental shift-share research designs. *The Review of Economic Studies*, *89*(1), 181-213.

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: methods and applications*. Cambridge university press.

Coble, K. H., Knight, T. O., Pope, R. D., & Williams, J. R. (1997). An expected-indemnity approach to the measurement of moral hazard in crop insurance. *American journal of agricultural economics*, *79*(1), 216-226.

Connor, L., & Katchova, A. L. (2020). Crop insurance participation rates and asymmetric effects on US corn and soybean yield risk. *Journal of Agricultural and Resource Economics*, *45*(1), 1-19.

Cunningham, S. (2021). Causal inference. In *Causal Inference*. Yale University Press.

DeLay, N. (2019). The impact of federal crop insurance on the conservation reserve program. *Agricultural and Resource Economics Review*, *48*(2), 297-327.

Feng, S., Han, Y., & Qiu, H. (2021). Does crop insurance reduce pesticide usage? Evidence from China. *China Economic Review*, *69*, 101679.

Fernandez-Cornejo, J., & Jans, S. (1995). Quality-adjusted price and quantity indices for pesticides. *American Journal of Agricultural Economics*, *77*(3), 645-659.
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).

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, *110*(8), 2586-2624.

Goodwin, B. K., Vandeveer, M. L., & Deal, J. L. (2004). An empirical analysis of acreage effects of participation in the federal crop insurance program. *American Journal of Agricultural Economics*, *86*(4), 1058-1077.

Horowitz, J. K., & Lichtenberg, E. (1993). Insurance, moral hazard, and chemical use in agriculture. *American journal of agricultural economics*, *75*(4), 926-935.

Horowitz, J. K., & Lichtenberg, E. (1994). Risk‐reducing and risk‐increasing effects of pesticides. *Journal of Agricultural Economics*, *45*(1), 82-89.

Lichtenberg, E., & Zilberman, D. (1986). The econometrics of damage control: why specification matters. *American Journal of Agricultural Economics*, *68*(2), 261-273.

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. *Agric. Product. Prod. Behav*.

Möhring, N., Dalhaus, T., Enjolras, G., & Finger, R. (2020a). Crop insurance and pesticide use in European agriculture. *Agricultural Systems*, *184*, 102902.

Möhring, N., Bozzola, M., Hirsch, S., & Finger, R. (2020b). Are pesticides risk decreasing? The relevance of pesticide indicator choice in empirical analysis. *Agricultural Economics*, *51*(3), 429-444.

O'Donoghue, E. J., Roberts, M. J., & Key, N. (2009). Did the federal crop insurance reform act alter farm enterprise diversification?. *Journal of Agricultural Economics*, *60*(1), 80-104.

Roberts, M. J., Key, N., & O'Donoghue, E. (2006). Estimating the extent of moral hazard in crop insurance using administrative data. *Review of Agricultural Economics*, *28*(3), 381-390.

Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of educational Psychology*, *66*(5), 688.

Smith, V. H., & Goodwin, B. K. (1996). Crop insurance, moral hazard, and agricultural chemical use. *American Journal of Agricultural Economics*, *78*(2), 428-438.

USDA Risk Management Agency. (n.d.). *About the risk management agency Overview*. RMA. Retrieved May 9, 2022, from https://www.rma.usda.gov/About-RMA

Weber, J. G., Key, N., & O'Donoghue, E. (2016). Does federal crop insurance make environmental externalities from agriculture worse?. *Journal of the Association of Environmental and Resource Economists*, *3*(3), 707-742.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

Wu, J. (1999). Crop insurance, acreage decisions, and nonpoint-source pollution. *American Journal of Agricultural Economics*, *81*(2), 305-320.

Yu, J., Smith, A., & Sumner, D. A. (2018). Effects of crop insurance premium subsidies on crop acreage. *American Journal of Agricultural Economics*, *100*(1), 91-114.

References for Hurricane Incidence Results in Increases in Damages: Evidence from the Mississippi Delta

Biram, H., Coble, K., Harri, A., Park, E., & Tack, J. (2022). Mitigating Price and Yield Risk Using Revenue Protection and Agriculture Risk Coverage. *Journal of Agricultural and Applied Economics*, 1-15. doi:10.1017/aae.2022.8

Blanc, E., & Strobl, E. (2016). Assessing the impact of typhoons on rice production in the Philippines. *Journal of Applied Meteorology and Climatology*, *55*(4), 993-1007.

Boose, E. R. (2004). A method for reconstructing historical hurricanes. *Hurricanes and Typhoons: Past, Present, and Future*, *99*, 120.

Chen, C. C., & Chang, C. C. (2005). The impact of weather on crop yield distribution in Taiwan: some new evidence from panel data models and implications for crop insurance. *Agricultural economics*, *33*, 503-511.

Emanuel, K. (2005). Increasing destructiveness of tropical cyclones over the past 30 years. *Nature*, *436*(7051), 686-688.

Emanuel, K., Ravela, S., Vivant, E., & Risi, C. (2006). A statistical deterministic approach to hurricane risk assessment. *Bulletin of the American Meteorological Society*, *87*(3), 299-314.

Fuss, S., Havlík, P., Szolgayová, J., Schmid, E., Reuter, W. H., Khabarov, N., ... & Kraxner, F. (2015). Global food security & adaptation under crop yield volatility. *Technological Forecasting and Social Change*, *98*, 223-233.

Hardaker, J. B., Lien, G., Anderson, J. R., & Huirne, R. B. (2015). *Coping with risk in agriculture: Applied decision analysis*. Cabi.

Jagger, T. H., & Elsner, J. B. (2006). Climatology models for extreme hurricane winds near the United States. *Journal of Climate*, *19*(13), 3220-3236.

Masutomi, Y., Iizumi, T., Takahashi, K., & Yokozawa, M. (2012). Estimation of the damage area due to tropical cyclones using fragility curves for paddy rice in Japan. *Environmental Research Letters*, *7*(1), 014020.

McCarl, B. A., Villavicencio, X., & Wu, X. (2008). Climate change and future analysis: is stationarity dying?. *American Journal of Agricultural Economics*, *90*(5), 1241-1247.

Miller, N., Tack, J., & Bergtold, J. (2021). The impacts of warming temperatures on US Sorghum yields and the potential for adaptation. *American Journal of Agricultural Economics*, *103*(5), 1742-1758.

National Hurricane Center. National Hurricane Center. Retrieved May 9, 2022, from https://www.nhc.noaa.gov/

Office for Coastal Management. *Hurricane Costs*. NOAA Office for Coastal Management. Retrieved May 9, 2022, from https://coast.noaa.gov/states/fast-facts/hurricane-costs.html

Peng, S., Huang, J., Sheehy, J. E., Laza, R. C., Visperas, R. M., Zhong, X., ... & Cassman, K. G. (2004). Rice yields decline with higher night temperature from global warming. *Proceedings of the National Academy of Sciences*, *101*(27), 9971-9975.

Rejesus, R. M., Coble, K. H., Miller, M. F., Boyles, R., Goodwin, B. K., & Knight, T. O. (2015). Accounting for weather probabilities in crop insurance rating. *Journal of Agricultural and Resource Economics*, 306-324.

Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of sciences*, *106*(37), 15594-15598.

Strobl, E. (2012). The economic growth impact of natural disasters in developing countries: Evidence from hurricane strikes in the Central American and Caribbean regions. *Journal of Development economics*, *97*(1), 130-141.

Tack, J., Harri, A., & Coble, K. (2012). More than mean effects: Modeling the effect of climate on the higher order moments of crop yields. *American Journal of Agricultural Economics*, *94*(5), 1037-1054

Tsiboe, F., & Tack, J. (2022). Utilizing Topographic and Soil Features to Improve Rating for Farm-Level Insurance Products. *American Journal of Agricultural Economics*, *104*(1), 52-69.

Trenberth, K. (2005). Uncertainty in hurricanes and global warming. *Science*, *308*(5729), 1753-1754.

Webster, P. J., Holland, G. J., Curry, J. A., & Chang, H. R. (2005). Changes in tropical cyclone number, duration, and intensity in a warming environment. *Science*, *309*(5742), 1844-1846.

Wooldridge, J. (2021). Two-way fixed effects, the two-way mundlak regression, and difference-in-differences estimators. *Available at SSRN 3906345*.

Woodard, J. D., Sherrick, B. J., & Schnitkey, G. D. (2011). Actuarial impacts of loss cost ratio ratemaking in US crop insurance programs. *Journal of Agricultural and Resource Economics*, 211-228.

