THREE ESSAYS ON FARM POLICY AND AGRICULTURAL FINANCE

BY

JUO-HAN TSAY

DISSERTATION

Submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in Agricultural and Applied Economics
in the Graduate College of the
University of Illinois Urbana-Champaign, 2022

Urbana, Illinois

Doctoral Committee:

Professor Nicholas D Paulson, Chair and Director of Research
Professor Gary Donald Schnitkey
Assistant Professor Joe Janzen
Associate Professor Todd Kuethe, Purdue University

ABSTRACT

Partially justified by the objectives of ensuring a safe and stable food supply and providing a resilient production environment, U.S. agricultural policy has been rather important for both consumers and producers. Agricultural policy, also known as farm policy, generally follows a 5-year legislative cycle of "Farm Bill" which governs broad range of agricultural and food program areas. Understanding how farm policy works and the impact under different farm bills helps agricultural sectors to manage their business more efficiently. It also provides useful information for policy makers to address relevant issues regarding agricultural and food systems in the future farm bills. These three essays therefore apply econometrics methods and simulation techniques to answer key issues on farm and risk management regarding commodity program and crop insurance programs under different farm bills.

The first essay revisits the question regarding who really benefits from federal support government subsidies. While subsides are paid directly to farmers, landlords may capture a portion of the benefits through increased farmland rental rates. A panel fixed effect model is used with farm-level data from Illinois to estimate the incidence of government subsidies on cash rental rates. We also investigate how estimated incidence rates might vary under different government program designs and farm income environments. Consistent with previous work, the results suggest there is a positive relationship between cash rental rates and government payment levels. However, consistent with previous work in the area, the extent to which government payments are passed through to rental rates, or the level of incidence, varies across time and modeling specifications. Results imply that landowners may capture a greater portion of government payments during periods of higher farm income and when government payments levels are more certain. Asymmetric information and payment uncertainty are potential explanations for why only a share of government payments accrues to landowners.

In the 2014 Farm Bill, new shallow loss area insurance coverage options with higher coverage protection were added. Starting with the 2021 crop year, a new supplemental area insurance program with even higher coverage option has been introduced as well. Since these area plans are triggered based on losses at county level, indemnities may not always match losses experienced at the farm-level, resulting in what is often referred to as basis risk. Therefore, to better understand potential impacts on farmers' risk exposure under these new crop insurance programs, the second essay utilizes simulation techniques to build a stylized county-level crop revenue model to assess the basis risk and risk reduction of one of the recently introduced supplemental area plans – the Supplemental Coverage Option (SCO). The results show increasing the coverage level of the supplemental area plan reduces the likelihood of under-compensation (insufficient payments from area plans to cover farm-level losses), but increases the likelihood of over-compensation (indemnity payments from the area plan will be larger than what is needed to fully cover farm-level losses). We also find of the magnitude of basis risk associated with the supplemental area plan differs across regions. Supplemental area plans do have the potential to provide additional risk reduction; however, the level of risk reduction is inversely proportional to the level of basis risk.

One concern which has been raised since the introduction of the supplemental area plans is whether farmers will make changes to their existing insurance coverage. Specifically, questions exist over whether farmers might choose to reduce, or "buy down" their individual coverage and purchase the new supplemental area plans to cover the band of coverage created by the reduction. Such behavior might result in inferior risk coverage for farmers (due to basis risk) that is more costly to taxpayer to deliver (due to the marginal differences in subsidy rates across the individual and area insurance plans). The third essay thus extends the second essay to examine whether there is empirical evidence of this buy down behavior. An endogenous switching regression approach is employed to address potential selection bias and unobserved factors in crop insurance enrollment decisions observed in the aggregate at the county level using data from the Risk Management Agency of the USDA. The results provide mixed evidence of buy down behaviors. We find a buy down effect of up to 4% on for insured corn acreage, but no evidence of any buy down effect for insured soybean acreage.

ACKNOWLEDGMENTS

First of all, I would like to express my gratitude to my advisor, Dr. Nicholas Paulson, for all of his guidance, patience, and motivation throughout my Ph.D. academic career. I would also like to thank my committee members: Dr. Gary Schnitkey, Dr. Joe Janzen, and Dr. Todd Kuethe for their encouragement, assistance, and insightful comments on this work.

I would like to thank Luoye Chen, Yuying Xing, and Joshua Huang for their support and team effort in the first-year Ph.D. program. I am grateful for the friendship with Ian Chong, Jared Hutchins, Noé Nava, James Kim, Linh Nguyen, Jacob Jett, Simone Stone, and many others. Your great friendship has made Champaign Illinois a delightful home for me over the past six years.

Lastly, this dissertation is dedicated to my loving family: my father (Huel-Sheng Tsay), my mother (Ru-Miaw Hwang), my brother (Bing-Ruei Tsay), my sister (Juo-Tzu Tsay), my brother-in-law (Guangming Wang), and my newborn niece (Jing-Lei Wang). My deepest gratefulness to them for their endless love and encouragement throughout my life.

TABLE OF CONTENTS

CHAPTER 1: REVISITING THE INCIDENCE OF GOVERNMNET PROGRAMS ON ILLINOIS CASH RENTAL MARKET 1

CHAPTER 2: QUANTIFYING BASIS RISK ASSOCIATED WITH SUPPLEMENTAL AREA-BASED CROP INSURANCE.. 27

CHAPTER 3: DOES SUPPLMENTAL COVERAGE OPTION CROWD OUT INDIVIDUAL CROP INSURANCE COVERAGE?.. 52

REFERENCES 81

CHAPTER 1: REVISITING THE INCIDENCE OF GOVERNMNET PROGRAMS ON ILLINOIS CASH RENTAL MARKET

Introduction

Farmers face significant income volatility, and one of the primary justifications for federal support is income stabilization to ensure a reliable food supply for consumers. However, a persistent question in agricultural economics is to what extent federal support payments actually benefit farmers. While subsidies are paid directly to farmers, resulting input market adjustments may result in farmers capturing only a portion of these benefits. The impact of federal payments on cash rental rates paid to landowners provides a classic example.

This is a particularly important issue for grain farms throughout the Midwest for three reasons. First, program participants in Illinois received nearly 9% of U.S. agricultural subsidies from 1995 to 2020[1] based on USDA Economic Research Service (ERS) data. Second, according to the 2017 Census of Agriculture, 40 percent of farmland in Illinois is rented and 60 percent is owned. Third, there has been a steady shift from crop-share to cash rent leases[2]. Fixed cash rent leases allow landowners to reduce risk and management related to production and prices, resulting in increased risk borne by the farmer tenant. (Lattz, 2017)

A significant amount of research has examined the relationship between cash rent levels and government payments. However, existing studies have shown substantial divergence in their estimates of incidence, or the proportion of government payments received by the landowner. (Roberts et al., 2003; Patton et al., 2008; Kirwan, 2009; Goodwin et al., 2011; Hendricks et al., 2012) What's more, it is still unknown how changes in government policies and farmers' economic conditions ultimately provide signals for adjustments in agricultural cash rental markets.

---

[1] Only fixed direct payment, production flexibility contract, counter-cyclical payments, loan deficiency payments, ACRE, ARC, and PLC were calculated. If calculation includes other payments such as insurance or conservation programs, the amount would be even larger.

[2] There are two types of cash rent: variable and fixed cash rent. This study focuses on fixed cash rent.

In this paper, we test the extent to which government payments flow to landowners through cash rents paid by farmers. Also, we offer insight into how government payments and farmers' profitability levels might impact cash rent levels and incidence rate estimates. Using unique farm-level data from the Illinois Farm Bureau Farm Management Association (FBFM), we examine the relationship between cash rent levels and government payments received. The data allows us to control for both farm-level and time-level fixed effects, in addition to measures of expected returns and crop insurance use.

There are several contributions and extensions to previous work made in this study. First, we replicated previous literatures and found different time periods in the analysis may be the main factor explaining the divergence of estimated incidence rate of government payments. Second, existing studies have focused on periods from 1990 to 2010. This paper utilizes data from 1995 to 2020. In addition to covering more current time periods, the longer dataset allows us to observe how incidence rates may change under different economic conditions, and how this might result in time-varying signals when negotiating cash rent leases. For example, net farm income tends to be lower between 1995 to 2005 vs. 2006 to 2013 where net farm income increases with higher volatility. Furthermore, the 2014 Farm Bill resulted in major modifications to commodity programs leading to the potential for more asymmetric information due to the more complex design of the programs. Third, the FBFM data provides specific farm-level variables that are not available to researchers using farm-level data from other regional farm management associations. For example, unlike previous studies, cash rented acres is separate from share rented acre in our panel dataset. Cash rent per acre is better measured and calculated at cash rent paid divided by cash rented acres. Lastly, in an attempt to make the model specification more closely fit farmers' real behaviors, the standard decision-making timeline for setting cash rent levels is taken into account.

Similar to previous work, we find a statistically significant relationship between government payments and cash rental rates. Different from most previous work, where incidence estimates tend to be less than 50 percent, we find higher incidence rates which suggest landowners may extract a larger portion of the government payments received by farmers via higher rental rates. We also find evidence that incidence rates likely vary across time based on market conditions and policy regimes. For example, our incidence rate estimates are larger during 1) periods of higher farm income, and, and 2) periods when farm program design results in more stable, easier to anticipate support levels.

Background

Estimates of subsidy incidence on farmland rents varies widely in the existing literature. Lence & Mishra (2003), using 1996-2000 county-level data for Iowa within a spatial model, found incidence of aggregate government payments of 0.131. Hendricks et al. (2012), using a dynamic panel approach with farm-level data from Kansas, estimated the incidence of aggregate subsidies on cash rental rates of just 0.12 in the short run, and 0.37 in long run. Goodwin et al. (2011) and Patton et al. (2008) are examples at the other end of the spectrum, with estimates more closely approaching full incidence.

Other work has attempted to examine how the specific design of subsidy programs might impact the incidence rate, specifically the effect of decoupled vs. coupled programs, on both farmland values and cash rental rates. This area of research has also yielded varying results. Roberts et al. (2003) reported an incidence of direct payments on land rent between 0.34 to 0.41 per acre using Census of Agriculture farm-level data. In a later study Kirwan (2009) employed the same data and found an even lower incidence rate of 0.25.

Lence & Mishra (2003) found that the market loss assistance program (MLA) and production flexibility contract (PFC) payments have an incidence rate of 0.80, but payments from the Conservation Reserve Program have no significant impact on the cash rents paid by farmers for their tillable acres. Goodwin et al. (2011) showed incidence of direct payments is about 0.73. Patton et al. (2008) estimated incidence rates approaching 1 for agricultural subsidy payments in the EU.

The range of results in the existing literature suggests that the portion of government payments which are captured by farmers versus landlords is still very much up for debate. Kirwan & Roberts (2016) argued the relatively large incidence rates found by Goodwin et al. (2011) and Patton et al. (2008) is due to the fact that they fail to account for land productivity. Unobserved land productivity obscures the effect of subsidies on farmland rental rate because both subsidies and rental rates depend on land's productivity. They utilized fertilizer-decision yield goal reported in the Fertilizer section of ARMS as control variables and found considerable reduction in incidences of government payments for soybean and cotton fields. In our study we use soil productivity ratings as control variable for land productivity. However, we do not find significant change in incidence estimate.

Proper identification represents the biggest challenge to obtaining clean estimates for incidence rates. Cash rents should be based on expectations about the stream of net returns, which include government payments, during the term of the lease agreement. What researchers observe from the data are return, cash rent, and government payment realizations under a set of policy instruments and market conditions (Goodwin et al., 2003). In order to deal with expectation errors, most researchers have applied proxy variables and instrumental variables to examine the causal relationship between cash rental rates and government payments (Goodwin et al., 2003; Roberts et al., 2003; Patton et al., 2008; Kirwan, 2009; Goodwin et al., 2011).

Other types of measurement errors may also be induced when aggregating data from field-level to farm-level or county-level units (Kirwan & Roberts, 2016). They found farm-level averages for subsidies received tend to overestimate the incidence range from 50%-100%. In our dataset, we do not observe field-level data – all measures are aggregated to the farm-level. However, since our study only focuses on the cash rental market for commercial grain farms in FBFM, we argue that the farms/farmers are more homogeneous in our analysis. Thus, estimates based on these farm-level aggregates should reflect the true effects at the microstructural unit (i.e. field level) in this study.

Policy Background

Our panel data covers time periods capturing six different farm bills and varying subsidy program designs: Food, Agriculture, Conservation, and Trade (FACT) Act of 1990; Federal Agriculture Improvement and Reform (FAIR) Act of 1996; Farm Security and Rural Investment (FSRI) Act of 2002; Food, Conservation, and Energy (FCE) Act of 2008; Agricultural Act of 2014; and Agriculture Improvement Act of 2018. Six major commodity programs administered by Farm Service Agency (FSA) are relevant: production flexibility contracts (PFC), loan deficiency payments (LDPs), the direct payment program (DPs), the counter-cyclical program (CCP), the Agricultural Risk Coverage (ARC) program, and the Price Loss Coverage (PLC) program.

PFCs were created in the 1996 farm bill covering crop years from 1996 to 2002. The 2002 farm bill modified PFCs which were renamed DPs. Both PFCs and DPs are examples of decoupled payment programs, meaning they are not tied to current crop production or market conditions (i.e. prices). The decoupled payments provide flexibility that farmers are not restricted to produce crops for which they are receiving direct payments. Payments were made based on historical "base" acres specific to a covered commodity. For example, farmers are allowed to plant wheat on their corn base acres where they are receiving corn payment. The direct payments were based on 85% of the eligible base acres multiplied by fixed direct payment yields and payment rates which varied by commodity.

CCPs were first implemented in 1973 but then eliminated in the 1996 farm bill. In the 2002 farm bill, CCPs were reinstated and extended payments to several crops such as grains, cotton, soybeans, oilseeds, and peanuts. CCPs were decoupled from current production, but contingent on market outcomes. Although counter-cyclical payments were tied to historical base acres similar to DPs, they were only issued when the market price of covered commodities was less than the fixed target price set by statute in the farm bill.

Loan deficiency payments (LDPs) were established in the 1985 farm bill. Farmers receive payments tied to current production when market prices are lower than commodity loan rates, which are fixed by legislation. Therefore, LDPs are viewed as coupled due to the linkage between payments and actual production.

The 2008 farm bill introduced revenue-based program design into commodity programs through the Average Crop Revenue Election (ACRE) program. ACRE provided revenue protection using state-level triggers. Enrollment was optional for producers and involved a 20% reduction in their direct payments support as well as foregoing any potential CCP payments.

The 2014 farm bill eliminated the DP, CCP, and ACRE programs, and created the Agricultural Risk Coverage (ARC) and Price Loss Coverage (PLC) programs. The ARC program is a revenue-based program which provides options for coverage of county-based (ARC-CO) or individual, farm-level (ARC-IC) revenues. The ARC program replaced the ACRE program established in the previous farm bill. The PLC program was introduced as the replacement for the price based CCP. ARC payments made if actual county (farm) revenues fall below a county (farm) benchmark based on the preceding 5-years of yield and price history. The revenue shortfall, if applicable, is paid out on historical base acres. PLC payments are issued when the marketing year average price of a covered commodity is less than the legislatively set reference price. Similar to CCP, PLC payments are made based on fixed program yields and base acres that have been established based on production histories for each farm.

ARC-CO and ARC-IC are revenue-based programs where ARC-CO (ARC-IC) issue payment when revenue is below 86% of the county's (ARC-IC farm unit) guaranteed revenue. Both programs are capped at 10% of their benchmark revenue, implying payments may not exceed 10% of the ARC-CO (ARC-IC) guarantee price multiplied by the ARC-CO (ARC-IC) guaranteed yield. Another difference between ARC-CO and ARC-IC is ARC-CO pays on 85% of base acres while ARC-IC pays on 65% of base acres. ARC-CO payments are crop specific while ARC-IC payments are ARC-IC farm unit specific. The ARC-IC farm unit is sum of a producer's interest in all FSA farms which are enrolled in ARC-IC in a state. Both Agricultural Risk Coverage (ARC) program and Price Loss Coverage (PLC) program are not depended on current acreage or production decisions, while ARC-IC is necessarily tied to current cropping decisions.

In summary, over the past 30 years, commodity programs have shifted from offering price support and fixed direct payments to an arguably more complicated system with both price- and revenue-based support designs. Farmers now might receive support from different programs on different tracts of land, with payment levels contingent a price and yields measured at varying levels of aggregation from the farm to county, and to national.

