The Demand for Crop Insurance: Elasticity and the Effect of Yield Shocks

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The political and economic climate has changed significantly since previous studies explored the effect of prices on the demand for crop insurance. One aim is to update these elasticities for corn and soybeans using a simultaneous system of equations and a county-level panel dataset covering states in the Corn Belt, the Lake States, and the Northern Plains. Further, we examine whether producers react to yield shocks by entering (or exiting) crop insurance. If producers' behavior changes after yield shocks, then producers effectively treat yield shocks as correlated over time – where past outcomes can be used to predict future outcomes. Current estimates of price elasticities appear to be higher than those previously reported in past studies. For corn, the demand for crop insurance remains inelastic while for soybeans, results suggest an elastic response, which may be due to a substitution effect that could take place between the two crops if budget constraints are an issue. Results also suggest that while yield shocks appear to have a statistically significant effect, the effect is minimal at best.

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Introduction

What determines the quantity demanded of crop insurance? Price is certainly one of the largest determinants, along with available substitutes that help producers manage the various risks that they face. Many papers have explored how premium subsidies that lower the price of crop insurance affect the demand for crop insurance. Understanding how the price affects the demand for crop insurance helps to inform policymakers and other stakeholders about how the crop insurance program will be used. For example, if demand is highly reactive to price, then small changes in the price of crop insurance might induce large changes in demand. Alternatively, if demand is not very reactive to price, then even large increases in producers' cost of crop insurance might not dissuade them from enrolling in the program.

While previous literature has explored the responsiveness of the demand for crop insurance to the price of crop insurance, much of this literature focuses on a policy environment that differs from the current one, and would therefore benefit from an updated analysis. This literature largely focuses on rather specific points in time where different types of government programs, which may be viewed as substitutes for the crop insurance program, were in effect. Most of the current literature on this topic explores years prior to 2000, and only a few explore past the very early 2000s. This paper seeks to update this literature to explore whether the demand for crop insurance has grown either more or less responsive to the price of crop insurance in the wake of new sets of programs and a different economic climate.

Some of the major changes since the early 2000s have involved the types of programs made available to producers, including policies made available through the crop insurance program. Within the crop insurance program, the popularity of revenue policies has grown significantly and has overtaken the previously popular yield protection policies. For example, in 2001 the top two revenue policies that producers enrolled in (Crop Revenue Coverage, or CRC, and Revenue Assurance, or RA) covered approximately 86.5 million acres and $13.3 billion in liabilities while the top yield protection policy (Actual Production History, or APH) covered more than 110 million acres and over $15.7 billion in liabilities. By 2012, producers enrolled just over 14.5 million acres worth roughly $11.6 billion in the APH policy, while enrolling 180 million acres into the top two revenue programs (now Revenue Protection, or RP, and Revenue Protection with Harvest Price Exclusion, or RPHPE), covering crops worth more than $85 billion.

Another factor that may help determine the quantity demanded of crop insurance stems from shocks. If unanticipated negative yield shocks drive down the levels of revenue that growers receive, does this induce them to enroll in the crop insurance program in subsequent years (or to enroll in higher levels of crop insurance, if they were already enrolled in the program)? Similarly, does a year—or perhaps a series of consecutive years—with no (or positive) yield shocks induce farmers to either enroll in lower levels of coverage or leave the program entirely?

Farmers' reactions to yield shocks could have important implications for how government programs and policies are run. A better understanding of the nature and the magnitude of these reactions could benefit program managers and policymakers. Program managers could have a better understanding of the demand they may face for crop insurance, which would allow them to better prepare for the wants and needs of the producers who wish to participate in the program. Policymakers, constantly faced with budgetary restrictions, would better understand how the crop insurance program will be used and from where costs will stem. Furthermore, policymakers would better understand how growers react to the risk environment within which they produce. Do recent events drive their actions or are shocks immaterial to program use for risk management purposes?

Previous literature has used yield shocks in many different ways, including to provide examples of how programs work, which indirectly gets at the question of enrollment in the program (e.g., Woolverton and Young, 2009). Other literature explores how yield shocks affect other aspects of agriculture, such as farm structure (Roberts and Key, 2002), migration patterns (Feng, et al., 2013), and food price volatility (Berry, et al., 2013). Most closely to what we intend to examine, Chong and Ifft (2016) have a working paper that provides evidence that precipitation patterns may alter growers' use of crop insurance.

Using county-level panel data stretching from 1997 through 2012, we explore two main issues that directly relate to the demand for crop insurance. Updating the previous literature, we seek to provide estimates of the degree to which crop insurance demand changes in relation to changes in the price of crop insurance. This will provide a new set of crop insurance demand elasticities that reflect the most recent set of data available. Furthermore, we look to expand upon this research by including yield shocks in the analysis. With the exception of Chong and Ifft (2016), previous literature has not explored the possibility that yield shocks may help drive the demand for crop insurance.

Our empirical study relies on Risk Management Agency (RMA) administrative data, which contains information about all U.S. crop insurance policy contracts, and National Agricultural Statistics Service (NASS) county-level yield and state-level price data. We construct a panel dataset by combining these datasets at the county level over 16 years—from 1997 through 2012—and 10 states that span the Corn Belt, the Lake States, and the Northern Plains. While previous studies have typically focused on narrower regions, we include the bulk of U.S. production of corn and soybeans to explore how both crop insurance prices and yield shocks affect the demand for crop insurance at a more national level, which can help policymakers and program managers better understand how the Federal Crop Insurance program runs. Furthermore, the data allow us to control for state level time-invariant characteristics such as land quality and climate that may be correlated with both the price of crop insurance and the demand for crop insurance as well as for spatially-invariant characteristics that may change over time, such as changes in technology and in the economic and political climate.

Previous studies have typically explored the decision to enroll in crop insurance as a logit or probit process (e.g., Coble et al., 1996), as a two step-procedure where the first step utilizes a logit or probit model to forecast adoption and the second step models the level of insurance adopted conditional on adoption (e.g., Smith and Baquet, 1996), or as a single-equation framework using a panel of data and assuming the exogeneity of several key variables (e.g., Goodwin 1993). We follow the footsteps of Goodwin et al. (2004) who created a structural model to deal with the various endogenous variables required to specify the process. Using a set of two equations to be solved simultaneously, we examine producers' decisions to enroll in the federal crop insurance program as a function of the price of crop insurance. Over time, Congress has lowered the price of crop insurance through the use of premium subsidies. Exploring how these changes have affected producers' decisions to use the program allows us to better understand the demand for crop insurance. Furthermore, we also explore how yield shocks affect the demand for crop insurance.

