Journal of Agricultural and Resource Economics 43(1):61–77 ISSN 1068-5502

Does Crop Insurance Influence Commercial Crop Farm Decisions to Expand? An Analysis Using Panel Data from the Census of Agriculture

Christopher B. Burns and Daniel L. Prager

The Agricultural Act of 2014 increased the role of risk-mitigating policies in U.S. agricultural policy and focused attention on how crop insurance affects farm production decisions. Using detailed farm-level data from the Census of Agriculture and supplemental county-level data, this paper seeks to understand whether purchasing crop insurance influences commercial crop farms' decisions to expand. After instrumenting for the endogenous decision to purchase crop insurance, we find that paying higher net premiums had no statistically significant effect on crop farm expansion from 2007 to 2012. We also find that farms expanded more when they were located in counties with more acres enrolled in the Conservation Reserve Program.

Key words: acreage response, farm exits, government payments

Introduction

The effect of government policies on farm production and survival has been a longstanding area of interest to economists and policy makers. The expansion of crop insurance and other risk-mitigating programs in the Agricultural Act of 2014 (the 2014 Farm Bill) has increased attention on how these changes will affect farm production decisions. As the suite of farm programs funded by the federal government shifts focus from income support to risk management, understanding how crop insurance has historically affected farm acreage decisions is important to future policy considerations.

From the decoupling of government payments in the 1996 Farm Bill through 2014, two of the largest federal agricultural commodity programs were fixed direct payments and crop insurance. The 2014 Farm Bill ended fixed direct payments to producers based on historical production and created new programs tied to annual or multi-year fluctuations in prices, yields, or revenues. These programs include those that pay producers when prices fall below a reference price (Price Loss Coverage (PLC)) or when revenue falls below a benchmark (Agricultural Risk Coverage (ARC)) as well as programs aimed at providing support for shallow revenue or yield losses (Supplemental Coverage Option (SCO) and Stacked Income Protection Plan (STAX)).

The 2014 Farm Bill also has potential World Trade Organization (WTO) implications, specifically whether the new programs will be considered production distorting (e.g., "amber box" policies) under the latest negotiated rules (Glauber and Westhoff, 2015). An examination of the

Christopher B. Burns and Daniel L Prager are research economists at the Economic Research Service, USDA.
The authors thank two anonymous reviewers for their helpful comments as well as Jeffrey Hopkins for his suggestions during the revision process. The views expressed are those of the authors and should not be attributed to the Economic Research Service or the USDA.
Review coordinated by David K. Lambert.

historic impact of crop insurance on farm-level exit and expansion decisions can clarify whether these subsidies are distorting in practice.

This paper uses Census of Agriculture data to understand the effect of crop insurance participation on farm expansion while accounting for selection effects. While earlier studies looked at the effects of crop insurance on farm expansion using cross-sectional or aggregate data at the county level, this study is the first we are aware of to use farm-level data from the nationally representative Census of Agriculture. We also make use of improvements in the tracking of farm operations that began with the 2007 Census. Relative to previous studies, these data will help us better identify the determinants of farm exits. Using supplementary crop insurance data from the USDA Risk Management Agency (RMA) and soil productivity data from the Natural Resources Conservation Service (NRCS), we estimate a three-stage model for farm acreage decisions that accounts for sample-selection bias and addresses the endogeneity of crop insurance participation decisions. We focus on operations that generated at least $10,000 in gross cash farm income (i.e., commercial farms); produced corn, soybeans, or wheat; and were located in the Heartland and Northern Great Plains, a combined region that encompasses nine states.[1]

U.S. Crop Insurance Program Participation

Federal crop and revenue insurance programs are delivered through private insurance companies with the USDA Risk Management Agency (RMA) playing a coordinating role, subsidizing insurance premiums and administrative costs, and sharing the underwriting risk of the loans. According to the RMA's Summary of Business files, acres enrolled, policies issued, and coverage levels have seen striking gains over the last two decades. From 1998 to 2011, enrolled acres increased from 182 to 265 million, with more than 70% of enrolled acres having at least 70% insurance coverage. Due in part to higher commodity prices and higher expected revenues, total premiums for crop insurance rose from $6.5 billion to $12 billion between 2007 and 2011. Premium subsidies also rose from $3.8 billion to $7.3 billion during this period, as the premium subsidy is based on the value of the premium as well as the coverage level. Revenue policies such as the Average Crop Revenue Election (ACRE) program totaled more than 173 million acres in 2011, and yield policies accounted for less than 20% of insured acres (Glauber, 2013). In 2012, 80% of planted acreage of corn, cotton, soybeans, and wheat were covered by crop insurance. Between 2011 and 2013 average insurance payouts to farmers net of premiums rose from $2.5 billion to $9.1 billion, exceeding direct payments in each year (Orden and Zulauf, 2015). In 2014, total premium subsidies declined to about $6 billion, reflecting the drop in crop prices, while direct payments decreased substantially as part of the planned phase out from the 2014 Farm Bill (U.S. Deparment of Agriculture, Economic Research Service, 2016).

Background

With the passing of the 2014 Farm Bill, fixed direct payments were eliminated, crop insurance payments rose, and the focus of U.S, farm support shifted to risk mitigation. In addition to the PLC and ARC programs, which are triggered when prices or revenues fall below a benchmark, federal programs include (longstanding) agricultural disaster payments, which can provide payouts in the event of uncommon disasters such as drought, floods, or disease. Though the overall level of government expenditures has remained similar in magnitude, the composition of these supports may affect farms in unexpected ways. Government payments (specifically direct payments) and

[1] These two regions include the states of Illinois, Indiana, Iowa, Minnesota, Missouri, Montana, Nebraska, North Dakota, and South Dakota.

crop insurance represent a large outlay of federal government spending. Between 2007 and 2012, insurance premium subsidies averaged $5.7 billion dollars per crop year.[2]

At the same time, the farm sector has consolidated, with larger farms representing an increased share of production in major crop and livestock categories. By underwriting insurance throughout the sector, government support may affect not just individual farms through altered input mix or expansion decisions but the structure of agricultural production. This motivates an examination of how crop insurance may have historically affected farm production. As of early 2017, discussion of the forthcoming Farm Bill is already focusing on whether to revise or expand crop insurance premium subsidies.