Figure 1.1. shows the average payments provided by major commodity programs per year in Illinois from 1995 to 2020. The total amount of government payments was higher in 1995-2005 when net farm

income and prices were relatively low. During this era, support payments came from the DP, CCP, and marketing loan (LDP) programs. During the period 2006 to 2013, government payments declined by approximately 50 percent due to higher commodity prices. Support in this period came mainly from direct payments, with little support from LDPs or the CCP. After 2014, previous programs except LDP were discontinued and support shifted to ARC and PLC.

Data

This study uses farm-level data from the Illinois Farm Business Farm Management Association (FBFM) covering periods from 1995 to 2020. FBFM is comprised of over 5,000 farmer members (cooperators) who work with around 100 field staff to provide financial and agronomic data for tax purposes, financial statement preparation, and benchmarking. The data provides detailed accounting, management, and agronomic information for more than 5,000 farmers members.

The full FBFM data was cleaned to exclude any reporting errors. Since FBFM data is collected and categorized based on calendar year, county, farm operation (farm ID), and operator (farmer ID), there may be multiple farmers reporting for the same farm operation. A typical example might be a father and children, or siblings, who farm together. Therefore, data was aggregated to the farm-level unit as one observation. Another characteristic of the FBFM data is that observations include certification status. The certification status indicates whether the data has been “certified” as useable for research and benchmarking purposes by the field staff compiling the records. In this study we drop non-certified farms and only focus on grain farms since management and financial information of grains farms have huge distinction from farms with livestock.

Measuring the cash rent correctly is a problem that has arisen in previous studies. One advantage of FBFM data is that average cash rent per acre is directly and accurately recorded (actual cash rent paid divided by total cash rented acres). The government payment variable includes all Farm Service Agency payments (agricultural subsidies), comprising those from commodity programs as well as other payments such as conservation programs.

While the effect of inclusion of conservation payments may be a concern, we argue that any bias they might introduce to incidence estimate results will be minimal. The main source of conservation payments in Illinois would come from the conservation reserve program, and the data we use focuses on farms that have a very high percentage of total acres as tillable in in crop production[3].

In addition, Lence & Mishra (2003) investigated effects of four different government categories and found the point estimate of payments corresponding to conservation reserve program is economically and statistically insignificant. Hence, it is expected the effect of conservation payments would be statistically insignificant in our study as well.

The timeline of farmers' decision making is also important to consider in estimating incidence of government policies. Since year-to-year lease of farmland in most regions of Illinois is presumed to end on the last day of February and 4-month notice must be given on or before the last day of October (Uchtmann, 2006), farms in the Midwest usually negotiate farmland leases for the upcoming year in November towards the end of harvest. Therefore, the available information for negotiation is usually current-year returns and government payments, and expectations for returns and government support in the year of the lease (Goodwin et al., 2003; Roberts et al., 2003; Kirwan, 2009). For instance, 2020 cash rent is negotiated in November 2019 and the information farmers received is based on economic conditions in 2019 and expectations for 2020. In terms of lease characteristics and data attributes, we use actual realizations of variables to instrument conditional expectations.

The number of observations in the FBFM data from 1995 to 2020 are reported in table 1.1. The final data is an unbalanced panel with 18,507 observations comprising 2,860 farms during 1995 to 2020. Since farmers join and leave the FBFM association voluntarily, constructing a balanced panel severely limits use of available data, particularly as the length of the time series increases (only 4 farms exist in the data

---

[3] In our data, there are no producers who produce corn, soybean, or wheat and have some of their land in the set-aside.

consistently across all 26 years). Analysis based on an unbalanced panel may introduce various sources of potential bias, such as survivorship or attrition bias. As long as the factors impacting the decision to join FBFM are not systematically related to the response variable – cash rent per acre - the model specification should not suffer from attrition bias. (Wooldridge, 2010) The primary reason for farmers to join FBFM is the association provides detailed financial statements and assists with tax planning and preparation. Since this reason is unlikely to be correlated with cash rent, we argue that the missing observations in the data are missing at random and therefore it is allowable to employ unbalanced panel instead of balanced panel.

Variables

The dependent variable, cash rent per acre, is calculated as total cash rent paid divided by total cash rented acres. Government payments per acre is calculated as total government payments received from FSA programs divided by total acres of the farm.

Expected revenue per acre is the product of an average futures price and trend yield at the county level. Trend yields are based on a simple linear trend fit to yields from 1972 to 2019. Since farmers and landlords usually negotiate cash rent leases in the fall, we average futures prices for the harvest (December/November) contract for the next crop year during the previous October. For instance, for 2020 expected corn revenue, we average prices of 2020 December corn futures contracts which was settled in October 2019 and multiply by 2020 trended corn yield. Total expected revenue at a farm is based on proportion of corn and soybeans planted acres.

Average insurance premiums paid per acre in the county, average taxes per owned acre in the county, and farm size (tillable acres) are also included as controls. Insurance premiums and taxes, similar to expected revenue, are average at the county level to provide a representation of the local "market" from which competing cash rent bids may come. Observations with zero operated acres and zero cash rental rate were eliminated. Outliers were winsorized with observations values more than three standard deviations away from the mean. All variables, with the exception of farm size, are measured in real (2020) dollars per acre by Producer Price Index.

Table 1.2. shows brief summary statistics from 1995 to 2020. How cash rents change with government payments is our estimate of interest, and higher government payments are expected to result in higher cash rent since landlords and farmers view government payments as extra revenue in net farm income. Similarly, increases in expected revenue would be expected to result in higher cash rents paid. Taxes represent an expense of ownership. Landowners may try to recover increases in taxes by charging higher rents. Insurance premiums are an expense paid by the farmer for insurance coverage. Insurance provides risk reduction benefits, and since crop insurance in the US is subsidized by the federal government, farmers should expect to earn a positive "return" on insurance. Therefore, larger insurance expenses are expected to be associated with higher cash rent levels.

Empirical Identification Challenge

Measurement Error

Farmers in Illinois usually negotiate cash rental rates in the fall towards the end of harvest. At the time of lease negotiation, future yields and prices are unknown and can change considerably according to FBFM Cash Rent Lease Fact Sheet. In terms of this characteristic, cash rental rates must be determined based on expectations for future returns at the time of negotiation. Collected data however only reflects historical, realized values of revenues, government payments, and expenses. The difference between realized (observed) x_k and expected values (unobserved) x_k^* is defined as expectation error (measurement error),

$$e_k = x_k - x_k^* \tag{1.1}$$

If expectation errors are uncorrelated with the unobserved explanatory variables $Cov(x_k^*, e_k) = 0$, regressing cash rent on realized government payments results in attenuation bias. This measurement error may not apply to all independent variables across time in our analysis. For example, decoupled payments such as direct payments do not suffer from expectation error because they do not depend on current production or unknown future market conditions. In contrast, support triggered by market conditions such as countercyclical payments is unknown when rents are negotiation. Thus, farmer expectations must be modeled or the unknown government payments must be instrumented. In our analysis we do not have separate payment categories; therefore, attenuation bias in this analysis is viewed as a general problem for the government payments variable of interest.

Several studies have proposed different strategies to solve attenuation bias caused by expectation error. The standard approach is the use of instrumental variables. Kirwan (2009) used government payments in 1997 as an instrument for change in rent levels from 1992 and 1997. Lence & Mishra (2003), Patton et al. (2008), and Goodwin et al. (2011) used generalized method of moments (GMM) with lagged realized variables as instruments. A relevant and valid instrumental variable should be correlated with the endogenous variables and orthogonal to the residual. Based on the timing of farmers decision making, the residual in our regression would be the difference between the conditional expectation and the actual realization. Lence & Mishra (2003) argued that lagged realizations (instrumental variables in our analysis) are uncorrelated with the residual since lagged realizations are in the information set available at the time of farmers' decision making. Bellemare et al. (2017) pointed out two assumptions are necessary for lagged values to be appropriate as instrumental variables in the context of unobserved confounding: 1) no dynamics impact any relevant unobservable, and 2) the lagged endogenous variable is a stationary autoregressive process. Therefore, in our case we assume that while there may be a dynamic relationship in government payments across years, there are no dynamic relationships in the unobservable which may affect cash rental contracts because the cash rental contract in our model is assumed to be negotiated annually. These unobservable related to the expectation error may include relationship characteristics between the landowner and farmer, such as bargaining power.

Inasmuch as we discussed before that our data is an unbalanced panel, meaning not every farm is observed every year, it is thus difficult to construct instrumental variables at farm level. Goodwin et al. (2011) argued that values in the county more closely represent the long-run potential benefits associated with agricultural policy and the rental "market" within which the landowner and farmer negotiate within.

To represent the expected values, we construct previous-year average government payments in the county where the individual farm is located as instrumental variables. We argue that previous-year county average values provide the most recent available and relevant information for farmers and landowners who negotiate their cash rent leases annually.

Another type of measurement error is aggregation error. Kirwan & Roberts (2016) argued that using farm-average subsides violates the classical measurement error assumption. Errors between farm-average subsidies and real field-level or lease-level data are correlated with other field/lease-level factors. What's more, most data do not report subsidized and unsubsidized land separately. Therefore, measuring rent per acre or subsidies per acre via overall cropland causes measurement error from unsubsidized rented farmland and owner-operated subsidized farmland. Estimates of aggregate data is consistent only when it reflects the true field-level data (Kirwan & Roberts, 2016). In our analysis we argue that the study only focuses on farms in Illinois where operations tend to be more homogeneous with similar types of soil quality and major crops. Thus, we argue that heterogeneity between field-level and farm-level units is negligible in the FBFM data. Our farm-level data is assumed to be consistent with true microparameters.

Omitted Variable Bias

Unobserved farm characteristics that are related with government payments, such as farmers' management skill, is a challenge in this study. To deal with omitted variable bias, previous studies tend to use a fixed effects approach to account for time-invariant factors such as land productivity and farmer skill. Kirwan & Roberts (2016) claimed that both subsidies and rental rates are correlated with land productivity. Failure to account for land productivity would cause bias in incidence estimates. They used fertilizer-decision yield goals reported in the ARMS survey as their underlying land productivity and found that incidence estimate were cut in half after including yield goal as a control for productivity. In this study we observe a farm-level soil productivity rating and utilize it as a control for land productivity.

Column (1) and (2) in table 1.3. report the estimates before and after including soil productivity ratings under pooled OLS estimation. Reports of incidence suggests little difference after adding soil productivity ratings as control variable and the R^2 remains of similar magnitude. These results indicate land associated with farms in Illinois do not change much over time. Based on evidence of fixed underlying land productivity, using farm-level fixed effects to control for time-invariant farm factor such as management skills in the analysis is reasonable. In addition to farm-level fixed effects, annual fixed effects are also included in our estimation in order to control for common shocks in each year such as extreme weather conditions or price swings.

Empirical Method

For our empirical approach, we estimate the relationship between government payments and cash rental rates over the entire panel and under different time regimes. First, we analyze data between 1996 to 2020. Second, we separate timeframes into 1996-2005, 2006-2013, and 2014-2020 based on the structural break of net farm income and farm program payment design regimes[4]. Under the assumption of annual negotiation, we use farm-level and time fixed effect to deal with time-invariant farm characteristics and yearly common shocks. The fixed effect model with cash rent y_{it} as dependent variable in farm i and year t between 1996 to 2020 is specified as follow,

$$y_{it} = \beta_0 + \beta_g X_{it}^{g*} + \beta_r X_{it}^{r*} + \beta_{tax} X_{t-1}^{tax} + \beta_{ins} X_{t-1}^{ins} + \beta_{till} X_{it}^{till} + f_i + \delta_t + \varepsilon_{it} \qquad (1.2)$$

where y_{it} is cash rent per acre for farm i in year t. X_{it}^{g*} and X_t^{r*} are expectation of government payment per acre, and expectation of revenue per acre respectively. As we discussed before, in this analysis previous-year average government payments per acre in the county where individual farm is located is instrumental variable for expected value. Expected revenue per acre is the product of an average futures price and trend yield at the county level. Total expected revenue per acre at farm level is based on proportion of corn and soybeans planted acres. X_{t-1}^{tax} and X_{t-1}^{ins} are previous-year average taxes per owned acre and average crop

---

[4] In this study, we also separated timeframes based on change of price support:1996-2002, 2003-2013, and 2014-2020. We found estimated incidence rates are slightly lower but still much higher than estimated incidence rates in previous literatures.

insurance expenses per acre in the county where individual farm is located. Tillable acres are used to represent farm size. X_{it}^{till} is log of tillable acres for farm i in year t.

It is assumed that at the time of rental rate negotiation (year $t-1$), farmers and landowners use settlement prices from the harvest futures contracts for corn and soybeans (December for corn; November for soybeans) in year t, trend yields for year t, farmland taxes paid in year $t-1$, crop insurance expenses paid in year $t-1$, and tillable acres of the farm in year t. f_i is fixed effect for farm i and δ_t is annual fixed effect for year t. Robust standard errors are clustered at the county level.

Empirical Results

Table 1.3. reports estimates of regressions from 1996 to 2020. First column of table 1.3 reports pooled OLS regressions between cash rental rate and government payment per acre with other control variables. In second column we add soil productivity ratings as control variable for underlying land productivity. Third column includes farm-level fixed effect, and fourth column employs farm-level and time-level fixed effects. Finally, the fifth column reports estimates after using past year county-level government payments, taxes, and insurance premiums as instrumental variables.

From column (1) we find the incidence of government payment on cash rental rate is around 0.32 under OLS approach, indicating landlords capture approximately $0.32 cash rent per acre when $1 of government payment per acre is given to farmers. From column (2), the estimated incidence of government payment is 0.29 and incidence of soil productivity ratings is statistically significant of 1.124; in other words, cash rental rate increases by $0.29 for each $1 of government payment paid to farmers and cash rental rate increases by $1.124 with marginal soil productivity ratings. We do not find substantial difference between incidence of government payment after adding soil productivity ratings into the model. This finding is counter to previous study. Kirwan & Roberts (2016) reported an almost 50% decrease in estimated incidence of government payment when including the fertilizer-decision yield goal as a control variable. Failure to find significant difference in incidence suggests land productivity associated with FBFM farms in Illinois does not change much over time. That is, it is reasonable to employ farm-level effect for presumably fixed underlying land productivity.

Column (4) shows the point estimates of 0.389 when including farm-level and year fixed effects. Cash rental rates tend to increase $0.389 for each $1 of additional government payments. As we noted before, the estimate may be subject to expectation error bias since most payments are unknown to farmers until after harvest. To deal with this issue, previous-year county-level realizations are used as instruments for expected values. Column (5) in table 1.3. reports and estimated incidence rate of 0.851, implying landlords in FBFM increase cash rental rate by $0.85 for each $1 of additional government payment. The magnitude of this estimate is large relative to findings in previous studies. The null hypothesis that the incidence estimate equals 1 cannot be rejected based on the chi-squared test statistic of 0.29 and associated p-value of 0.5896. In other words, the estimate from this model specification cannot reject the null hypothesis of full incidence of government payments on cash rent levels.

All control variables in column (5) of table 1.3. have the same signs as expected. Every additional dollar of expected revenue increase cash rent per acre by $0.057. Cash rents paid are estimated to increase by nearly $0.18 per acre for every one percent increase in size. Increases in real estate taxes would result in marginal increases in cash rents, with every additional dollar in tax expense associated with an increase of $0.602 in rent levels. Recall our arguments in prior section that the risk reduction and return effects of subsidized insurance was expected to result in a positive relationship between insurance expense and cash rent levels. In table 1.3., the positive sign of insurance coefficient estimates follows these expectations. However, the estimates imply relatively small effects, and are not statistically different from zero.

Column (5) in table 1.3. is based on 1,203 fewer observations than the other specifications. This is due to the use of lagged values as instruments, and not being able to observe these lagged values for the first year in our panel (i.e. lagged values for 1995). Therefore, we also provide estimates across all specifications using a consistent data set; these results are shown in table 1.4. where we find very similar magnitudes and significance levels for all estimates compared with those reported in table 1.3.

Our findings so far indicate relatively large incidence rate of government payments similar to Patton et al. (2008) and Goodwin et al. (2011). As we mentioned in previous sections, the literature has shown divergence of incidence estimates. In order to better understand the reasons for this divergence, we collect variables and follow the estimation design in Kirwan (2009) and Goodwin et al. (2011) in an attempt to partially replicate their results with our data. Kirwan (2009) employed two years of the farm-level U.S. Census of Agriculture, 1992 and 1997, using first-differencing estimation. He utilized the 1997 subsidy level as instrument for the deterministic component of the 1992-1997 subsidy change. He found the landlord (tenant) captures 25 (75) percent of every government payment dollar. In our data we use 1995 as 1992 to replicate the estimation due to data availability. Table 1.5. shows our replication results. Column (4') of table 1.6. shows estimated incidence in FBFM is 0.327 in fixed effects with instrumental variable context. The result is close to the Kirwan (2009) estimate of 0.25. However, our estimate is not significantly different from 0 due to limited numbers of observations in 1995 and 1997 (190 observations).

