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

Crop Insurance Participation Rates and Asymmetric Effects on U.S. Corn and Soybean Yield Risk

Lawson Connor and Ani L. Katchova

Lawson Connor is an assistant professor in the Department of Agricultural Economics and Agribusiness at Louisiana State University and Ani L. Katchova is an associate professor and the Farm Income Enhancement Chair in the Department of Agricultural, Environmental and Development Economics at The Ohio State University.

Abstract

Crop insurance and its related components, such as premium subsidies, have impacts on farm management decisions, production practices, and output. We use county-level USDA survey data combined with instrumental variables analysis to investigate asymmetric impacts of crop insurance on corn and soybean yield variance. Our results indicate an increase in yield downside risk as crop insurance participation rates increase. We also find an increase in drought susceptibility, likely due to expansion to lower-quality farmland and changes in input use. Increased yield variability could have effects on prices, farm income variability and farmer welfare.

Keywords: asymmetric effects, crop insurance, yield risk

Introduction

Agricultural sustainability has increased in political significance, even occupying significant space in the 2018 Farm Bill. The farm financial downturn that started in 2013 has shown the effect that weather shocks, such as droughts, can have on farm incomes and the farm economy. Increased frequency and increased susceptibility to these events are therefore of concern to farmers going forward. Since farm policy plays a role in protecting farmers from such downturns, it is important to investigate their effectiveness and to determine the existence of any unintended effects.

Many studies have investigated moral hazard and adverse selection in crop insurance. As the proportion of insured acres has increased to above 80%, concerns over adverse selection have decreased but not disappeared in recent years. Subsidies in the insurance market only increase these concerns. Several studies have noted recent increases in drought susceptibility for major crops in the Midwest (Lobell et al. 2014) and, perhaps as a result, recent increases in price volatility (Newman and McGroarty, 2017). Increased price and yield volatility in agricultural markets can affect production planning and therefore farm incomes over time. We investigate whether crop insurance and moral hazard play a role in changing variability and drought susceptibility of U.S. corn and soybean yields. Specifically, we explore the impact of crop insurance on the partial variance of corn and soybean yields. Exploring partial moments will reveal much richer information than an analysis of full moments alone and will specifically allow an analysis of the effects due to droughts.

Several studies have investigated the existence of moral hazard in crop insurance, with most focusing on how moral hazard can affect input use. Wu (1999), Goodwin et al. (2004), and Yu, Smith, and Sumner (2018) independently show that crop insurance and its subsidies can have a small but statistically significant effect on crop acreage. Others have shown that crop insurance can affect chemical input use on the farm (Smith and Goodwin, 1996; Claassen, Langpap, and Wu, 2017). O'Conner (2013) suggests that reductions in on-farm risk management, such as conservation till or cover cropping, are possible while covered by crop insurance if crop insurance is seen as a (cost- and time-saving) substitute to these practices. Such reductions in on-farm risk management practices can make farm output more susceptible to negative shocks such as droughts. However, Weber, Key, and O'Donoghue (2016) find little effect on input use. Schoengold, Ding, and Headlee (2015) find no significant evidence of moral hazard related to crop insurance participation, though indemnity payments were found to increase the use of no-till and decrease the use of conservation till.[1] This finding may suggest that the ease of use (and time savings) may be of higher value than other cost factors.

Few studies have looked at how output (yield) is potentially affected by crop insurance. Coble et al. (1997) show that expected indemnities can affect crop production of covered crops in poor production years. Cornaggia (2013) finds that crop insurance can increase farm productivity by allowing farmers to gain greater access to financing options. Annan and Schlenker (2015) show increased sensitivity of corn and soybean yields to extreme heat under crop insurance but no significantly different effect from moderate heat. On the other hand, Yu and Babcock (2010) use a drought index formed from observations of precipitation and temperature and find that corn and soybean yields have become more drought tolerant over time, although this finding is not linked to crop insurance use. Both Annan and Schlenker (2015) and

---

[1] We define no-till here as any practice in which residue cover was found on >30% of the farmed area.

Yu and Babcock (2010) use measures of extreme weather that do not account for various factors that affect yield losses, such as available soil moisture.

We draw on the work of Annan and Schlenker (2015), Yu and Babcock (2010), and Lobell et al. (2014) and update their findings in a few important ways. Primarily, we expand on findings in Lobell et al. (2014) and attempt to identify the contribution of crop insurance to changes in yield risk, particularly to drought sensitivity. As in Lobell et al. (2014), we use the vapor pressure deficit as our measure of extreme weather to account for soil moisture and other factors that better explain yield losses during drought events. Additionally, we specifically account for the issue of endogeneity in crop insurance use, unlike studies such as Annan and Schlenker (2015). Unlike prior studies, we investigate yield variance as the outcome variable and account specifically for asymmetric effects, which can help distinguish between productivity-enhancing versus downside-risk-increasing effects. Finally, we account for the proliferation of genetically modified (GM) crops and other economic factors that have affected yield risk profiles concurrently with the expansion of crop insurance. Hence, our study gives better insights into risk changes from factors related to underlying resource management shifts.

Our results suggest that crop insurance is associated with increases in yield variability and in drought sensitivity. Increases in yield risk can be considered an expected and allowable byproduct of crop insurance as farmers are able to take on more risk to expand production. Indeed, the expansion in crop insurance since the mid-1990s has also been accompanied by considerable increases in yields, perhaps not coincidentally. However, our results suggest that some adverse effects potentially exist and are worth further study. Increases in drought susceptibility can mean an increase in the frequency of extreme events that occurred post-2012, especially under expected increases in crop stress from climate change.

Crop Insurance and Yield Variability

Crop insurance can affect crop yield variability and drought sensitivity through various channels. Studies on the effect of moral hazard in crop insurance have yielded differing conclusions, though some have found changes in input use and acreage. Acreage expansion will typically increase yield variance for several reasons. Primarily, however, variance in land quality and management abilities increases as acres increase (Yang, Koo, and Wilson, 1992), affecting overall yield variance. Productivity increases (higher yields) can also lead to higher yield variance. Interactions between weather and high productivity factors can mean that yields are high during good growing conditions but fall to typical levels when conditions are less favorable. Similar factors contribute to yield-increasing inputs such as fertilizer often being categorized as risk-increasing inputs in the literature (Antle 2010).

Similarly, nonagronomic factors can also play a role in determining a link to yield variance and crop insurance through increased access to short-term financing that can increase productivity (Cornaggia, 2013; Ifft, Kuethe, and Morehart, 2015). Decreases in risk exposure can also increase technology adoption (Aldana et al. 2011) which can affect yield risk in ways that are difficult to determine *ex ante*.

Changes in land management can also be a factor that cause changes in crop yield variance both in the near term and over time. If crop insurance leads to changes in tillage practices or allows substitution from practices that maintain land quality over time, then yields can become more variable in the long run. One effect that results from such changes over a relatively short window is a change in drought susceptibility of yields. As acres expand, changes in planting density and increases in soil tilling can also reduce organic matter in the topsoil and decrease the water-holding capacity of the soil (Balesdent, Chenu, and Balabane, 2000).

Different sources can create changes in yield variance under crop insurance. Their effects on the symmetry of the distribution of crop yields likely also differ. Understanding how the upper tail of the distribution of yield changes relative to the lower tail under crop insurance is important from a policy perspective. Changes in the upper tail typically imply increases in productivity and can sometimes be accompanied by changes in the lower tail (downside risk) as well. Weighing the costs and benefits of these changes is important for policy makers. Some understanding of the source of these changes is also important. Particularly for field-crop agriculture, changes to land management and soil traits that affect drought and other downside risks can increase the cost of providing crop insurance over time and can also affect long-run productive capacity. Therefore, understanding how policy affects the symmetry of yields is of significant policy relevance.