Our results suggest that the price of crop insurance matters to producers, and that the price response is stronger for soybeans than for corn. The elasticities found here tend to be larger on average than what was found in most previous studies. In total, changes in the price of crop insurance appear to lead to a smaller than one-for-one percent change in the demand for crop insurance for corn, and larger than a one-for-one percent change in the demand for crop insurance for three of the four measures of demand that are used in this paper for soybeans. Furthermore, we find limited evidence that yield shocks directly affect the use of the Federal crop insurance program. Although we do find statistically significant results that can stretch back several years, the point estimates remain small, suggesting a minimal economic effect of yield shocks on the demand for crop insurance. We also find an indirect effect of yield shocks on the demand for crop insurance – as they work their way through the price of crop insurance. Yield shocks have a negative correlation with the price of crop insurance and through this route, can affect crop insurance demand. However, as with the direct effect, these effects can also be considered economically insignificant.

Crop Insurance Demand and Prices

As with any economic good, the market for crop insurance exhibits a downward sloping demand function. This demand elasticity was first explored in the early 1990s as policymakers and academics wondered why, even with subsidies, the program had not grown as expected. Studies showed that the demand for crop insurance was inelastic – in other words, changes in demand were small relative to the change in the price of crop insurance (Shaik et al., 2008; Goodwin et al., 2004; Serra et al., 2003; Coble et al., 1996; Goodwin, 1993; Gardner and Kramer, 1986). Some of the largest results were found by one of the more recent studies (O'Donoghue, 2014), however even these results remained inelastic, and this study utilized the lagged dependent variable as an instrument, a less than ideal approach (Angrist and Piscke, 2009).

Studies exploring the early years of subsidies often attributed the low level of enrollment to adverse selection, wherein the producers most likely to receive indemnity payments were the most likely to enroll in the program (e.g., Glauber 2004; Goodwin, 1993). The Federal crop insurance program was mandated by Congress to maintain actuarially fair policies (meaning that the total premium was required to be as close as possible to the indemnities paid out), so if those first entering the program were likely to receive indemnity payments they would drive up the price of crop insurance, making it a bad business decision for other, less risky producers, to enroll. It was posited that premium subsidies needed to be higher in order to overcome the adverse selection and bring the crop insurance prices to levels where it made economic sense for producers to enroll. The studies at that time found, for the most part, that for a 1 percent change in the price of crop insurance, demand would change by between 0.1 and 0.4 percent. In other words, producer demand for crop insurance remained inelastic with respect to the price.

Since then, however, the political and economic landscapes have changed significantly. With the passage of both the 1994 Federal Crop Insurance Reform Act (FCIRA) and the 2000 Agricultural Risk Protection Act (ARPA), Congress greatly increased the premium subsidies in order to make the federal crop insurance program more attractive to producers (Fig. 1).

FCIRA had the greater immediate impact on overall enrollment, while ARPA, which increased premium subsidies particularly at the higher levels of coverage, provided incentives for producers to use the program more intensely. This helped to sustain and increase a steady upward climb in total premiums, one measure of participation in the federal crop insurance program (Figs. 2a and 2b).

Over time, the federal crop insurance (FCI) program continued to grow. As more producers enrolled, it eliminated the adverse selection problem—if everyone is in the program, risk is shared and the price of insurance no longer becomes an obstacle to participation. The growth of FCI culminated in the 2014 Farm Act when the FCI program became the largest single program providing support to farmers. Congress also introduced other programs that worked with or supplemented FCI in the 2014 Farm Act, providing further evidence of the program’s central role.

The Model

Due to data constraints, the demand for crop insurance is modeled at the county level and individually for each crop. In the notation that follows, we will suppress the subscripts for county and crop since it is understood to be at the county and crop level. Demand is a function of several variables, including the price of crop insurance, the number of agricultural acres in the county, measures of risk, and time and state-level fixed effects. Later in the paper, we also test whether or not yield shocks play a role in the demand for crop insurance. Combining these variables together, we can write this more formally as:

$$\begin{aligned} Q_t^{CI} &= \alpha + \beta_1 \ln\left(P_t^{CI}\right) + \beta_2 \ln\left(A_{1997}\right) + \beta_3 \mathrm{sd}\left(Y_t\right) + \beta_4 \ln E\left(Y_t\right) \\ &\quad + \omega_{t-1} + \omega_{t-2} + \ldots + \omega_{t-n} + t_{fe} + s_{fe} + \varepsilon_t \end{aligned} \tag{1}$$

where Q^{CI}_t denotes the quantity demanded of crop insurance in time *t*. P^{CI}_t represents the price of crop insurance at time *t*, A_t denotes the number of acres of agricultural land in that county in 1997, $E[Y_t]$ is the expected county-level yield in time *t*, and $sd(Y_t)$ captures the standard deviation of the county-level yield. Finally, s_{fe} denotes state fixed effects while ω_{t-i} denotes the yield shock in time *t-i*, which is incorporated in order to further explore whether past yield shocks affect the demand for crop insurance.

Following the law of demand and holding all else equal, it is assumed that the price of crop insurance will be negatively associated with the demand for crop insurance. The expected level of yield controls for how producers purchase crop insurance relative to the mean yield. *A priori*, it is not clear whether an increase in yield would cause a producer to enroll in higher or lower levels of crop insurance. It is possible that a higher level of expected yield could generate an income effect for the producer, making them less risk averse, or it could be that the higher level of potential losses due to the higher level of attainable yields could cause the producer to enroll in higher levels of crop insurance.

The number of acres per county controls for county size. Suppose that there were two counties, one with a large number of acres and the other with a small number of acres. The former could experience much larger changes in crop insurance uptake than the latter simply because it is a much larger county. This data is taken from the 1997 Agricultural Census, but is generally stable across years in the states on which this paper focuses.

As the standard deviation of yields increases, it will appear more risky to the producer. This suggests that the producer would be more willing to purchase crop insurance, and demand for crop insurance products would increase.

It is expected that yield shocks would be negatively correlated with the demand for crop insurance. This would suggest, for example, that after a negative shock (one where yields and/or revenues were lower than expected) the producer would be more inclined to enroll in crop insurance than before the shock. Similarly, if a producer experiences a year (or more) of better than expected yields or revenues, they may be less likely to enroll in crop insurance. Several years of yield shocks are included in order to capture accumulated or delayed effects.