Contrary to Kirwan (2009), Goodwin et al. (2011) found full incidence rate of 1.0137. The primary source of farm-level data in Goodwin et al. (2011) is from USDA's National Agricultural Statistics Service (NASS) Agricultural Resources Management Survey (ARMS) project, covering the years 1998-2005. We collect population data from USDA Economic Research Service (ERS) and calculate population growth rate by compound annual growth rate. Farm acres at county level are planted acres collected from USDA NASS. Goodwin et al. (2011) utilized preceding five-year county-level payments to form instruments that represent expected payments in a generalized method of moments (GMM) estimation. Our replicated results are reported in table 1.6. Column (2') shows FBFM incidence estimate of government payments from 1998 to 2005 is 0.604 under IV-GMM. Although it is not significantly different from 0, we find similar magnitude of estimates compared to Goodwin et al. (2011).

Based on our Kirwan (2009) and Goodwin et al. (2011) replication results, we find that the estimates from Illinois FBFM dataset are comparable to the estimates using national fam-level agricultural dataset. We also notice that time periods in the analysis may be the main factor to the divergence of estimated incidence rate of government payments. Different periods of time cover different designs of government payments. Compared to previous literatures where the time series aspect is relatively short, our panel is longer term covering periods from 1995 to 2020. In order to capture the dynamics of government payments incidence rates under different farm bills, we conduct the analysis under three timeframes: 1996-2005, 2006-2013, and 2014-2020.

The results in table 1.7. examine whether incidence estimates and the effects of other controls might vary across time. Columns (1), (2) and (3) are estimated from 1996 to 2005. This is a time period of relatively low incomes, and a combination of direct payments and price supports at high levels. Column (4), (5), and (6) are estimated from 2006 to 2013, a period of increased farm incomes and lower levels of government support. Columns (7), (8), and (9) cover period from 2014 to 2020, a return to low incomes and a transition to more complicated farm program designs with both price- and revenue-based program options.

Under pooled OLS and fixed effect, incidence rate estimates range from 0.1 to 0.6. Estimates under IV-GMM are reported in column (3), (6), and (9). The results indicate most effects build into government payments after incorporating instrumental variable. It also implies that government payments play an important role in lease negotiation. The highest incidence rate estimate of government payment is reported during periods 2006 to 2013. Expected revenue also has larger impact on cash rental rate of about 25% during 2006-2013 compared to periods in 1996-2005 and 2014-2020. We fail to reject the null hypothesis that the incidence rate estimates are equal to 1 when the instrumental variable approach is used. This suggests landlords extract the full portion of government payments through higher cash rent levels.

The magnitude of the incidence estimates under different time frames provide insights into behaviors in the Illinois cash rental market. First, the incidence of government payments tends to be higher from 2006 to 2013. For 2006-2013, cash rents are estimated to increase by $1.178 for each government payment dollar. Incidence estimates are 0.889 for 1996-2005, and 0.267 in 2014-2020.

During the period from 2006 to 2013 farmers earned relatively high net farm income and faced high commodity prices, resulting in a greater willingness and ability to increase cash rent bids. In addition, government support in this era was decoupled and comprised of easily observed and predicted direct payments. Price supports were also available (CCP and LDP programs), but due to high commodity prices did not trigger significant levels of support for corn and soybean farmers in Illinois. Therefore, higher cash rental rate could also be due to transparency and certainty between farmers and landowners. This result of greater incidence associated with decoupled payments is similar to the findings in Lence & Mishra (2003); Patton et al. (2008); Goodwin et al. (2011).

Second, the magnitude of incidence in 2014-2020, 0.267, becomes relatively small and less significant. The possible reason of lower incidence may be decrease in farmers' net farm income and substantial changes to support programs in the 2014 farm bill. In 2014 farm bill, ARC/PLC replaced most commodity programs from 1996 to 2013 and farmers only receive government payments when revenue and/or prices are sufficiently low. Under these circumstances, the expectation error associated with government support levels for the coming year is arguable greater than when at least of portion of government support is based on fixed payment levels. We also argue that the contingent design of the 2014 Farm Bill programs introduces greater potential for information asymmetries between the farmer tenant and landowner, particularly absentee landowners or those less involved with market and production conditions, resulting in impacts on the incidence of government payments that may favor the farmer.

Summary and Conclusions

This study employs farm-level data from Illinois Farm Business Farm Management Association (FBFM) to estimate the incidence of government payments on cash rent levels using IV-GMM estimation. The incidence estimates in our paper suggest that government payments play an important role in the Illinois cash rental market. The incidence estimates from our preferred specification are at the higher end of those previously reported in the literature. Our replication of previous literature indicates different time periods in existing studies may be the main factor to the divergence of estimated incidence rate of government payments.

The unique farm-level data allows us to measure cash rent per acre more accurately. Specific farm-level characteristics also increases variation and provides more information compared to previous work which relied entirely on aggregate county-level data. We also incorporate the typical timing of farmers' decision making and rental negotiations with landowners in specifying the model and defining control variables.

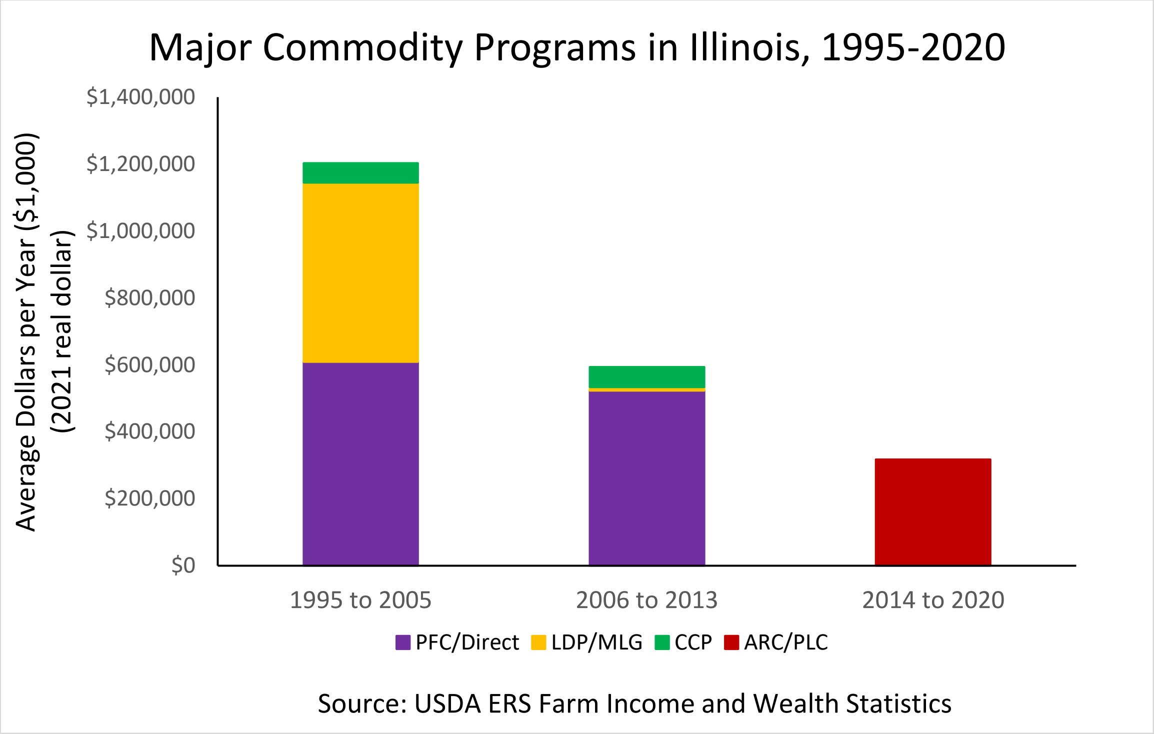
The evidence of incidence rates also varies over time based on different economic conditions and farm policy design. During periods of higher farm incomes, landowners might receive a greater share of government support through higher cash rents than during periods of lower farm income. Incidence estimates for the most recent time period are the lowest, suggesting that the increased complexity of farm program design may have made it more difficult to form accurate expectations for future support to build into cash rent levels.

These findings contribute to the literature in this area by providing more support for potentially high rates of incidence. This result is important for policymakers to consider in future modifications to support levels and design. If the desire is for government programs to provide as much support to producers as possible, it seems the more complicated designs of current programs may result in a lower-rate of pass-through to landowners via higher cash rental rates.

Future extensions to this research could focus on heterogeneity across farms, and farm-level spatial dependence characteristics. Considering these factors could be helpful to examine different levels of bargaining power among landowners and different farm types, and to understand dynamic spillover effects across farms. Results from this study can also help contribute to outreach efforts through development of extension publications, presentation materials, and decision tools. Understanding how the farm financial safety net impact cash rental markets allows us to help farmers and landowners make more efficient decisions when negotiating cash rental rates.

Tables and Figure

Figure 1.1. Major commodity programs in Illinois: 1995-2020
(USDA ERS information calculated by author)



Source: USDA ERS Farm Income and Wealth Statistics

Table 1.1. The sample

	Year	**Number of observations**	**Number of farms**
Unbalanced	1995-2020	18,507	2,860
	1995-2005	6,408	1,729
	2006-2013	6,282	1,672
	2014-2020	5,817	1,758
Balanced	1995-2020	104	4
	1995-2005	308	28
	2006-2013	1,360	170
	2014-2020	1,190	170

Table 1.2. Summary statistics

	N	**Mean**	**Std. Dev.**	**Min**	**Max**
Cash rent ($/acre)	18,507	228.88	130.47	0.34	632.68
Government payment ($/acre)	18,507	76.18	94.43	0.00	342.28
Expected revenue ($/acre)	18,507	638.31	247.65	178.70	1,420.16
County tax ($/acre)	18,457	45.68	28.98	0.16	219.93
County insurance ($/acre)	18,507	27.33	12.30	1.32	77.78
Farm size (tillable acres)	18,507	1,177.55	762.73	157.39	6,058.729

Table 1.3. Unbalanced panel 1996-2020

Dependent Variable: Cash rent $_t$ (\$/acre)

	Pooled OLS	**Pooled OLS with Soil Rating**	**Farm Fixed Effects**	**Farm and Time Fixed Effects**	**Farm and Time Fixed Effects with IV**
1996-2020	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Government Payment $_t$ (\$/acre)	0.318***	0.294***	0.303***	0.389***	0.851***
	(0.023)	(0.024)	(0.016)	(0.019)	(0.388)
Revenue $_t$ (\$/acre)	0.203***	0.200***	0.162***	0.193***	0.057***
(Expected yields*futures)	(0.016)	(0.016)	(0.015)	(0.023)	(0.027)
County Tax $_{t-1}$ (\$/acre)	0.453***	0.580***	0.423***	0.351***	0.602***
	(0.020)	(0.105)	(0.113)	(0.057)	(0.208)
County Insurance $_{t-1}$ (\$/acre)	0.587**	0.737***	1.252***	0.125	0.131
	(0.240)	(0.269)	(0.209)	(0.177)	(0.325)
Tillable $_t$ (log acre)	18.411***	17.183***	11.168***	12.157**	17.566***
	(1.854)	(1.619)	(2.449)	(2.573)	(4.045)
Soil Productivity Rating		1.124***			
		(0.154)			
Farm fixed effect	No	No	Yes	Yes	Yes
Time fixed effect	No	No	No	Yes	Yes
Cragg-Donald Wald F statistics					17.810
Observation	18,455	18,455	18,455	18,455	17,252
R^2	0.3883	0.4124	0.3803	0.4144	0.4639

Note. Robust standard errors are presented in parentheses. Significance: *p<0.1; **p<0.05; ***p<0.01

Table 1.4. Unbalanced panel 1996-2020

Dependent Variable: Cash rent $_t$ ($/acre)

1996-2020	**Pooled OLS** **(1)**	**Pooled OLS with Soil Rating** **(2)**	**Farm Fixed Effects** **(3)**	**Farm and Time Fixed Effects** **(4)**	**Farm and Time Fixed Effects with IV** **(5)**
Government Payment $_t$ ($/acre)	0.286*** (0.025)	0.217*** (0.024)	0.245*** (0.024)	0.362*** (0.020)	0.851*** (0.388)
Revenue $_t$ ($/acre) ***(Expected yields*futures)***	0.197*** (0.016)	0.195*** (0.016)	0.156*** (0.014)	0.089*** (0.023)	0.057*** (0.027)
County Tax $_{t-1}$ ($/acre)	0.332*** (0.013)	0.454*** (0.101)	0.498*** (0.105)	0.163** (0.063)	0.602*** (0.208)
County Insurance $_{t-1}$ ($/acre)	0.611** (0.253)	0.758** (0.285)	1.252*** (0.219)	0.126 (0.142)	0.131 (0.325)
Tillable $_t$ (log acre)	18.331*** (1.828)	17.096*** (1.606)	10.330*** (2.562)	11.372*** (2.631)	17.566*** (4.045)
Soil Productivity Rating		1.110*** (0.162)			
Farm fixed effect	No	No	Yes	Yes	Yes
Time fixed effect	No	No	No	Yes	Yes
Cragg-Donald Wald F statistics					17.810
Observation	17,252	17,252	17,252	17,252	17,252
R^2	0.3908	0.4138	0.3821	0.4154	0.4639

Note. Robust standard errors are presented in parentheses. Significance: *p<0.1; **p<0.05; ***p<0.01

Table 1.5. Results of estimations based on (Kirwan, 2009)

Dependent Variable: Cash rent $_t$ ***(\$/acre)***

	Pooled **(1)**	**Pooled *FBFM*** **(1’)**	**Pooled** **(2)**	**Pooled *FBFM*** **(2’)**	**Fixed Effect** **(3)**	**Fixed Effect *FBFM*** **(3’)**	**Fixed Effect with IV** **(4)**	**Fixed Effect with IV *FBFM*** **(4’)**
Government Payment $_t$ ***(\$/acre)***	0.658*** (0.011)	0.378** (0.180)	0.439*** (0.013)	0.350* (0.179)	0.134*** (0.017)	0.249 (0.347)	0.206*** (0.041)	0.327 (0.850)
Sales $_t$ ***(\$/acre)***			0.044** (0.001)	0.124*** (0.029)	0.044*** (0.001)	0.147* (0.083)	0.0311*** (0.0019)	0.148 (0.073)
Variable Costs $_t$ ***(\$/acre)***			-0.018*** (0.002)	-0.032 (0.036)	-0.0049*** (0.0023)	-0.052 (0.488)	-0.0051** (0.0023)	-0.055 (0.091)
Farm Size $_t$ ***(log acre)***			-2.188*** (0.183)	2.799 (3.845)	-8.1073*** (0.5268)	35.901 (25.316)	-7.976*** (0.5305)	36.397 (24.79)
Proportion Irrigated			15.617*** (0.740)		11.325*** (2.2797)		11.102*** (2.2815)	
Proportion Pasture			-18.689*** (0.819)		-6.776*** (1.5997)		-6.518*** (1.6025)	

Note. Standard errors are presented in parentheses. Significance: *p<0.1; **p<0.05; ***p<0.01

Table 1.6. Results of estimations based on (Goodwin et al., 2011)

Dependent Variable: Cash rent $_t$ ($/acre)

1998-2005	Current Year Realized Values (1)	Current Year Realized Values *FBFM* (1')	IV-GMM (2)	IV-GMM *FBFM* (2')
Total Payments	0.3207*** (0.0081)	0.352*** (0.015	1.0137*** (0.0192)	0.604 (0.467)
Aggregate Market Returns	0.0785*** (0.0025)	0.067*** (0.011)	0.1159*** (0.0030)	0.091 (0.130)
Population Growth	3.6276*** (0.2726)	-38.801 (90.048)	5.5842*** (0.2750)	161.415 (180.483)
Urban1	-15.3141*** (1.5652)		-12.9287*** (1.1460)	
Urban2	-14.7203*** (1.5652)		-13.3325*** (1.5482)	
Urban3	-17.2977*** (1.6046)		-15.6342*** (1.5869)	
Population/Farm Acres	0.7389*** (0.0825)	-0.244 (0.459)	0.8131*** (0.0917)	-6.007 (7.700)
Observation	50,611	5,247	50,571	3,926
R^2	0.0601	0.0959	0.0806	0.0586