Woodard, J. D., & Verteramo-Chiu, L. J. (2017). Efficiency impacts of utilizing soil data in the pricing of the federal crop insurance program. *American Journal of Agricultural Economics*, *99*(3), 757-772.

Appendix A - Dissertation Appendix for Crop Insurance Participation has Heterogeneous Impacts on Pesticide Use

This appendix contains supplementary material that is referenced in the main text. It contains 2 sections: Section 1. Pesticide Growth Represented by Expenditure and Quantity Use Indexes and Section 2. Model Robustness to GMO Seed Adoption, Weather, and Prices.

Appendix A Section 1. Pesticide Growth Represented by Expenditure and Quantity Use Indexes

The purpose of this section is to briefly discuss the patterns of pesticide use growth across the six crops considered in the current study. This discussion is useful for interpreting the ATTs in the main text. We focus the discussion on growth rates between 1965 and 2019, which are calculated as the difference in natural logarithms for pesticide use in 2019 and use in 1965. Growth rates vary greatly across crops ranging from 13% for quality-unadjusted pesticide use per acre for cotton to 8341% for pesticide expenditures per acre for wheat.

Growth rates by crop are given in Table A.1, while plotted growth rates are given in Figure A.2. There are a few general patterns to note. First, pesticide use is increasing across time for all three measures. Second, expenditures per acre and quality-adjusted pesticide use seems to follow a similar pattern of variation. Third, quality-adjusted pesticide use is typically greater than quality-unadjusted pesticide use, which corresponds to the theory of indexes using hedonic pricing models to measure quality-adjustment (Fernandez-Cornejo and Jans, 1995). Fourth, expenditures per acre grow at a much greater magnitude than either quantity measure.

Table A.1 Growth Rates by Crop (1965-2019)

	Corn	Soybeans	Sorghum	Wheat	Cotton	Rice
Expenditures ($/ac)	2042.44%	5755.65%	916.34%	8341.16%	785.85%	5107.51%
Quality-Unadjusted Quantity (lbs/ac)	339.38%	1853.96%	314.22%	254.21%	12.96%	483.07%
Quality-Adjusted Quantity (lbs/ac)	1173.33%	4598.82%	671.72%	1168.10%	287.14%	2109.10%

Note: Growth rates were calculated by taking the log-difference of pesticide use in 2019 and 1965.

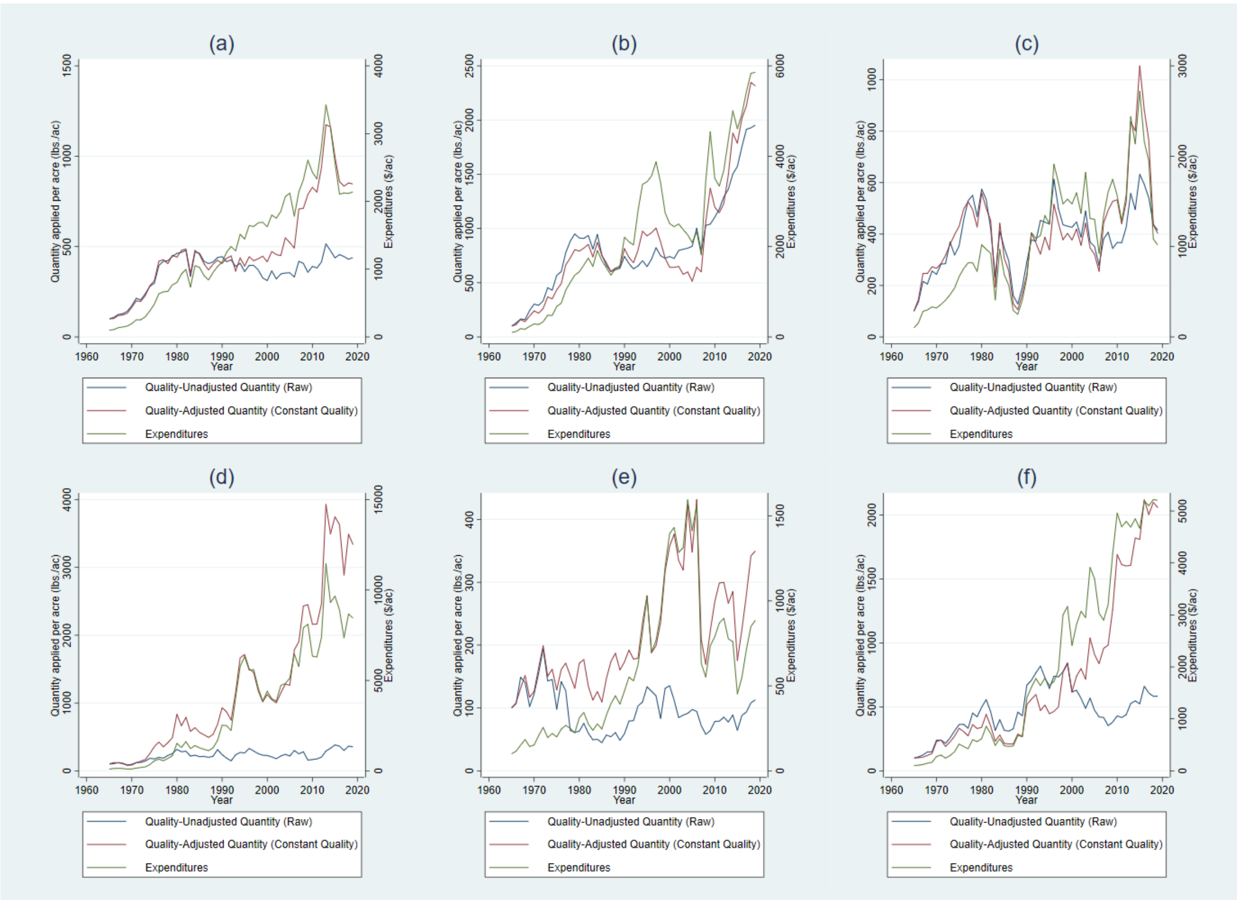

Figure A.1 Pesticide Use Growth Across Six Crops (1965-2019) This figure gives pesticide use over the span of our sample in three different measures across the six crops used in the study. Panels (a) – (c) show pesticide use growth over the span of our sample for corn, soybeans, and sorghum. Panels (d) – (f) give pesticide use growth for wheat, cotton, and rice.

Appendix A Section 2. Model Robustness to GMO Seed Adoption, Weather, and Prices

This section provides results testing model robustness referenced in the Results section of the main text. We give results under models with additional covariates, which may influence both the insurance participation and pesticide use decisions. The tables are organized by crop insurance participation measure where we give results for all six crops using EBP first (Tables A.2 – A.7), then give results using LBP (Tables A.8 – A.13).

Results for models including additional controls are compared to a base model, which was chosen based on the model with the highest first-stage F-statistic. The baseline model for all crops except sorghum and rice consists of quadratic trends, while the baseline model for sorghum and rice is consists of linear trends. Regressions including weather variables are only for the years 1980-2019 since PRISM monthly data begins in 1980. We note that results remain largely unchanged and that ATTs tend to become stronger in magnitude with the inclusion of GMO-adoption, weather, and prices.