Time and state fixed effects round out the explanatory variables. These control for unobservables that do not change over location but can vary across time (for time fixed effects) and for unobservables that do not change over time but can vary geographically (for state fixed effects). Note that the yield shock varies across both time and space, so should not be wiped out by the fixed effects.

However, equation (1) cannot be estimated in isolation. The price of crop insurance is endogenous. As a result, we use a set of equations to be solved simultaneously. The second equation shows that the price of crop insurance (the portion that the farmer pays) is a function of the government subsidy, the crop price, the mean and standard deviation of the crop's yield, the yield shocks, and time and state fixed effects. Formally, the relationship can be written as:

$$(1) \quad P_t^{CI} = \gamma + \theta_1 \ln(G_t) + \theta_2 sd(Y_t) + \theta_3 \ln[E(Y_t)] + \omega_{t-1} + \omega_{t-2} + \cdots + \omega_{t-n} + t_{fe} + s_{fe} + \eta_t$$

where G_t represents the government subsidy. Over time, it is likely that the price of the crop insurance policy and the government subsidy move in the same direction. Since the government subsidy is calculated as a fraction of the price, if the price increases the subsidy would increase as well.[1] Hence it is expected that the government subsidy will be positively correlated with the price of crop insurance. The correlation between the expected yield and the price of crop insurance is also expected to be positive since an insurance policy is established to cover losses incurred which will be a function of the expected value of the crop being covered – which is a function of the expected yield. Riskier, more uncertain outcomes are more expensive to insure against, hence we expect a positive relationship between the standard deviation of the commodity yield and the price of crop insurance. Previous yield shocks ought to have a negative relationship with the price of crop insurance. The price of crop insurance updates annually, taking into account the previous year's outcomes. A positive yield shock would translate into lower prices the following year, and vice versa. Finally, time and state fixed effects are again used. In this model, we assume that commodity prices remain constant within a state. The effect of crop prices – which one would expect to help explain the price of crop insurance – is therefore captured by the state fixed effects.

[1] An exception to this framework would arise if using an event study to explore an explicit change in the subsidy structure. If, for example, the subsidy rate increased, it would mean the price that the farmer pays would decrease. Assuming prices remained relatively stable over the event study, this would lead to a negative relationship between the subsidy and the price that the farmer paid.

Both equations are run using a log-log specification. This allows us to generate elasticities both for the demand for crop insurance to compare to other estimates generated in the literature and to explore the effect of the yield shocks on the use of the crop insurance program.

Exclusion restrictions

In order to ensure that we can identify the parameters of the model we need to make sure that we have proper exclusion restrictions in place. In equation (1), which models the demand for crop insurance, the government subsidy is excluded (out of the list of variables in both equations of the model). The government subsidy affects the demand for crop insurance through the price of crop insurance, but does not do so directly. Therefore, the government subsidy is included in equation (2), which models the price of crop insurance, but is excluded from equation (1).

The number of agricultural acres within a county is excluded from equation (2). While the number of acres within the county can directly affect the demand for crop insurance (more land means more potential planted acres to cover with crop insurance), the number of acres does not affect the price of crop insurance. The price of crop insurance is based on the type of crop being grown, the characteristics of the land and climate, and the history of the producer, but not the amount of land.

Examining the rank condition tells us that the system of equations is identified. The order condition, however, suggests that the second equation is over-identified. When running our analysis, we ran the Sargan-Hansen test to examine the validity of the over-identifying restrictions and found them to be valid.

Data

To explore the question of how responsive the demand for crop insurance is to changes in the price of crop insurance, we collect data from a variety of sources. Unfortunately, there is no nationwide data available at the individual farm level, meaning we cannot explore this topic using producer-level data. The next best step is to use county-level data. We collect corn- and soybean-related data for 10 of the major corn and soybean producing states in the United States. Illinois, Indiana, Iowa, and Ohio represent the Corn Belt; Michigan, Minnesota, and Wisconsin represent the Lake States; and Kansas, Nebraska, and South Dakota represent the Northern Plains. Together, farmers in these states generated 79 percent of the national corn production and 70 percent of the national soybean production in 2012.

RMA data is collected at the county level and is available through their Summary of Business online. Data used in this paper includes the total premiums, total liabilities, subsidies, insurance plan type, coverage level, acres insured, and crop year insured. Using the Producer Price Index for farm products, all dollar values were converted to real 2012 dollars.

NASS collects county yield and state price information about crops annually, available online from their *QuickStats* online tool. We collect yield data from 1966 through 2012 for each county and model the yield trends using a non-parametric procedure (loess, or local polynomial regression). The loess procedure uses weighted least squares to regress time on the yields where years nearby the year being estimated are given more weight than years farther away. Not only does this allow for nonlinear estimation of yields, it also minimizes the influence of the endpoints, a concern when using linear regression to estimate yield trends. This procedure allows us to compute predicted yields for each year for each county, which we use as the expected yield for the given year. Subtracting this predicted value from the realized yield generates a deviation from the trend which we use as the yield shock.

Various measures of demand for crop insurance allow us to explore how producers use crop insurance, including the total premium, the total liability, total acres insured, and total acres of buy-up (those insured with more than just catastrophic [CAT] levels of insurance). Using these various measures, we examine both the price elasticity of demand for crop insurance as well as whether past yield shocks affect the demand for crop insurance.

Total premiums are measured as the total premiums of all policies taken out in each county. Because total premiums are mandated by Congress to be actuarially fair, this variable should measure the amount of risk covered by the policy. This variable measures the intensity of use of the program, since a policy with a higher level of coverage will have a higher total premium than a policy with a lower level of coverage. Furthermore, different policies will be priced differently based on the level of risk that they are covering; the total premium captures these differences while taking into account the probability of a loss.

Total liabilities measure the total value of the crops covered by this insurance, capturing the amount that the crop insurance program would need to pay out if total crop losses were to occur. While this provides a measure of intensity of use of the crop insurance program, unlike the total premium, it does not take into account the probability of losses. Note that total liabilities and total premiums can change due to changes in commodity prices, so these price changes need to be controlled for.

Two other measures of crop insurance participation are total acres and acres of buy-up. These variables capture the change in the amount of land covered by crop insurance. Note that these measures do not suffer from the potential for commodity prices to change, but cannot capture the intensity of farmers' use of the program. For example, an acre insured in the crop insurance program may be insured at the lowest coverage level possible or at the highest—and these acreage measures cannot distinguish between the two. Acres of buy-up does provide a first step to ameliorate this concern, by removing from the analysis those acres that only have the free (fully subsidized), catastrophic measure of insurance.