Literature Review

Previous work on farm survival has identified several factors influencing farm exits, with operator age and farm profitability emerging as the two most important factors (Kimhi, 1999; Hoppe and Korb, 2006). Farms often open, expand, and close following the lifecycle of the principal operator. All else equal, older operators are more likely to exit; however, in many cases, the operation may be sold or passed down to the next generation of farmers. Past studies have found beginning and retired farmers are also more likely to exit farming altogether. Farmers that supply higher levels of off-farm labor or households with greater dependence on off-farm income have been found to exit at lower rates (Ahearn, Yee, and Korb, 2009).

A number of previous studies have examined the impact of government payments on farm-level labor and production decisions. Ahearn, El-Osta, and Dewbre (2006) found that income supports influence on-farm and off-farm labor decisions and thus would affect production and decisions to exit farming. Goetz and Debertin (2001) observed that farmers quit farming at faster rates as the transaction costs of moving into full-time off-farm employment decrease. Key and Roberts (2006, 2007) used Census of Agriculture data and found that per acre government payments have small, positive effects on farm business survival and expansion. The effect was shown to be stronger for crop farms operating more acreage. Mishra and Goodwin (2006) explored the effect of marketing loans assistance (MLA) payments and fixed-direct payments on both farm-level production and county-level acreage using multiple years of Agricultural Resource Management Survey (ARMS) data. They found a significant but modest positive effect on agricultural production. Finally, Weber and Key (2012) estimated the effect of direct payments on total acres harvested and value of production (both measured at the ZIP-code level) using census data from 1997, 2002, and 2007. They found that changes in direct payments from 2002 to 2007 had no significant effect on total acres harvested or value of production in 2007.

Studies on crop insurance participation have found that the most consistent predictors include business and yield risk, operator age, farm size, level of wealth, and leverage. A study by Sherrick et al. (2004) found that the likelihood of crop insurance usage is higher for larger, older, less tenured, and more highly leveraged farms with higher perceived yield risks. Velandia et al. (2009) used a simultaneous multivariate probit approach to model the decision to adopt risk management tools—such as crop insurance, forward contracting, and sales spreading—and found that factors that were significant in adopting these tools included the proportion of owned acres, off-farm income, education, age, and level of business risk. Mishra and Goodwin (2006) found that cash grain farmers with higher wealth or off-farm income tend to self-insure rather than purchase revenue insurance or opt to participate in production and marketing contracts.

Crop insurance may affect the production and expansion decisions of producers through several channels. Young and Westcott (2000) show that crop insurance can change expected revenues by reducing the financial risk associated with crop production variability. Subsidized insurance, which

[2] Historical information on government farm payments maintained by the USDA's Economic Research Service are available at https://www.ers.usda.gov/data-products.aspx

increases expected returns, might encourage production on marginal land. Goodwin, Vandeveer, and Deal (2004) investigated the impact of crop insurance on acreage decisions for corn, soybean, wheat, and barley farms in the Corn Belt and Northern Great Plains. Using county-level data, they found that increased insurance program participation provokes a statistically significant acreage response in some cases, but the magnitude of the effect is rather modest. They also found that producers with higher than average historical loss ratios (measured at the county level) are less responsive to change in insurance premium rates.[3] Guaranteeing a certain level of revenue to a producer may make lenders more willing to lend, allowing the farm to expand more quickly. Ifft, Kuethe, and Morehart (2015) examined debt use by farms that enroll in crop insurance using ARMS data and found that federal crop insurance participation is associated with an increase in short-term, but not long-term, debt use.

The role that government policy has played in the shift toward more production occurring on large farms over the last few decades remains an area of research. Ahearn, Yee, and Korb (2005) examined the impact of government payments on U.S. farm structure. They found that farmers use government payments to expand their farms and that government payments may have increased the share of large farms between 1982 and 1997. Roberts and Key (2008) explored the impact of per acre government payments on cropland consolidation (i.e., cropland becoming concentrated on fewer farms) using ZIP-code data from the 1987–2002 Censuses of Agriculture. Their analysis shows government payments were strongly associated with growth in cropland concentration.

Data

We use the 2007 and 2012 Censuses of Agriculture to understand how factors such as demographics, farm enterprise characteristics, and government programs affect farm survival and expansion. The Census of Agriculture surveys the entire U.S. farm sector every five years and contains data on U.S. farm holdings (acres and agricultural products produced), operator demographics, production inputs and outputs, and government payments. Improvements in the methodology used to track operations beginning with the 2007 Census allow us to estimate factors that affect farm exits for this portion of the farm sector more accurately than in previous studies.[4]

From the 2007 Census, we use a full slate of farm and operator characteristics, including county-level and operator demographics along with program participation. We then create a panel by matching this data with 2012 data from the same operations on acres operated and a dummy variable for whether the farm is observed again or has exited.[5]

To control for geographical elements affecting farm exits and expansion, we focus on crop farms located in the Heartland and Northern Great Plains regions specializing in corn, wheat, and soybeans. These regions represented 72% of total value of production for corn, wheat, and soybeans in 2012. Because the Census of Agriculture does not cover all farms and some farms do not respond, all summary statistics and regression analyses reported in this study are weighted to account for undercoverage and nonresponse.[6] We also limit our analysis to commercial farms (e.g., those with least $10,000 in sales in 2007) with an operator under 70 years of age.

---

[3] The loss ratio is the ratio of claims paid by an insurer (total indemnities) to total premiums collected for a given period.

[4] The USDA National Agricultural Statistical Service (NASS) is responsible for maintaining a list frame that contains a record of all current U.S. farm operations. This list frame is maintained and updated for each Census of Agriculture to reflect operations that exit and enter. Starting in 2007, NASS created a variable called Operation_ID (OID), based on a state-level variable called state_OID (State Operation_ID), in order to track operations in each succeeding census period. This change in the operation identifier resulted from a need for a more standardized method for tracking farms longitudinally. It will improve the quality of inter-census links over time.