Empirical Specification

To investigate the effect of crop insurance on downside risk, we follow a method outlined in Antle (2010) that uses partial moments to estimate asymmetric effects of explanatory variables on yield distributions. Antle points out that when factors induce a symmetric effect on a probability distribution, a partial and full moment analysis yield identical results when looking at even moments. However, when effects are asymmetric, estimated coefficients are different and have different behavioral implications if individuals are assumed to value upside and downside risks differently.

To derive estimation equations, we first treat corn or soybean yield (Y) as a random variable with a lower bound 0 and an upper bound, g g, which is determined by factors such as crop/variety genetics . Thus, we define the conditional probability density function of yield as $\phi(Y \mid \mathbf{x})$ on the finite interval $(0, g)$; $\mathbf{x}$ is a vector of factors that affect the moment of interest. The conditional expectation of yield, which we represent as $\mu_1(\mathbf{x})$, is defined as

(1) $$\mu_1(\mathbf{x}) = \int_0^g Y\phi(Y \mid \mathbf{x})dY.$$

Higher-order moments are defined as

(2) $$\mu_p(\mathbf{x}) = \int_0^g \left(Y - \mu_1(\mathbf{x})\right)^p \phi(Y|\mathbf{x})dY$$
$$\text{for } p = 2, 3, 4, \ldots$$

The partial moment is taken with respect to a reference point, r. Given a reference point, we define the partial moments as

(3) $$\mu_p^+(\mathbf{x}, r) \equiv \int_r^g \{Y - r\}^p \phi(Y \mid \mathbf{x});$$

(4) $$\mu_p^-(\mathbf{x}, r) \equiv \int_0^r \{Y - r\}^p \phi(Y \mid \mathbf{x}),$$

where μ_p^+ refers to the upper partial moment and μ_p^- to the lower partial moment. In this study, we set $r = \mu_1(\mathrm{t})$ such that $\mu_p^+(\mathbf{x}, r)$ and $\mu_p^-(\mathbf{x}, r)$ are defined with respect to a quadratic trend of yield of the specific crop of interest. Empirical equivalents of equations (1), (3), and (4) can be specified as

(5) $$Y = \hat{\mu}_1(\mathbf{X}) + e;$$

(6) $$e^{p+} = \hat{\mu}_p^+(\mathbf{X}) + \upsilon_p;$$

(7) $$e^{p-} = \hat{\mu}_p^-\left(\mathbf{X}\right) + \nu_p,$$

where e^{p+} and e^{p-} are the predicted residuals (e) from equation (5) raised to the power p for values of $e > 0$ and $e \le 0$, respectively, given the reference, $r = \mu_1\left(\mathrm{t}\right)$. Specifically, we generate predicted values of e in two steps. We first fit a quadratic trend to both corn and soybean yields. The predicted residuals are scaled proportionally to their distance from the trend yield and centered on 2016 predicted yields to approximate a stationary distribution for corn and soybeans. Equation (5) is then estimated using the new yield distributions. Predicted residuals from equation (5) are used to estimate equations (6) and (7). As Pope and Just (1977) point out, the predicted residuals of equation (5) can serve as unbiased estimators of the disturbance terms that give rise to the distribution of Y. In general, ν_p and υ_p are heteroskedastic, and heteroskedasticity-corrected estimation procedures must be used. Finally, we combine equations (6) and (7) to estimate them as a single equation. Expanding to reveal key parameters, we derive

(8) $$e^p = \delta\hat{\mu}_p^+\left(\gamma I + \lambda\mathbf{X}_{-\mathbf{I}}\right) + \left(1-\delta\right)\hat{\mu}_p^-\left(\gamma I + \lambda\mathbf{X}_{-\mathbf{I}}\right) + \delta\upsilon_p + \left(1-\delta\right)\nu_p;$$

(9) $$e^p = \delta\hat{\mu}_p^+\left(\gamma I\left(1+\eta D\right) + \lambda\mathbf{X}_{-\mathbf{I,D}}\right) + \left(1-\delta\right)\hat{\mu}_p^-\left(\gamma I\left(1+\eta D\right) + \lambda\mathbf{X}_{-\mathbf{I,D}}\right) + \delta\upsilon_p + \left(1-\delta\right)\nu_p,$$

where δ is an indicator such that $\delta = 1$ when $e > 0$ and 0 otherwise; D is an indicator that represents the occurrence of a drought; $\mathbf{X}_{-\mathbf{I,D}}$ is a vector of exogenous covariates that affect crop yield variability and excludes the measures of crop insurance use and drought.[2] Equation (8)

[2] Exogenous here refers to variables not directly under the influence of farmers. Hence, they are unlikely to suffer from issues that are a threat to causal identification. Variables such as crop insurance premiums have been excluded from $\mathbf{X}$ since insurance premiums, in addition to representing relative risks across counties, are also influenced by management practices.

estimates the effect of crop insurance use on yield variance. Equation (9) includes an interaction of crop insurance use and the occurrence of a drought to determine the relative sensitivity of crop yield to the occurrence of a drought. The parameters $\delta\gamma$ and $\left(1-\delta\right)\gamma$ represent the effect of crop insurance participation rates (I) on the upper and lower partial moments, respectively; $\left(1-\delta\right)\eta D$ is a final variable of interest, representing the additional effect of crop insurance participation on yield downside risk given a drought occurred. For this study, we take $p = 2$, making $\hat{\mu}_p^+$ and $\hat{\mu}_p^-$ similar to the definition of the semi-variance. We also estimate the upper and lower partial variances of both corn and soybeans in the same equation.[3]

Endogeneity of Crop Insurance Participation with Yield Variance

Direct estimation of equations (8) and (9) would yield biased estimates of the effect of crop insurance use on yield partial variances. A few studies have discussed potential endogenous factors that would affect a study of crop insurance impacts at the national level and with the use of aggregated data. Glauber (2013) points out that crop insurance adoption tends to be highest in low-risk regions, which would lead to a downward bias in estimating the effect of crop insurance on yield variance. Yet weather risks have potentially increased over time as the use of crop insurance has also increased, driving the direction of bias in the opposite direction.

Finger (2012) points out that data aggregation leads to a downward bias in the estimation of a variance effect in farming; negative correlations across farms often lead to aggregate-level

[3] The underlying assumption that drives our empirical analysis is that once controlling for crop specific fixed effects and our included covariates, the variation that remains will be identical for each crop.

estimates of yield variance to be lower than individual-level estimates. Farmers may also change coverage levels based on anticipated outcomes before the season, which would play a role in affecting identification. Such changes, related to intertemporal adverse selection discussed in Coble et al. (1996), would induce a spurious positive relationship between crop insurance participation and yield variability due to the timing of sign-up rather than through a causal impact of crop insurance on farm yield variability. We include fixed effects in our estimation, which helps to reduce the impact of some of these potential biases. However, fixed effects alone are unlikely to eliminate all endogeneity issues. To further control for endogeneity, we apply an instrumental variables (IV) technique.

Crop Insurance Policies and Their Use as Instruments

The literature on crop insurance has previously identified two instruments for crop insurance participation based on national policy changes. Schoengold, Ding, and Headlee (2015) proposed an instrument for crop insurance participation based on changes in national policy that shifted trends in participation at specific points in time. Key Farm Bill updates in 1994, 2000, 2008, and 2014 affected crop insurance participation. The instrument exploits changes in crop insurance use from policies that initially involved mandates then, later, other incentives. The Crop Insurance Reform Act of 1994 was passed to decrease farmer reliance on ad hoc government payment programs. The program tied access to some federal programs to participation in crop insurance. The act also introduced catastrophic risk protection (CAT), which covered 50% of yield losses at 60% (now 55%) of the expected market price. This policy shifted participation along the extensive margin, with most sign-up happening at the catastrophic level after its passage (Glauber, 2013).