Since we want to explore how the demand for crop insurance changes with yield shocks, we need to be able to control for changes in the price of crop insurance that producers observe. Subsidies play a major role in the pricing that producers see, and subsidy rates changed significantly over this time frame. In 2000, Congress locked in larger subsidy rates—particularly at the upper levels of coverage—to encourage higher levels of adoption of crop insurance. However, simply using the producer premium or subsidy is not feasible because these measures depend on the insurance choices that producers make. Furthermore, new insurance policies came into being over this time frame, making it difficult to compare policy prices over time.

As a result, we generated a basket of policies that were in effect over the time frame studied and used the changes in the price of this fixed basket of policies as a measure of the change in the price of insurance for producers. Because policies changed over time, we created our basket at the crop-reporting district (CRD) level and only used only those plans that were consistent over this timeframe.

These included an area-based policy, two revenue-based policies, and a yield-based policy. Using this basket of goods, we then created a price of crop insurance and the subsidy levels used in the analysis.

Variation in yields across time may help determine why producers adopt specific levels of crop insurance. To control for this variation, we construct the standard deviations of yields by first generating variances of yields for every 10-year period in our sample. Taking the square root of these variances then provides us with a 10-year "rolling" standard deviation for both prices and yields.

If the average yield changes over time, this could cause the value of the crop to change as well, and could have implications for whether or how a producer might want to insure the crop. For example, if a crop has a low expected yield, the producer may be less inclined to insure the crop. If the expected yield was high, however, the planted crop would be more valuable and the potential losses greater, which might induce the producer to insure (or to insure at higher levels of coverage). Alternatively, a higher expected yield may generate a wealth effect that may induce the producer to insure at lower levels of coverage. Therefore, to control for the expected yield we include it in the analysis. This variable is generated from the aforementioned loess procedure that was used to generate the yield shocks.

As mentioned previously, larger counties are more likely to have higher levels of premiums associated with them simply because they are larger. To control for this, we include the number of agricultural acres in a county of the particular crop, obtained directly from NASS. Prices also fluctuate over time and need to be controlled for since the commodity prices may play a role in whether a grower chooses to insure and at what levels. Unlike yields, prices do not vary much by region – any variation is simply due to issues like transportation costs. As a result, we control for this using time fixed effects – which will control for the national price levels that change across time but do not vary across space.

Tables 1 and 2 provide county-level descriptive statistics for the main variables used in the analysis for each year in the study, for corn and soybeans respectively. Crop insurance use has clearly jumped over the timeframe examined, increasing fivefold from an average of roughly \$800,000 in total premiums per county to over \$4 million dollars' worth of demand for corn and fourfold for soybeans, with an increase from roughly half a million dollars to over \$2 million. Premium subsidies increase more dramatically, with more than a sevenfold increase for corn and over a sixfold increase for soybeans.

Our estimated price of crop insurance started around \$14 per acre for corn in 1997 but dropped to just under \$9 per acre in 2001, after Congress introduced ARPA. The surge in demand for corn due to biofuel policies caused corn prices to spike in 2007, driving up crop insurance costs to pre-ARPA levels, and the corn prices likely drove the major subsequent changes in crop insurance prices. The price of crop insurance for soybeans reacted more slowly to the corn price shocks, but by 2008 the county average crop insurance prices looked very similar to the pre-ARPA crop insurance prices.

Not surprisingly, expected yields increased – faster for corn than for soybeans. The standard deviation of crop yields, however, remained relatively constant over time.

Results and Discussion

We estimated equations (1) and (2) using a structural equations modeling framework with the SEM STATA procedure which implements a linear structural equation model. SEM is a procedure that allows for flexible specification based on the linear model. We took advantage of this flexibility to run a system of simultaneous equations while allowing for correlation between the error terms of the two equations and estimated the system using maximum likelihood methods. Because we found evidence of heteroscedasticity in the errors, we invoked the Huber/White/Sandwich estimator of the variance-covariance matrix of the parameters to obtain robust standard errors.

When estimating equations (1) and (2) using the total premium measure as the measure of demand, results suggest that producers respond to the price of crop insurance for soybeans much more than for corn (Tables 3 and 4). A 10 percent increase in the price of crop insurance is associated with just under a 1 percent decrease in the demand for crop insurance for corn and an 8 percent decrease in the demand for crop insurance for soybeans. This suggests an inelastic response for both corn and soybeans.

County size (number of agricultural acres within the county) has a positive relationship with demand for crop insurance for both corn and soybeans, with a slightly larger than 1-for-1 increase in demand for a given increase in county size. As predicted, results for corn suggest that increases in the expected yield lead to higher levels of crop insurance, with a 10 percent increase in the expected yield associated with a 20 percent increase in the demand for crop insurance.

In contrast, the results for soybeans show that expected yield has the opposite, albeit inelastic, effect with a 10 percent increase in the expected yield associated with an almost 7 percent *decrease* in demand. This could come about if producers have a limited budget for crop insurance and they want to insure corn (or other crops) more than soybeans – effectively substituting away from soybean insurance and towards corn insurance if insurance prices increase (as they did when corn prices, and hence other commodity prices as well, increased over this period due in large part to biofuels policy). If we look at the rolling standard deviation of yields (Tables 1 and 2), soybeans are much more stable with a standard deviation between 6 and 7 bushels per acre while corn has a standard deviation between 18 and 22 bushels per acre (however, also note that the coefficient of variation for soybeans is very similar – in fact, slightly larger – than that of corn – suggesting that the two crops have very similar yield risks associated with them). If budget constraints exist, this could imply that producers would prefer to insure corn first since financial losses could be much higher for corn, which could substitute away from soybeans. As the expected soybean yields increase over time, the higher expected yield may offset some of the risk and induce producers to substitute towards insuring corn (or other crops).

For both corn and soybeans, increases in the variance of yield—which is a measure of risk—also leads to higher levels of crop insurance. However, the elasticity is small, with a 10 percent increase in the standard deviation of yields leading to a drop in total premiums of 0.3 percent.

In the second equation, the level of subsidies is positively correlated with the price of crop insurance for both corn and soybeans. This makes sense given that the subsidies are determined from subsidy rates – as the price of crop insurance increases, the subsidy also increases, so the two are positively correlated. Increases in expected yields also increase the price of crop insurance, since higher yields lead to higher overall revenues and the price of crop insurance reflects the level of crop yields. Increased yield variation also gives rise to increased crop insurance prices as expected. However, these results are driven by subsidies, since the effects of the expected yields and volatility of yields are statistically significant but small in magnitude.