[5] The production and demographic data for the 2012 Census were collected prior to the 2013 planting season, but farms were considered to be "in-scope" for the 2012 Census if the operation was in business in the spring of 2012. As a result, the 2012 drought, which negatively affected returns for many cash grain operations in the Midwest and Corn Belt but did not occur until later in the 2012 planting season, should not influence our models for farm exit or expansion.

[6] In these regions, a total of 82,724 farm operations responded, representing a total of 108,631 farms, a nonresponse rate of 23.8%

We use two additional sources of county-level information in order to better model the decisions individual farms face. First, to account for crop insurance payments and premiums, we include 2007 data from the Summary of Business files produced by the U.S. Deparment of Agriculture, Risk Management Agency (2017). We include average premiums paid per acre for both yield and revenue-based programs at the county level. Second, we use soil data from the National Commodity Crop Productivity Index (NCCPI), produced by the NRCS. This index evaluates soils according to their inherent capacity to produce dryland (non-irrigated) commodity crops. Most of the NCCPI criteria relate directly to the ability of soils, landscapes, and climates to foster crop productivity. A few criteria relate to factors that can limit use of the land (e.g., surface boulders).

Table 1 shows the weighted summary statistics for all variables used in our regression models. For 2007, we observed a weighted total of 108,631 farms, of which 93% produced corn or soybeans and 7% grow wheat. About 76% of these farms had insured acreage in 2007. The average farm in this group operated 836 acres in 2007, 564 of which were insured, receiving approximately $13,767 in government payments (including direct payments, counter-cyclical payments, conservation payments, and other state and local payments) and paid an average of $9,806 in crop insurance premiums. The average farm operator was 52 years old, was more likely to rent at least some land, worked off-farm at some point during the year, and had an average household size of 2.7. Of the crop farms we observe in 2007, 7.2% exited between 2007 and 2012. The surviving farms observed in 2012 operated 948 acres on average.

Empirical Model

As noted earlier, the literature has taken many approaches to modeling the effects of crop insurance on producer decisions to expand. We model the producer's acreage and crop insurance optimization problem based on previous empirical studies for producer acreage decisions (e.g., Goodwin, Vandeveer, and Deal, 2004; Key and Roberts, 2006). We use a reduced-form approach to model producer acreage decisions, describing the next period's acreage decision as a function of the previous period's values.

We measure the effects of crop insurance on acreage by controlling for factors that are correlated with acreage decisions and by addressing the endogenous decision to purchase crop insurance. We use net premiums paid (NPP) as our measure of crop insurance. To instrument for NPP in 2007, we use average per acre indemnities from 2002–2006. We posit that this instrument is not related to acreage decisions in 2012 but is plausibly related to crop insurance participation in 2007. We later test for this exclusions restriction and show that this instrument is strongly correlated with NPP.

Our empirical model makes the assumption that each producer faces the same prices in each period (i.e., homogeneous input and output prices). We also assume that each producer makes decisions to maximize his or her net present value expected utility. Thus, we expect that farms losing money over the long term would exit between census periods.

Model Specification

Let $y_{i,2012}$ be the natural log of total acres operated for farm i in 2012. The outcome variable depends on the lagged value of the natural log of acres operated in 2007, $y_{i,2007}$; a vector of farm and operator characteristics, $\mathbf{X}_i$; and net crop insurance premiums paid, NPP_i.

The acreage decision for producer i in 2012 is approximated with the linear function

$$y_{i,2012} = \alpha_0 + \alpha_1 y_{i,2007} + \mathbf{X}_i'\boldsymbol{\beta}_1 + \gamma_1 NPP_i + \varepsilon_i. \tag{1}$$

All right-side variables are from 2007, representing lagged variables. The vector of farm and operator characteristics (**X**) includes farm size, legal organization, total government payments (direct payments, conservation payments, countercyclical payments, and other state and local payments),

Table 1. Summary Statistics

	Mean	Std. Err.
Government payments	13,767.270	70.196
Indemnities per acre (2002–2006)	9.965	0.064
Corn/soybean farm	0.929	0.002
Wheat farm	0.071	0.001
Sole proprietor	0.832	0.002
Partnership	0.085	0.001
Corporation	0.075	0.001
Other legal org	0.008	0.000
Proportion acres irrigated	0.074	0.001
Specialized farm	0.202	0.002
Full land owner	0.263	0.002
Partial land renter	0.563	0.002
Full land renter	0.174	0.002
Operator age 35 or under	0.099	0.001
Beginning farmer	0.190	0.002
Operator worked 0 days off-farm	0.397	0.002
Operator worked 1–49 days off-farm	0.116	0.001
Operator worked 50–99 days off-farm	0.056	0.001
Operator worked 100–199 days off-farm	0.096	0.001
Operator worked 200+ days off-farm	0.335	0.002
Household size	2.732	0.006
Number of operators	1.431	0.003
Operator retired	0.072	0.001
Soil productivity index	0.647	0.001
Rural population (2010)	13,471.970	33.875
Insured acres	563.630	3.480
Farmer premiums paid	9,805.620	64.870
Farm had insured acreage	0.756	0.002
Operator age	51.526	0.047
Acres operated (2007)	836.042	4.569
Exit	0.072	0.001
Acres operated (2012)	948.086	6.301

Notes: N= 108,631. All summary statistics are for 2007 unless otherwise noted. All statistics are weighted using Census of Agriculture population weights.

land ownership status, percentage of land that was irrigated, a county-level soil productivity index, whether the farm is specialized, operator age, whether the operator is beginning or retired, number of days the principal operator worked off-farm, and state-level fixed effects.

Calculating Net Premiums Paid

Our measure of crop insurance participation is net premiums paid (NPP). We estimate the amount a farmer pays in net premiums as

$$NPP_i = per\_acre\_net\_premium_{c(i)} \times insured\ acres_i, \tag{2}$$

where per acre net premium is equal to total premiums less total subsidies divided by net reported acres insured in the county (U.S. Deparment of Agriculture, Risk Management Agency, 2017).[7]

[7] On average, a farmer paid 42% of their insurance premium in 2007.