To encourage higher buy-up coverage, the Agricultural Risk Protection Act of 2000 increased subsidy rates at higher buy-up levels. Buy-up policies covered 9% of eligible acres before the act was passed but rose to above 60% by the late 2000s. The 2000 act therefore had a bigger effect on the intensive margin of crop insurance participation. The 2008 and 2014 Farm Bills also introduced subsidy rate changes and additional changes that further encouraged higher buy-up rates. To form the first instrument, we use indicators that are set to 1 for years within the respective policy periods and 0 otherwise and regress these on the crop insurance participation rates in the first stage of a multistage routine.

The second instrument is based on policy changes to subsidy rates, defined as the total national subsidies granted divided by the total national premiums. Hence, for each of the yield and revenue protection coverages, we use total subsidies divided by total premiums for each of the 75% and 65% coverage levels for yield and revenue protection. Like Yu, Smith, and Sumner (2018), we exclude the 1999 policy year because of potential bias, where policies were themselves influenced by weather events. This second instrument differs from the first instrument as crop insurance subsidies directly influence demand for crop insurance and are unrelated to other programs. As in Yu, Smith, and Sumner, we use the 65% and 75% coverage levels because observations exist for all years.

Comparing the results produced from the two instruments will help us to understand how well we have identified the effect of interest. We expect that both instruments, if generating exogenous variation, will produce similar results. The timing of passing crop insurance legislation was typically outside of years in which shocks to yields of corn and soybeans occurred. Additionally, our specification uses the lag of crop insurance participation averaged over the prior 3 years to reduce the effect of intertemporal adverse selection. We also include fixed effects to control for systemic differences in yield risks across counties. Crop-county-specific trends are also included.

Instrumental Variables Estimation

IV estimation of equations (8) and (9) requires consideration of two additional empirical challenges. First, the crop insurance participation rate, I, is continuous and bounded between 0 and 1. In a two-stage procedure, as used in Schoengold, Ding, and Headlee (2015) and Yu,Smith, and Sumner (2017), first-stage estimation proceeds via

$$I = \beta\mathbf{Z} + \rho\mathbf{X} + \varepsilon, \tag{10}$$

where $\mathbf{Z}$ are instruments and equation (10) is typically a linear function. However, Papke and Wooldridge (2008) point out that I being continuous and bounded between 0 and 1 implies a nonlinear function that links $\boldsymbol{Z}$ and $\boldsymbol{X}$ to I, making equation (10) biased if using a linear specification. Logit and probit functions are also incompatible here given their likelihood functions are derived by assuming I is a binary (0,1) variable. Papke and Wooldridge (2008) propose a quasi-maximum likelihood procedure that allows for a fractional dependent variable, bounded by 0 and 1. We use this method in our first-stage estimation.[4]

Second—unlike in Schoengold, Ding, and Headlee (2015) and Yu, Smith, and Sumner (2018)—the parameters of interest, $\delta\gamma$, $\left(1-\delta\right)\gamma$, and $\left(1-\delta\right)\eta D$, are interaction terms. Angrist and Pischke (2008) point out that predicted instruments in a second-stage regression where similar interaction do not appear in the first stage may result in a violation of the $E\left(\mathbf{X},\varepsilon\right)=0$ condition. A similar issue arises because of the nonlinear first stage we employ. Angrist and

[4] Table S1 of the Supplementary Material presents results based on a linear first stage.

Pischke (2008) recommend first generating predictions from the first stage then using the predictions themselves, along with appropriate interactions, as instruments in a one-step generalized method of moments (GMM IV regression. We use this multistage implementation of the IV here.[5]

Finally, to account for slow-changing effects of crop insurance that affect yield risks over time (e.g., acreage expansion), we form the instrument by taking the prior 3-year average of the predicted values of crop insurance participation $\hat{I}$ from equation (10).[6] This specification also helps reduce the effect of year-to-year crop insurance participation decisions that may be more related to intertemporal adverse selection rather than permanent changes in the risk structure of yields. The final equations of interest are

(11) $$e^p = \delta\hat{\mu}_p^{+}\left(\gamma\hat{I} + \lambda\mathbf{X}_{-\mathbf{I}}\right) + \left(1-\delta\right)\hat{\mu}_p^{-}\left(\gamma\hat{I} + \lambda\mathbf{X}_{-\mathbf{I}}\right) + \delta\upsilon_p + \left(1-\delta\right)\nu_p;$$

(12) $$e^p = \delta\hat{\mu}_p^{+}\left(\gamma\hat{I}\left(1+\eta D\right) + \gamma\mathbf{X}_{-\mathbf{I}}\right) + \left(1-\delta\right)\hat{\mu}_p^{+}\left(\gamma\hat{I}\left(1+\eta D\right) + \gamma\mathbf{X}_{-\mathbf{I}}\right) + \delta\upsilon_p + \left(1-\delta\right)\nu_p;$$

which estimate the effect of crop insurance on the partial moments of yield and drought susceptibility. $\hat{I}$ is the instrumented 3-year average value of the crop insurance participation

[5] Alternatively, we could use the heterogeneous treatment method described in Angrist and Pischke (2008). Table S4 in the Supplementary Material briefly describes the specification and results.

[6] We chose a 3-year average because the first policy year used as an instrument is 1994. Given that our first observation was in 1989, the 3-year window allows for 2 years of pre-1994 observations to be included in the estimation for proper identification of the instrument and the results of interest.

rate. Estimates from this procedure can be interpreted as the effect of sustained (or average) county-level crop insurance participation rate on the partial variance of corn and soybean yields.

Data Description

Data for this study are drawn from several sources. The Risk Management Agency's (RMA) summary of business provides county-level crop insurance data. The year 1989 was the first year available at the time the data was gathered, and we use it as our starting date in this study. The National Agricultural Statistics Service (NASS) provides agronomic variables such as corn and soybean yields. We use data from 1989–2016 to conform with the RMA data. Futures prices were obtained from the Quandl database, and weather variables were obtained from the Oregon State PRISM database. Finally, for the proportion of GM corn and soybeans, we used Economic Research Service (ERS) county-level data from June Agricultural Survey results (2000–2016) and state-level data published in Fernandez-Cornejo and Mcbride (2002) for 1996–1999.[7] Prior studies have shown that GM crop affect yield risk, so we include them to reduce omitted variable bias.

We also generate several key variables from the data gathered. The primary variable of interest is the crop insurance participation rate. We use the definition introduced in Goodwin et al. (2004), which is the total actual liabilities insured divided by the total insurable liabilities of specific commodities within each county. The variable accounts for variation along the extensive and intensive margins of crop insurance participation (use versus nonuse or amount of buy-up coverage purchased).

[7] Results were similar when estimated with the variable defined at the national level for all years.

Actual liabilities insured can be obtained from the RMA summary of business. We use the sum of acres under yield or revenue insurance plans for corn and soybeans to calculate actual liabilities insured by crop. We exclude acres covered under a group or area plan.[8] Total insurable liabilities are unobserved. Goodwin et al. (2004) suggest approximating total insurable liabilities by taking the product of corn or soybeans acres planted, the average yield in each county in the previous 10 years, the mean of the daily settle prices for December corn or November soybean futures contracts during the month of February, and the maximum coverage level of 0.85. Dividing actual liabilities by total insurable liabilities gives the crop insurance participation rate. Our final version of the crop insurance participation rate is found as the average rate of the 3 years prior to the year in which yields were observed.