When exploring other measures of demand, including total liabilities and the number of insured acres, demand for crop insurance for corn becomes less inelastic, and for soybeans the results for those other three measures of demand suggest an elastic response to the price of crop insurance. The elasticities of demand range from roughly 0.09 up to 0.92 in absolute value for corn, and for soybeans the elasticities range from 0.83 to 1.6 in absolute value, suggesting that the choice of dependent variable matters (Table 5). Among the various measures of demand used, the measure of total liabilities appears to be the most responsive to price for both corn and soybeans. The measure of crop insurance demand that is least responsive to the price of crop insurance, for both corn and soybeans, is total premiums. As expected, buy-up acres appear more responsive to price than total acres insured—which consists of buy-up plus CAT coverage (and recall that CAT is fully subsidized). This difference is larger for corn—with elasticities of 0.82 and 0.55 in absolute value, respectively—than for soybeans with elasticities of 1.5 and 1.3 in absolute value, respectively.

One additional set of variables that might have an impact on demand for crop insurance and that has not been explored yet are yield shocks. As detailed in the previous section, we add in variables that capture the shocks that occurred over the past five years to see whether or not yield shocks (or the lack thereof) cause producers to enter (or exit) the crop insurance market (Tables 7 and 8). Overall, yield shocks do not appear to have affected crop insurance demand in a meaningful way.

While the lagged shocks are found to be statistically significant at a variety of lags—depending on the crop and the measure of demand—pointing to the possibility that the impact of some shocks may persist longer than others, the magnitude of the effects appear to be small. Generally, the largest effect was found in the most recent year, with the effect dwindling as time went on. Suppose producers felt a negative 1 percent shock in each of the five years for which we included shock variables. For corn, this would lead to a 0.25 percent increase in the demand when measuring demand as total premiums, a drop of 0.05 percent when measuring as total liability, a 0.06 percent increase when measuring demand as total insured acres, and an increase of 0.36 percent when measuring demand as total buy-up acres insured. In other words, an effect appears to exist, but the effect remains inelastic and small.

While small shocks that occur every year may be one way for shocks to impact producers, perhaps it is the immediately preceding year when a large shock occurs that might be a driver of grower behavior. To explore this scenario, suppose a producer felt a 50 percent yield shock (loss) the year before. Our regression results suggest that this would translate into a roughly 5 to 6 percent increase in crop insurance in the current year for corn when measuring demand as total premiums, total liabilities, or acres covered with buy-up policies. It would translate into approximately 2.5 percent increase in total acres covered by crop insurance. In other words, even with a very large shock, which would wipe out half of the producer's crop, changes in crop insurance demand remain modest the following year – suggesting the producers understand that such yield shocks are random events and are not likely to reoccur with a new probability such that they need to revisit their insurance decisions.

For soybeans, if every year experienced a negative 1 percent shock, results suggest an increase in uptake of crop insurance measured by total premiums of 0.18 percent. Results also suggest that a negative 1 percent shock experienced each year would induce a drop of 0.17 percent in total liabilities – an unexpected sign, but close to zero, suggesting an economically insignificant effect—as well as a 0.13 percent decrease in total acres insured (again an unexpected sign but close to zero), and a 0.05 percent increase in acres of buy-up. As with corn, the aggregate effect of past years' yield shocks on demand for crop insurance for soybeans exists but is small and inelastic.

Following the example above, if soybean yields experienced a 50 percent loss the previous year, producers would increase their insurance decisions by 0.1 percent (when demand is measured as total premiums) up to 4 percent (when demand is measured by total liabilities or acres insured). While the sign of the coefficient suggests the substitution effect as discussed before, the effect again is minimal. Finally, adding in the yield shocks do not improve the overall fit of any of the regression equations.

The yield shocks do enter in the system of equations twice, in both the first equation explaining demand for crop insurance and in the second equation, helping to explain the price of crop insurance. As yield shocks occur, the shocks are used to update the price of the insurance. Once more, results suggest a negative yet small relationship between the yield shock and the price of crop insurance. As expected, a negative yield shock increases the price of crop insurance and vice versa. While the sign of the coefficient is what we expected, the magnitude suggests that the effects are economically insignificant.[2]

Together, these results suggest that yield shocks do not appear to play a large role when modeling the price elasticity of demand of crop insurance. In summary, producers appear to respond to crop insurance prices more heavily for soybeans than for corn. Demand for crop insurance for soybeans shows an elastic response to the price of crop insurance for three of the four measures of demand, and demand for crop insurance shows a response to the price of crop insurance that ranges from slightly inelastic to very inelastic, depending on the measure of demand.

Conclusions

The demand for crop insurance depends, in part, on the price of crop insurance. However, as previous studies have found, results suggest that the relationship between price and demand remains inelastic for corn – where a one percent increase in the price of crop insurance would lead to a less than one percent decrease in demand. While inelastic, the results found in this study tend to be larger than what had been found previously.

In contrast to previous findings, for soybeans our results suggest an elastic response for demand measured as total liability and acres insured, both total acres and acres of buy-up insurance. This could be due to the fact that producers may view soybeans as a crop that does not require crop insurance in the same way that corn may, and so might substitute away from insuring soybeans if budget constraints become binding. Alternatively, producers may view corn, a crop subject to more yield volatility, as more likely to require crop insurance to smooth their income over time, and hence the demand for crop insurance for corn shows a more inelastic response to prices.