Total premiums, total subsidies and net reported acres insured are aggregated across all insurance plans and coverage levels for each of our three commodities. As a result, per acre NPP vary only by county and commodity. The NPP is then multiplied by the total acres insured (reported at the farm-level), creating a proxy measure for each farmer's total NPP.

Additional Assumptions and Data Measurement Issues

Although the majority of our data are measured at the farm-level, several variables are measured at the county level. We believe this has a negligible effect on our parameter estimates because of several mitigating factors. As farmers can choose among a variety of insurance plans and coverage levels, per acre NPP is an aggregate variable that understates the true variation in farm-level per acre NPP. However, when multiplied with a farm-level measure of acres insured, the downward bias in variability should be less pronounced, giving a reasonable proxy for insurance outlays for the farmer. We also control for farm and operator characteristics using farm-level data, which should mitigate the effects of aggregation bias.

Another important point is that NPP and indemnities received are an inexact measure of crop insurance intensity/coverage when measured at the county level. These quantities reflect historic yields and prices received by farms in each county. Measurement error could potentially be an issue when using aggregated data such as county-level premiums. While we cannot test whether measurement error is present, it is well known that inconsistent parameter estimates may result when the measurement error is correlated with the model disturbance.[8] We assume the measurement error in the county-level measure of premiums, subsidies, and indemnities is random, conditional on the variables in the acreage model. This means the measurement error should not be correlated with other variables in the model, leading to consistent parameter estimates (Greene, 2008). We performed a robustness test on the NPP variable by using a dummy variable equal to 1 if the farm has any insured acres and 0 otherwise. The estimates of this model are reported in the results section.

Finally, because census data only provide the number of acres insured at the farm level, we make an additional assumption that all insured acres are for the crop that represents the majority of production value on the farm. Given that most farms in our sample are highly specialized, this assumption seems reasonable. To mitigate concerns, we control for whether the farm is highly specialized and accommodate common crop rotations by grouping corn/soybean farms together as the same type of operation.[9]

Before we can estimate acreage equation (1), two additional methodological issues need to be addressed. First, because some farms observed in 2007 exited before 2012, we do not observe their acreage decision in 2012, resulting in sample-selection bias. This could bias the effect of crop insurance purchases on acreage decisions upwards, as there may be a relationship between farm exits and decisions to purchase crop insurance. Second, because crop insurance participation is endogenous to acreage decisions, we need an appropriate instrumental variable to get an unbiased estimate of the effect of NPP.

Sample-Selection Bias

To address sample-selection bias, we use a Heckman selection model (Heckman, 1976) to control for factors that affect farm exits between 2007 and 2012. Without controlling for these factors, we run the risk of sample-selection bias in the model for decisions to expand acreage by 2012.

---

[8] The classic outcome of measurement error in the explanatory variable of a simple linear regression is that it leads to attenuation bias, but in a multiple regression framework there is no way to know in which direction the parameter will be biased without additional information.

[9] Our results were similar treating corn and soybean farms as distinct categories. However, in 2005 and 2006, roughly two-thirds of corn and soybean acres were in a corn-soybean rotation, while only 10% of soybean and 17% of corn was in continuous cropping (O'Donoghue et al., 2011).

The sample selection model for the probability of a farm exiting between 2007 and 2012 is written as

$$\text{(3)} \qquad \Pr(Exit_i = 1|\mathbf{X}_i) = \Phi(\mathbf{X}_i'\boldsymbol{\theta}),$$

where $Exit_i$ is equal to 1 if the ith farm exited between 2007 and 2012 and 0 otherwise and Φ is the standard normal cumulative density link function. The vector of farm and operator characteristics ($\mathbf{X}$) is the same as in equation (1) but also includes an exclusion-restriction variable in order to identify the selection model. We propose using a measure of the rural population for the county in which the farm is located (based on 2010 U.S. Census data).This reasonably meets the exclusions criteria, since larger rural communities can strengthen the support network available for individual farms, but is plausibly exogenous to acreage decisions. We test this assumption in the results section. One drawback of the Heckman selection model is that it makes the assumption that the errors are jointly normal. As a robustness check, we also estimate the acreage model without the first-stage Heckman selection correction.[10]

Once the selection model parameters are estimated, we calculate the inverse Mills ratio:

$$\text{(4)} \qquad \hat{\lambda}_i = \frac{\phi(\mathbf{X}_i'\hat{\boldsymbol{\theta}})}{\Phi(\mathbf{X}_i'\hat{\boldsymbol{\theta}})},$$

where ϕ is the probability density function for a standard normal distribution and Φ is the cumulative density of a standard normal distribution. The inverse Mills ratio is then used to control for sample-selection bias in our model for acreage decisions.

2SLS Model for Acreage Expansion

Following Wooldridge (2010), we first estimate the selection model in equation (2), which includes the instrumental variable and all exogenous variables from equation (1). We then use the predicted the inverse Mills ratio, $\hat{\lambda}_i$, in the two-stage least squares (2SLS) model for acreage expansion. Let $\bar{z}$ denote our instrumental variable, discussed in the next section. The first stage of the 2SLS model instruments for farmer NPP using a reduced form equation:

$$\text{(5)} \qquad NPP_i = \delta_0 + \mathbf{X}_i\boldsymbol{\rho} + \mu_1\bar{z}_i + \hat{\lambda}_i + \omega_i.$$

With a valid instrument, the error term from equation (5) will be exogenous to the error term in equation (1), after controlling selection bias and farm and operator characteristics. This allows us to acquire a consistent estimate of the effect of NPP on decisions to expand acreage (γ_1). In the last step, we estimate equation (1) using the fitted values for crop insurance participation from equation (5). These last two steps are done using the ivreg procedure in STATA with Huber-White sandwich standard errors.

Instrumental Variable for Net Premiums Paid

To identify the effect of NPP in 2007 on producer acreage decisions in 2012 in equation (1) we propose a just-identified instrumental variables approach. Although we use lagged measures of crop insurance, endogeneity may persist by biasing the effect of the causal variable through a separate channel (Bellemare, Masaki, and Pepinsky, 2015). A valid instrument for NPP must meet both the exclusion-restriction criteria and pass the weak instrument test.