Table A.2 Robustness of EBP Crop Insurance on Pesticide Use with Additional Covariates (Corn)

	Dependent Variable: Ln of Expenditures per acre					Dependent Variable: Ln of 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)
Covariates	(FE-IV)	(GMO)	(Weather)	(Prices)	(All Controls)	(FE-IV)	(GMO)	(Weather)	(Prices)	(All Controls)	(FE-IV)	(GMO)	(Weather)	(Prices)	(All Controls)
Enrollment-Based Participation	-0.58	-0.59	-0.49	-0.74*	-0.73	-2.39***	-2.38***	-2.32***	-2.41***	-2.32***	-2.15***	-1.60***	-2.13***	-2.46***	-2.03***
	(0.39)	(0.43)	(0.39)	(0.42)	(0.49)	(0.81)	(0.78)	(0.79)	(0.87)	(0.85)	(0.78)	(0.65)	(0.79)	(0.86)	(0.78)
Bt-Adoption		-0.09			-0.01		-0.33			-0.34		-1.16***			-0.96**
		(0.24)			(0.24)		(0.41)			(0.39)		(0.38)			(0.41)
HT-Adoption		-0.06			-0.24		-0.15			-0.17		0.81**			0.48
		(0.25)			(0.25)		(0.33)			(0.34)		(0.36)			(0.39)
Precipitation			0.00		0.00			0.00		0.00			0.00		0.00
			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)
Precipitation Squared			-0.00		-0.00			-0.00		-0.00			-0.00		-0.00
			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)
Degree Days (10-30)			-0.00**		-0.00*			0.00		-0.00			-0.00		-0.00
			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)
Degree Days (30-inf)			-0.00		-0.00			-0.00		-0.00			0.00		-0.00
			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)
Futures Price/PPI				0.39**	0.36*				0.04	0.05				0.75***	0.65***
				(0.19)	(0.20)				(0.25)	(0.26)				(0.22)	(0.24)
First-Stage F-Statistic (EBP)	10.91	12.23	10.29	10.55	10.58	10.91	12.23	10.29	10.55	10.58	10.91	12.23	10.29	10.55	10.58
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

Parameter estimates are robust to heteroskedasticity and are clustered at the year level.
*Standard errors 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 A.3 Robustness of EBP Crop Insurance on Pesticide Use with Additional Covariates (Soybeans)

	Dependent Variable: Ln of Expenditures per acre					Dependent Variable: Ln of 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)
Covariates	(FE-IV)	(GMO)	(Weather)	(Prices)	(All Controls)	(FE-IV)	(GMO)	(Weather)	(Prices)	(All Controls)	(FE-IV)	(GMO)	(Weather)	(Prices)	(All Controls)
Enrollment-Based Participation	-3.00***	0.03	-2.90***	-2.90***	0.21	-0.62***	-0.48***	-0.63***	-0.57***	-0.39***	-1.07**	-0.14	-1.08**	-0.97**	0.06
	(1.00)	(0.25)	(1.00)	(0.97)	(0.19)	(0.20)	(0.13)	(0.20)	(0.20)	(0.12)	(0.44)	(0.28)	(0.44)	(0.42)	(0.24)
HT-Adoption		-1.02***			-1.02***		-0.05			-0.07		-0.31***			-0.35***
		(0.14)			(0.11)		(0.06)			(0.06)		(0.11)			(0.10)
Precipitation			0.00		-0.00			0.00		0.00			0.00		-0.00
			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)
Precipitation Squared			-0.00		0.00			-0.00		-0.00			-0.00		0.00
			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)
Degree Days (10-30)			-0.00		-0.00***			-0.00		-0.00			-0.00		-0.00
			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)
Degree Days (30-inf)			0.00		0.00			0.00		0.00			0.00		0.00
			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)
Futures Price/PPI				0.19	0.15**				0.10***	0.10***				0.20***	0.19***
				(0.17)	(0.08)				(0.04)	(0.03)				(0.05)	(0.06)
First-Stage F-Statistic (EBP)	13.59	8.19	13.76	13.28	8.29	13.59	8.19	13.76	13.28	8.29	13.59	8.19	13.76	13.28	8.29
Observations	497	497	497	497	497	497	497	497	497	497	497	497	497	497	497
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

Parameter estimates are robust to heteroskedasticity and are clustered at the year level.

*Standard errors 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 A.4 Robustness of EBP Crop Insurance on Pesticide Use with Additional Covariates (Sorghum)

	Dependent Variable: Ln of Expenditures per acre				Dependent Variable: Ln of 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)
Covariates	(FE-IV)	(Weather)	(Prices)	(All Controls)	(FE-IV)	(Weather)	(Prices)	(All Controls)	(FE-IV)	(Weather)	(Prices)	(All Controls)
Enrollment-Based Participation	-3.09	-2.83	-2.92	-2.96	-3.22*	-3.30*	-2.91	-3.21	-3.72*	-3.82*	-3.87*	-4.19*
	(2.12)	(1.99)	(2.35)	(2.19)	(1.83)	(1.84)	(2.05)	(2.07)	(2.18)	(2.17)	(2.38)	(2.32)
Precipitation		-0.00		-0.00		-0.00		-0.00		-0.00		-0.00
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Precipitation Squared		0.00		0.00		0.00		0.00		0.00		0.00
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Degree Days (10-30)		-0.00**		-0.00**		-0.00		-0.00		-0.00*		-0.00**
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Degree Days (30-inf)		0.00***		0.00**		0.00		0.00		0.00*		0.00
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Futures Price/PPI			0.19	-0.18			0.34	0.12			-0.17	-0.51
			(0.70)	(0.7)			(0.70)	(0.75)			(0.73)	(0.78)
First-Stage F-Statistic (EBP)	6.27	5.79	5.83	5.60	6.27	5.79	5.83	5.60	6.27	5.79	5.83	5.60
Observations	206	206	206	206	206	206	206	206	206	206	206	206
States	10	10	10	10	10	10	10	10	10	10	10	10
Years	21	21	21	21	21	21	21	21	21	21	21	21

Parameter estimates are robust to heteroskedasticity and are clustered by year.

*Standard errors 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 A.5 Robustness of EBP Crop Insurance on Pesticide Use with Additional Covariates (Wheat)

	Dependent Variable: Ln of Expenditures per acre		Dependent Variable: Ln of Raw Quantity per acre		Dependent Variable: Ln of Quality-Adjusted Quantity per	
Covariates	(1) (FE-IV)	(2) (Weather)	(3) (FE-IV)	(4) (Weather)	(5) (FE-IV)	(6) (Weather)
Enrollment-Based Participation	-3.61	-2.51	7.42	6.35	-11.93	-9.66
	(16.37)	(12.89)	(14.49)	(10.82)	(28.16)	(20.85)
Precipitation		0.00		0.00		0.00
		(0.00)		(0.00)		(0.00)
Precipitation Squared		-0.00		-0.00		-0.00
		(0.00)		(0.00)		(0.00)
Degree Days (10-30)		0.00		-0.00		0.00
		(0.00)		(0.00)		(0.00)
Degree Days (30-inf)		0.00		0.00		0.00
		(0.00)		(0.00)		(0.00)
First-Stage F-Statistic (EBP)	0.22	0.31	0.22	0.31	0.22	0.31
Observations	855	855	855	855	855	855
States	28	28	28	28	28	28
Years	39	39	39	39	39	39

Parameter estimates are robust to heteroskedasticity and are clustered at the state-year level.
*Standard errors 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 A.6 Robustness of EBP Crop Insurance on Pesticide Use with Additional Covariates (Cotton)

	Dependent Variable: Ln of Expenditures per acre					Dependent Variable: Ln of 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)
Covariates	(FE-IV)	(GMO)	(Weather)	(Prices)	(All Controls)	(FE-IV)	(GMO)	(Weather)	(Prices)	(All Controls)	(FE-IV)	(GMO)	(Weather)	(Prices)	(All Controls)
Enrollment-Based Participation	1.04***	1.25***	1.00***	0.97***	1.23***	-0.08	0.27	-0.09	-0.08	0.26	0.94***	1.08***	0.90***	0.88***	1.05***
	(0.26)	(0.26)	(0.25)	(0.25)	(0.27)	(0.24)	(0.21)	(0.21)	(0.23)	(0.20)	(0.24)	(0.24)	(0.24)	(0.23)	(0.26)
Bt-Adoption		-1.10***			-1.04***		-0.33			-0.33*		-1.12***			-1.07***
		(0.31)			(0.32)		(0.23)			(0.23)		(0.28)			(0.29)
HT-Adoption		0.40			0.18		-0.37			-0.42*		0.54			0.36
		(0.51)			(0.47)		(0.23)			(0.23)		(0.45)			(0.42)
Precipitation			0.00		-0.00			0.00		0.00			-0.00		-0.00
			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)
Precipitation Squared			-0.00		0.00			-0.00		-0.00			0.00		0.00
			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)
Degree Days (10-30)			0.00		-0.00			-0.00**		-0.00***			-0.00		-0.00
			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)
Degree Days (30-inf)			-0.00		0.00			0.00		0.00			0.00		0.00
			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)
Futures Price/PPI				-2.80*	-3.96***				0.19	-1.41				-2.18	-3.16**
				(1.46)	(1.61)				(1.13)	(1.01)				(1.60)	(1.63)
First-Stage F-Statistic (EBP)	23.86	26.29	25.06	28.61	29.94	23.86	26.29	25.06	28.61	29.94	23.86	26.29	25.06	28.61	29.94
Observations	377	377	377	377	377	377	377	377	377	377	377	377	377	377	377
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