This paper also examined the effect of yield shocks on the demand for crop insurance. If producers believe that weather and pest events are correlated across time (so that past outcomes are

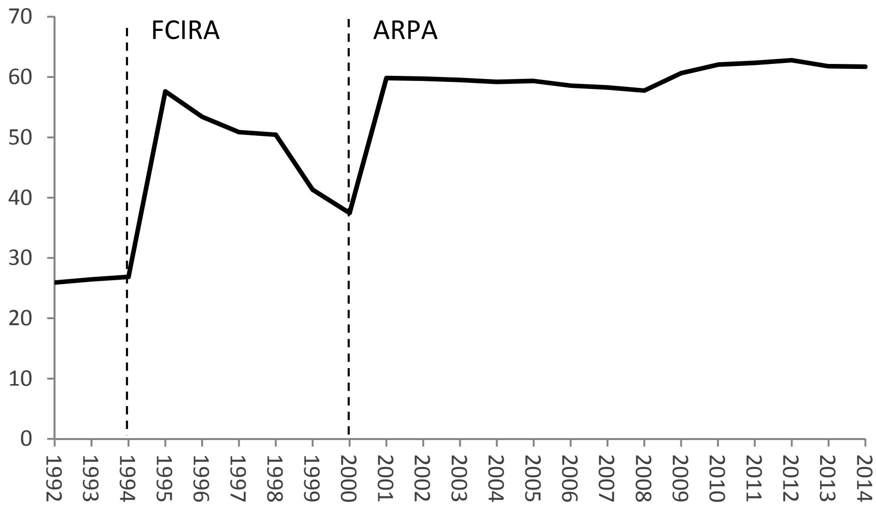
[2] Results for the second equation can be found in the appendix. Note that we have four specifications for each crop yet only one set of results for each crop in the appendix –this is because the results for the second equation remained stable across all specifications.

predictive of future outcomes) then we would expect yield shocks to matter. Absorbing the impact of a yield shock in one year may cause producers to purchase (or increase their demand for) crop insurance the next. Alternatively, if producers do not believe that such correlations exist—that yield shocks are random—then yield shocks should not affect producers' decisions to insure their crops.

Examining corn and soybean farmers in ten of the major corn and soybean producing states across the U.S., we did not find any compelling evidence that yield shocks matter to producers. While our results suggest that yield shocks extending up to 5 years into the past were, on average, statistically significant, the coefficients were sufficiently small that from an economic point of view, the effect of the shocks were minimal on crop insurance demand. Note that this does not suggest that yield variability does not matter to producers – such variability can still drive, and is likely built into producers' current production decisions. However, it does suggest that producers appear to understand that such shocks are not easily predicted and that once they have a model of what to expect, they do not tend to update their expectations by placing a large weight on the occurrence of a recent shock.

Due to data constraints, we were unable to examine this question using farm level data. Work is underway to try to obtain farm level data by combining various administrative datasets, and this represents an opportunity to better understand the decisions that individual producers make regarding crop insurance. This could allow for the analysis of idiosyncratic versus systemic shocks and to focus on the individual decisions that are being made with respect to crop insurance. Future work will hopefully be able to focus on individual-level behavior and be able to map individual characteristics to crop insurance choices. In the meantime, focusing on county-level data, we do not find evidence that yield shocks help to drive producer behavior.

Figure 1. Subsidies' Share of Total Premiums



Source: ERS calculations based on USDA, Risk Management Agency Administrative data, 1992-2014

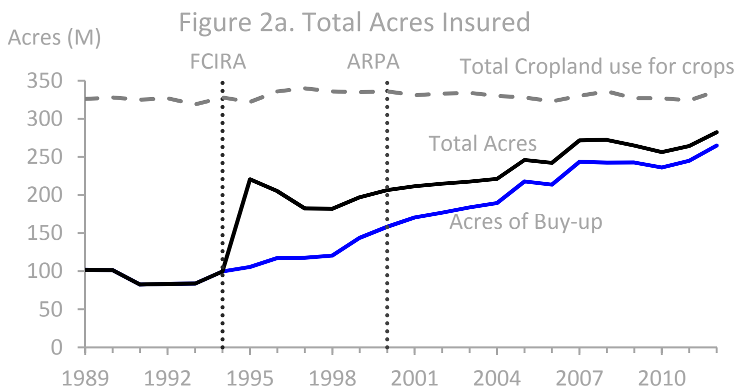


Figure 2a. Total Acres Insured
Acres (M)
FCIRA
ARPA
Total Cropland use for crops
Total Acres
Acres of Buy-up
350
300
250
200
150
100
50
0
1989
1992
1995
1998
2001
2004
2007
2010

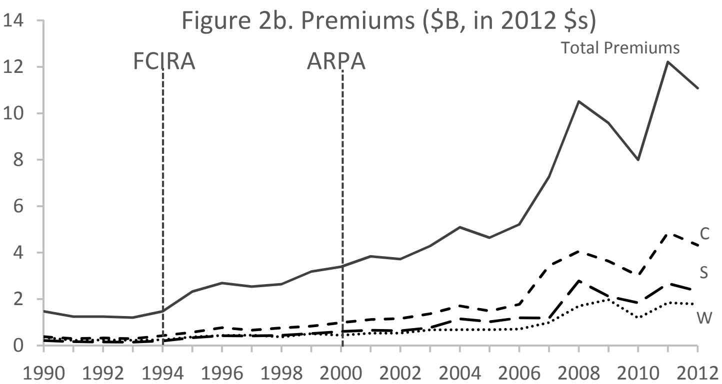


Figure 2b. Premiums ($B, in 2012 $s)
FCIRA
ARPA
Total Premiums
C
S
W
14
12
10
8
6
4
2
0
1990
1992
1994
1996
1998
2000
2002
2004
2006
2008
2010
2012

Table 1. County average values for Corn, 1997-2012 (standard deviations in gray)

	Total Premiums ($M)	Premium Subsidies ($M)	Planted Acres (,000)	Price of Crop Insurance ($/per acre)	Expected Corn Yield (bu/acre)	Std Dev Corn Yield (10 yr. rolling avg.)
1997	0.82 (0.78)	0.34 (0.29)	79 (59)	13.56 (2.34)	123 (21)	21.4 (5.2)
1998	1.0 (0.95)	0.40 (0.35)	78 (59)	16.05 (2.62)	125 (21)	21.7 (5.3)
1999	1.2 (1.1)	0.63 (0.55)	78 (58)	10.28 (1.63)	127 (21)	19.2 (4.8)
2000	1.5 (1.3)	0.64 (0.54)	80 (58)	10.41 (1.67)	129 (22)	19.6 (4.7)
2001	1.7 (1.5)	0.92 (0.78)	76 (56)	8.74 (1.45)	131 (23)	20.4 (4.7)
2002	1.8 (1.5)	0.97 (0.83)	78 (58)	8.82 (1.60)	132 (23)	19.4 (4.8)
2003	1.9 (1.6)	1.0 (0.8)	78 (59)	8.84 (1.58)	134 (24)	20.2 (5.0)
2004	2.2 (1.8)	1.2 (1.0)	81 (60)	9.35 (1.67)	136 (24)	17.3 (4.5)
2005	2.1 (1.6)	1.2 (0.9)	82 (61)	8.67 (1.79)	137 (25)	19.5 (4.8)
2006	2.7 (2.3)	1.5 (1.2)	80 (60)	8.79 (1.78)	139 (24)	18.9 (4.8)
2007	4.3 (3.5)	2.4 (1.9)	92 (67)	12.36 (2.52)	140 (25)	18.6 (4.9)
2008	4.8 (3.9)	2.6 (2.1)	88 (64)	14.94 (3.34)	143 (24)	18.4 (5.0)
2009	5.0 (3.8)	2.9 (2.2)	89 (64)	14.60 (3.82)	144 (25)	18.6 (5.2)
2010	3.6 (2.8)	2.1 (1.7)	88 (63)	11.58 (3.29)	143 (26)	19.5 (5.7)
2011	5.0 (3.8)	3.0 (2.2)	92 (66)	13.69 (3.47)	144 (27)	19.6 (6.1)
2012	4.2 (3.3)	2.5 (2.0)	93 (67)	11.73 (3.15)	144 (29)	19.3 (6.6)