Since NASS planted acres are based on survey estimates and RMA planted acres are based on reported acres from insured farmers, there are several cases in which planted acres from RMA (in our numerator) is greater than planted acres from NASS (used to calculate our denominator). As a result, our calculated crop insurance participation rate is sometimes greater than 1. As a fix, we use the maximum crop insurance rate found for a county to adjust all other rates within the county.[9] The fix ensures that the participation rate is bounded between 0 and 1 without losing variation from censoring rates above 1.

---

[8] A majority of corn and soybean acres are covered under revenue and yield protection plans. Incentive structures under area-based policies are also likely different than those under revenue and yield protection plans.

[9] Table S2 in the Supplementary Material presents results with affected counties removed.

Other variables generated include several market/economic variables that influence farmer agronomic decisions. The soybean-to-corn price ratio is the ratio of the average futures price (the average daily closing price between January 1 and March 15) of soybeans and corn before crop insurance sign-up. The price of soybeans relative to corn prior to planting can affect relative acres of corn and soybeans planting intentions and likely influences other production practices going forward. We use expected price as a measure of the information about harvest-time prices contained in the average futures price prior to crop insurance sign-up. The variable is generated as in Yu, Smith, and Sumner (2018) by regressing the average daily closing futures price from January to the crop insurance sign-up deadline, state fixed effects, and a year trend on harvest time prices. The ratio of sign-up to in-season futures price is the ratio of the futures price prior to sign-up to the average futures price during the growing season (we use April 1 to September 30) and captures changes in profitability expectations as the growing season progresses.

Generated weather variables include cumulative growing-season precipitation and total heating degree days (HDD). As in Roberts, Schlenker, and Eyer (2013) and Tolhurst and Ker (2015) we define the heating degree days as the number of days above 29°C. We include a 10-year rolling average of growing-season precipitation variance to capture differences in weather risks across counties. To obtain incidences of drought, we follow Daly, Smith, and Olson (2015) and calculate the county-level growing-season vapor pressure deficit (VPD) using daily mean and dew point temperatures from the PRISM database.[10] Since there is no agreed-upon standard

[10] An alternative is the Palmer Drought Severity Index (PDSI); we discuss its performance relative to the VPD and present results in the Supplementary Materials and Table S3.

for identifying a drought using VPD, we use the 90th percentile of the VPD as our threshold for drought.

After dropping counties with missing observations to produce a balanced panel, the final dataset contained 23,296 county-crop-year observations. After forming our 3-year averaged crop insurance participation rate, the final-stage dataset contained 20,800 observations. Table 1 summarizes the variables included in the estimation.

Results and Discussion

We modify for instrumental variables, a procedure presented in Antle (2010) to estimate asymmetric effects of crop insurance on yield variances of corn and soybeans. Crop insurance participation rate, defined as a lagged 3-year average participation rate at the county level, is used to determine the effect of average crop insurance use on yield variability and drought risk. Tables 4–6 present the results. Table 4 reports the results of the ordinary least squares (OLS) and fixed effects specifications. Tables 5 and 6 report the fixed effects IV results. Table 6 contains the drought interaction results. We use appropriate modifications to allow for the interaction of the instrument in each case as described in the empirical section.

Estimated Effect of Included Controls

Table 2 reports the behavior of the standard deviation of log yields over time. The variance of yield for both corn and soybeans initially dipped between 1994 and 1999. For corn, the initial decrease was followed by a steady increase in variance, while the variance for soybeans varied over time. The overall effect is a decrease in the variance of corn and soybean yields over 1994–1999. It is important to point out that several confounding factors make it difficult to assess the impact of crop insurance on variances during this period. As crop insurance has expanded, other changes have taken place simultaneously, such as increased adoption of GM crops. Our analysis next aims to control for these factors to the extent possible to gain insights into the effect of crop insurance on yield variance resulting from land management and potential moral hazard issues.

We include economic variables in our procedures to capture changes in market conditions that can affect yield variability. As they capture multiple simultaneous economic factors, their coefficients are difficult to interpret. However, their coefficients generally agree across all specifications in both sign and magnitude, with statistical significance, suggesting the variables are able to absorb some of the year-to-year market factors that would confound our results.

Our agronomic variables perform as expected. Results in Tables 5 and 6 agree with the literature, showing that GM adoption has decreased overall yield variance, with the decrease primarily coming from the lower partial variance (decrease in downside risk). Specifically, a 1-percentage-point increase in the GM adoption rate decreases downside risk by 1.8%–2.1%. As noted earlier, increases in planted acres increases the overall variability of corn and soybean yields. Our results indicate that land expansion has a greater effect on the lower partial variance than on the upper partial variance. Tests of equality of the two coefficients are rejected at greater than the 1% significance level. As previously mentioned, acreage expansion is expected to increase yield variance (particularly on the lower tail of the distribution) as the variance of management and land quality, among other factors, increases as acres expand. More irrigated acres are associated with increasing yields and reduced downside yield risks, although we do not recover statistical significance on the lower partial variance.

The included climate variables also perform as expected. Increasing the number of HDD increases downside risk (positive effect on the lower partial variance) indicating the effect of heat stress on corn and soybeans. Growing-season precipitation is associated with a decrease in downside risk and has an increasing effect on the upper partial variance, indicating the benefit that sufficient rainfall during the growing season has on yields. The 10-year variance of growing-season rainfall in associated with approximately a 4% increase in downside risk, indicating the stress that weather variability can create for crop growing conditions. As expected, droughts are associated with a 9.3% increase in the lower partial variance of corn and soybean yield from a 1-percentage-point increase in drought severity.

Estimated Effect of Crop Insurance

The naïve (fixed effect only) specification in Table 5 shows a minimal effect of crop insurance on yield variance, slightly leaning toward a reducing effect. Glauber (2013) and Table 4 gives some context for interpreting this result. Glauber mentions that the highest use of crop insurance is in the highest-productivity, lowest-variance areas of the United States (i.e., the Corn Belt, mostly situated in the Midwest). The OLS results in Table 4 without including fixed effects support this conclusion. We recover a significant negative coefficient for crop insurance on the lower partial variance and a moderate increase in the upper partial moment (albeit without statistical significance). Adding fixed effects reduces the size of the effect and brings the significance level closer to 0 (on the lower partial variance), as expected. However, the location concentration effect (and likely other endogenous factors) are not completely eliminated.

To recover the effects of interest, our analysis therefore uses IVs, which use exogenous variation based on policy changes that affect demand for crop insurance. Incentives for the policy changes have largely been to reduce reliance on ad hoc payments and encourage farmers to use crop insurance as their primary means of risk management. The first IV is based on the timing of the passage of policies that have affected crop insurance use through multiple channels. The second IV is based on changes to the subsidy rate of crop insurance, and so it exploits exogenous changes to the cost of acquiring crop insurance. Finally, we compare the results produced from both IVs to gain some insight into their performance.