Parameter estimates are robust to heteroskedasticity and are clustered at the year level.
*Standard errors 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 A.7 Robustness of EBP Crop Insurance on Pesticide Use with Additional Covariates (Rice)

	Dependent Variable: Ln of Expenditures per acre				Dependent Variable: Ln of 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)
Covariates	(FE-IV)	(Weather)	(Prices)	(All Controls)	(FE-IV)	(Weather)	(Prices)	(All Controls)	(FE-IV)	(Weather)	(Prices)	(All Controls)
Enrollment-Based Participation	0.53**	0.47**	0.69**	0.60*	-1.17**	-1.18**	-1.66**	-1.74**	-0.54	-0.56	-0.41	-0.47
	(0.22)	(0.21)	(0.36)	(0.34)	(0.53)	(0.51)	(0.73)	(0.76)	(0.40)	(0.40)	(0.50)	(0.50)
Precipitation		-0.00		-0.00		0.00		0.00		-0.00		-0.00
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Precipitation Squared		0.00		0.00		-0.00		-0.00		0.00		0.00
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Degree Days (10-30)		0.00		0.00		-0.00		-0.00		-0.00		-0.00
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Degree Days (30-inf)		0.00		0.00		0.00		0.00		0.00*		0.00
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Futures Price/PPI			0.10	0.08			-0.29	-0.32			0.08	0.06
			(0.11)	(0.11)			(0.19)	(0.22)			(0.14)	(0.15)
First-Stage F-Statistic (EBP)	14.19	14.77	7.74	6.59	14.19	14.77	7.74	6.59	14.19	14.77	7.74	6.59
Observations	148	148	148	148	148	148	148	148	148	148	148	148
States	5	5	5	5	5	5	5	5	5	5	5	5
Years	30	30	30	30	30	30	30	30	30	30	30	30

Parameter estimates are robust to heteroskedasticity and are clustered at the year level.

*Standard errors 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 A.8 Robustness of LBP Crop Insurance on Pesticide Use with Additional Covariates (Corn)

	Dependent Variable: Ln of Expenditures per acre					Dependent Variable: Ln of 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)
Covariates	(FE-IV)	(GMO)	(Weather)	(Prices)	(All Controls)	(FE-IV)	(GMO)	(Weather)	(Prices)	(All Controls)	(FE-IV)	(GMO)	(Weather)	(Prices)	(All Controls)
Liability-Based															
Participation	-0.53**	-0.50*	-0.45	-0.65***	-0.58**	-2.18***	-2.03***	-2.14***	-2.11***	-1.84***	-1.97***	-1.37***	-1.97***	-2.17***	-1.61***
	(0.27)	(0.28)	(0.28)	(0.25)	(0.29)	(0.42)	(0.36)	(0.42)	(0.42)	(0.35)	(0.53)	(0.41)	(0.53)	(0.53)	(0.41)
Bt-Adoption		-0.08			-0.02		-0.25			-0.36*		-1.11***			-0.98***
		(0.20)			(0.18)		(0.20)			(0.20)		(0.26)			(0.25)
HT-Adoption		0.05			-0.07		0.3			0.39**		1.11***			0.97***
		(0.19)			(0.16)		(0.19)	-0.00		(0.19)		(0.26)			(0.25)
Precipitation			0.00		0.00			(0.00)		-0.00			0.00		-0.00
			(0.00)		(0.00)			-0.00		(0.00)			(0.00)		(0.00)
Precipitation Squared			-0.00		-0.00			(0.00)		0.00			0.00		0.00
			(0.00)		(0.00)			0.00		(0.00)			(0.00)		(0.00)
Degree Days (10-30)			-0.00**		-0.00**			(0.00)		0.00			-0.00		-0.00
			(0.00)		(0.00)			-0.00		(0.00)			(0.00)		(0.00)
Degree Days (30-inf)			-0.00		-0.00			(0.00)		-0.00			0.00		0.00
			(0.00)		(0.00)					(0.00)			(0.00)		(0.00)
Futures Price/PPI				0.32**	0.28**				-0.18	-0.22*				0.53***	0.41**
				(0.15)	(0.14)				(0.14)	(0.13)				(0.20)	(0.18)
First-Stage F-Statistic															
(LBP)	33.68	40.60	32.58	30.90	32.54	33.68	40.60	32.58	30.90	32.54	33.68	40.60	32.58	30.90	32.54
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

Parameter estimates are robust to heteroskedasticity and are clustered at the year level.
*Standard errors 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 A.9 Robustness of LBP Crop Insurance on Pesticide Use with Additional Covariates (Soybeans)

	Dependent Variable: Ln of Expenditures per acre					Dependent Variable: Ln of 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)
Covariates	(FE-IV)	(GMO)	(Weather)	(Prices)	(All Controls)	(FE-IV)	(GMO)	(Weather)	(Prices)	(All Controls)	(FE-IV)	(GMO)	(Weather)	(Prices)	(All Controls)
Liability-Based Participation	-3.54***	0.05	-3.41***	-3.44***	0.40	-0.73***	-0.89***	-0.74***	-0.67***	-0.74***	-1.27***	-0.27	-1.27***	-1.15***	0.12
	(0.72)	(0.47)	(0.74)	(0.70)	(0.34)	(0.21)	(0.24)	(0.21)	(0.21)	(0.23)	(0.43)	(0.54)	(0.43)	(0.43)	(0.46)
HT-Adoption		-1.02***			-1.06***		0.05			0.02		-0.29*			-0.37***
		(0.16)			(0.12)		(0.06)			(0.06)		(0.15)			(0.13)
Precipitation			0.00		-0.00			0.00		0.00			-0.00		-0.00
			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)
Precipitation Squared			-0.00		0.00			-0.00		-0.00			0.00		0.00
			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)
Degree Days (10-30)			-0.00		-0.00***			-0.00		0.00			-0.00		-0.00
			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)
Degree Days (30-inf)			-0.00		0.00			0.00		0.00			0.00		0.00
			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)
Futures Price/PPI				0.16*	0.16**				0.09***	0.10***				0.19***	0.19***
				(0.10)	(0.08)				(0.04)	(0.03)				(0.05)	(0.06)
First-Stage F-Statistic (LBP)	55.45	10.86	54.61	56.38	10.83	55.45	10.86	54.61	56.38	10.83	55.45	10.86	54.61	56.38	10.83
Observations	497	497	497	497	497	497	497	497	497	497	497	497	497	497	497
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

Parameter estimates are robust to heteroskedasticity and are clustered at the year level.
*Standard errors 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 A.10 Robustness of LBP Crop Insurance on Pesticide Use with Additional Covariates (Sorghum)

Covariates	Dependent Variable: Ln of Expenditures per acre (1) (FE-IV)	(2) (Weather)	Dependent Variable: Ln of Raw Quantity per acre (3) (FE-IV)	(4) (Weather)	Dependent Variable: Ln of Quality-Adjusted Quantity per (5) (FE-IV)	(6) (Weather)
Liability-Based Participation	9.57**	10.44**	6.84***	7.88***	9.88**	10.68**
	(4.03)	(4.55)	(2.37)	(2.59)	(4.21)	(4.68)
Precipitation		0.00		-0.00		-0.00
		(0.00)		(0.00)		(0.00)
Precipitation Squared		-0.00		-0.00		0.00
		(0.00)		(0.00)		(0.00)
Degree Days (10-30)		-0.00		-0.00		-0.00
		(0.00)		(0.00)		(0.00)
Degree Days (30-inf)		-0.00		-0.00		-0.00
		(0.00)		(0.00)		(0.00)
First-Stage F-Statistic (LBP)	11.10	7.94	11.10	7.94	11.10	7.94
Observations	206	206	206	206	206	206
States	10	10	10	10	10	10
Years	21	21	21	21	21	21

Parameter estimates are robust to heteroskedasticity and are clustered by year.
*Standard errors 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 A.11 Robustness of LBP Crop Insurance on Pesticide Use with Additional Covariates (Wheat)

	Dependent Variable: Ln of Expenditures per acre				Dependent Variable: Ln of 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)
Covariates	(FE-IV)	(Weather)	(Prices)	(All Controls)	(FE-IV)	(Weather)	(Prices)	(All Controls)	(FE-IV)	(Weather)	(Prices)	(All Controls)
Liability-Based Participation	9.97	9.45	9.78	9.25	22.47	23.38	21.72	22.63	10.79	10.45	10.73	10.40
	(12.64)	(13.10)	(11.35)	(11.73)	(22.02)	(24.14)	(17.45)	(19.01)	(12.79)	(13.41)	(12.15)	(12.79)
Precipitation		0.00		0.00		-0.00		-0.00		0.00		0.00
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Precipitation Squared		-0.00		-0.00		0.00		0.00		0.00		0.00
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Degree Days (10-30)		-0.00		-0.00		-0.00		-0.00		0.00		0.00
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Degree Days (30-inf)		0.00		0.00		-0.00		0.00		-0.00		0.00
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Futures Price/PPI			-0.74	-0.80			-2.79	-3.12			-0.23	-0.20
			(1.80)	(1.96)			(2.81)	(3.20)			(1.86)	(2.06)
First-Stage F-Statistic (LBP)	0.80	0.73	1.39	1.28	0.80	0.73	1.39	1.28	0.80	0.73	1.39	1.28
Observations	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
Years	39	39	39	39	39	39	39	39	39	39	39	39

Parameter estimates are robust to heteroskedasticity and are clustered at the state-year level.