Source: ERS calculations based on RMA and NASS data, 1987-2012

Table 2. County average values for Soybeans, 1997-2012 (standard deviations in gray)

	Total Premiums ($M)	Premium Subsidies ($M)	Planted Acres (,000)	Price of Crop Insurance ($/per acre)	Expected Soybean Yield (bu/acre)	Std Dev Soy Yield (10 yr. rolling avg.)
1997	0.48 (0.50)	0.20 (0.18)	68 (53)	10.10 (2.10)	39 (6)	6.2 (1.5)
1998	0.56 (0.56)	0.22 (0.20)	71 (53)	11.12 (2.06)	39 (6)	6.4 (1.5)
1999	0.71 (0.67)	0.38 (0.35)	74 (54)	7.00 (1.34)	40 (6)	5.6 (1.7)
2000	0.88 (0.77)	0.40 (0.34)	75 (53)	7.39 (1.44)	40 (6)	5.5 (1.6)
2001	0.94 (0.80)	0.52 (0.43)	76 (54)	5.94 (1.30)	40 (7)	5.7 (1.7)
2002	0.94 (0.78)	0.51 (0.41)	74 (53)	5.94 (1.29)	40 (7)	5.6 (1.7)
2003	1.0 (0.87)	0.56 (0.47)	74 (52)	5.98 (1.42)	41 (7)	5.7 (1.7)
2004	1.4 (1.2)	0.78 (0.63)	73 (51)	6.61 (1.61)	41 (7)	5.7 (1.7)
2005	1.4 (1.1)	0.77 (0.57)	71 (49)	6.19 (1.67)	42 (7)	6.0 (1.7)
2006	1.7 (1.3)	0.94 (0.67)	74 (50)	6.81 (1.98)	42 (7)	6.2 (1.7)
2007	1.4 (1.1)	0.76 (0.59)	62 (43)	7.37 (2.29)	43 (7)	6.2 (1.6)
2008	3.2 (1.7)	1.7 (1.2)	74 (47)	11.79 (3.18)	43 (7)	6.4 (1.6)
2009	2.7 (1.8)	1.6 (1.0)	75 (47)	10.30 (3.09)	44 (7)	6.4 (1.7)
2010	2.0 (1.4)	1.2 (0.82)	74 (48)	8.23 (2.80)	44 (8)	6.5 (1.8)
2011	2.6 (1.7)	1.5 (1.0)	72 (46)	9.45 (2.91)	44 (8)	6.6 (1.7)
2012	2.1 (1.5)	1.3 (0.94)	71 (47)	7.92 (2.71)	44 (8)	6.7 (1.8)

Source: ERS calculations based on RMA and NASS data, 1987-2012

Table 3. Corn – Demand measured by Total Premiums

(Standard Errors in gray)

	ln(tot_prem)	$\ln(P_{CI})$
$\ln(P_{CI})$	-0.09^{**} 0.04	--
ln(subsidies)	--	0.80^{***} 0.005
ln(agland)	1.1^{***} 0.02	--
ln(E[yield])	2.0^{***} 0.06	0.04^{***} 0.01
sd_{yield}	0.03^{***} 0.001	0.003^{***} 0.0002
Constant	-9.9^{***} 0.36	0.74^{***} 0.03
Time fe's	Y	Y
State fe's	Y	Y
$R^{2\,*}$	0.78	0.92
N	12,062	12,062

*The R^2 is the Bentler-Raykov squared multiple correlation coefficient.

Source: U.S. Department of Agriculture, Economic Research Service, regression results

Table 4. Soybeans – Demand measured by Total Premiums

(Standard Errors in gray)

	ln(tot_prem)	$\ln(P_{CI})$
$\ln(P_{CI})$	-0.83*** 0.04	--
ln(subsidies)	--	0.86*** 0.004
ln(agland)	1.2*** 0.02	--
ln(E[yield])	-0.67*** 0.07	0.08*** 0.01
sd_{yield}	0.03*** 0.005	0.007*** 0.0005
Constant	2.5*** 0.32	0.53*** 0.02
Time fe's	Y	Y
State fe's	Y	Y
R^2 *	0.70	0.95
N	11,180	11,180

*The R^2 is the Bentler-Raykov squared multiple correlation coefficient.

Source: U.S. Department of Agriculture, Economic Research Service, regression results

Table 5. Corn – Various Demand Measures Standard Errors in gray (Results for equation 1 only)

	ln(tot prem)	ln(tot liability)	ln(tot ins acres)	ln(buy-up acres)
$\ln(P_{CI})$	-0.09** 0.04	-0.92*** 0.05	-0.55*** 0.04	-0.82*** 0.05
ln(agland)	1.1*** 0.02	1.1*** 0.02	1.08*** 0.02	1.1*** 0.02
ln(E[yield])	2.0*** 0.06	3.0*** 0.07	1.9*** 0.06	2.1*** 0.07
sd_{yield}	0.03*** 0.001	0.03*** 0.001	0.02*** 0.001	0.03*** 0.001
Constant	-9.9*** 0.36	-10*** 0.38	-11*** 0.32	-12*** 0.38
Time fe's	Y	Y	Y	Y
State fe's	Y	Y	Y	Y
R^2	0.78	0.80	0.76	0.75
N	12,062	12,061	12,061	12,056

Source: U.S. Department of Agriculture, Economic Research Service, regression results