Tables 5 and 6 show that both IVs have very similar coefficients for the effect of crop insurance on yield variance. Since the partial variance is log-transformed and the crop insurance participation rate is bounded between 0 and 1, the coefficients indicate percentage changes if the crop insurance participation rate rose to 100%. Interpreting the results based on a 1-percentage-point change in crop insurance is more practically meaningful. Both IV specifications show that a 1-percentage-point increase in the 3-year average county-level crop insurance participation rate is associated with a 5.2%–5.5% increase in the lower partial variance of yields at the county level. In output terms, this translates to an additional 2.2 bu/acre on average for corn and 0.8 bu/acre for soybeans in a year when yield losses occur. We also find an increase in the upper partial variance of 3.7%–4.2% due to a 1-percentage-point increase in the crop insurance participation rate. This translates to an additional 1.7 bu/acre on average for corn and 0.6 bu/acre for soybeans in years of good yields. Overall, Table 5 shows that yield variance under crop insurance has increased to a small extent with a slight increase in skew toward the left tail of the crop yield distribution. Work from Sandmo (1971) suggests that this is a reasonable expectation. As farmers have gained access to crop insurance, they have been able to take on more risk; perhaps as a result, yields have seen significant increases over the last few years. New technologies, access to financing (Cornaggia, 2013), and even increased use of chemical inputs (Claassen, Langpap, and Wu, 2017) have meant increased productivity, while increasing risks (and, to a slightly greater extent, downside risk) to some degree (Antle, 2010).

Table 6 presents the results after we include an interaction that represents the occurrence of a severe drought (a 10% probability event). The results are consistent with those in Table 5. An increase in crop insurance participation rates increases the drought susceptibility of corn and soybean yields. Specifically, a 1-percentage-point increase in the 3-year average use of county-level crop insurance participation rate accounts for a 1.2% increase or an additional 0.3 bu/acre for corn and 0.1 bu/acre for soybeans of additional yield losses during a drought. Table 7 presents the over-identifying and weak instrument tests.

The finding of an increased drought effect links crop insurance to an effect found in Lobell et al. (2014) of increased crop susceptibility to drought. The increased drought susceptibility combined with controlling for planted acres suggests that acreage expansion alone is insufficient to explain the overall increase in yield risk that we find and that factors related to soil moisture retention potentially play a role as well. Several factors could cause changes in average moisture retention of farmed land. Acreage expansion under crop insurance has likely drawn in more low-quality land than the scenario in which crop insurance is absent. Table 8 provides some evidence that suggests that acreage expansion under crop insurance is associated with lower average land quality. The National Crop Productivity Index (NCCPI) from the National Resources Conservation Service (NRCS) is a land quality measure that accounts for soil water-holding capacity in addition to other characteristics related to yield performance. Mean NCCPI across the entire sample is 0.62 (on a scale of 0.00 to 1.00). Table 8 presents the results of OLS regression analysis that suggests that a 1% increase in crop acreage under crop insurance is associated with a 0.4-percentage-point decrease in the NCCPI. The acreage channel was likely less important prior to the 1996 Freedom to Farm Act but is a likely an important factor in later periods of our sample. Other factors likely contribute as well.

Lobell et al. (2014) point out that increases in planting density could also be linked to our finding of an increase in drought sensitivity. The downside protection provided by crop insurance may encourage higher planting density since increasing the planting density can increase yields in good growing conditions but can also increase the risk of greater loss during dryer years. Crop insurance coverage reduces the cost of such a risk. The results in Schoengold, Ding, and Headlee (2015) also hint that time costs might also be important. Payments from crop insurance were linked to increased use of no-till compared to conservation till, despite conservation till being a lower cost investment (Epplin et al., 2005; Schoengold, Ding, and Headlee, 2015). However, no-till reduces time costs compared to conservation till. Therefore, time-saving aspects of crop insurance may also substitute for more time-consuming practices on the farm that reduce risks over time or maintain soil water holding capacity. Investigating the relative contributions of these various factors is outside the scope of this paper.

Conclusion

In this study, we investigate the relationship between crop insurance and its asymmetric impacts on corn and soybean yields. Crop insurance has become an integral component of the U.S. farm economy, and significant research has been conducted to ensure its optimal performance. Crop insurance has certainly served its function of maintaining farm incomes (Key, Prager, and Burns, 2018). However, some understanding of potential long-term impacts is also necessary to ensure the efficiency of the program and U.S. agriculture in general. We find evidence of a relationship between average crop insurance participation rates and an increase in downside risk for corn and soybean yields. Across two IV specifications, we find an approximately 5.2%–5.5% increase in the lower partial variance of yield from a 1-percentage-point increase in the average county-level crop insurance participation rate and a simultaneous increase of approximately 3.7%–4.2% in the upper partial variance. Similarly, we find that drought susceptibility increases by approximately 1.2% when the average crop insurance participation rate increases by 1 percentage point, linking crop insurance, at least partially, to a finding in Lobell et al. (2014) of increased drought susceptibility of yields.

Our findings translate to an average increase of 1.6 bu/acre for corn and 0.6 bu/acre for soybeans in yield upside in favorable years and average increase of 2.2 bu/acre and 0.8 bu/acre of additional yield losses for corn and soybeans, respectively, during unfavorable years. This increases to an additional 0.3 bu/acre for corn and 0.1 bu/acre for soybean in severe drought years. The relative sizes of changes suggest that crop insurance could potentially reduce farm income variability (as found in Key, Prager, and Burns, 2018), despite changes to yield variance. The combination of crop insurance payments during down years and the ability to smooth income across favorable and unfavorable years would help maintain farm income stability. Our results also suggest that crop insurance has allowed farmers to take on additional yield risk, likely contributing to the increased productivity and yield expansion observed over the past several years.

We used the 90th percentile of the distribution of VPD to represent drought. Therefore, our results imply that increasing average coverage level from CAT to 70% coverage under a yield guarantee can increase underwriting costs by approximately $3.0 billion for corn and soybeans combined over a 10-year period. Revenue coverage costs likely increase by a smaller amount given the offsetting price effect. It is uncertain how such yield losses would affect farmers, as some may benefit in drought years if prices increase to the point that high revenues are achieved. This gain though, is unlikely to be evenly distributed across all farms, particularly where yield losses are especially severe. Nevertheless, increased drought susceptibility comes with additional costs, including increased price volatility, which can affect nonadopters of crop insurance and firms at higher vertical distances in the supply chain. Price variations are likely to spill over to other related markets as well.

Further research is needed to understand the sources of increased downside risk. Several factors likely contribute to this effect with different long-run implications. To the extent that increases in planting densities play a role, optimal planting densities can be investigated such that yield gains can still be realized while minimizing the cost of drought losses. Also important is understanding the relationship between conservation practices and crop insurance and the extent to which relative time/cost factors are involved. Premium rates may be adjusted to reflect the long-run benefits conferred on farmers adopting such practices. Recent interest in conservation practices show recognition of the role of such practices in reducing externalities from farming and maintaining long-run productive capacity.

Long-run implications differ if planting density and new, lower-quality land brought into agriculture are sufficient to explain our results compared to the case of significant changes to land already under production. The latter suggests that our effect increases in magnitude over time. Nevertheless, as droughts are one of the most significant sources of losses in U.S. agriculture and the possibility exists of increased exposure to drought as a result of climate change, attention is still needed to safeguard yields and the cost of providing crop insurance during drought conditions. Future research will continue to build our understanding of the role that crop insurance can play in potential solutions.

References

Aldana, U., J.D. Foltz, B.L. Barham, and P. Useche. 2011. "Sequential Adoption of Package Technologies: The Dynamics of Stacked Trait Corn Adoption." *American Journal of Agricultural Economics* 93(1): 130–143. doi: 10.1093/ajae/aaq112.

Angrist, J.D., and J.-S. Pischke. 2008. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, NJ: Princeton University Press.

Annan, F., and W. Schlenker. 2015. "Federal Crop Insurance and the Disincentive to Adapt to Extreme Heat." *American Economic Review* 105(5): 262–266. doi: 10.1257/aer.p20151031.