We propose using average per acre county-level indemnities from 2002–2006 as an instrumental variable, obtained from the RMA Summary of Business data (U.S. Deparment of Agriculture,

[10] In this case, we estimate the effect of crop insurance on acreage expansion for farms only observed in both 2007 and 2012.

Risk Management Agency, 2017). Crop insurance indemnities are paid out in the event of a substantial yield or revenue loss. We hypothesize that after controlling for farm, operator, and soil characteristics, average per acre county-level indemnities from 2002–2006 are uncorrelated with farm-level acreage decisions in 2012. We assume that past indemnities are tied to stochastic events such as weather or pests and should not influence future planting or acreage decisions more than five years later.[11] This assumption allows us to identify our acreage expansion model in the second stage.

Higher expected crop insurance indemnities have been found to predict crop insurance participation in past studies (Goodwin, Vandeveer, and Deal, 2004). A recent study by Babcock (2015) used a cumulative prospect theory framework to model crop insurance participation. This framework theorizes that farmers may view crop insurance similar to a lottery. In such a framework, a farmer "wins" the lottery when he receives a crop insurance indemnity. Viewed in this manner, higher indemnities may lead to higher demand for crop insurance. Neighboring farms in the county would also be more likely to participate if they view indemnities in a similar framework.

In order to use our instrumental variable, we must satisfy the exclusion restriction. We test this by estimating an OLS model for natural log of acres operated in 2012, similar to equation (1), but that includes both our endogenous variable (NPP) and our instrumental variable. We then perform a test for significance on the instrumental variable. A finding of no significant effect of lagged indemnities on acres operated will support the assumption that it meets the exclusion criteria. We then perform a weak instrument test in the first stage of 2SLS. A finding that our instrument has a significant effect (F-statistic > 10) on NPP will provide additional evidence that it is a valid instrument.

Results

We begin by describing the selection model for farm exits, including the size of the marginal effects of farm characteristics on farm survival. We then discuss the acreage expansion results, including a few different model specifications, and compare the effect of NPP under OLS and 2SLS estimation strategies. We conclude by reporting the test results for the validity of our instrumental variable and provide evidence that the exclusion restriction and weak instrument assumptions are met.

Selection Model Results

Table 2 displays estimated coefficients and marginal effects for the selection model. Lifecycle effects are clearly significant as younger, less established and older, retired operators were more likely to exit between 2007 and 2012. The marginal effects show that retired farmers were 1.1% more likely to exit, as were beginning farmers (2.1%) and operators under the age of 35 (3.1%). Larger farms (measured in acres) and farms with larger households—and more potential for sources of off-farm income—were less likely to exit. Farms organized as a partnership or corporation were 2.4% and 1.8%, more likely to exit compared to sole proprietorships, respectively. Compared to farms where the operator did not work off-farm, farms where an operator worked at least 100 days or more off-farm were less likely to exit. Farms that received higher levels of government payments were also less likely to exit. Finally, farms that were highly specialized (more than 90% of value of production came from one commodity) were 1.4% more likely to exit.

In the selection model, the exclusion-restriction variable (2010 rural county population) is found to be statistically significant.[12] Farms located in counties with larger rural populations (i.e., have greater population living in towns smaller than 10,000 people) were less likely to exit. The effect of rural population is consistent with evidence that strong rural social networks and robust rural economies can play a positive role in farm survival (e.g., Storm, Mittenzwei, and Heckelei, 2015).

---

[11] The level of indemnities will also reflect production history, coverage levels, and projected prices during 2002–2006.
[12] Including rural population in the acreage model did not produce a significant result, supporting the exclusion restriction.

Table 2. Selection Model Coefficients and Marginal Effects

Variable	$\Pr(Exit = 1)$	Marginal Effects
Ln(acres operated 2007)	−0.065	−0.008
	(0.012)***	(0.002)***
Wheat farm	0.182	0.022
	(0.043)***	(0.005)***
Partnership	(0.198)	0.024
	(0.028)***	(0.003)***
Corporation	0.148	0.018
	(0.032)***	(0.004)***
Other legal org	0.343	0.042
	(0.069)***	(0.008)***
Percent irrigated	0.132	0.016
	(0.046)***	(0.006)***
Specialized	0.115	0.014
	(0.023)***	(0.003)***
Part renter	−0.314	−0.039
	(0.022)***	(0.003)***
Full renter	−0.070	−0.009
	(0.027)***	(0.003)***
Government payments	−1.60E-06	−1.96E-07
	(7.52E-07)**	(9.22E-08)**
Ln(operator age)	0.690	0.085
	(0.068)***	(0.008)***
Operator age 35 or under	0.256	0.031
	(0.048)***	(0.006)***
Beginning farmer	0.173	0.021
	(0.025)***	(0.003)***
Operator worked 1–49 days off-farm	−0.092	−0.011
	(0.027)***	(0.003)***
Operator worked 50–99 days off-farm	−0.049	−0.006
	(0.038)	(0.005)
Operator worked 100–199 days off-farm	−0.133	−0.016
	(0.031)***	(0.004)***
Operator worked 200+ days off-farm	−0.123	−0.015
	(0.022)***	(0.003)***
Household size	−0.024	−0.003
	(0.008)***	(0.001)***
Number of operators	0.035	0.004
	(0.011)***	(0.001)***
Operator retired	0.091	0.0112
	(0.030)***	(0.004)***
Soil productivity index	−0.110	−0.013
	(0.098)	(0.012)
Per acre indemnities (2002–2006)	3.23E-04	3.97E-07
	(6.14E-04)	(7.55E-07)
Rural population (2010)	−3.98E-06	−4.90E-07
	(1.26E-06)***	(1.54E-07)***
Constant	−3.615	
	(0.306)***	
State FE	*Y*	

Notes: N = 108,631. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. Huber–White standard errors in parentheses.

Acreage Expansion Results

The results of our main specification are shown in column 1 of table 3. When we examine our main policy question using an instrumental variable approach, we find no significant effect of higher NPP on acres operated in 2012. This is consistent with previous literature, which has shown small or insignificant effects of crop insurance participation on production decisions. In contrast, the OLS model finds a small but significant effect for NPP on acres operated on the order of about one one-thousandth of an acre for each additional $10 in NPP (see Appendix A). Similar results were found using a conditional model, in which we estimate the acreage expansion model only for farms observed in both 2007 and 2012.