Note. Numbers in parentheses are standard errors. Significance: *p<0.1; **p<0.05; ***p<0.01. Column (1) and (1') are current year realized values for payments and market returns. Column (2) and (2') use average values of payments and market return over the preceding five-year period to represent expected values. (Goodwin et al., 2011)

Table 1.7. Unbalanced panel under different periods

Dependent Variable: Cash rent $_t$ ***(\$/acre)***

	Pooled OLS (1)	**Farm and Time Fixed Effects (2)**	**Farm and Time Fixed Effects with IV (3)**	**Pooled OLS (4)**	**Farm and Time Fixed Effects (5)**	**Farm and Time Fixed Effects with IV (6)**	**Pooled OLS (7)**	**Farm and Time Fixed Effects (8)**	**Farm and Time Fixed Effects with IV (9)**
	1996-2005			**2006-2013**			**2014-2020**		
Government Payment $_t$ ***(\$/acre)***	0.265*** (0.023)	0.127*** (0.042)	0.889** (0.424)	0.605*** (0.085)	0.563*** (0.080)	1.178** (0.580)	0.076** (0.033)	0.186*** (0.027)	0.267** (0.125)
Revenue $_t$ ***(\$/acre)***	0.258*** (0.025)	0.173*** (0.056)	0.110 (0.092)	0.215*** (0.016)	0.279*** (0.044)	0.250*** (0.046)	0.238*** (0.038)	0.247*** (0.041)	0.178*** (0.047)
County Tax $_{t-1}$ ***(\$/acre)***	0.420*** (0.111)	0.350*** (0.114)	0.856*** (0.251)	1.014*** (0.226)	0.469** (0.235)	1.096** (0.448)	0.799*** (0.174)	0.663*** (0.151)	1.391*** (0.250)
County Insurance $_{t-1}$ ***(\$/acre)***	1.024*** (0.265)	0.760** (0.357)	0.907 (0.943)	0.394* (0.212)	0.163 (0.214)	0.800** (0.334)	0.311 (0.399)	0.608* (0.363)	0.629 (0.805)
Tillable $_t$ ***(log acre)***	14.618*** (2.552)	13.777*** (2.671)	17.533*** (3.069)	16.345*** (1.888)	15.286*** (1.738)	17.164*** (2.030)	23.333*** (2.870)	24.623*** (3.054)	24.954*** (4.164)
Cragg-Donald Wald F statistics			27.059			93.816			12.026
Observation			5,427			5,818			6,007
$\mathbf{R^2}$	0.3156	0.3175	0.2983	0.3065	0.2944	0.1431	0.3658	0.3489	0.2335

Note. Robust standard errors are presented in parentheses. Significance: *p<0.1; **p<0.05; ***p<0.01

CHAPTER 2: QUANTIFYING BASIS RISK ASSOCIATED WITH SUPPLEMENTAL AREA-BASED CROP INSURANCE

Introduction

Under the Federal Crop Insurance Program, farmers have both individual (farm-level) and area (county-level) coverage plan options. Individual plans provide coverage levels from 50% to 85%. In the 2014 Farm Bill, there were significant changes in commodity programs as well as crop insurance programs. Most commodity programs from previous Farm Bills were discontinued and replaced with new programs.[5] Two new "shallow loss" area insurance coverage options, Supplemental Coverage Option (SCO) and Stacked Income Protection Plan (STAX), were added to the Federal Crop Insurance Program.

Starting with the 2021 crop year, another new supplemental area insurance program, the Enhanced Coverage Option (ECO), has also been introduced. Responses from farmers during extension education efforts suggest there is a large amount of interest in the ECO program. Stakeholders desire to better understand how the new policy might impact risk exposure, and how or if this new policy should be incorporated into the farm's overall risk management plan.

Different from previous crop insurance area plans, both SCO and ECO provide add-on coverage on top of individual crop insurance plans. SCO covers county-level losses from 86% down to a farmer's underlying individual plan of insurance such as Revenue Protection (RP), Revenue Protection with the Harvest Price Exclusion (RP-HPE), or Yield Protection (YP). SCO's design and eligibility ties to a producer's commodity program choice.[6] This limitation, among other factors, was associated with the relatively low uptake of the product. In the 2021 crop year, ECO was introduced and is available for

---

[5] The Agricultural Risk Coverage (ARC) and Price Loss Coverage (PLC) commodity programs in the 2014 Farm Bill replaced the Average Crop Revenue Election (ACRE) program and counter-cyclical payments. The ARC program is a revenue-based program which provides options for coverage of county-based or farm-level revenues. The PLC program is a price-based program where the payments are issued when the marketing year average price is less than legislatively set reference price.

[6] It is available on acres where the farmers chose PLC, but acres covered by the ARC program are not eligible.

purchase on 31 spring-planted crops including corn, soybean, and wheat. The coverage level of ECO is up to 90% or 95% down to 86%, conceptually providing more significant coverage of a farmer's deductible, and use of the program is not limited in any way by commodity program choice.

Since supplemental program payments are triggered based on losses at the county-level, indemnities may not always match losses experienced at the farm-level, an issue commonly referred to as basis risk. We consider two dimensions of basis risk: under-compensation (indemnity is insufficient to cover actual farm-level losses) and over-compensation (indemnity is more than what is needed to cover actual farm-level losses). Under-compensation results in insufficient coverage at the farm level and concerns over the effectiveness of risk protection offered by the supplemental area plans. Over-compensation results in concerns related to program efficiency, particularly since the crop insurance program is supported with public resources through subsidization of the premiums farmers pay, and administration and risk-sharing costs borne by the federal government.

The objective of this paper is to quantify the basis risk (under-compensation and over-compensation) and risk reduction when adding SCO and ECO to farmers' risk management portfolios. We utilize simulation techniques and the *farmdoc* crop insurance premium tool to develop a stylized, county-level model for representative corn and soybean farms across the United States. We define measures of false-negative and false-positive probabilities as the likelihood of under-compensation and over-compensation, respectively. Coefficient of variation and expected shortfall analysis at the 10% quantiles are used to measure the risk reduction. While existing literature has discussed the basis risk of these supplemental area plans from a conceptual perspective, to our knowledge, there have not been studies which directly quantify this basis risk. Therefore, we contribute to the literature by quantifying the basis risk and risk reduction associated with combining individual plans and supplemental area plans such as RP-80+SCO, RP-80+SCO+ECO-90, and RP-80+SCO+ECO-95 relative to baseline coverage scenarios of complete individual coverage.

Our results show the classic tradeoff between Type I and Type II errors. Increasing the coverage level of the supplemental area plan reduces the likelihood of under-compensation (insufficient payments from area plans to cover farm-level losses), but increases the likelihood of over-compensation (indemnity payments from the area plan will be larger than what is needed to fully cover farm-level losses). We also find differences in basis risk across regions of the U.S. Counties in the heart of the Corn Belt tend to have lower likelihoods of under-compensation and higher likelihoods of over-compensation compared to other corn and soybean production regions. Finally, our results show that the supplemental area plans do have the potential to provide additional risk reduction to farmers, but the extent of that risk reduction is inversely proportional to the level of basis risk for the area.

Literature Review

Numerous literatures have discussed the potential for area- or index-based designs for crop insurance programs. Halcrow (1949) first proposed an area yield insurance plan, providing farmers with an indemnity only when average yields across all farms in the area fall below a critical yield. Miranda (1991) decomposed yield risk into systemic and non-systemic components and found area yield insurance would provide better risk protection than individual yield insurance. There are several advantages of area plans over individual plans. Since indemnities and premiums of area plans are not based on farm-level outputs, it is less expensive for administration to collect relevant data. Belasco, Cooper, and Smith (2020) showed that a weather-based disaster program could save around 30% of all crop insurance expenditures. Also, since farmers have limited ability to impact historical and current area-based yield measures, area-based designs can significantly increase actuarial fairness, and decrease the potential for moral hazard and adverse selection associated with asymmetric information. (Chambers 1989; Miranda 1991; Smith, Chouinard, and Baquet 1994)

Barnett et al. (2005) showed that the Group Risk Plan (GRP) which is the first area yield crop insurance plan offered in the U.S. federal crop insurance system, provides risk reduction at least as good as individual yield plans. However, Glauber (2013) notes the participation rate of area plans such as GRP and Group Risk Income Protection (GRIP) are relatively low, likely due to the fact that farmers prefer crop insurance policies that can cover their individual losses. The potential mismatch in loss coverage between farm and area insurance products is often referred to as basis risk suggested by Smith et al. (1994). Basis risk occurs when there is imperfect correlation between farm yields and area yields, or how closely farm yields tend to follow the area (such as county) yield over time. The stronger the correlation between a farm and a county, the lower the basis risk. (Miranda 1991) Stronger correlation means a county-level product will more closely match coverage from a farm-level product.

In recent years, more studies have examined the basis risk of index insurance in developing countries. Index insurance does not insure farmers against risk of individual yields or revenue. Instead, indemnities of index insurance are based on the realization of an aggregate index measure (i.e. average yield) of an area such as a county, or a specific weather parameter measured over a period of time at a particular location. Elabed et al. (2013) proposed using frequency of basis risk occurrence as a way of quantifying basis risk. The frequency of basis risk occurrence is defined as the false negative probability (FNP) in their paper. Other literatures also pointed out basis risk reduces the demand for index insurance. (Binswanger-Mkhize 2012; Clarke 2016; Elabed et al. 2013; Elabed and Carter 2015; Giné, Townsend, and Vickery 2008; Yu et al. 2019)

A developing stream of U.S. crop insurance research related to basis risk focuses on rainfall-based index insurance for the Pasture, Rangeland, and Forage Program (PRFIP). Maples, Brorsen, and Biermacher (2016) found rainfall index is highly correlated with actual rainfall; however, it does not reduce yield loss risk for forage in Oklahoma. Yu et al. (2019) estimated and decomposed basis risk into non-precipitation risk and index-related risk. They found in Kansas and Nebraska most of the basis risk in the PRFIP is from non-precipitation risk that affect forage yields. Keller and Saitone (2022) utilized the Normalized Difference Vegetation Index (NDVI) as proxy for forage production in California. They showed that for 36% of the cases in the state the indemnity payments are not sufficient to compensate for forage-related losses. Instead of looking at the PRFIP, our study contributes to literature by examining the magnitude of basis risk and risk reduction of the supplemental area options in U.S. federal crop insurance programs. As far as we know, this study has been the first paper offering insights into the basis risk through the implementation of the 2014 Farm Bill supplemental area plan (SCO) and the 2021 Enhanced Coverage Option (ECO).

Data and Methodology

This study utilizes simulation techniques to generate a representative farm model at the county level. The representative farms are assumed to be 100-acre enterprise units. Crops in the analysis are corn and soybean from the 17 states included in USDA's Crop Progress Reports as of 2021[7]. These 17 states represent at least 90% of the 2020 corn and soybean acreage. This section provides a brief overview of the simulation process.

Our simulation inputs include county-level and state-level yields from USDA National Agricultural Statistics Service (NASS) covering the period from 1972 to 2020, historical futures harvest prices, historical U.S. Marketing Year Average (MYA) prices, and projected insurance prices and volatility factors from the USDA Risk Management Agency (RMA) for the 2021 crop year. Futures harvest prices for corn and soybean are the average settlement prices on the December contracts during October. For yields data, we exclude missing entries and counties with less than 30 years of data.

Our simulation procedures were employed in the MATLAB software package. The simulation algorithm includes the following steps:

---

[7] Corn states include Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, North Carolina, North Dakota, Ohio, Pennsylvania, South Dakota, Tennessee, Texas, and Wisconsin. Soybean states include Arkansas, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Michigan, Minnesota, Mississippi, Missouri, Nebraska, North Dakota, Ohio, South Dakota, Tennessee, and Wisconsin.

Step 1 – County Yields

The NASS county-level yields data for corn and soybean were detrended to 2021 equivalents following Vedenov et al. (2004) and Paulson et al. (2008). We fitted Weibull distributions to the detrended county yields and obtained estimated shape parameters by maximum likelihood. 5000 draws of simulated county-level yields for each county are then generated from the fitted Weibull distribution with estimated shape parameters.

Step 2 – Farm-level Yields

We assume an average (expected) yield for the representative farm equal to the average detrended county yields, and then calibrate the farm-level yield volatility (standard deviation) to match the crop insurance premium rates in that county. The target premium rates are those for the 85% Yield Protection (YP) policy. Rates were obtained from the *farmdoc* insurance premium calculator. It is noted that *farmdoc* tool is based on data and computations directly from RMA, which means they are the same rates used in the federal crop insurance program. The use of premium rates to calibrate farm-level yield volatility makes use of the implicit assumption that RMA ratings procedures are actuarially fair.

The types and practices used in *farmdoc* tool follow the codes from RMA's actuarial data master (ADM) records. Type and practice of corn in this analysis are grain and non-irrigated, respectively. Types of soybean include commodity and no type specified. Practices of soybean include irrigated, non-irrigated, or Not Following Another Crop (NFAC) non-irrigated. Trend-adjusted (TA) yields are set to equal the average detrended yields. APH yields and Rate yields are defined as 8 bushels per acre less than TA yields.

We used target means (average yields for representative farm) and calibrated standard deviation for farm-level yield distribution to calculate Weibull distribution parameters using Method of Moments, and then generate 5000 farm-level yield draws using MATLAB's random number generator.

Step 3 – Futures/Insurance Prices

We calibrated lognormal distributions for futures harvest prices based on the projected insurance prices and volatility factors from RMA for the 2021 crop year. The corn projected price is $4.58/bushel and corn price volatility factor is 0.23. The soybean projected price is $11.87/bushel with price volatility factor of 0.19. A set of 5000 corn price draws and soybean price draws were then generated with these characteristics using MATLAB’s random number generator.

Step 4 – County Yield and Futures/Insurance Price Correlation

We imposed the correlation structure between the simulated county-level yields and simulated harvest prices based on the correlation between state-level yields from USDA NASS and the deviations between historical harvest price and projected price. The approach used is a sorting method outlined by Iman and Conover (1982). The advantage of the technique is that it preserves the marginal distributions for each random variable, and simply re-sorts the random variates to achieve the target correlation structure . For example, the correlation between NASS state-level yields and deviation of prices for Illinois is found to be around -0.3. We thus set the correlation between Illinois simulated county-level yields and simulated harvest prices as -0.3. The Iman and Conover method then re-sorted the variables to obtain the target correlation coefficient (-0.3) by fixing the Illinois county yields data series and sorting the simulated harvest prices.

Step 5 – Cash/MYA Prices

We regressed historical MYA prices on historical futures harvest prices to obtain coefficients and residuals. We then drew 5000 samples from normal distribution for calibrated residual using residual from linear regression. Simulated MYA is generated using estimated coefficients, calibrated residual, and simulated harvest from previous step.

Step 6 – Farm and County Yield Correlation

We applied Iman and Conover (1982) method again to impose the correlation between simulated county yields and simulated farm yields. The target correlation coefficient between county-level yields and farm-level yields is set to be 0.8.

The simulation procedure generates 5000 draws of yields and prices for a representative farm in each county. These 5000 draws represent 5000 different economic market conditions of the representative farm. The outputs for each draw are simulated county-level yields, simulated farm-level yields, simulated futures harvest prices, and simulated Marketing Year Average (MYA) prices. We use these outputs to calculate farm and county revenue, insurance indemnities, program payments for a given crop insurance option. We also compute basis risk and risk reduction for different market conditions. Premium rates are assumed to be actuarially fair, and set to equal the average of simulated indemnities.

Basis risk

Supplemental Coverage Option (SCO) and Enhanced Coverage Option (ECO) are area revenue or yield policy where indemnity payments are triggered when realized county revenues or yields fall below set guarantees. Since the indemnities are not direct measures of individual losses, it is possible that SCO and ECO could result in indemnities being paid when individual losses are not realized, or indemnities being paid which are insufficient to cover the farm-level loss. This potential mismatch in loss coverage between farm and area insurance products is often referred to as basis risk. (Miranda 1991; Smith et al. 1994)

There are two potential mismatches, or errors, that can result from the use of area-based coverage. For our purposes, we define the false negative probability (FNP) and false positive probability (FPP) followed by Elabed et al. (2013) as a measure of basis risk.:

1) Indemnity payments from the area plan will be insufficient to cover farm-level losses when they occur (under-compensation or a false-negative error)
2) Indemnity payments from the area plan will be larger than what is needed to fully cover farm-level losses (over-compensation or a false-positive error).

In this paper FNP is defined as the likelihood of under-compensation and FPP is defined as the likelihood of over-compensation. To quantify these basis risk measures, we compute the frequency of mismatch occurrence across the 5000 simulated draws. Mismatch means there is difference in indemnity payments between benchmark policy and alternatives. In the next section, we will discuss the baseline policies and policy alternatives used in this study to quantify FNP and FPP.