Antle, J.M. 2010. "Asymmetry, Partial Moments and Production Risk." *American Journal of Agricultural Economics* 92(5): 1294–1309. doi: 10.1093/ajae/aaq077.

Balesdent, J., C. Chenu, and M. Balabane. 2000. "Relationship of Soil Organic Matter Dynamics to Physical Protection and Tillage." *Soil and Tillage Research* 53(3): 215–230. doi: 10.1016/S0167-1987(99)00107-5.

Claassen, R., C. Langpap, and J. Wu. 2017. "Impacts of Federal Crop Insurance on Land Use and Environmental Quality." *American Journal of Agricultural Economics* 99(3): 592–613. doi: 10.1093/ajae/aaw075.

Coble, K.H., R.O. Knight, R.D. Pope, and J.R. Williams. 1996. "Modeling Farm-Level Crop Insurance Demand with Panel Data." *American Journal of Agricultural Economics* 78(2): 439–447. doi: 10.2307/1243715.

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

Cornaggia, J. 2013. "Does Risk Management Matter? Evidence from the U.S. Agricultural Industry." *Journal of Financial Economics* 109(2): 419–440. doi: 10.1016/j.jfineco.2013.03.004.

Daly, C., J.I. Smith, and K.V. Olson. 2015. "Mapping Atmospheric Moisture Climatologies across the Conterminous United States." *PLoS One* 10(10): e0141140. doi: 10.1371/journal.pone.0141140.

Epplin, F., C. Stock, D. Kletke, and T. Peeper. 2005. "Cost of Conventional Tillage and No-till Continuous Wheat Production for Four Farm Sizes." *Journal of the ASFMRA* 2005: 69–76. doi: 10.22004/ag.econ.190714.

Fernandez-Cornejo, J., and W. McBride. 2002. *Adoption of Bioengineered Crops*. Agricultural Economic Report AER-810. Washington, DC: U.S. Department of Agriculture, Economic Research Service.

Finger, R. 2012. "Biases in Farm-Level Yield Risk Analysis Due to Data Aggregation." *German Journal of Agricultural Economics* 61(1): 1–14. Available online at https://ideas.repec.org/a/ags/gjagec/199770.html. [Accessed Oct. 15, 2019].

Glauber, J.W. 2013. "The Growth of the Federal Crop Insurance Program, 1990--2011." *American Journal of Agricultural Economics* 95(2): 482–488. doi: 10.1093/ajae/aas091.

Goodwin, B.K., M.L. Vandeveer, and J.L. Deal. 2004. "An Empirical Analysis of Acreage Effects of Participation in the Federal Crop Insurance Program." *American Journal of Agricultural Economics* 86(4): 1058–1077. doi: 10.1111/j.0002-9092.2004.00653.x.

Ifft, J.E., T. Kuethe, and M. Morehart. 2015. "Does Federal Crop Insurance Lead to Higher Farm Debt Use? Evidence from the Agricultural Resource Management Survey (ARMS)." *Agricultural Finance Review* 75(3): 349–367. doi: 10.1108/AFR-06-2014-0017.

Key, N., D.L. Prager, and C.B. Burns. 2018. "The Income Volatility of U.S. Commercial Farm Households." *Applied Economic Perspectives and Policy* 40(2): 215–239. doi: 10.1093/aepp/ppy006.

Lobell, D.B., M.J. Roberts, W. Schlenker, N. Braun, B.B. Little, R.M. Rejesus, and G.L. Hammer. 2014. "Greater Sensitivity to Drought Accompanies Maize Yield Increase in the U.S. Midwest." *Science* 344(6183): 516–519. doi: 10.1126/science.1251423.

Newman, J., and P. McGroarty. 2017, February 8. "The Next American Farm Bust Is Upon Us." *Wall Street Journal*. Available online at https://www.wsj.com/articles/the-next-american-farm-bustis-upon-us-1486572488.

Northwest Alliance for Computational Science & Engineering. *PRISM Climate Data*. Corvallis, OR: Northwest Alliance for Computational Science & Engineering, Oregon State University. Available online at http://www.prism.oregonstate.edu/. [Accessed Jan. 30, 2018].

O'Conner, C. 2013. *Soil Matters: How the Federal Crop Insurance Program Should Be Reformed to Encourage Low-Risk Farming Methods with High-Reward Environmental Outcomes.* NDRC Issue Paper IP:13-04-A. New York, NY: Natural Resource Defence Council.

Papke, L.E., and J.M. Wooldridge. 2008. "Panel Data Methods for Fractional Response Variables with an Application to Test Pass Rates." *Journal of Econometrics* 145(1–2): 121–133. doi: 10.1016/j.jeconom.2008.05.009.

Pope, R.D., and R.E. Just. 1977. “On the Competitive Firm Under Production Uncertainty.” *Australian Journal of Agricultural Economics* 21(2): 111–118. doi: 10.1111/j.1467-8489.1977.tb00198.x.

Quandl. “Barchart CME U.S. Futures” Quandl Inc. Available online at https://www.quandl.com/data/BCCME-Barchart-CME-U-S-Futures. [Accessed Jan. 30, 2018].

Roberts, M.J., W. Schlenker, and J. Eyer. 2013. “Agronomic Weather Measures in Econometric Models of Crop Yield with Implications for Climate Change.” *American Journal of Agricultural Economics* 95(2): 236–243. doi: 10.1093/ajae/aas047.

Sandmo, A. 1971. “On the Theory of the Competitive Firm under Price Uncertainty.” *American Economic Review* 61(1): 65–73.

Schoengold, K., Y. Ding, and R. Headlee. 2015. “The Impact of AD HOC Disaster and Crop Insurance Programs on the Use of Risk-Reducing Conservation Tillage Practices.” *American Journal of Agricultural Economics* 97(3): 897–919. doi: 10.1093/ajae/aau073.

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

Tolhurst, T.N., and A.P. Ker. 2015. “On Technological Change in Crop Yields.” *American Journal of Agricultural Economics* 97(1): 137–158. doi: 10.1093/ajae/aau082.

U.S. Department of Agriculture. 2018. “Adoption of Genetically Engineered Crops in the U.S.” Washington, DC: U.S. Department of Agriculture, National Agricultural Statistical Service. Available online at https://www.ers.usda.gov/data-products/adoption-of-genetically-engineered-crops-in-the-us.aspx [Accessed Jan. 30, 2018].

U.S. Department of Agriculture. 2018. “Quick Stats.” Washington, DC: U.S. Department of Agriculture, Economic Research Service. Available online at https://quickstats.nass.usda.gov/ [Accessed Jan. 30, 2018].

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

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

Yang, S.-R., W.W. Koo, and W.W. Wilson. 1992. “Heteroskedasticity in Crop Yield Models.” *Journal of Agricultural and Resource Economics* 17(1): 103–109. doi: 10.22004/ag.econ.30738.

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

Yu, T., and B.A. Babcock. 2010. “Are U.S. Corn and Soybeans Becoming More Drought Tolerant?” *American Journal of Agricultural Economics* 92(5): 1310–1323. doi: 10.1093/ajae/aaq074.