In our main specification, we found effects with the expected economic relationships. Between 2007 and 2012, larger farms expanded more than small farms, in absolute acreage. Farms in counties with more productive soil expanded less, though this may indicate that they reside in areas where all available land is already in production. We also observed operator lifecycle effects in the expansion model. Farms with older operators expanded less, as did those with principal operators who considered themselves retired. Farms with a principal operator who worked at least 200 days off-farm expanded less than those that did not. This is consistent with an operator who spends most of his time off-farm and would have little incentive to expand the operation. We also find that farms that rented in most of their land expanded much more than those that owned all of it. Farmers in the latter category would be more likely to be older and closer to retirement. We also find that higher levels of government payments were not significantly related to acreage expansion once we control for farm, operator, and soil characteristics. This finding is consistent with previous studies (e.g., Weber and Key, 2012).

We ran a robustness check on our main results by replacing NPP with an indicator variable equal to 1 if a farm had any insured acres and 0 otherwise. The 2SLS results are shown in column 2 of table 3. We again found that crop insurance did not significantly influence expansion after controlling for endogeneity in insured acres, while the OLS estimates are found to have a significant effect.[13]

Finally, we explore the impact of idled acreage, specifically land enrolled in the Conservation Reserve Program (CRP).[14] We do this in two ways. First, we estimated our main model with a subset of farms: those located in counties with a large number of acres enrolled in CRP in 2007. We focused on farms located in counties in the 75th and 90th percentiles of CRP acres. Our model estimates (not shown) in both cases found no significant effect of crop insurance on acreage expansion.[15]

We also ran our main model specification with an additional variable that measures county-level acres enrolled in CRP in 2007. Results are shown in column 3 of table 3. We find that farms located in counties with a greater number of acres enrolled in the CRP expanded more than those that did not. This finding is consistent with a land supply effect caused by a declining cap in total acres enrolled in CRP. We note the CRP acreage cap dropped over this period, with total enrolled acres falling from about 37 million acres to 30 million. Combined with the high prices for cash grains and oilseeds observed in 2010–2012, it seems plausible that farms with productive land enrolled in CRP would have been less likely to re-enroll if the opportunity costs were high (e.g., they could earn more by renting the land out or putting it back into production). This would have led to greater acreage expansion for farms with access to productive land that had formerly been enrolled in CRP.

---

[13] Results available from the authors upon request.

[14] The CRP is a land conservation program run by the Farm Service Agency (FSA). In exchange for yearly rental payments, farmers remove environmentally sensitive land from production and plant species that will improve environmental health. CRP contracts are typically 10–15 years in length.

[15] Results available from the authors on request.

Table 3. 2SLS Results for Acreage Expansion Model

Variable	Main Specification	Indicator Variable (=1 if Acres Insured)	CRP Acres in County
Net premiums paid	8.27E-06		9.60E-06
	(8.49E-06)		(8.80E-06)
Crop insurance (=1)		−0.266	
		(0.278)	
Ln(acres operated 2007)	0.814	0.887	0.807
	(0.045)***	(0.032)***	(0.047)***
Inverse mills ratio	0.105	−0.035	0.101
	(0.124)	(0.216)	(0.125)
CRP acres in county			3.64E-07
			(1.50E-07)**
Soil productivity	−0.094	−0.080	−0.074
	(0.036)***	(0.043)*	(0.039)*
Wheat farm	0.135	0.023	0.142
	(0.079)*	(0.047)	(0.081)*
Partnership	−0.002	−0.009	−0.007
	(0.038)	(0.044)	(0.038)
Corporation	0.063	0.040	0.063
	(0.019)***	(0.030)	(0.019)
Other legal org	−0.051	−0.081	−0.054
	(0.057)	(0.074)	(0.057)
Proportion acres irrigated	0.067	0.007	0.075
	(0.027)**	(0.054)	(0.028)***
Specialized farm	0.003	0.000	−0.001
	(0.025)	(0.028)	(0.026)
Partial land owner	0.013	0.061	0.016
	(0.037)	(0.075)	(0.038)
Full land renter	0.049	0.086	0.049
	(0.014)***	(0.040)**	(0.014)***
Government payments	−1.14E-06	2.52E-06	−1.73E-06
	(3.59E-06)	(4.10E-07)	(3.72E-06)
Ln(operator age)	−0.461	−0.583	−0.457
	(0.079)***	(0.135)***	(0.080)***
Operator age 35 or under	0.022	−0.013	0.024
	(0.034)	(0.046)	(0.035)
Beginning farmer	−0.009	−0.028	−0.010
	(0.023	(0.035)	(0.023)
Operator worked 1–49 days off-farm	−0.009	0.001	−0.008
	(0.014)	(0.021)	(0.014)
Operator worked 50–99 days off-farm	0.004	0.010	0.005
	(0.016)	(0.020)	(0.016)
Operator worked 100–199 days off-farm	−0.013	0.002	−0.011
	(0.021)	(0.032)	(0.021)
Operator worked 200+ days off-farm	−0.063	−0.044	−0.063
	(0.016)***	(0.029)	(0.016)***
Household size	2.63E-04	0.005	1.76E-04
	(0.004)	(0.005)	(0.004)
Number of operators	−0.004	0.003	−0.006
	(0.014)	(0.007)	(0.014)
Operator retired	−0.049	−0.070	−0.050
	(0.019)***	(0.034)**	(0.019)***
Constant	2.701	3.078	3.161
	(0.527)***	(0.139)***	(0.154)***
State FE	*Y*	*Y*	*Y*
R-squared	0.765	0.761	0.763

Notes: N = 81,585. All models have the same dependent variable, natural log of acres operated 2012. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. Huber–White standard errors in parentheses.