Table 6. Soybeans – Various Demand Measures Standard Errors in gray (Results for equation 1 only)

	ln(tot prem)	ln(tot liability)	ln(tot ins acres)	ln(buy-up acres)
$\ln(P_{CI})$	-0.83^{***} 0.04	-1.6^{***} 0.05	-1.3^{***} 0.04	-1.5^{***} 0.04
ln(agland)	1.2^{***} 0.02	1.2^{***} 0.02	1.2^{***} 0.02	1.2^{***} 0.02
ln(E[yield])	-0.67^{***} 0.07	0.30^{***} 0.08	-0.62^{***} 0.07	-0.64^{***} 0.07
sd_{yield}	0.03^{***} 0.005	0.03^{***} 0.006	0.02^{***} 0.006	0.04^{***} 0.006
Constant	2.5^{***} 0.32	3.2^{***} 0.34	1.3^{***} 0.33	0.44^{*} 0.26
Time fe's	Y	Y	Y	Y
State fe's	Y	Y	Y	Y
R^2	0.70	0.70	0.65	0.66
N	11,180	11,180	11,180	11,180

Source: U.S. Department of Agriculture, Economic Research Service, regression results

Table 7. Corn – Various Demand Measures with Yield Shocks Standard Errors in gray (Equation 1 only)

	ln(tot_prem)	ln(tot liability)	ln(tot insured acres)	ln(buy-up acres)
ln(P_{CI})	-0.10** 0.04	-0.92*** 0.05	-0.56*** 0.04	-0.83*** 0.05
ln(agland)	1.1*** 0.02	1.1*** 0.02	1.1*** 0.01	1.1*** 0.02
ln(E[yield])	2.0*** 0.06	3.0*** 0.07	1.9*** 0.06	2.1*** 0.07
sd_{yield}	0.03*** 0.001	0.03*** 0.001	0.02*** 0.001	0.03*** 0.001
lag_ln($shock_{corn}$)	-0.12** 0.06	-0.10 0.06	-0.05 0.05	-0.10* 0.06
lag2_ln($shock_{corn}$)	-0.01 0.06	0.04 0.06	0.03 0.05	-0.02 0.06
lag3_ln($shock_{corn}$)	0.01 0.06	0.04 0.06	0.03 0.05	-0.05 0.06
lag4_ln($shock_{corn}$)	-0.09* 0.05	-0.02 0.05	-0.03 0.05	-0.12** 0.05
lag5_ln($shock_{corn}$)	-0.04 0.05	-0.01 0.05	-0.04 0.04	-0.07 0.05
Constant	-10*** 0.36	-10*** 0.38	-11*** 0.32	-12*** 0.38
Time fe's	Y	Y	Y	Y
State fe's	Y	Y	Y	Y
R^2	0.78	0.80	0.76	0.75
N	12,062	12,061	12,061	12,056

Source: U.S. Department of Agriculture, Economic Research Service, regression results

Table 8. Soybeans – Various Demand Measures with Yield Shocks Standard Errors in gray (Equation 1 only)

	ln(tot_prem)	ln(tot liability)	ln(tot insured acres)	ln(buy-up acres)
$\ln(P_{CI})$	-0.83^{***} 0.04	-1.7^{***} 0.05	-1.4^{***} 0.04	-1.5^{***} 0.04
ln(agland)	1.2^{***} 0.02	1.2^{***} 0.02	1.2^{***} 0.02	1.2^{***} 0.02
ln(E[yield])	-0.67^{***} 0.07	0.29^{***} 0.08	-0.62^{***} 0.07	-0.65^{***} 0.07
sd_{yield}	0.03^{***} 0.01	0.03^{***} 0.01	0.02^{***} 0.006	0.04^{***} 0.01
$lag\_\ln(shock_{soy})$	0.002 0.05	0.08 0.06	0.08 0.05	0.08 0.06
$lag2\_\ln(shock_{soy})$	-0.03 0.05	0.07 0.06	0.05 0.05	0.01 0.05
$lag3\_\ln(shock_{soy})$	0.05 0.06	0.14^{**} 0.06	0.13^{**} 0.06	0.10^{*} 0.06
$lag4\_\ln(shock_{soy})$	-0.17^{***} 0.05	-0.11^{**} 0.05	-0.11^{**} 0.05	-0.17^{***} 0.05
$lag5\_\ln(shock_{soy})$	-0.03 0.05	-0.01 0.06	-0.02 0.05	-0.07 0.05
Constant	2.5^{***} 0.32	3.3^{***} 0.26	1.3^{***} 0.33	0.47^{*} 0.33
Time fe's	Y	Y	Y	Y
State fe's	Y	Y	Y	Y
R^2	0.70	0.70	0.65	0.66
N	11,180	11,180	11,180	11,180

Source: U.S. Department of Agriculture, Economic Research Service, regression results

Appendix

Regression Results for Equation (2) – results remain constant across all specifications:

Appendix Table 1. Corn – Equation 2 Standard Errors in gray

	Without Shocks	With Shocks
ln(G)	0.80** 0.005	0.80** 0.005
ln(E[yield])	0.04*** 0.005	0.04*** 0.005
sd_{yield}	0.003*** 0.0002	0.003*** 0.0002
lag_ln($shock_{corn}$)	--	-0.06*** 0.005
lag2_ln($shock_{corn}$)	--	-0.04*** 0.005
lag3_ln($shock_{corn}$)	--	-0.05*** 0.005
lag4_ln($shock_{corn}$)	--	-0.0003 0.006
lag5_ln($shock_{corn}$)	--	0.02*** 0.006
Constant	0.74*** 0.03	0.72*** 0.03
Time fe's	Y	Y
State fe's	Y	Y

Source: U.S. Department of Agriculture, Economic Research Service, regression results

Appendix Table 2. Soybeans – Equation 2 Standard Errors in gray

	Without Shocks	With Shocks
ln(G)	0.86** 0.004	0.86** 0.004
ln(E[yield])	0.08*** 0.006	0.08*** 0.006
sd_{yield}	0.007*** 0.0005	0.007*** 0.0005
lag_ln($shock_{corn}$)	--	-0.03*** 0.004
lag2_ln($shock_{corn}$)	--	-0.02*** 0.004
lag3_ln($shock_{corn}$)	--	-0.02*** 0.004
lag4_ln($shock_{corn}$)	--	-0.01*** 0.004
lag5_ln($shock_{corn}$)	--	-0.02*** 0.005
Constant	0.53*** 0.02	0.52*** 0.02
Time fe's	Y	Y
State fe's	Y	Y

Source: U.S. Department of Agriculture, Economic Research Service, regression results

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