Policy Scenarios

False Negative Probability (Under-Compensation)

To measure false negative probability (FNP) basis risk, we compute the frequency of occurrence when indemnity payments of policy alternatives are less than losses under a baseline policy. Revenue protection with 85% (RP-85) policy is assumed to be the baseline while alternatives are the combinations of individual coverage with supplemental area coverage. The RP plan is by far the most popular individual plan of insurance, and farmers in the Midwest tend to choose the highest coverage levels available. (Schnitkey, Paulson, Zulauf, et al. 2021) Therefore, we selected RP-85 as the baseline so that indemnity payments provide a measure of true farm-level losses.

We compare the RP-85 baseline to three alternatives: revenue protection at 80% with SCO (RP-80+SCO), revenue protection at 80% with SCO and ECO at 90% (RP-80+SCO+ECO-90), and revenue protection at 80% with SCO and ECO at 95% (RP-80+SCO+ECO-95). The policy alternatives and baseline comparison are shown in table 2.1.

In 2021, RP-80 with SCO results in some premium cost savings relative to RP-85. RP-80 with SCO and ECO-90 generally results in similar farmer-paid premium costs as RP-85 and with a slightly higher total coverage level of 90%. Some farmers may have considered lowering the RP coverage level to 80% and then using SCO and ECO to provide protection above 80% due to budget constraint. Using ECO-95 increases both the coverage level and premium cost relative to RP-85 alone. (Schnitkey, Paulson, Swanson, et al. 2021; Tsay, Paulson, and Schnitkey 2021)

False Positive Probability (Over-Compensation)

The false positive probability (FPP) is calculated as frequency of occurrence when indemnity payments of policy alternatives are greater than indemnity payments of baseline policy. For FPP, our baseline policies are RP-85, RP-90, and RP-95. Although RP-85 policy is the most popular individual plan in recent years, comparing the combinations with ECO-90 or ECO-95 to RP-85 is relatively unfair because ECO-90 or ECO-95 provides higher coverage protections than RP-85. Therefore, for the purpose of measuring "over-compensation", we define a baseline that is more appropriate and can isolate effect of difference between individual coverage and a combination of individual and area coverage where, conceptually, total coverage under both the alternative and baseline are the same. The policy scenarios for false positive probability analysis are shown in table 2.2.

It is noted that RP-90 and RP-95 are not available plans of insurance in the current crop insurance program. However, the benchmark set up in this analysis is intended to examine whether there is over-compensation occurred between high coverage level of individual plan and high coverage level of alternatives that combine individual and area plans. Therefore, if there is over-compensation observed under our policy scenarios, it is anticipated that more significant inefficient allocations of crop insurance programs are shown under current policy mechanisms.

Risk Reduction

An additional focus of this study is the impacts on revenue risk in the context of combining individual coverage with supplemental coverage options versus individual coverage on its own. Two different summary statistics of the farmer's revenue distribution are reported to quantify the risk reduction of alternative crop insurance choices: the coefficient of variation (CV) and the expected shortfall (ES).

The first risk reduction measurement is coefficient of variation (CV), which can be expressed as,

$$CV = \frac{\sigma}{\mu} \tag{2.1}$$

where $\sigma =$ standard deviation and $\mu =$ mean of the farmer's net revenue distribution. The coefficient of variation allows us to determine how much net revenue volatility or risk the farmer is facing in comparison to the amount of expected return from underlying crop insurance policy. The lower the ratio, the higher the risk reduction is provided.

To provide a measure of tail-risk, or downside risk, we also analyze the expected shortfall (ES) measure. ES is the conditional expected value of the revenue distribution in the tail for the worst k outcomes. It is a risk assessment measure that quantifies the amount of tail risk of the distribution. ES can be expressed as follow,

$$ES_k = \frac{1}{k} \sum_{i=1}^{I=Nk} {R_i}/_{N} \tag{2.2}$$

where R_i is the ith order statistic of farm revenue plus net indemnities distribution, N is the sample size (in our case $N = 5000$), k is the percentile of the distribution. For instance, the ES 10% means the average of all simulated observations below the 10^{th} percentile. The larger the value of ES, the higher the risk reduction is provided. In this study, we examine the expected shortfall at the 10% percentile.

Results

In this section, we present summaries for false negative probabilities (under-compensation basis risk) and false positive probabilities (over-compensation basis risk) from our simulation model under different policy scenarios. We also calculate average indemnity payments of under-compensation or over-compensation when it occurs. Lastly, we show the results associated with the risk reduction measures of the coefficient of variation (CV) and expected shortfall (ES) at 10%.

Indemnity Payments and Under-Compensated Basis Risk

Farmer-paid premium costs ($/acre) for the policy and county scenarios that incorporate subsidy discounts of under-compensation are given in table 2.3. Champaign County (low yield risk) and Monroe County (high yield risk) in Illinois are presented as specific examples. Estimated premiums for each policy combination are calculated as the average indemnity across the simulations.

Premiums for RP-80+SCO are generally lower than for RP-85. Farmer-paid premiums for RP-85 and RP-80+SCO+ECO-90 are very similar for Champaign County, while the RP-80+SCO+ECO-90 premium is cheaper per acre than RP-85 for Monroe County. Premium costs further increase for the RP-80+SCO+ECO-95 policy reflecting the increase in coverage level from 90% to 95%. Premiums for corn farms are more expensive per acre than premiums for soybean farms.

To examine basis risk, the indemnity payments from the policy combinations using the supplemental area plans are compared against indemnities for RP-85 coverage. RP-85 is assumed to be the benchmark comparison, and the true measure of whether farm-level losses occurred. Figure 2.1. shows the likelihood of 17 states that the individual and area plan coverage combinations will trigger indemnity payments less than the RP-85 policy. These likelihoods measure how often the individual and area plan combinations will under-compensate farm-level losses as defined by the RP-85 benchmark. The maps in panels (a), (c), and (e) are likelihoods of under-compensation for corn while the maps in panels (b), (d), and (f) are likelihoods for soybeans. The darker the color in the map suggests higher chances that indemnity payments of policy combinations with supplemental area plans are less than indemnity payments of the RP-85 policy. Overall, we find the likelihoods of under-compensation for corn is lower than likelihoods for soybean. Counties located in the heart of the Corn Belt, from southern Minnesota through northern and central Iowa, Illinois, Indiana, and western Ohio, have lower likelihoods of under-compensation. Most of these counties tend to buy average coverage levels of individual plan (RP policy) over 80% due to lower production risks and lower premiums than areas outside the heart of the Corn Belt. (Schnitkey, Paulson, Zulauf, et al. 2021) Major production areas outside Midwest shows higher likelihoods of under-compensation. The under-compensation of indemnities declines when ECO-90 or ECO-95 is added.

For counties with corn production, an average likelihood of RP-85 would trigger an indemnity payment across all counties is 45%. RP-80+SCO indemnity payments would be less than RP-85 with an average likelihood of 37%. The average likelihood of zero payments from the RP-80 combinations when RP-85 would trigger payments is 3.7%. The average likelihood of under-compensation declines to 28% and 12% when ECO-90 and ECO-95, respectively, are also added to the coverage plan. The average likelihood of zero payments from the individual and county coverage combinations with ECO when RP-85 would trigger payments falls to 3% (ECO-90) and 1.7% (ECO-95) across all counties.

For counties in soybean production regions, the average likelihood of RP-85 triggering payments is 47% across all counties. For RP-80+SCO, the indemnity payments would be less than RP-85 with an average likelihood of 42%. The likelihood of under-compensation declines to 34% and 26% when ECO coverage is added at 90% and 95%, respectively. On average, soybean producing counties tend to have higher chances of under-compensation than corn production. The likelihood of zero payments from the RP-80 combinations when RP-85 would trigger payments for soybean is 3.4%. The average likelihood of zero payments from the individual and county coverage combinations with ECO across all counties when RP-85 would trigger payments falls to 2.8% (ECO-90) and 1.8% (ECO-95).

Figure 2.2. shows an average measure of the difference in indemnity payments (in $/acre), conditional on the alternative plan under-compensating losses. The darker the color in the map suggests higher average payments difference between RP-85 and policy alternative.

Panels (a), (c), and (e) in figure 2.2. are for corn while panels (b), (d), and (f) are for soybeans. For counties in corn producing region, the average level of under-compensation between RP-85 and RP-80+SCO is about $9.60 per acre. The average indemnity payments difference between RP-85 and policy alternatives decreases to $7.00 and $4.40 per acre when ECO-90 and ECO-95 are added respectively. It is also found that the corn belt regions have smaller difference in average indemnity payments compared to counties outside corn belt.

For soybean, the average levels of payment difference is similar to corn farms. The average indemnity payment difference between RP-85 and RP-80+SCO is $9.70 per acre. When ECO-90 is added, the indemnity payments difference is an average of $7.60 per acre. When ECO-95 is added, the average payment difference decreases to $5.20 per acre. Counties in corn belt regions also show smaller payment difference between RP-85 and policy combinations of individual and area plan.

Indemnity Payments and Over-Compensated Basis Risk

To measure the likelihood of over-compensation, the outcomes from the simulation where indemnity payments are triggered from the alternative policy combinations are compared to payments triggered by RP-85, RP-90, and RP-95. As we mentioned in previous section, RP-90 and RP-95 are not available in current policy options; however, it provides the same coverage level as the individual and area plan combinations to which they are being compared.

Figure 2.3. shows the likelihood these alternative policies will trigger indemnity payments that exceed indemnities from RP-85, RP-90, and RP-95 (i.e. payments from the alternative policies exceed losses actually experienced at the farm-level). Maps in panel (a), (c), and (e) are the likelihoods of over-compensation for corn. Maps in panel (b), (d), and (f) are the likelihoods of over-compensation for

soybeans. Contrary to what we find for under-compensation, counties in the heart of the Corn Belt have the highest likelihood of over-compensation. The over-compensation of indemnities increases when ECO-90 or ECO-95 is added.

In general, the likelihood of over-compensation is relatively low for soybeans compared with corn. This may be associated with the lower level of variability in soybean yields compared with corn. In corn producing regions, the RP-80+SCO indemnity exceeds the RP-85 indemnity with an average of 17% likelihood across all counties. The average likelihood of a RP-80+SCO indemnity when no farm-level losses occur (RP-85 indemnities are zero) is 8.6%. The average likelihood of RP-80+SCO+ECO-90 indemnities being greater than farm-level losses at a 90% coverage level is about 17%. The average likelihood increases to 23% when ECO-95 is added. The average likelihoods across all counties that the alternative policies trigger payments when no farm-level loss occurs also increases when ECO is added (10% with ECO-90 vs. RP-90 and 12.7% with ECO-95 vs. RP-95).

For soybeans, the average likelihood of over-compensation from the alternative policies across all counties are smaller than in corn (11% of RP-80+SCO being greater than RP-85, 12% of RP-80+SCO+ECO-90 being greater than RP-90, and 18% of RP-80+SCO+ECO-95 being greater than RP-95). The average likelihood of indemnity payments being triggered when no farm-level losses occur across all counties is 6.5% for RP-80+SCO, 8.4% with ECO-90, and 11.7% with ECO-95. The extent of false positives increases with the coverage level of the supplemental area plan being used in combination with individual coverage.

Figure 2.4. shows the average dollar-amount difference in indemnity payments for outcomes where the alternatives policies over-compensate for farm-level losses. Maps in panel (a), (c), and (e) are corn while maps in panel (b), (d), and (f) are soybeans. On average, the level of over-compensation from RP-80+SCO is about $4.40 per acre for counties in corn producing regions. The average indemnity payments average

between RP-90 and RP-80+SCO+ECO-90 is $7.70 per acre. The difference increases to $13.60 per acre when comparing RP-80+SCO+ECO-95 to an RP-95 baseline.

For soybeans, the average dollar-amount difference in indemnity payments are smaller than corn. The average level of over-compensated basis risk from RP-80+SCO is $2.60 per acre. When comparing RP-90 to RP-80+SCO+ECO-90, the average indemnity payment difference is $4.80 per acre. This average over-compensated dollar amount increases to $9.20 per acre when RP-95 indemnity is less than RP-80+SCO+ECO-95 indemnity payments.

Risk Reduction

In addition to quantifying basis risk, we also assess whether adding the supplemental area plans on top of the individual plans provides more risk reduction. To measure the level of risk reduction, we use coefficient of variation (CV) and expected shortfall (ES) measures for the net farm revenue (revenue plus net insurance indemnities) distributions. Figures 2.5. and 2.6. present the risk reduction comparisons using CV and ES at 10%, respectively. The maps in panels (a), (c), and (e) in both figures 2.3. and 2.4. are for corn while panels (b), (d), and (f) are for soybeans. Green areas in the maps indicates the individual and area plan combinations provide risk reduction compared to the benchmark policy of RP-85. Red counties on the other hand indicates the combination policy results in greater risk than the baseline policy of RP-85.

From figures 2.5. and 2.6., greater levels of supplemental area coverage provide additional risk reduction relative to the RP-85 policy. In terms of CV, the RP-80+SCO combination provides more risk reduction than RP-85 in corn producing counties associated with lower yield risk. The amount of additional risk reduction for soybean is rather minimal. This may be due to lower loss ratio of soybean than corn.

When measuring risk using the 10% ES (i.e. downside risk), we find most individual and area plan combinations for corn result in more risk reduction than RP-85. For soybeans, the coverage level on the supplemental area plan needs to be at the 90% level (i.e. ECO-95) in order to obtain significant risk reduction relative to RP-85 on its own. Downside risk reduction potential introduced by the area plans is greatest in areas of relatively low production risk, such as the main Corn Belt region.

Conclusion and Policy Implications

In this study simulation techniques are utilized to build a stylized county-level crop revenue model to assess and quantify the basis risk and risk reduction potential of recently introduced supplemental area plans of insurance in the U.S. We evaluate the effectiveness of the new crop insurance options through quantifying the basis risk and risk reduction of the Supplemental Coverage (SCO) and Enhanced Coverage Options (ECO). We find the overall likelihood of under-compensation of farm-level losses differs across regions. Specifically, this measure of basis risk is lower in relatively low risk production regions (the heart of the Corn Belt). Furthermore, this aspect of basis risk declines as the coverage level of the supplemental area plan is increased.

However, over-compensation becomes more likely as greater levels of supplemental area coverage are added. Our result indicates there is a trade-off between likelihood of over-compensation and under-compensation – the classic tradeoff between type I and type II errors. Thus, while farmers can reduce the basis risk associated with inadequate loss coverage by increasing the coverage level of the area plan used with their individual plan of insurance, this increases the likelihood of indemnity payments which exceed losses experienced at the farm level. We also find the supplemental coverage options provide more risk reduction when the coverage level increases.

To sum up, while the supplemental area plans have provided farmers with the ability to add coverage to an underlying individual plan of insurance, farmers need to be aware of the potential mismatch in coverage introduced by using area plans to cover portion of their risk. At the same time, this study shows supplemental programs which are partially supported by taxpayers through premium discounts may also result in an inefficient allocation of resources compared to individual level crop insurance with the same coverage level.

The policy changes since the 2014 Farm Bill offer producers significant new crop insurance options. It also suggests the linkage between commodity programs and crop insurance options has been stronger in recent Farm Bills, implying the complexity of crop insurance choices has remarkably increased. The results from this study can be used in extension education to help inform stakeholders about existing programs and the implications of their use through the current Farm Bill.