Testing Validity of the Instrumental Variable

We find evidence that our instrumental variable, average per acre indemnities (2002–2006), meets the exclusion-restriction criteria and passes the weak instrument test. We test the exclusion restriction by including our instrumental variable in an OLS regression of equation (1). If the instrumental variable has no significant effect on acres operated, we can plausibly identify the second-stage acreage equation (Greene, 2008). A t-test for the effect of average per acre indemnities (2002–2006) on ln(acres operated 2012), after including our exogenous control variables and NPP, has a p-value of 0.43. This result provides evidence that our proposed instrument does not affect acres operated directly and meets the exclusion-restriction criteria.

In the first stage of 2SLS, we find a strong positive relationship between lagged per acre indemnities and premiums paid. We find a $1 increase in average per acre indemnities (2002–2006) was associated with a $23.50 increase in NPP in 2007. An F-test for the significance of our instrument in the first-stage of 2SLS gives a value of 30.5, exceeding the rule of thumb that the F-statistic should be greater than 10 (Staiger and Stock, 1994). Thus, our instrument appears to be strongly correlated with NPP in 2007 but uncorrelated with acres operated in 2012. A Wu-Hausman test for endogeneity of the model gives a p-value of 0.82, confirming that the 2SLS model parameters are consistent. This provides further evidence that our instrumental variable addresses the endogeneity in NPP.

Conclusions and Discussion

The 2014 Farm Bill shifted U.S. agricultural policy toward risk management (crop insurance, ARC, and PLC) and away from income support programs (direct payments). This paper examines how crop insurance policies affected acreage decisions for corn, wheat, and soybean farms between the years of 2007 and 2012. We improve upon previous studies by combining farm-level data from the U.S. Census of Agriculture with county-level data on crop insurance premiums and subsidies, rural population, and soil productivity to estimate a panel model for crop farm expansion between 2007 and 2012. We make use of advancements in the Agricultural Census that better track operations from 2007 to 2012. For instance, Ahearn, Yee, and Korb (2009) report an exit rate of 37% between 1992 and 1997. The new tracking method finds a much lower exit rate for the sector at 12.7% from 2007 to 2012, and we observe an exit rate of 7.2% among our subset of crop farms. This allows us to better measure determinants of farm exits and to better account for sample-selection bias. We also address issues of endogeneity decisions to purchase crop insurance by using an instrumental variable approach.

Consistent with some (though not all) previous studies, we find that crop insurance (whether measured by participation or NPP) had no statistically significant effect on decisions to expand acreage, bolstering the case that they are not distortionary under WTO guidelines. We also show that not controlling for the endogenous decision to purchase crop insurance leads to a conclusion that premiums have a small but statistically significant effect on acreage. We find that farms located in counties with a greater number of Conservation Reserve Program (CRP) acres expanded acreage more. This finding is consistent with a land supply effect, caused both by a drop in the CRP acreage cap making more land available and the effect of higher cash grain and oilseed prices. Farms with enrolled CRP acreage on productive land would have higher opportunity costs to keeping that land enrolled during the period of high commodity prices observed between 2007 and 2012. Other types of government payments (e.g., direct payments, conservation payments, etc.) were not found to influence production. In our analysis, farm and operator characteristics had the expected economic relationships with regard to acreage decisions. Larger farms and those with younger operators expanded their operations more than smaller farms or older operators. Farms where the operator works off-farm full time (more than 200 days in the year) expanded less than those who did not work off-farm.

We find that operator lifecycle plays an important role in farm exits, with older farmers more likely to exit farming. Operations with beginning principal operators (those with 10 years or fewer of farming experience) were similarly more likely to exit. Farms located in counties with a larger non-urban population remained in farming at higher rates. This result suggests that strong rural networks and the rural economy have an effect on farm survival. We also find that farms with principal operators that work more days off-farm were generally less likely to exit, suggesting that households that rely on off-farm income are able to better withstand the cyclical nature of farm income.

As the next farm bill discussions commence, efforts to limit government financial exposure in the federal farm support programs remains a contested topic. This motivates research into the farm-level effects of a cut (or increase) in premium subsidies. Future research will examine how a change in subsidy rate will impact farm production decisions as well as farm survival. As the costs of crop insurance participation become internalized to the farm, will greater numbers of farm operators forego crop insurance to cut costs, leading to increased exits? As the amount of productive farmland has remained relatively stable over past decades, will this lead to further consolidation in the farm sector? Alternatively, these results underscore the importance of research into how insurance payments may affect farm production and farm household decision-making. As farm programs shift to risk management, these programs could supplant other risk-mitigation strategies, such as off-farm employment. Likewise, they may limit downside price or revenue risk, inducing farmers to put more marginal lands back into production and reducing the number of acres enrolled in the Conservation Reserve Program.

[Received December 2016; final revision received November 2017.]

References

Ahearn, M., J. Yee, and P. Korb. "Producer Dynamics in Agriculture: Empirical Evidence." In T. Dunne, J. Jensen, and M. J. Roberts, eds., *Producer Dynamics: New Evidence from Micro Data,* Chicago: Chicago University Press, 2009, 369–391. Available online at 10.7208/chicago/9780226172576.003.0011.

Ahearn, M. C., H. El-Osta, and J. Dewbre. "The Impact of Coupled and Decoupled Government Subsidies on Off-Farm Labor Participation of U.S. Farm Operators." *American Journal of Agricultural Economics* 88(2006):393–408. doi: 10.1111/j.1467-8276.2006.00866.x.

Ahearn, M. C., J. Yee, and P. Korb. "Effects of Differing Farm Policies on Farm Structure and Dynamics." *American Journal of Agricultural Economics* 87(2005):1182–1189. doi: 10.1111/j.1467-8276.2005.00805.x.

Babcock, B. A. "Using Cumulative Prospect Theory to Explain Anomalous Crop Insurance Coverage Choice." *American Journal of Agricultural Economics* 97(2015):1371–1384. doi: 10.1093/ajae/aav032.

Bellemare, M., T. Masaki, and T. Pepinsky. "Lagged Explanatory Variables and the Estimation of Causal Effects." SSRN Scholarly Paper, Social Science Research Network, Rochester, NY, 2015. Available online at https://papers.ssrn.com/abstract=2568724.

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

Glauber, J. W., and P. Westhoff. "The 2014 Farm Bill and the WTO." *American Journal of Agricultural Economics* 97(2015):1287–1297. doi: 10.1093/ajae/aav023.