*Standard errors 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 A.12 Robustness of LBP Crop Insurance on Pesticide Use with Additional Covariates (Cotton)

	Dependent Variable: Ln of Expenditures per acre					Dependent Variable: Ln of 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)
Covariates	(FE-IV)	(GMO)	(Weather)	(Prices)	(All Controls)	(FE-IV)	(GMO)	(Weather)	(Prices)	(All Controls)	(FE-IV)	(GMO)	(Weather)	(Prices)	(All Controls)
Liability-Based Participation	2.39***	3.36***	2.28***	2.30***	3.25***	-0.19	0.73	-0.21	-0.18	0.69	2.16***	2.91***	2.05***	2.10**	2.80***
	(0.74)	(1.06)	(0.71)	(0.73)	(1.11)	(0.55)	(0.60)	(0.49)	(0.55)	(0.57)	(0.70)	(0.98)	(0.68)	(0.69)	(1.02)
Bt-Adoption		-2.19***			-2.09***		-0.56			-0.55		-2.07***			-1.97***
		(0.56)			(0.57)		(0.38)			(0.36)		(0.51)			(0.51)
HT-Adoption		0.81			0.62		-0.28			-0.32		0.89*			0.73
		(0.54)			(0.50)		(0.25)			(0.25)		(0.49)			(0.46)
Precipitation			-0.00		-0.00			0.00		0.00			-0.00		-0.00
			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)
Precipitation Squared			0.00		0.00			-0.00		-0.00			0.00		0.00
			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)
Degree Days (10-30)			-0.00		-0.00			-0.00*		-0.00***			-0.00		-0.00
			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)
Degree Days (30-inf)			0.00		0.00			0.00		0.00			0.00		0.00
			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)
Futures Price/PPI				-1.54	-2.61				-0.03	-0.99				-1.03	-2.00
				(1.25)	(1.65)				(0.02)	(1.01)				(1.43)	(1.63)
First-Stage F-Statistic (LBP)	14.52	13.02	15.21	15.24	12.75	14.52	13.02	15.21	15.24	12.75	14.52	13.02	15.21	15.24	12.75
Observations	377	377	377	377	377	377	377	377	377	377	377	377	377	377	377
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

Parameter estimates are robust to heteroskedasticity and are clustered at the year level.
*Standard errors 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 A.13 Robustness of LBP Crop Insurance on Pesticide Use with Additional Covariates (Rice)

	Dependent Variable: Ln of Expenditures per acre				Dependent Variable: Ln of 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)
Covariates	(FE-IV)	(Weather)	(Prices)	(All Controls)	(FE-IV)	(Weather)	(Prices)	(All Controls)	(FE-IV)	(Weather)	(Prices)	(All Controls)
Liability-Based Participation	-5.94	-7.25	-1.46	-1.25	13.16	18.02	3.51***	3.60**	6.10	8.59	0.86	0.97
	(15.82)	(26.12)	(1.13)	(1.08)	(30.75)	(58.82)	(1.40)	(1.51)	(14.57)	(28.19)	(1.04)	(1.04)
Precipitation		0.00		0.00		-0.00		-0.00		-0.00		-0.00
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Precipitation Squared		-0.00		-0.00		0.00		0.00		0.00		0.00
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Degree Days (10-30)		0.00		-0.00		-0.00		0.00		-0.00		-0.00
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Degree Days (30-inf)		0.00		0.00		-0.00		-0.00		-0.00		0.00
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Futures Price/PPI			-0.24	-0.23			0.51**	0.55**			0.28*	0.29**
			(0.19)	(0.18)			(0.22)	(0.25)			(0.15)	(0.15)
First-Stage F-Statistic (LBP)	0.15	0.08	4.90	4.56	0.15	0.08	4.90	4.56	0.15	0.08	4.90	4.56
Observations	148	148	148	148	148	148	148	148	148	148	148	148
States	5	5	5	5	5	5	5	5	5	5	5	5
Years	30	30	30	30	30	30	30	30	30	30	30	30

Parameter estimates are robust to heteroskedasticity and are clustered at the year level.
*Standard errors 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.

Appendix B - Appendix B - Dissertation Appendix for Hurricane Incidence Results in Significant Increases in Crop Damages: Evidence from the Mississippi Delta

This document contains supplementary material that is referenced in the main text. It contains 2 sections: Section 1 - Breakdown of Treated and Control Groups in the Samples Used to Estimate Treatment Effects of Hurricanes and Section 2 - Regression Results by Hurricane Event.

Appendix B Section 1. Breakdown of Treated and Control Groups in the Samples Used to Estimate Treatment Effects of Hurricanes

This section contains tables listing the percentage of treated and control observations in the samples used to estimate the treatment effects of hurricanes. Each table gives a breakdown of these percentages based on the hurricane components considered as the rainfall field tended to assign treatment to more counties than wind. Tables are given by crop and by the types of insurance products considered with Tables B.1 – B.4 giving a breakdown for the models which aggregate across both yield and revenue insurance, Tables B.5 – B.8 giving a breakdown by crop for individual yield insurance plans only, and Tables B.9 – B.12 giving percentages of treated and control observations for individual revenue plans only.

Table B.1 Percentage of Treated and Control Observations by Hurricane Effect (Rice - All Plans)

Tropical Cyclone	Treated	Control	% Treated
Wind Effects			
Hurricane Lili	40	82	33%
Hurricane Rita	23	79	23%
Hurricane Humberto	10	46	18%
Hurricane Gustav	22	84	21%
Hurricane Ike	23	76	23%
Hurricane Isaac	22	64	26%
Hurricane Barry	14	102	12%
Hurricane Laura	40	89	31%
Hurricane Delta	54	82	40%
Rain Effects			
Hurricane Lili	77	45	63%
Hurricane Rita	56	46	55%
Hurricane Humberto	9	47	16%
Hurricane Gustav	67	39	63%
Hurricane Ike	29	70	29%
Hurricane Isaac	31	55	36%
Hurricane Barry	24	92	21%
Hurricane Laura	61	68	47%
Hurricane Delta	38	98	28%

Table B.2 Percentage of Treated and Control Observations by Hurricane Effect (Corn - All Plans)

Tropical Cyclone	Treated	Control	% Treated
Wind Effects			
Hurricane Lili	32	130	20%
Hurricane Katrina	25	100	20%
Hurricane Rita	18	112	14%
Hurricane Gustav	14	126	10%
Hurricane Ike	14	125	10%
Hurricane Isaac	18	137	12%
Hurricane Laura	34	126	21%
Hurricane Delta	48	130	27%
Rain Effects			
Hurricane Lili	110	52	68%
Hurricane Katrina	12	113	10%
Hurricane Rita	62	68	48%
Hurricane Gustav	67	73	48%
Hurricane Ike	26	113	19%
Hurricane Isaac	63	92	41%
Hurricane Laura	62	98	39%
Hurricane Delta	88	90	49%

Table B.3 Percentage of Treated and Control Observations by Hurricane Effect (Soybeans - All Plans)

Tropical Cyclone	Treated	Control	% Treated
Wind Effects			
Hurricane Lili	48	150	24%
Hurricane Rita	31	151	17%
Hurricane Gustav	38	153	20%
Hurricane Ike	28	163	15%
Hurricane Isaac	36	150	19%
Hurricane Laura	46	140	25%
Hurricane Delta	71	138	34%
Rain Effects			
Hurricane Lili	119	79	60%
Hurricane Rita	80	102	44%
Hurricane Gustav	84	107	44%
Hurricane Ike	35	156	18%
Hurricane Isaac	67	119	36%
Hurricane Laura	62	124	33%
Hurricane Delta	88	121	42%