Tables and Figures

Table 2.1. Policy Scenarios Under False Negative Probability

	Benchmark Policy (Baseline)	**Policy Alternatives**
Policy scenario 1	RP-85	RP-80 + SCO
Policy scenario 2	RP-85	RP-80 + SCO + ECO-90
Policy scenario 3	RP-85	RP-80 + SCO + ECO-95

Table 2.2. Policy Scenarios Under False Positive Probability

	Benchmark Policy (Baseline)	**Policy Alternatives**
Policy scenario 1	RP-85	RP-80 + SCO
Policy scenario 2	RP-90	RP-80 + SCO + ECO-90
Policy scenario 3	RP-95	RP-80 + SCO + ECO-95

Table 2.3. Estimated Farmers' Paid Premium for Insurance for Coverage Scenarios

		RP-85	**RP-80+SCO**	**RP-80+SCO +ECO-90**	**RP-80+SCO +ECO-95**
Corn	Champaign County	$20.83	$14.39	$22.98	$37.71
	Monroe County	$34.87	$29.31	$29.31	$40.53
Soybean	Champaign County	$19.02	$13.51	$20.38	$32.14
	Monroe County	$36.14	$22.55	$26.10	$32.49

Figure 2.1. False Negative Probability (FNP) Basis Risk: Likelihood that RP-85 Indemnities will be More than Combination Indemnities Payments

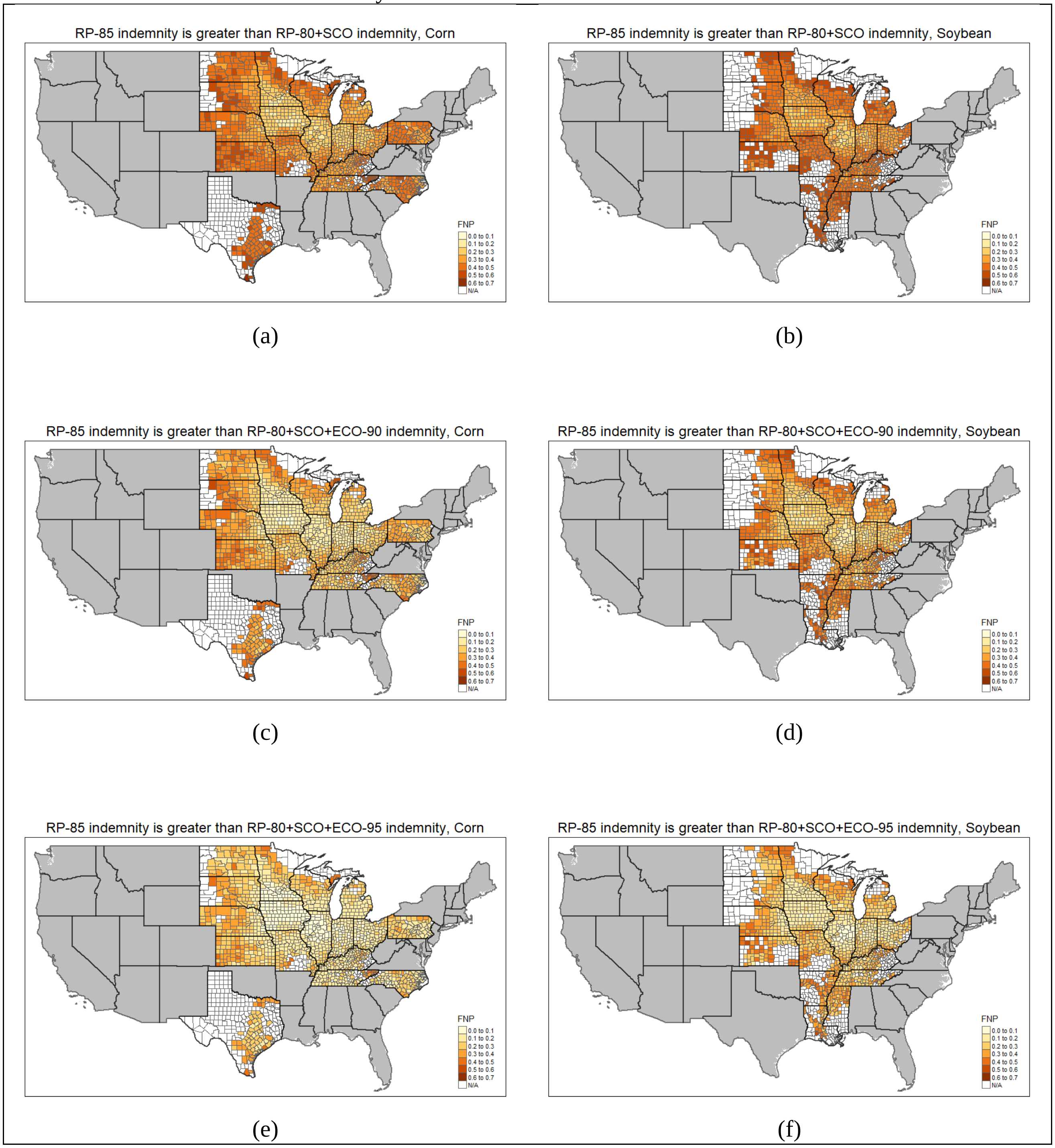
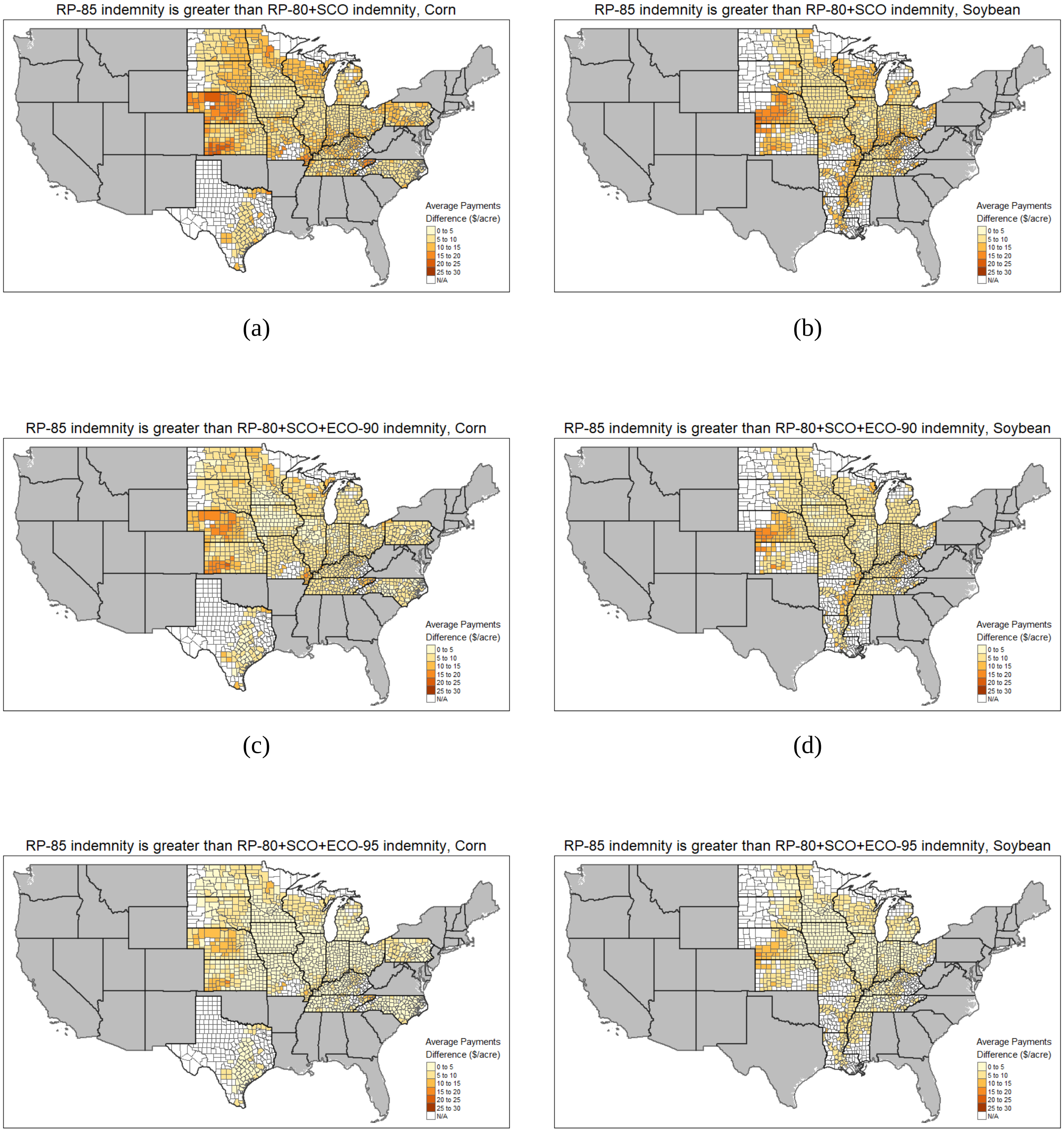


Figure 2.2. Average Indemnity Payments Difference from Under-Compensation Basis Risk

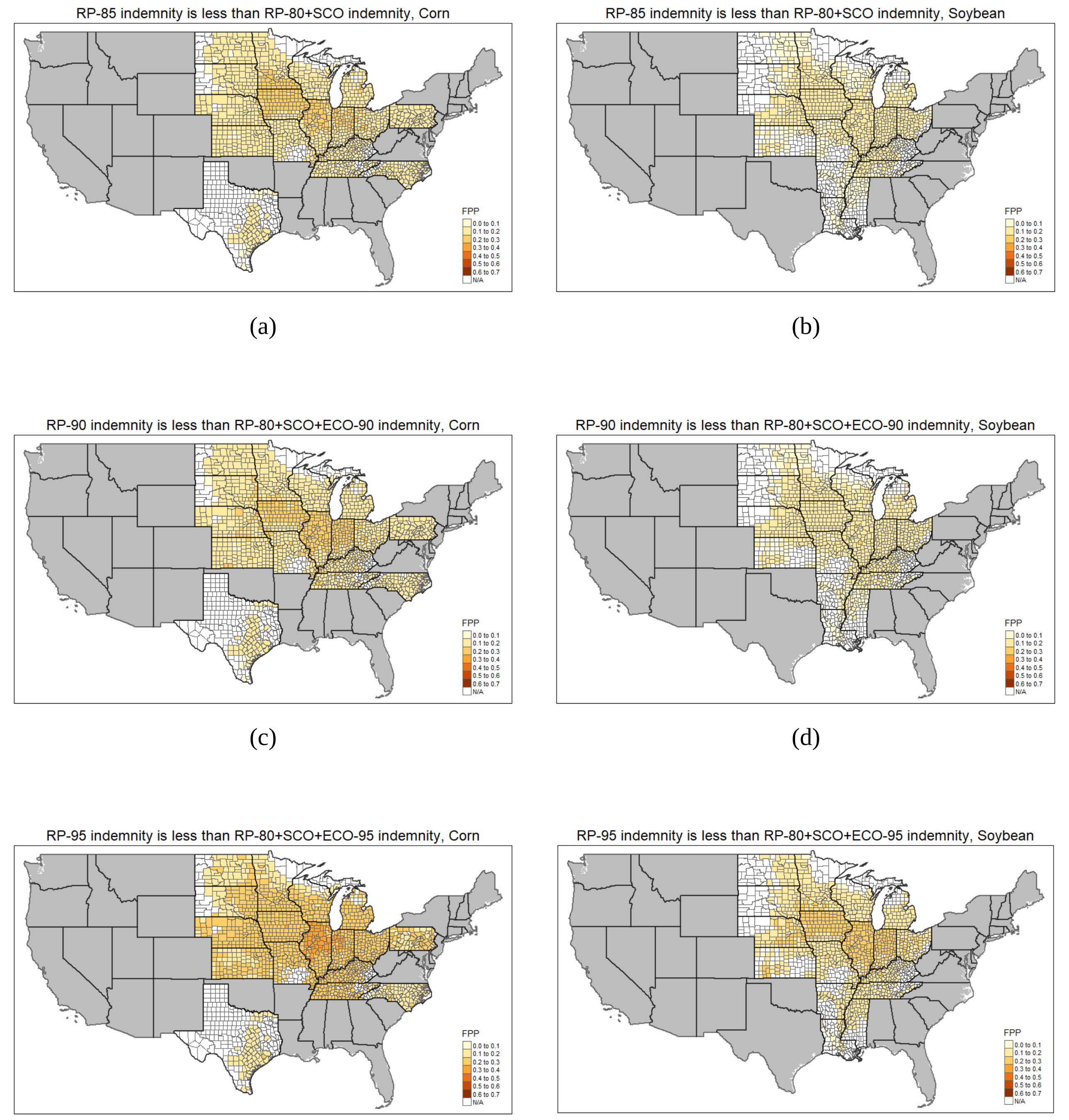


(a) (b)

(c) (d)

(e) (f)

Figure 2.3. False Positive Probability (FPP) Basis Risk: Likelihood that RP-85, RP-90, and RP-95 Indemnities will be Less than Combination Indemnities Payments

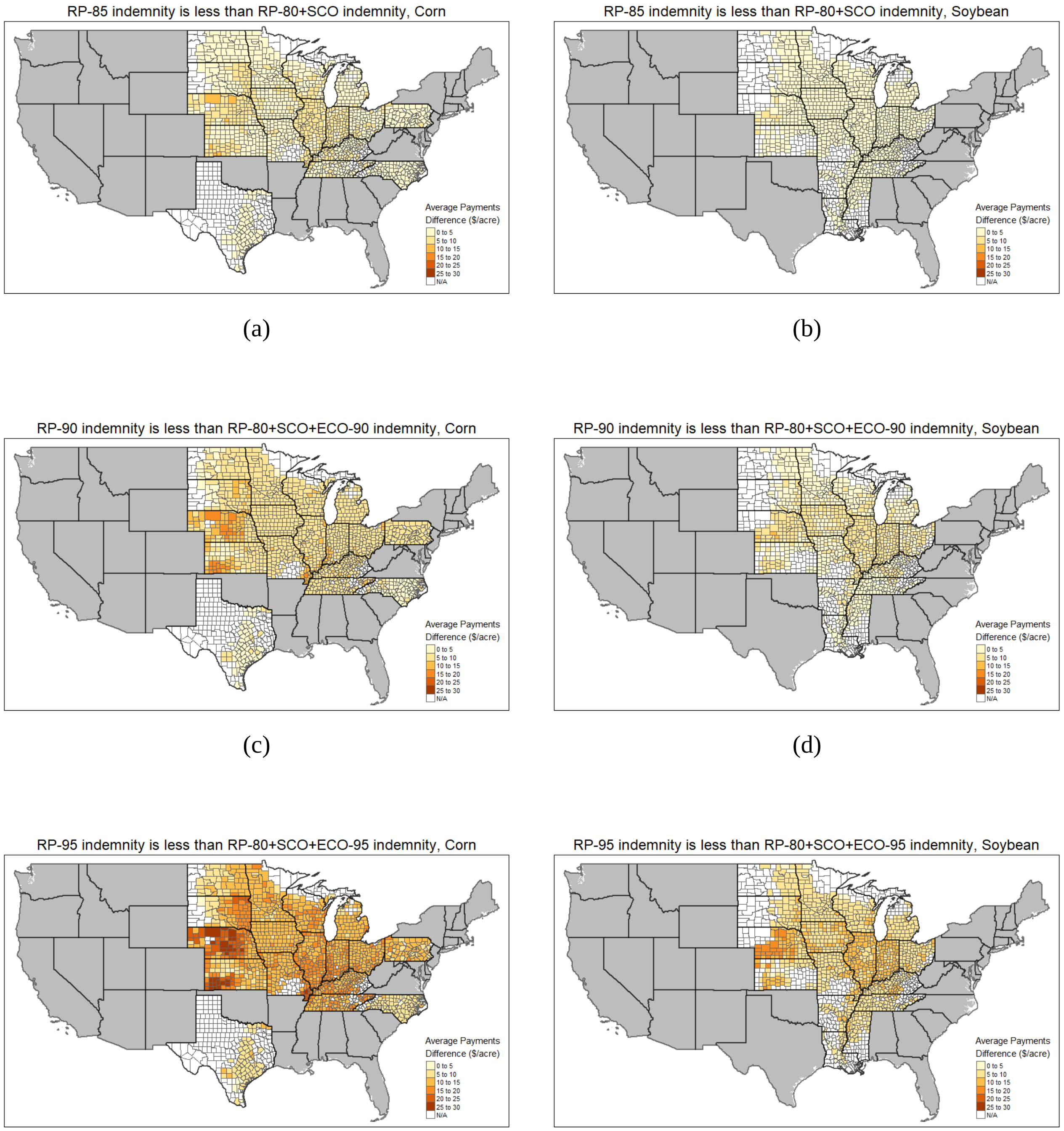


(a) (b)

(c) (d)

(e) (f)

Figure 2.4. Average Indemnity Payments Difference from Over-Compensation Basis Risk


RP-85 indemnity is less than RP-80+SCO indemnity, Corn

RP-85 indemnity is less than RP-80+SCO indemnity, Soybean

(a) (b)