Goetz, S. J., and D. L. Debertin. "Why Farmers Quit: A County-Level Analysis." *American Journal of Agricultural Economics* 83(2001):1010–1023. doi: 10.1111/0002-9092.00226.

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

Greene, W. H. *Econometric Analysis*. New York: Prentice Hall, 2008, 6th ed.

Heckman, J. "The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for Such Models." *Annals of Economic and Social Measurement* 5(1976):475–492. Available online at https://www.nber.org/chapters/c10491.pdf.

Hoppe, R., and P. Korb. "Understanding U.S. Farm Exits." Economic Research Report ERR-21, U.S. Department of Agriculture, Economic Research Service, Washington, DC, 2006. Available online at https://www.ers.usda.gov/publications/pub-details/?pubid=45570.

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

Key, N., and M. J. Roberts. "Government Payments and Farm Business Survival." *American Journal of Agricultural Economics* 88(2006):382–392. doi: 10.1111/j.1467-8276.2006.00865.x.

Key, N. D., and M. J. Roberts. "Do Government Payments Influence Farm Size and Survival?" *Journal of Agricultural and Resource Economics* 32(2007):330–348.

Kimhi, A. "Family Farm Dynamics in Canada and Israel: The Case of Farm Exits." *Agricultural Economics* 21(1999):69–79. doi: 10.1016/S0169-5150(99)00015-8.

Mishra, A. K., and B. K. Goodwin. "Revenue Insurance Purchase Decisions of Farmers." *Applied Economics* 38(2006):149–159. doi: 10.1080/00036840500367724.

O'Donoghue, E., R. Hoppe, D. E. Banker, R. Ebel, K. O. Fuglie, P. Korb, M. Livingston, C. Nickerson, and C. Sandretto. "The Changing Organization of U.S. Farming." Economic Information Bulletin EIB-88, U.S. Department of Agriculture, Economic Research Service, Washington, DC, 2011. Available online at https://www.ers.usda.gov/publications/pub-details/?pubid=44620.

Orden, D., and C. Zulauf. “Political Economy of the 2014 Farm Bill.” *American Journal of Agricultural Economics* 97(2015):1298–1311. doi: 10.1093/ajae/aav028.

Roberts, M. J., and N. Key. “Agricultural Payments and Land Concentration: A Semiparametric Spatial Regression Analysis.” *American Journal of Agricultural Economics* 90(2008):627–643. doi: 10.1111/j.1467-8276.2008.01144.x.

Sherrick, B. J., P. J. Barry, P. N. Ellinger, and G. D. Schnitkey. “Factors Influencing Farmers’ Crop Insurance Decisions.” *American Journal of Agricultural Economics* 86(2004):103–114. doi: 10.1111/j.0092-5853.2004.00565.x.

Staiger, D., and J. Stock. “Instrumental Variables Regression with Weak Instruments.” Technical Working Paper 151, Cambridge, MA, 1994. Doi: 10.3386/t0151.

Storm, H., K. Mittenzwei, and T. Heckelei. “Direct Payments, Spatial Competition, and Farm Survival in Norway.” *American Journal of Agricultural Economics* 97(2015):1192–1205. doi: 10.1093/ajae/aau085.

U.S. Deparment of Agriculture, Economic Research Service. *Projected Spending Under the 2014 Farm Bill*. Washington, DC: U.S. Department of Agriculture, Economic Research Service, 2016. Available online at https://www.ers.usda.gov/topics/farm-economy/farm-commodity-policy/projected-spending-under-the-2014-farm-bill.aspx.

U.S. Deparment of Agriculture, Risk Management Agency. *Summary of Business Reports and Data*. Washington, DC: U.S. Department of Agriculture, Risk Management Agency, 2017. Available online at http://www.rma.usda.gov/data/sob.html.

Velandia, M., R. M. Rejesus, T. O. Knight, and B. J. Sherrick. “Factors Affecting Farmers’ Utilization of Agricultural Risk Management Tools: The Case of Crop Insurance, Forward Contracting, and Spreading Sales.” *Journal of Agricultural and Applied Economics* 41(2009):107–123. doi: 10.1017/S1074070800002583.

Weber, J. G., and N. Key. “How Much Do Decoupled Payments Affect Production? An Instrumental Variable Approach with Panel Data.” *American Journal of Agricultural Economics* 94(2012):52–66. doi: 10.1093/ajae/aar134.

Wooldridge, J. M. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press, 2010, 2nd ed.

Young, C. E., and P. C. Westcott. “How Decoupled Is U.S. Agricultural Support for Major Crops?” *American Journal of Agricultural Economics* 82(2000):762–767.

Appendix A: Acreage Expansion Model Using OLS

	Ln(Acres Operated 2012) **OLS**
Net premiums paid	1.57E-06
	(2.48E-07)***
Ln(acres operated 2007)	0.849
	(0.009)***
Inverse mills ratio	0.132
	(0.12)
Soil productivity	−0.101
	(0.035)***
Wheat	0.076
	(0.025)***
Government payments	1.67E-06
	(3.37E-06)***
Partnership	0.021
	(0.023)
Corporation	0.062
	(0.018)***
Other legal organization	−0.034
	(0.053)
Proportion acres irrigated	0.057
	(0.023)**
Specialized farm	0.019
	(0.016)
Partial land renter	0.00043
	(0.034)
Full land renter	0.05
	(0.014)***
Ln(operator age)	−0.472
	(0.077)***
Operator age 35 or less	0.017
	(0.034)
Beginning farmer	−0.003
	(0.021)
Operator worked 1-49 days off-farm	−0.013
	(0.013)
Operator worked 50-99 days off-farm	−0.003
	(0.014)
Operator worked 100-199 days off-farm	−0.022
	(0.017)
Operator worked 200+ days off-farm	−0.067
	(0.015)***
Household size	0.001
	(0.004)
Number of operators	0.005
	(0.006)
Operator retired	−0.044
	(0.017)**
Constant	2.519
	(0.481)***
State FE	*Y*
R-squared	0.770

Notes: N = 81,585. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. Huber–White standard errors in parentheses.