Table B.4 Percentage of Treated and Control Observations by Hurricane Effect (Cotton - All Plans)

Tropical Cyclone	Treated	Control	% Treated
Wind Effects			
Hurricane Lili	30	111	21%
Hurricane Katrina	19	75	20%
Hurricane Gustav	13	67	16%
Hurricane Laura	24	90	21%
Hurricane Delta	38	103	27%
Rain Effects			
Hurricane Lili	94	47	67%
Hurricane Katrina	9	86	10%
Hurricane Gustav	29	52	36%
Hurricane Ike	11	69	14%
Hurricane Laura	49	65	43%
Hurricane Delta	77	64	55%

Table B.5 Percentage of Treated and Control Observations by Hurricane Effect (Rice - Yield Plans)

Tropical Cyclone	Treated	Control	% Treated
Wind Effects			
Hurricane Lili	40	82	33%
Hurricane Rita	23	79	23%
Hurricane Gustav	20	66	23%
Hurricane Ike	18	62	23%
Hurricane Isaac	22	24	48%
Hurricane Barry	12	80	13%
Hurricane Laura	35	67	34%
Hurricane Delta	47	71	40%
Rain Effects			
Hurricane Lili	77	43	64%
Hurricane Rita	56	46	55%
Hurricane Gustav	55	31	64%
Hurricane Ike	28	52	35%
Hurricane Isaac	9	37	20%
Hurricane Barry	20	72	22%
Hurricane Laura	56	46	55%
Hurricane Delta	30	88	25%

Table B.6 Percentage of Treated and Control Observations by Hurricane Effect (Corn - Yield Plans)

Tropical Cyclone	Treated	Control	% Treated
Wind Effects			
Hurricane Lili	26	108	19%
Hurricane Katrina	25	74	25%
Hurricane Rita	12	92	12%
Hurricane Gustav	13	117	10%
Hurricane Ike	14	113	11%
Hurricane Isaac	12	72	14%
Hurricane Laura	34	98	26%
Hurricane Delta	46	96	32%
Rain Effects			
Hurricane Lili	90	44	67%
Hurricane Katrina	11	88	11%
Hurricane Rita	48	56	46%
Hurricane Gustav	64	66	49%
Hurricane Ike	26	101	20%
Hurricane Isaac	42	42	50%
Hurricane Laura	62	70	47%
Hurricane Delta	67	75	47%

Table B.7 Percentage of Treated and Control Observations by Hurricane Effect (Soybeans - Yield Plans)

Tropical Cyclone	Treated	Control	% Treated
Wind Effects			
Hurricane Lili	48	147	25%
Hurricane Rita	30	142	17%
Hurricane Gustav	36	136	21%
Hurricane Ike	25	146	15%
Hurricane Isaac	32	120	21%
Hurricane Laura	38	109	26%
Hurricane Delta	66	109	38%
Rain Effects			
Hurricane Lili	117	78	60%
Hurricane Rita	80	92	47%
Hurricane Gustav	81	91	47%
Hurricane Ike	34	137	20%
Hurricane Isaac	60	92	39%
Hurricane Laura	60	87	41%
Hurricane Delta	76	99	43%

Table B.8 Percentage of Treated and Control Observations by Hurricane Effect (Cotton - Yield Plans)

Tropical Cyclone	Treated	Control	% Treated
Wind Effects			
Hurricane Lili	30	111	21%
Hurricane Katrina	17	68	20%
Hurricane Gustav	13	51	20%
Hurricane Laura	21	60	26%
Hurricane Delta	30	64	32%
Rain Effects			
Hurricane Lili	94	47	67%
Hurricane Katrina	9	76	10%
Hurricane Gustav	20	44	31%
Hurricane Ike	8	56	13%
Hurricane Laura	34	47	42%
Hurricane Delta	48	46	51%

Table B.9 Percentage of Treated and Control Observations by Hurricane Effect (Rice - Revenue Plans)

Tropical Cyclone	Treated	Control	% Treated
Wind Effects			
Hurricane Lili	11	38	22%
Hurricane Rita	12	36	25%
Hurricane Gustav	16	59	21%
Hurricane Ike	16	55	23%
Hurricane Isaac	12	58	17%
Hurricane Barry	11	86	11%
Hurricane Laura	39	85	31%
Hurricane Delta	50	79	39%
Rain Effects			
Hurricane Lili	38	11	78%
Hurricane Rita	32	16	67%
Hurricane Gustav	47	28	63%
Hurricane Ike	20	51	28%
Hurricane Isaac	26	44	37%
Hurricane Barry	22	75	23%
Hurricane Laura	60	64	48%
Hurricane Delta	38	91	29%

Table B.10 Percentage of Treated and Control Observations by Hurricane Effect (Corn - Revenue Plans)

Tropical Cyclone	Treated	Control	% Treated
Wind Effects			
Hurricane Lili	31	94	25%
Hurricane Rita	12	92	12%
Hurricane Gustav	14	95	13%
Hurricane Ike	10	96	9%
Hurricane Isaac	14	126	10%
Hurricane Laura	34	126	21%
Hurricane Delta	48	129	27%
Rain Effects			
Hurricane Lili	79	46	63%
Hurricane Rita	48	56	46%
Hurricane Gustav	53	56	49%
Hurricane Ike	17	89	16%
Hurricane Isaac	61	79	44%
Hurricane Laura	62	98	39%
Hurricane Delta	88	89	50%

Table B.11 Percentage of Treated and Control Observations by Hurricane Effect (Soybeans - Revenue Plans)

Tropical Cyclone	Treated	Control	% Treated
Wind Effects			
Hurricane Lili	30	105	22%
Hurricane Rita	24	124	16%
Hurricane Gustav	28	140	17%
Hurricane Ike	19	149	11%
Hurricane Isaac	32	149	18%
Hurricane Laura	44	139	24%
Hurricane Delta	66	136	33%
Rain Effects			
Hurricane Lili	89	46	66%
Hurricane Rita	66	82	45%
Hurricane Gustav	77	91	46%
Hurricane Ike	35	133	21%
Hurricane Isaac	67	114	37%
Hurricane Laura	62	121	34%
Hurricane Delta	88	114	44%

Table B.12 Percentage of Treated and Control Observations by Hurricane Effect (Cotton - Revenue Plans)

Tropical Cyclone	Treated	Control	% Treated
Wind Effects			
Hurricane Lili	15	39	28%
Hurricane Gustav	12	41	23%
Hurricane Laura	22	86	20%
Hurricane Delta	38	99	28%
Rain Effects			
Hurricane Lili	39	15	72%
Hurricane Gustav	19	34	36%
Hurricane Ike	6	46	12%
Hurricane Laura	45	63	42%
Hurricane Delta	74	63	54%

Appendix B Section 2. Regression Results by Hurricane Event

This section contains tables which give regression results by hurricane event and are the values contained in the histograms in Figures 2.2 – 2.4 contained in the main text. There are four columns highlighted which reflect the different models discussed in the main text with the fourth column being broken down into two sub-columns. This is to show the parameter estimates for the ATTs of the wind and rainfall components to hurricane incidence. The two parameter estimates under column 4 are added together and create the values reported in column 4 of Figures 2.2 – 2.4 in the main text. Tables are given by crop and by the types of insurance products considered with Tables B.13 – B.16 giving a breakdown for the models which aggregate across both yield and revenue insurance, Tables B17 – B20 giving a breakdown by crop for individual yield insurance plans only, and Tables B21 – B24 giving percentages of treated and control observations for individual revenue plans only.