RP-90 indemnity is less than RP-80+SCO+ECO-90 indemnity, Corn

RP-90 indemnity is less than RP-80+SCO+ECO-90 indemnity, Soybean

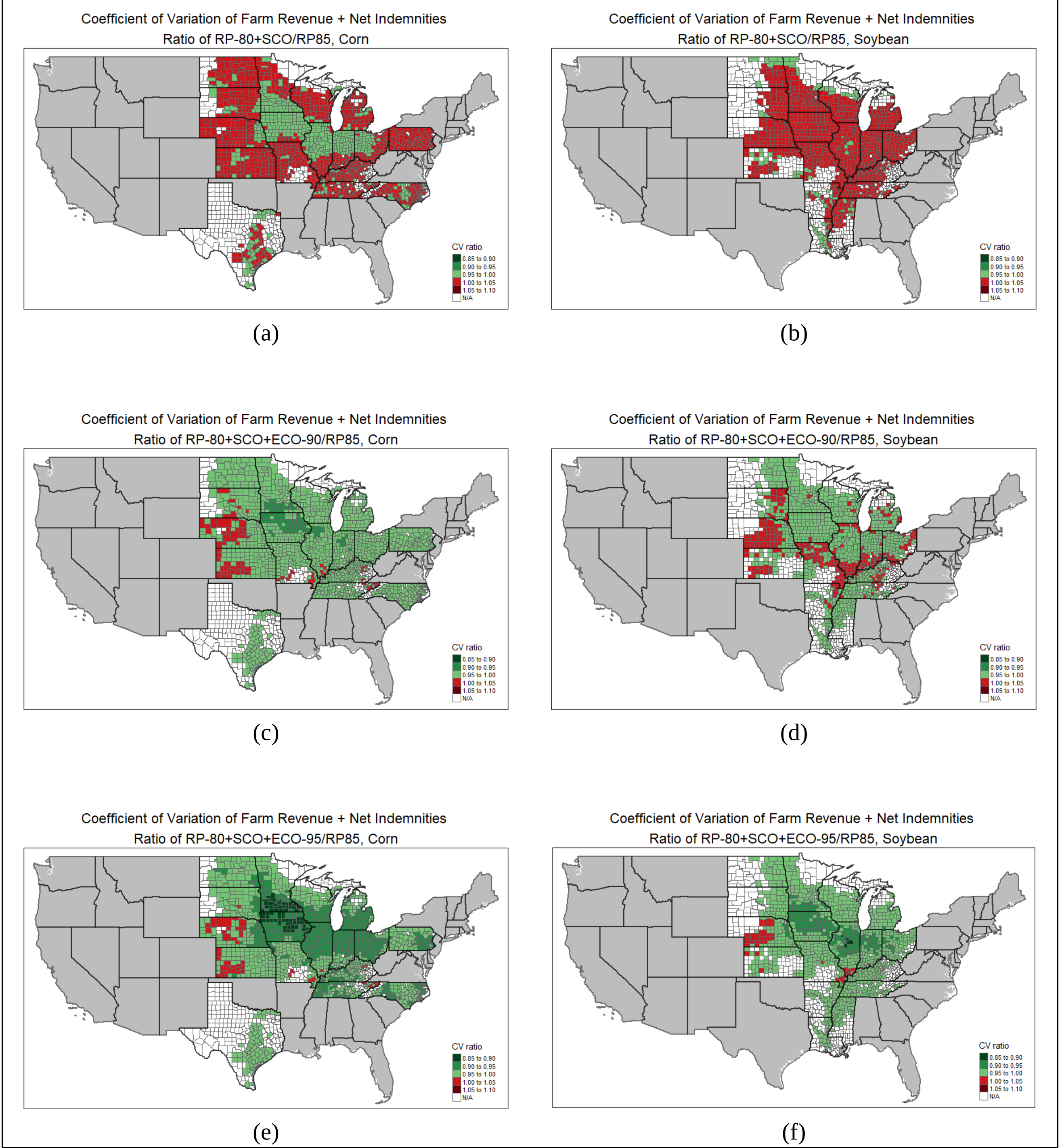
(c) (d)

RP-95 indemnity is less than RP-80+SCO+ECO-95 indemnity, Corn

RP-95 indemnity is less than RP-80+SCO+ECO-95 indemnity, Soybean

(e) (f)

Figure 2.5. Ratio of Coefficient of Variation (CV) of Farm Revenue and Net Indemnities under combination policy to Coefficient of Variation (CV) of Farm Revenue and Net Indemnities under RP-85



Coefficient of Variation of Farm Revenue + Net Indemnities
Ratio of RP-80+SCO/RP85, Corn

(a)

Coefficient of Variation of Farm Revenue + Net Indemnities
Ratio of RP-80+SCO/RP85, Soybean

(b)

Coefficient of Variation of Farm Revenue + Net Indemnities
Ratio of RP-80+SCO+ECO-90/RP85, Corn

(c)

Coefficient of Variation of Farm Revenue + Net Indemnities
Ratio of RP-80+SCO+ECO-90/RP85, Soybean

(d)

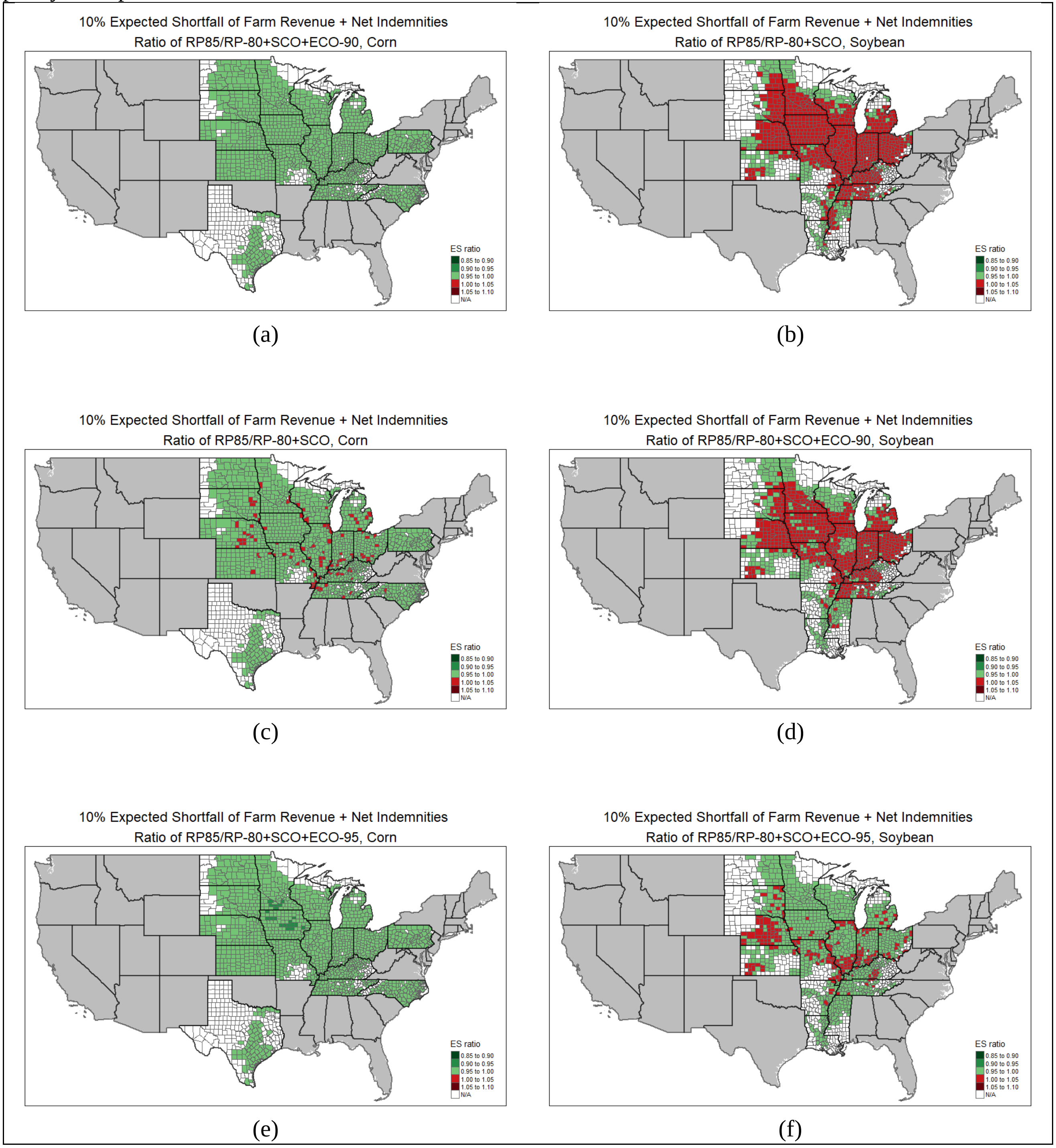
Coefficient of Variation of Farm Revenue + Net Indemnities
Ratio of RP-80+SCO+ECO-95/RP85, Corn

(e)

Coefficient of Variation of Farm Revenue + Net Indemnities
Ratio of RP-80+SCO+ECO-95/RP85, Soybean

(f)

Figure 2.6. Ratio of Expected Shortfall of Farm Revenue and Net Indemnities at 10% under combination policy to Expected Shortfall of Farm Revenue and Net Indemnities at 10% under RP-85



(a) (b)

(c) (d)

(e) (f)

CHAPTER 3: DOES SUPPLMENTAL COVERAGE OPTION CROWD OUT INDIVIDUAL CROP INSURANCE COVERAGE?

Introduction

The 2014 Farm Bill, which also known as the Agricultural Act of 2014, issued new area-based insurance programs to supplement the existing crop insurance program, the Stacked Income Protection (STAX) for cotton and the Supplemental Coverage Option (SCO) for other crops. Both STAX and SCO are county-level area plans and provide coverage for a portion of deductible on top of an underlying farm-level products such as Yield Protection (YP), Revenue Protection (RP), or Revenue Protection with Harvest Price Exclusion (RP-HPE).

STAX coverage, available only for cotton, covers at least 90% of the expected county revenue down to 70% or greater or the coverage level oof any underlying YP, RP, RP-HPE plan. SCO, on the other hand, was made available for a number of commodities and covers county-level losses from 86% down to farmers' underlying YP, RP, RP-HPE policy. The highest RP coverage level is 85%. In this paper we focus on RP and RP with SCO for counties in corn and soybeans producing regions because RP represents more than 90% of the Federal crop insurance policies sold in 2020. (Schnitkey, Paulson, et al. 2020; Schnitkey et al. 2021)

Offering larger subsides are often likely to increase the participation of crop insurance. (Glauber 2013) Farmers are encouraged to purchase more crop insurance because they do not need to pay full premiums by themselves. The farmers' paid premium increases as coverage levels rise and the premium is subsidized by the government from 38% to 100%. For federal crop insurance, products with higher coverage level would receive lower subsidy rate. For example, the enterprise unit subsidy rate for RP at 75%, 80%, and 85% coverage levels are 77%, 68%, and 53% respectively. However, surprisingly the subsidy rate for SCO is set as 65%. As we mentioned in previous paragraph, highest coverage level of RP is 85% while SCO provides protection up to 86%. It is noticed that although there is only 1% difference in coverage level, SCO provides 12% more of subsidy rate in premiums.

These traits in SCO potentially incentivizes farmers to crowd out the individual plan such as their RP policy. Here crowd out refers to potential “buy down” behavior where farmers choose to lower their individual coverage level (i.e. shifting from 85% RP coverage to 80%) and using the supplemental area plans to cover the loss range created by the coverage reduction (Bulut and J. Collins 2014; Bulut 2018). The potential issues with crowd out behavior is area plans is that they 1) may not provide the same level of risk protection as the individual plans, and 2) the costs to taxpayers to provide this inferior coverage to the farmer increases because of the higher marginal subsidy rate for SCO (Bulut and J. Collins 2014) As we discussed in Chapter 2, imperfect correlation between farm yields and county yields results in basis risk. Lower correlation between farm yields and county yields reduces the risk protection of the area products.

Several studies have already examined change in coverage level of individual policy after adding supplemental area plans and buy down or crowd out effect from supplemental area plans. (Bulut and J. Collins 2014; Cooper et al. 2015; Yehouenou et al. 2018; Bulut 2018) However, these studies usually apply the simulation techniques, and assume farmers are expected utility maximizers choosing optimal insurance coverage based on their certainty equivalent (CE).

Figure 3.1. shows the difference in weighted RP coverage level for acres insured with RP alone and acres insured with RP+SCO by county. The weighted RP coverage levels are calculated based on enrolled acres only in RP and enrolled acres in RP+SCO within the same county. Orange areas indicate some evidence of potential buy down behavior in the county while green areas indicate there is no buy down behavior. Panel (a), (c), (e) are counties in corn producing states from 2019 to 2021, respectively. Panel (b), (d), (f) are counties in soybeans producing states from 2019 to 2021, respectively. What we find from figure 3.1. is counties in the Midwest tend to lower their RP coverage level with RP+SCO while counties outside Midwest suggest no buy down behaviors. However, it is unable to conclude whether there is crowd out effect existing in the U.S. federal crop insurance program based on figure 3.1. Therefore, in this paper our contribution is to examine whether there is empirical evidence of crowd out or buy down behaviors using

public RMA and FSA data and econometric methods. This approach attempts to find empirical analysis of the theoretical results from previous work based on simulation analysis.

We utilize the endogenous switching regression with the Full Information Maximum Likelihood (FIML) to address the selection bias and unobserved factors. Our selection equation considers factors which impact famers' decision to use SCO. We find the higher crop insurance reference rates (higher production risk) increases the likelihood of purchasing SCO on top of the RP policy. A "false-negative" measure of basis risk reduces the likelihood of purchase while a "false-positive" measure of basis risk increases the likelihood of buying SCO. Our outcome equation considers factors which impact farmers' individual insurance coverage choice separately for SCO adopters and non-adopters. The results provide mixed evidence of buy down behavior. When including basis risk measures as determinants of the SCO adoption decision as well as individual coverage level choice, we estimate an average buy-down effect of approximately 4% on RP coverage levels for corn. However, we do not observe any estimated crowd out effect for soybeans.

Literature Review

The participation of crop insurance program and average coverage level for crop insurance revenue protection products in the U.S. have been increasing. (Bulut 2018) The standard expected utility theory suggests that risk averse farmers should take up actuarially fair insurance and choose the contracts providing most amount of dollar subsidy. (Du, Feng, and Hennessy 2016) However, the observed data suggests agricultural producers are purchasing coverage levels that appear less than optimal. Schnitkey et al. (2021) showed counties in the heart of the Corn Belt have average coverage levels of revenue protection (RP) over 80% while counties in the Midwest outside the heart of the Corn Belt include Eastern Seaboard, South, Delta, and most of the Great Plain have average coverage levels between 70% to 80%.

Possible explanations in the existing crop insurance literature include information asymmetries, regret penalty, reluctant insurers, loss aversion, and budget heuristic constraint. Ramirez et al. (2017) employed a probabilistic model to explore the impact of the insurer and producer actuarially fair premium estimates on the likelihood that the producer will purchase the crop insurance. They found educational programs that enhances farmers' trust of Risk Management Agency (RMA) premium quotes and methods of estimation as well as reduces the asymmetric information between government and agricultural producers could sustain participation at a lower cost to taxpayers.

Another potential reason of this anomaly is some producers are reluctant to insure and they only buy crop insurance in order to access credit in which case agricultural lenders often require the crops to be insured. (Du et al. 2016) In their paper they found underinsurance even when producers are forced to insure. Du et al. (2016) also pointed out regret preference may be a separate motivation for underinsurance. Growers usually view crop insurance as type of business expenditures as well as investment. If there is no indemnity payments, crop insurance would be considered as an investment, or the actuaries were miscalculated.

Loss aversion in the prospect theory may be another explanation why farmers do not uptake the highly subsidized crop insurance contracts. (Du et al. 2016) The prospect theory indicates individuals value choices as gains and losses, and the probability of gains and losses are referred to as decision weights. (Kahneman and Tversky 2013) Prospect theory also value loss outcomes more negatively than compared gains that are positively valued. Du et al. (2016) concluded that probability of purchasing crop insurance declines as out-of-pocket premium increases, and to explain the anomalous insurance decision, prospect theory is more plausible with minimization of regret penalty.

Budget constraint may also be the potential explanation for this puzzle. This is often referred to as budget heuristic in behavior economics literature. (Thaler 2008; Kunreuther and Michel-Kerjan 2013; Bulut 2018) Bulut (2018) assumed farmer is an expected utility maximizer with a revealed budget constraint pertaining to farmers' out-of-pocket crop insurance expenditures. He found most farmers' choices in 2015 simulated farm situation are generally consistent with the expected utility maximization subject to the budget constraint. Overall, budget constraint is important for farmers to make decision on crop insurance products and coverage levels.

Several researchers have also examined the crowding out effect with respect to crop insurance program due to Samaritan’s dilemma. Samaritan’s dilemma is one type of moral hazard first mentioned by Buchanan (1975) that people who benefit from assistance or charity do not have desire to improve their situation. This is also referred to as charity hazard theory. Deryugina and Kirwan (2018) used third-party voting behavior as instrument for ad hoc disaster payments and found evidence of Samaritan’s dilemma in US federal crop insurance system that disaster relief reduces crop insurance coverage and increases the inefficiency in farmers’ investment decisions. Miglietta et al. (2020) also found charity hazard theory exists in Italian agricultural insurance program that crowd out effect of public aid and farm subsidies may be key factors to the low take-up rates of agricultural insurance.