Table 1. Summary of Included Variables

	1989–1993	2000–2008	2010–2016	Overall
Insurance	0.231	0.632	0.803	0.551
Participation Rate	(0.144)	(0.170)	(0.138)	(0.264)
Market controls				
Expected price				
Corn	2.052	2.608	3.022	2.676
	(0.193)	(0.681)	(0.514)	(0.618)
Soybeans	5.360	5.701	6.639	6.143
	(0.544)	(1.645)	(1.043)	(1.298)
Soybean/corn futures price ratio	2.440	2.201	2.306	2.302
	(0.139)	(0.215)	(0.079)	(0.175)
Sign-up/in-season futures price ratio				
Corn	0.990	1.012	0.994	1.003
	(0.058)	(0.087)	(0.059)	(0.071)
Soybeans	1.003	1.034	1.040	1.023
	(0.042)	(0.064)	(0.070)	(0.064)
Agronomic controls				
GM adoption (%)				
Corn	0.000	47.678	89.312	42.546
	(0.000)	(24.012)	(5.316)	(37.343)
Soybeans	0.000	80.351	93.579	56.923
	(0.000)	(12.917)	(3.065)	(39.642)
Irrigated acres (%)				
Corn	0.071	0.063	0.083	0.070
	(0.213)	(0.190)	(0.192)	(0.196)
Soybeans	0.043	0.062	0.087	0.062
	(0.138)	(0.185)	(0.206)	(0.178)
Planted acres				
Corn	95,476	102,402	113,384	103,027
	(60,087)	(62,880)	(67,353)	(63,446)
Soybeans	81,526	98,483	101,196	95,195
	(51,553)	(55,143)	(55,358)	(54,797)
Weather and climate controls				
In-season precipitation (mm)	935.738	917.484	963.786	926.400
	(303.171)	(270.393)	(280.133)	(277.473)
Log 10-year rain variation	9.420	8.837	9.092	8.974
	(2.161)	(2.219)	(2.319)	(2.257)
Heating degree days	1.723	3.104	4.990	3.182
	(5.265)	(8.822)	(14.303)	(10.017)
Drought years (%)	0.066	0.110	0.148	0.097
	(0.248)	(0.313)	(0.355)	(0.296)
N	4,160	7,488	5,824	23,296

Notes: Standard deviations are in parentheses. All prices deflated to year 2000 dollars.

Table 2. Summary of Average Yield Variance over Time

	1989–1993	1994–1999	2000–2005	2010–2016	Overall
Corn variance	0.298	0.213	0.246	0.248	0.248
	(0.066)	(0.020)	(0.028)	(0.047)	(0.049)
Soybean variance	0.319	0.287	0.299	0.285	0.295
	(0.034)	(0.029)	(0.022)	(0.017)	(0.028)
Combined variance	0.309	0.250	0.272	0.267	0.271
	(0.049)	(0.022)	(0.022)	(0.027)	(0.035)
N	4,160	5,824	6,656	5,824	23,296

Notes: Standard deviations in parentheses. Values expressed in standard deviations of log yield, which can be interpreted as approximately equal to average percent deviation of yield.

Table 3. First-Stage Regressions (N = 23,296)

Policy Trend Instrument		Subsidy Rate Instrument	
	Crop Insurance Participation		Crop Insurance Participation
Pre-1994	-0.194***	Subsidy Rate 65%	2.755***
	(0.021)		(0.173)
2000–2007	0.146***	Subsidy Rate 75%	-0.689***
	(0.019)		(0.112)
2008–2014	0.204***		
	(0.025)		
Post-2014	0.093**		
	(0.031)		
Log expected price	-0.289***	Log expected price	-0.331***
	(0.033)		(0.025)
Soybean/corn price ratio	-0.097**	Soybean/corn price ratio	0.019
	(0.031)		(0.031)
Sign-up/in-season	0.023	Sign-up/in-season	0.304***
futures price ratio	(0.074)	futures price ratio	(0.074)
GM adoption (%)	0.750***	GM adoption (%)	0.562***
	(0.038)		(0.034)
Log planted acres	0.205***	Log planted acres	0.208***
	(0.007)		(0.007)
Proportion irrigated land	-0.432***	Proportion irrigated land	-0.427***
	(0.033)		(0.033)
Growing-season	-0.626***	Growing-season	-0.637***
precipitation	(0.018)	precipitation	(0.018)
10-year rain variation	0.570***	10-year rain variation	0.650***
	(0.111)		(0.111)
Heating degree days	-0.005***	Heating degree days	-0.004***
	(0.001)		(0.001)
Drought	-0.226***	Drought	-0.223***
	(0.022)		(0.022)
County-level trends		County-level trends	
Corn	0.076***	Corn	0.078***
	(0.003)		(0.002)
Soybeans	0.076***	Soybeans	0.078***
	(0.003)		(0.002)
Constant	-150.077***	Constant	-155.615***
	(5.880)		(4.452)
Pseudo-R^2	0.158	Pseudo-R^2	0.159

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. Standard errors are in parentheses and are clustered at the agricultural district level. Model also includes county-crop-specific fixed effects. Policy trend instruments: Dummies that are 1 within the specified periods and 0 otherwise. Soybean/corn price ratio is ratio of futures price between January 1 and March 15. Sign-up to in-season futures price ratio is the ratio of the average February futures price to the average futures price from April 1 to September 1.

Table 4. Asymmetric Effect of 3-Year Crop Insurance Participation Rate on Yields ($N = 20{,}800$)

	OLS		Fixed Effects	
	Upper Partial Variance	**Lower Partial Variance**	**Upper Partial Variance**	**Lower Partial Variance**
Insurance Participation	0.248	-1.204**	-0.036	-0.484
	(0.472)	(0.523)	(0.308)	(0.386)
Market controls				
Log expected price	-0.430***	-0.648***	-0.524***	-0.605***
	(0.143)	(0.182)	(0.137)	(0.147)
Soybean/corn price ratio	0.116	0.897***	0.597***	-0.117
	(0.153)	(0.265)	(0.111)	(0.219)
Sign-up/in-season futures price ratio	-0.099	-0.054	0.083	-0.470
	(0.393)	(0.433)	(0.371)	(0.368)
Agronomic controls				
GM adoption (%)	-0.032	0.617*	0.297	-0.257
	(0.240)	(0.314)	(0.186)	(0.288)
Log planted acres	-0.507***	-0.019	0.297**	0.786***
	(0.100)	(0.117)	(0.136)	(0.106)
Proportion irrigated land	0.352	-1.210***	0.621	-0.913**
	(0.376)	(0.450)	(0.392)	(0.366)
Weather and climate controls				
Growing-season precipitation	0.405*	-0.553*	0.453**	-0.164
	(0.213)	(0.292)	(0.192)	(0.194)
10-year rain variation	0.034*	0.025	-0.003	0.077***
	(0.020)	(0.033)	(0.013)	(0.026)
Heating degree days	-0.036***	0.029***	-0.029**	0.023***
	(0.011)	(0.006)	(0.011)	(0.004)
Drought	0.483**	0.976***	0.788	0.687**
	(0.219)	(0.199)	(0.497)	(0.267)
County-level trends				
Corn	-0.010	-0.010	-0.010	-0.010
	(0.014)	(0.014)	(0.010)	(0.010)
Soybeans	-0.009	-0.009	-0.016	-0.016
	(0.014)	(0.014)	(0.010)	(0.010)
Constant	18.035	18.035	16.034	16.034
	(28.033)	(28.033)	(19.255)	(19.255)

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. Standard errors are in parentheses and clustered at the agricultural district level. Estimation weighted by the inverse log variance of yields to correct for heteroskedasticity. Variance of corn and soybean yields estimated jointly. The difference in number of observations between Tables 1–3 and Tables 4–6 is from averaging over the prior 3 years, meaning our first observation is in 1992. The average crop insurance participation rate for 1992 is the average rate for the years 1991, 1990, and 1989. Model includes county-crop-specific fixed effects. Sign-up to in-season futures price ratio is the ratio of the average February futures price to the average futures price from April 1 to September 1.