Table B.1 Estimated Treatment Effects of Hurricanes on On-Farm Damages (Rice – All Plans of Insurance)

	(1)	(2)	(3)	(4)	
Treatment Measure	(Wind)	(Wind)	(Wind)	(Wind)	(Rainfall)
Hurricane Lili	-0.0006	-0.0006	-0.0047	0.0060***	0.0107***
	(0.0030)	(0.0030)	(0.0043)	(0.0023)	(0.0037)
Hurricane Rita	0.0045	0.0203	0.0194	0.01944	0.0001
	(0.0032)	(0.0156)	(0.0156)	(0.0157)	(0.0019)
Hurricane Humberto	-0.0017	-0.0018	-0.0054	-0.0003**	0.0089
	(0.0016)	(0.0016)	(0.0050)	(0.0001)	(0.0083)
Hurricanes Gustav + Ike	0.0363*	0.0361*	0.0348*	0.0429**	0.0100
	(0.0199)	(0.0199)	(0.0210)	(0.0204)	(0.0095)
Hurricane Isaac	-0.0001	-0.0008	-0.0006	-0.0025	-0.0032
	(0.0007)	(0.0009)	(0.0010)	(0.0018)	(0.0017)
Hurricane Barry	-0.0281	-0.0295	-0.0354	-0.0500	-0.0452
	(0.0275)	(0.0276)	(0.0350)	(0.0503)	0.0508)
Hurricane Laura	0.0290**	0.0276**	0.0292**	0.0162	-0.0183**
	(0.0129)	(0.0129)	(0.0126)	(0.0144)	(0.0079)
Hurricane Delta	0.0132***	0.0133***	0.0181**	0.0203***	0.0045
	(0.0044)	(0.0044)	(0.0074)	(0.0077)	(0.0038)

*,**,*** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county level.

Table B.2 Estimated Treatment Effects of Hurricanes on On-Farm Damages (Corn – All Plans of Insurance)

	(1)	(2)	(3)	(4)	
Treatment Measure	(Wind)	(Wind)	(Wind)	(Wind)	(Rainfall)
Hurricane Lili	0.0011	0.0002	-0.0065	-0.0030	0.0039
	(0.0013)	(0.0015)	(0.0031)	(0.0025)	(0.0038)
Hurricane Katrina	-0.0081	-0.0190	-0.0154	-0.0191	-0.0248
	(0.0076)	(0.0140)	(0.0145)	(0.0168)	(0.0161)
Hurricane Rita	-0.0014	-0.0042	-0.0052*	-0.0077	-0.0033
	(0.0013)	(0.0029)	(0.0031)	(0.0064)	(0.0073)
Hurricane Gustav + Ike	0.0135	0.0135	0.0121	0.0263	0.0246*
	(0.0177)	(0.0177)	(0.0194)	(0.0179)	(0.0139)
Hurricane Isaac	-0.0047***	-0.0057***	-0.0058***	-0.0033***	0.0048*
	(0.0013)	(0.0015)	(0.0015)	(0.0011)	(0.0027)
Hurricane Laura	0.0724	0.0709	0.0704	0.0681	-0.0034
	(0.0575)	(0.0575)	(0.0573)	(0.0576)	(0.0047)
Hurricane Delta	-0.0025*	-0.0027	-0.0066***	-0.0157***	-0.0119**
	(0.0015)	(0.0015)	(0.0020)	(0.0045)	(0.0049)

*,**,*** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county level.

Table B.3 Estimated Treatment Effects of Hurricanes on On-Farm Damages (Soybeans – All Plans of Insurance)

	(1)	(2)	(3)	(4)	
Treatment Measure	(Wind)	(Wind)	(Wind)	(Wind)	(Rainfall)
Hurricane Lili	0.0407***	0.0407***	0.0583**	-0.0102	-0.0813
	(0.0157)	(0.0157)	(0.0238)	(0.0592)	(0.0557)
Hurricane Katrina	0.0081	0.0067	0.0225*	0.0258**	0.0403**
	(0.0098)	(0.0100)	(0.0125)	(0.0124)	(0.0202)
Hurricane Rita	0.0172	0.0243	0.0271	0.0185	-0.0142**
	(0.0176)	(0.0184)	(0.0185)	(0.0120)	(0.0072)
Hurricane Gustav + Ike	0.0277***	0.0280***	0.0260**	0.0330***	0.0132
	(0.0103)	(0.0102)	(0.0105)	(0.0109)	(0.0090)
Hurricane Isaac	0.0030	0.0030	0.0066	0.0080	0.0029
	(0.0046)	(0.0046)	(0.0056)	(0.0056)	(0.0028)
Hurricane Laura	0.0201	0.0201	0.0202	0.0104	-0.0181
	(0.0194)	(0.0194)	(0.0196)	(0.0229)	(0.0135)
Hurricane Delta	0.0359	0.0359	0.0318	-0.0015	-0.0492
	(0.0352)	(0.0352)	(0.0352)	(0.0451)	(0.0300)

*,**,*** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county level.

Table B.4 Estimated Treatment Effects of Hurricanes on On-Farm Damages (Cotton – All Plans of Insurance)

	(1)	(2)	(3)	(4)	
Treatment Measure	(Wind)	(Wind)	(Wind)	(Wind)	(Rainfall)
Hurricane Lili	0.0567**	0.0579**	0.0581**	0.0549**	-0.0035
	(0.0260)	(0.0259)	(0.0249)	(0.0259)	(0.0123)
Hurricane Katrina	0.0135	0.0137	0.0171	0.0159	-0.0083**
	(0.0128)	(0.0130)	(0.0128)	(0.0129)	(0.0035)
Hurricane Gustav + Ike	0.2122***	0.2122***	0.2491***	0.2588***	0.0169
	(0.0497)	(0.0497)	(0.0601)	(0.0632)	(0.0300)
Hurricane Laura	0.0180	0.0175	0.0553	0.0723*	0.0184
	(0.0140)	(0.0140)	(0.0433)	(0.0407)	(0.0171)
Hurricane Delta	0.0022	0.0022	0.0023	-0.0221**	-0.0234**
	(0.0023)	(0.0023)	(0.0039)	(0.0108)	(0.0108)

*,**,*** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county level.

Table B.5 Estimated Treatment Effects of Hurricanes on On-Farm Damages (Rice – Yield Plans of Insurance)

	(1)	(2)	(3)	(4)	
Treatment Measure	(Wind)	(Wind)	(Wind)	(Wind)	(Rainfall)
Hurricane Lili	0.0012	0.0012	-0.0018	0.0063***	0.0082**
	(0.0028)	(0.0028)	(0.0041)	(0.0024)	(0.0034)
Hurricane Rita	0.0018	0.0012	0.0004	-0.0010	-0.0017
	(0.0026)	(0.0027)	(0.0028)	(0.0028)	(0.0017)
Hurricanes Gustav + Ike	0.0271	0.0276	0.0278	0.0279	0.0002
	(0.0176)	(0.0176)	(0.0177)	(0.0181)	(0.0036)
Hurricane Isaac	0.0004	0.0004	0.0007	0.0006	-0.0002
	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0001)
Hurricane Barry	0.0033	0.0027	-0.0161	-0.0316	-0.0373
	(0.0059)	(0.0059)	(0.0356)	(0.0563)	(0.0549)
Hurricane Laura	0.0161	0.0121	0.0115	-0.0029	-0.0153
	(0.0103)	(0.0104)	(0.0104)	(0.0102)	(0.0075)
Hurricane Delta	0.0169***	0.0153**	0.0120*	0.0129*	0.0020
	(0.0061)	(0.0062)	(0.0064)	(0.0069)	(0.0043)

*,**,*** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county level.

Table B.6 Estimated Treatment Effects of Hurricanes on On-Farm Damages (Corn – Yield Plans of Insurance)

	(1)	(2)	(3)	(4)	
Treatment Measure	(Wind)	(Wind)	(Wind)	(Wind)	(Rainfall)
Hurricane Lili	0.0000	-0.0004	-0.0041*	-0.0062***	-0.0024
	(0.0000)	(0.0004)	(0.0023)	(0.0024)	(0.0035)
Hurricane Katrina	-0.0006*	0.0026	0.0011	0.0006	-0.0027
	(0.0003)	(0.0034)	(0.0037)	(0.0039)	(0.0018)
Hurricane Rita	-0.0001	-0.0003	-0.0005**	-0.0012*	-0.0010
	(0.0000)	(0.0002)	(0.0002)	(0.0007)	(0.0007)
Hurricane Gustav + Ike	0.0278	0.0278	0.0282	0.0262	-0.0030
	(0.0204)	(0.0204)	(0.0203)	(0.0205)	(0.0030)
Hurricane Isaac	-0.0004	-0.0004	-0.0004	-0.0025	-0.0025
	(0.0004)	(0.0004)	(0.0004)	(0.0023)	(0.0023)
Hurricane Laura	0.0574	0.0575	0.0570	0.0904	0.0334
	(0.0691)	(0.0690)	(0.0690)	(0.0610)	(0.0322)
Hurricane Delta	-0.0005	-0.0005	-0.0007	-0.0031***	-0.0025***
	(0.0006)	(0.0006)	(0.0006)	(0.0001)	(0.0006)

*,**,*** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county level.

Table B.7 Estimated Treatment Effects of Hurricanes on On-Farm Damages (Soybeans – Yield Plans of Insurance)

	(1)	(2)	(3)	(4)	
Treatment Measure	(Wind)	(Wind)	(Wind)	(Wind)	(Rainfall)
Hurricane Lili	0.0379***	0.0380***	0.0667***	0.0446*	-0.0263
	(0.0146)	(0.0146)	(0.0214)	(0.0242)	(0.0144)
Hurricane Katrina	-0.0017	-0.0017	0.0161	0.0170	0.0100
	(0.0022)	(0.0022)	(0.0105)	(0.0105)	(0.0095)
Hurricane Rita	0.0223	0.0223	0.0211	0.0156	-0.0082
	(0.0186)	(0.0186)	(0.0189)	(0.0197)	(0.0056)
Hurricane Gustav + Ike	0.0222**	0.0226**	0.0240***	0.0326***	0.0133**
	(0.0096)	(0.0095)	(0.0096)	(0.0089)	(0.0057)
Hurricane Isaac	0.0034	0.0034	0.0139*	0.0157**	0.0032*
	(0.0033)	(0.0033)	(0.0080)	(0.0080)	(0.0018)
Hurricane Laura	0.0267	0.0267	0.0278	0.0341	0.0074
	(0.0230)	(0.0230)	(0.0229)	(0.0228)	(0.0030)
Hurricane Delta	0.0040	0.0040	0.0338	-0.0481	-0.0949
	(0.0161)	(0.0161)	(0.0337)	(0.0884)	(0.0826)

*,**,*** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county level.

Table B.8 Estimated Treatment Effects of Hurricanes on On-Farm Damages (Cotton – Yield Plans of Insurance)

	(1)	(2)	(3)	(4)	
Treatment Measure	(Wind)	(Wind)	(Wind)	(Wind)	(Rainfall)
Hurricane Lili	0.0544**	0.0556**	0.0666***	0.0507**	-0.0177*
	(0.0234)	(0.0233)	(0.0216)	(0.0235)	(0.0100)
Hurricane Katrina	0.0303	0.0307	0.0312	0.0304	-0.0045
	(0.0245)	(0.0250)	(0.0250)	(0.0252)	(0.0038)
Hurricane Gustav + Ike	0.1703***	0.1703***	0.2266***	0.2459***	0.0358**
	(0.0473)	(0.0473)	(0.0658)	(0.0656)	(0.0163)
Hurricane Laura	-0.0042	-0.0042	-0.0033	0.0042	0.0075
	(0.0069)	(0.0069)	(0.0072)	(0.0031)	(0.0065)
Hurricane Delta	0.0000	0.0000	0.0004	0.0004	0.0000
	(0.0000)	(0.0000)	(0.0007)	(0.0006)	(0.0002)

*,**,*** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county level.

Table B.9 Estimated Treatment Effects of Hurricanes on On-Farm Damages (Rice – Revenue Plans of Insurance)

	(1)	(2)	(3)	(4)	
Treatment Measure	(Wind)	(Wind)	(Wind)	(Wind)	(Rainfall)
Hurricane Lili	-0.0028	-0.0028	-0.0054**	0.0001	0.0054**
	(0.0017)	(0.0017)	(0.0021)	(0.0001)	(0.0021)
Hurricane Rita	0.0029	0.0310	0.0307	0.0375	0.0068***
	(0.0045)	(0.0278)	(0.0278)	(0.0277)	(0.0024)
Hurricanes Gustav + Ike	0.0019	0.0006	-0.0012	0.0302**	0.0364*
	(0.0192)	(0.0194)	(0.0218)	(0.0138)	(0.0198)
Hurricane Isaac	-0.0006	-0.0012	-0.0012	-0.0033	-0.0036
	(0.0009)	(0.0011)	(0.0011)	(0.0020)	(0.0019)
Hurricane Barry	-0.0021	-0.0037	0.0107	0.0188**	0.0178
	(0.0037)	(0.0037)	(0.0092)	(0.0076)	(0.0112)
Hurricane Laura	0.0443***	0.0448***	0.0472***	0.0326*	-0.0201**
	(0.0159)	(0.0157)	(0.0153)	(0.0172)	(0.0084)
Hurricane Delta	0.0066**	0.0069**	0.0135*	0.0171**	0.0067***
	(0.0034)	(0.0035)	(0.0075)	(0.0074)	(0.0027)

*,**,*** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county level.

Table B.10 Estimated Treatment Effects of Hurricanes on On-Farm Damages (Soybeans – Revenue Plans of Insurance)

	(1)	(2)	(3)	(4)	
Treatment Measure	(Wind)	(Wind)	(Wind)	(Wind)	(Rainfall)
Hurricane Lili	0.0014	0.0004	-0.0075**	0.0021	0.0100***
	(0.0013)	(0.0017)	(0.0037)	(0.0013)	(0.0036)
Hurricane Rita	-0.0023	-0.0068	-0.0077	-0.0227	-0.0172
	(0.0023)	(0.0049)	(0.0052)	(0.0186)	(0.0193)
Hurricane Gustav + Ike	0.0758	0.0756	0.0722	0.1129	0.0562***
	(0.0729)	(0.0729)	(0.0727)	(0.0717)	(0.0203)
Hurricane Isaac	-0.0040***	-0.0046***	-0.0047***	-0.0036**	0.0018
	(0.0015)	(0.0015)	(0.0015)	(0.0016)	(0.0027)
Hurricane Laura	0.0674	0.0657	0.0649	0.0637	-0.0018
	(0.0575)	(0.0575)	(0.0574)	(0.0577)	(0.0045)
Hurricane Delta	-0.0025*	-0.0027*	-0.0066***	-0.0171***	-0.0133***
	(0.0014)	(0.0015)	(0.0020)	(0.0048)	(0.0051)

*,**,*** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county level.

Table B.11 Estimated Treatment Effects of Hurricanes on On-Farm Damages (Corn – Revenue Plans of Insurance)

	(1)	(2)	(3)	(4)	
Treatment Measure	(Wind)	(Wind)	(Wind)	(Wind)	(Rainfall)
Hurricane Lili	0.0217*	0.0217*	0.0510	0.0885***	0.0383***
	(0.0121)	(0.0121)	(0.0362)	(0.0346)	(0.0114)
Hurricane Rita	-0.0026**	0.0063	0.0157	0.0128	-0.0045
	(0.0012)	(0.0087)	(0.0137)	(0.0140)	(0.0038)
Hurricane Gustav + Ike	0.0360**	0.0360**	0.0339*	0.0543***	0.0374***
	(0.0173)	(0.0173)	(0.0176)	(0.0166)	(0.0126)
Hurricane Isaac	0.0008	0.0008	0.0169	0.0174	0.0010
	(0.00610	(0.00610	(0.0120)	(0.0189)	(0.0043)
Hurricane Laura	0.0338	0.0338	0.0348	0.0290	-0.0104
	(0.0219)	(0.0219)	(0.0219)	(0.0245)	(0.0121)
Hurricane Delta	0.0223**	0.0223**	0.0182	0.0138	-0.0063
	(0.0115)	(0.0115)	(0.0115)	(0.0121)	(0.0048)

*,**,*** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county level.

Table B.12 Estimated Treatment Effects of Hurricanes on On-Farm Damages (Cotton – Revenue Plans of Insurance)

	(1)	(2)	(3)	(4)	
Treatment Measure	(Wind)	(Wind)	(Wind)	(Wind)	(Rainfall)
Hurricane Lili	0.0789	0.0789	0.0886	0.1814*	0.0928***
	(0.0773)	(0.0773)	(0.0982)	(0.0926)	(0.0328)
Hurricane Gustav + Ike	0.2979**	0.2979**	0.3074***	0.2819*	-0.0365
	(0.1202)	(0.1202)	(0.1141)	(0.1489)	(0.1158)
Hurricane Laura	0.0771	0.0766	0.1187	0.1365*	0.0194
	(0.0726)	(0.0726)	(0.0809)	(0.0796)	(0.0186)
Hurricane Delta	0.0020	0.0020	-0.0007	-0.0223**	-0.0257**
	(0.0023)	(0.0023)	(0.0035)	(0.0108)	(0.0105)

*,**,*** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county level.