Table 5. Asymmetric Effect of 3-Year Crop Insurance Participation Rate on Yields (N = 20,800)

	FE-IV Policy Trends		FE-IV Subsidy Rates	
	Upper Partial Variance	Lower Partial Variance	Upper Partial Variance	Lower Partial Variance
Insurance	3.689***	5.495***	4.224***	5.154***
Participation	(1.095)	(1.677)	(1.038)	(1.570)
Market controls				
Log expected price	-0.335**	-0.249	-0.309**	-0.275*
	(0.138)	(0.168)	(0.137)	(0.161)
Soybean/corn price	0.675***	-0.196	0.660***	-0.139
ratio	(0.108)	(0.236)	(0.108)	(0.235)
Sign-up/ in- season	0.441	-0.403	0.508	-0.388
futures price ratio	(0.369)	(0.374)	(0.372)	(0.374)
Agronomic controls				
GM adoption (%)	-0.312	-2.051***	-0.524**	-1.772***
	(0.273)	(0.564)	(0.266)	(0.530)
Log planted acres	0.465***	0.796***	0.447***	0.816***
	(0.164)	(0.136)	(0.164)	(0.132)
Proportion irrigated	0.785*	-0.571	0.819*	-0.588
land	(0.476)	(0.413)	(0.490)	(0.417)
Weather and climate controls				
Growing-season	0.324	-0.002	0.328	-0.043
precipitation	(0.214)	(0.195)	(0.217)	(0.191)
10-year rain variation	-0.019*	0.044***	-0.019*	0.043***
	(0.011)	(0.014)	(0.011)	(0.014)
Heating degree days	-0.020*	0.025***	-0.019*	0.025***
	(0.011)	(0.004)	(0.011)	(0.004)
Drought	0.054	0.936***	0.053	0.927***
	(0.118)	(0.157)	(0.119)	(0.156)
County-level trends				
Corn	-0.090***	-0.090***	-0.095***	-0.095***
	(0.025)	(0.025)	(0.024)	(0.024)
Soybeans	-0.096***	-0.096***	-0.101***	-0.101***
	(0.026)	(0.026)	(0.025)	(0.025)

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. Standard errors are in parentheses and clustered at the agricultural district level. Estimation weighted by the inverse log variance of yields to correct for heteroskedasticity. Variance of corn and soybean yields estimated jointly. The difference in number of observations between Tables 1–3 and Tables 4–6 is from averaging over the prior 3 years, meaning our first observation is in 1992. The average crop insurance participation rate for 1992 is the average rate for the years 1991, 1990, and 1989. Model includes county-crop-specific fixed effects. Sign-up to in-season futures price ratio is the ratio of the average February futures price to the average futures price from April 1 to September 1.

Table 6. Effect of Crop Insurance Participation Rates on Partial Moments of Yield (N = 20,800)

	FE-IV: Policy Trends		FE-IV: Subsidy Rates	
	Upper Partial Variance	**Lower Partial Variance**	**Upper Partial Variance**	**Lower Partial Variance**
Insurance Participation	3.656***	5.035***	4.262***	4.825***
	(1.087)	(1.594)	(1.046)	(1.526)
Crop insurance × drought	0.140	1.201*	0.300	1.226*
	(0.967)	(0.685)	(0.970)	(0.674)
Market controls				
Log expected price	-0.345**	-0.275*	-0.316**	-0.293*
	(0.138)	(0.164)	(0.138)	(0.159)
Soybean/corn price ratio	0.680***	-0.180	0.667***	-0.125
	(0.107)	(0.233)	(0.108)	(0.233)
Sign-up/in-season futures price ratio	0.446	-0.329	0.522	-0.309
	(0.369)	(0.371)	(0.373)	(0.373)
Agronomic controls				
GM adoption (%)	-0.311	-1.874***	-0.533**	-1.636***
	(0.273)	(0.536)	(0.267)	(0.513)
Log planted acres	0.460***	0.800***	0.445***	0.820***
	(0.160)	(0.133)	(0.161)	(0.130)
Proportion irrigated land	0.805*	-0.552	0.849*	-0.558
	(0.468)	(0.411)	(0.484)	(0.415)
Weather and climate controls				
Growing-season precipitation	0.335	0.012	0.337	-0.027
	(0.213)	(0.192)	(0.216)	(0.188)
10-year rain variation	-0.019*	0.042***	-0.019*	0.041***
	(0.011)	(0.013)	(0.011)	(0.013)
Heating degree days	-0.020*	0.026***	-0.019*	0.025***
	(0.012)	(0.004)	(0.012)	(0.004)
Drought	-0.032	0.283	-0.136	0.261
	(0.642)	(0.388)	(0.643)	(0.381)
County-level trends				
Corn	-0.089***	-0.089***	-0.096***	-0.096***
	(0.025)	(0.025)	(0.024)	(0.024)
Soybeans	-0.095***	-0.095***	-0.102***	-0.102***
	(0.026)	(0.026)	(0.025)	(0.025)

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. Standard errors are in parentheses and clustered at the agricultural district level. Estimation weighted by the inverse log variance of yields to correct for heteroskedasticity. Variance of corn and soybean yields estimated jointly. The difference in number of observations between Tables 1–3 and Tables 4–6 is from averaging over the prior 3 years, meaning our first observation is in 1992. The average crop insurance participation rate for 1992 is the average rate for the years 1991, 1990, and 1989. Model includes county-crop-specific fixed effects. Sign-up to in-season futures price ratio is the ratio of the average February futures price to the average futures price from April 1 to September 1.

Table 7. Weak Instrument/Overidentification Tests for Subsidy and Policy Instruments

	3-Year Base Estimation		3-Year Drought Interaction Estimation	
	Policy IV	**Subsidy Rate**	**Policy IV**	**Subsidy Rate**
Cragg–Donald weak instrument test	276.770	354.327	175.502	216.987
Stock and Yogo 10% maximal IV	13.43	13.43	13.43	13.43
Sargan overidentification test	0.416 (0.519)	0.524 (0.469)	0.612 (0.434)	0.779 (0.377)

Notes: The Cragg–Donald test indicates that the instruments are highly correlated with the endogenous variable, suggesting strong instruments. *p*-value in parentheses for the overidentification tests. A *p*-value greater than 0.05 indicates failure to reject the null that the overidentification restrictions are valid.

Table 8. OLS Estimation of the Effect of Agricultural Factors on Average Land Quality (N = 21,267)

	Crop Insurance Use and Land Quality (NCCPI)
Crop insurance participation	0.600***
	(0.059)
Planted acres × crop insurance	-0.040***
	(0.005)
Planted acres × year	-0.000**
	(0.000)
Planted acres	0.215***
	(0.062)
Log expected price	0.037***
	(0.007)
Commodity price	-0.015***
	(0.006)
GM adoption (%)	-0.087***
	(0.007)
10-year rain variation	0.006***
	(0.001)
Proportion irrigated land	-0.270***
	(0.005)
Constant	-0.489***
	(0.034)
Adjusted R^2	0.257

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. Standard errors are in parentheses. As the NCCPI is a static measure, we used an OLS procedure without incorporating fixed effects. Coefficients therefore represent the average change in land quality associated with the listed variable. GM technology and irrigation are associated with lower quality land since they increase ability to produce on these land types. More-variable rainfall is associated with higher quality land, as lower quality land is riskier under these conditions. As pointed out in Glauber (2013), crop insurance adoption is highest on land of higher quality. However, acreage growth under crop insurance is associated with lower average quality of land farmed. Acreage expansion alone has the same effect (interaction of acreage and year), however the effect is smaller than under crop insurance. Expected price captures preseason incentives to shift acres while the annual market price captures multiple realized market conditions.