Another stream of crowd out literature focus on the impact of federal crop insurance on the Conservation Reserve Program (CRP). Wu (1999) showed crop insurance for corn incentivizes farmers to shift land from hay and pasture to corn production in the Central Nebraska Basin. Feng, Hennessy, and Miao (2013) found if crop insurance subsidies increase by $1 per acre, CRP enrollment would decrease about 6,000 acre. Miao et al. (2016) examined the CRP enrollment design and suggested that incorporating crop insurance subsidies into CRP’s Environmental Benefits Index would significantly increase the CRP acreage. DeLay (2019) showed crop insurance crowds out small but significant amount of CRP land that increasing insured land by 1,000 acres reduces an average of three acres in CRP land.

While many papers address the effect of crowd out insurance effect from public aids or crowd out effect of crop insurance on CRP, less attention has been paid on the buying down effects due to higher coverage supplemental area plans in the 2014 Farm Bill. Yehouenou et al. (2018) analyzed the Stacked Income Protection Plan (STAX) for cotton producers in Texas using Certainty Equivalent (CE). Their results suggest 70% coverage level for RP insurance is most commonly selected by cotton producers in Texas.

When premiums are subsidized, purchasing RP with either 70% or 60% coverage level layered with STAX generates higher CE than purchase RP with an 80% coverage level.

Cooper et al. (2015) examines the interaction of shallow loss support (Agricultural Risk Coverage ARC and Supplemental Coverage Option SCO) and traditional deep loss Federal crop insurance (Revenue Protection RP) using copula approach and regression analysis. What they found is producers will likely consider the trade-off between traditional crop insurance and SCO. The subsidy difference may cause producers to reduce their coverage level under traditional crop insurance and purchase an SCO policy to cover the remaining range of losses.

Bulut and J. Collins (2014) used simulation analysis to assess farmer choice between crop insurance and supplemental coverage options which is on top of the individual coverage option. Farmers value different choices based on the certainty equivalent (CE) measure of wealth. Bulut and J. Collins (2014) showed the incentive to increase crop insurance coverage level is maintained for Illinois farmers who tend to maximize values of RP with 85%. SCO or STAX under the base cases may result in buy down of five percentage points in crop insurance at high coverage level. Bulut (2018) also mentioned that since supplemental coverage option (SCO) costs money, farmer will consider buying down from an initial individual plan or switching to cheaper plans such as Yield Protection (YP) and Revue Protection with Harvest Price Exclusion (RP-HPE). In general, ARC of county or individual coverage and PLC do not cause buy down.

Our main contribution to literature is to examine whether there are empirically crowding out individual RP plan behaviors due to the enrollment of SCO. The analysis focuses on corn and soybeans farmers in the U.S. and utilize the public crop insurance and commodity program county-level data. To address the issue with selection bias and unobserved factors, we utilize the endogenous switching regression with the Full Information Maximum Likelihood (FIML) to estimate the selection and outcome equations as well as the estimated average treatment effect on the treated regarding the impact of purchasing SCO on the coverage level of RP policy.

Data

Variables

The data used in the analysis include county-level RP and RP-SCO data for corn and soybeans from 2019 to 2021 provided by the Risk Management Agency (RMA) Summary of Business (SOB) and ADM[8]. Farm Service Agency (FSA) enrolled base acres of the Agriculture Risk Coverage (ARC) and Price Loss Coverage (PLC) data for corn and soybeans over the same period were also collected for each county. Basis risk measurement in this paper were false negative probability (FNP) and false positive probability (FPP) of RP-80+SCO+ECO-90 calculated in Chapter 2. The values of FNP and FPP for each county would be the same from 2019 to 2021 because the simulation model were based on 2021 information in previous Chapter.

In this analysis in order to examine the impact of supplemental area plan SCO on coverage level of individual plan revenue protection (RP), we only include the counties who bought at least one acre of RP policy. The dependent variable thus in selection equation is dummy variable for RP+SCO policy. If the counties who bought RP policy also bought at least one acre of RP+SCO policy, the dummy variable equals one, and zero otherwise. We then calculate weighted RP coverage level within a county based on reported acres from RMA. The SOB data reports not only RP enrolled acres at different coverage level, but also the SCO companion/endorsed acres under different RP coverage level. To calculate the weighted RP coverage level, our weight is RP acres exclude any SCO companion/endorsed acres associated with the same RP coverage level. For example, Champaign County have enrolled 80,134 acres for corn with RP 80% in 2021. The SCO companion/endorsed acres with RP-80 are 23,161 acres. When calculating the average of RP coverage level, the RP acres of 80% coverage level would be 56,973 acres (80,134-23,161). The computed weighted average RP coverage level is the dependent variable in outcome equations.

---

[8] RMA SOB and ADM data were downloaded on May 12th, 2022.

Production risk is often related to crop insurance premiums and affects farmers' decision on whether to buy crop insurance or what coverage level to choose. In this paper we use reference rate for Yield Protection (YP) at 65% coverage level to capture the production risk across counties. Reference rate estimates the unloaded base rate at the county average yield and is a component used in calculating the base rate[9]. Higher reference rate indicates higher production risk for a county and is expected to induce farmers to buy supplemental area plans in addition to individual policy.

The performance of the crop insurance program is often judged by loss ratios, which equal insurance indemnity payments divided by total premium. A loss ratio of one means the indemnity payments are equal to premiums collected, and a loss ratio of more than one means the payments were more than premiums paid by farmers. In this paper we computed average loss ratio over all the COMBO policies (RP, YP, RPHPE) and COMBO with supplemental area plans combinations (RP+SCO, RP+ECO, YP+SCO, YP+ECO, RPHPE+SCO, RPHPE+ECO). Lagged loss ratio were used in estimation, assuming farmers take account of average loss ratio in previous year when making decision about purchasing crop insurance program.

The eligibility of buying SCO for farmers is choosing PLC in commodity programs. Therefore, in the selection equation we include proportion of PLC enrolled base acres as one of determinants. The proportion PLC acres is PLC enrolled base acres divided by sum of PLC and ARC base acres for corn and soybeans in each county from 2019 to 2021. Summary statistics of variables used in estimations are presented in table 3.1.

There are 3,489 observations for corn and 2,710 observations for soybeans from 2019 to 2021. The mean of weighted RP coverage level is 76% for both corn and soybeans. Counties with corn production have an average reference rate of 0.061 and lagged loss ratio of 0.685 which are higher than averages of 0.037 and

---

[9] Base rate is the rate associated with the risk of insuring the basic policy for a given crop, type and practice, and in a given location, for a given coverage level.

0.616 in counties with soybean production. Counties in corn producing regions also have lower under-compensated basis risk of 0.249 but higher over-compensated basis risk of 0.184 than counties in soybeans producing regions.

Table 3.2. presents the differences in the characteristics of counties at least bought one acre of RP+SCO and counties did not buy any RP+SCO in corn and soybean regions. The last column is the sample mean difference tested by t-statistics. It can be observed from the table that 33% of counties purchased RP+SCO in corn areas and 39% of counties purchased RP+SCO in soybeans areas. The sample mean difference indicates there are significant difference in explanatory variables between counties who bought RP+SCO and counties who didn't buy RP+SCO. For both corn and soybeans, the weighted average RP coverage level of counties purchased supplemental area plan was 4% higher than that of counties who did not purchase the product. The average loss ratio of counties with RP+SCO is lower than the average loss ratio of counties without RP+SCO. Counties bought RP+SCO also shows significant lower average under-compensated likelihood and higher average likelihood of over-compensation than those who did not buy the product.

Although the comparisons discussed above pointed out significant differences between counties with RP+SCO and counties without RP+SCO in terms of weighted RP coverage level, the difference calculated in table 3.2. are average difference from 2019 to 2021. It is not enough to explain the enrollment decision across farmers because the calculations did not account for other characteristics of farmers including both observed and unobserved.

The main disadvantage of our public crop insurance data in this analysis is we only have access to county-level information which means all the variables were aggregated to county level by RMA and FSA. Therefore, it is aware that our results may not fully exhibit the same pattern as in producer level.

Data Issues

The major challenge of accessing the impact of crop insurance is the non-randomized design of the program. Since crop insurance program is not mandatory, farmers voluntarily participate in the program which often results in selection bias in impact studies. In addition, SCO is limited to acres enrolled in PLC program which causes another selection bias in the causal inference.

To address the issue of selection bias under nonrandomized setting, one method has been used is the propensity score matching (PSM) method. PSM allows researchers to construct a counterfactual group by matching buyers and non-buyers of similar characteristics. The matching technique is based on observed characteristics assuming these observed variables are the main factors contributed to selection bias. (Adela et al. 2018) However, there may be an unobserved variable affects the selection and outcome simultaneously (Ravallion 2007). For example, farm managers with better management skills would be more likely to buy crop insurance plans to diversify their risk management portfolio. If the researchers do not have complete information on the management skills of a farm business, it would not give an accurate estimation about how enrollment in new crop insurance affects individual level coverage choices for farmer.

Several econometrics models have been developed to solve the problem with unobserved factors (private information) such as Heckman selection model and switching regressions. These models assess the impact based on different regimes in the variables. Heckman (1979) selection model include one selection equation, one outcome equation, and one equation examining the impact on the outcome of interests. One equation linking the covariates to outcome of interests is the main drawback of Heckman's model which mean sit does not provide estimates of unobserved counterfactual outcomes. The endogenous switching regression, allowing generality in specifying regression coefficients across alternatives, was therefore developed. (Lee 1982; Maddala 1983; Kai and Prabhala 2007) In the next section, we introduce the endogenous switching regression, and model the enrollment of SCO based on expected utility of purchasing the policy.

Switching Regression Model of Crop Insurance Enrollment

Let the decision to enroll in crop insurance programs be a binary choice resulting from the maximization of utility function. Farmers choose whether to enroll in revenue protection with supplemental coverage option (RP+SCO) by comparing the expected utility of buying the products to not buying the products. Variable Z represents a set of exogenous variables that determine expected utility and affects the enrollment decision. In this study variable Z include reference rate of crop insurance ratings, loss ratio, acres enrolled in Price Loss Coverage (PLC) program, and basis risk for RP-80+SCO+ECO-90 policy.

Assume the expected utility of buying SCO is I_E^* and the expected utility of not buying SCO is I_N^*. The enrollment of SCO occurs if $I_E^* > I_N^*$. However, I^* is the latent variable which cannot be observed by researchers but can be expressed as a function of observed factors, Z. The selection equation which is the enrollment of SCO can then be modeled as follow,

$$
\begin{gathered}
I_j = \gamma' Z_j + u_j \\
I_j = \begin{cases} 1, & I_{jE}^* > I_{jN}^* \\ 0, & I_{jE}^* \leq I_{jN}^* \end{cases}
\end{gathered}
\tag{3.1}
$$

where I_j is the dichotomous choice variable for farmer j which can be observed. I_j equals 1 for farmers who buy SCO and 0 otherwise. γ is a vector of parameters indicating the direction impacts of variable Z on the decision to buy SCO. u_j with mean zero and variance σ_u^2 is an error term captures the measurement errors and factors unobserved to researchers but known to the farmer. A farmer buys SCO only if the perceived expected utility of enrollment is higher.

Buying a new crop insurance option often affects other decisions, such as usage of fertilizer or crop insurance coverage level. In this study we mainly test whether there is buydown behaviors when SCO is introduced. That is to say, we are interested in examining the relationship between buying SCO and farmers decision on coverage level of revenue protection (RP) policy. Let Y represent outcome variable of interest which is weighted average RP coverage level in our paper. Variable X is a vector of exogenous variables determine the outcome variable. In the switching regression model, two regimes (outcome equations) for farmers who buy SCO and farmers who don't buy SCO can be written as follow,

$$\text{Regime 1 (SCO buyers)}: Y_{jE} = X'\beta_{jE} + \varepsilon_{jE} \text{ if } I = 1 \qquad (3.2a)$$

$$\text{Regime 2 (non} - \text{SCO buyers)}: Y_{jN} = X'\beta_{jN} + \varepsilon_{jN} \text{ if } I = 0 \qquad (3.2b)$$

where Y_{jE} denotes as weighted average RP coverage level when farmers buy supplemental area plan and Y_{jN} indicates weighted average RP coverage level without buying supplemental area plan. It is noted that the variable X in equation (3.2) may overlap the variable Z in equation (3.1). However, it is important that at least one variable in Z does not include in X for proper identification.

Since the choice of crop insurance is endogenous and unobserved by researchers, β_{jE} and βj_N would suffer from selection bias if unobservable factors affect both error terms in selection equation (u_j) and the outcome equations (ε_{jE} and ε_{jN}). In other words, the error terms in outcome equations are conditional on the sample selection criteria and thus the error terms in equation (3.2) result in nonzero expected value.

Lee (1982)'s approach accounts for sample selection on unobserved factors by treating the selectivity as an omitted variables problem. The three errors terms (u, ε_E, and ε_N) are assumed to have a joint normal distribution with mean vector zero and the following variance-covariance matrix,

$$cov(u, \varepsilon_E, \varepsilon_N) = \begin{bmatrix} \sigma_u^2 & \sigma_{Eu} & \sigma_{Nu} \\ \sigma_{Eu} & \sigma_E^2 & \sigma_{EN} \\ \sigma_{Nu} & \sigma_{EN} & \sigma_N^2 \end{bmatrix} \qquad (3.3)$$

where $var(u) = \sigma_u^2$, $var(\varepsilon_E) = \sigma_E^2$, $var(\varepsilon_N) = \sigma_N^2$, $var(u, \varepsilon_E) = \sigma_{Eu}$, $u, var(u, \varepsilon_N) = \sigma_{Nu}$, and $var(\varepsilon_E, \varepsilon_N) = \sigma_{EN}$. The expected values of the truncated error terms ($\varepsilon_e | I = 1$) and ($\varepsilon_n | I = 0$) are given as follow,

$$E(\varepsilon_E|I=1) = E(\varepsilon_E|u > -Z'\gamma) = \sigma_{Eu}\frac{\varphi\left(\frac{Z'\gamma}{\sigma}\right)}{\Phi\left(\frac{Z'\gamma}{\sigma}\right)} \equiv \sigma_{Eu}\lambda_E \qquad (3.4)$$

and

$$E(\varepsilon_N|I=0) = E(\varepsilon_N|u \leq -Z'\gamma) = \sigma_{Nu}\frac{-\varphi\left(\frac{Z'\gamma}{\sigma}\right)}{1-\Phi\left(\frac{Z'\gamma}{\sigma}\right)} \equiv \sigma_{Nu}\lambda_N \qquad (3.5)$$

where φ and Φ are the probability density and cumulative distribution function of the standard normal distribution, respectively. The ratio of φ and Φ evaluated at $Z'\gamma$ is referred to as the inverse Mills ratio, λ_E and λ_N in equation (3.4) and (3.5), and can be treated as omitted terms in equation (3.2). Therefore, in order to account for selection bias, we add them back to equation (3.2).

The procedure to estimate the model involves in two stages. The first stage is to determine the probability of buying SCO by a probit regression and provides the estimates of γ. The estimates of γ are then used to estimate λ_E and λ_N by plugging back into equation (3.4) and (3.5). In the second stage, we add the variables obtained from first stage to the equation (3.2a) and (3.2b). This two-step approach, however, is pointed out to be inefficient due to the fact that the generated residuals are heteroskedastistics and inconsistent; thus is in need of cumbersome adjustments. (Lokshin and Sajaia 2004; Abdulai and Huffman 2014; Adela et al. 2018) Lokshin and Sajaia (2004) suggested to use the Full Information Maximum Likelihood (FIML) method to overcome the standard errors issue by using simultaneous equations, which means they estimated the selection equation and outcome equation simultaneously. In this paper we follow (Lokshin and Sajaia 2004), employing the FIML method for our selection and outcome estimations.

The main interest of our analysis is the effect of supplemental area plans on weighted average RP coverage level. To examine the specified interest, we add the estimated error terms from equation (3.4) and (3.5) into the expected value of outcome equations. Thus, for a farmer who buys SCO with characteristics X and Z, the expected value of weighted average RP coverage level, Y_{jE}, is given as,

$$E(Y_{jE}|I=1) = X\beta_{jE} - \sigma_{Eu}\lambda_E \tag{3.6}$$

The last term in equation (3.6) has allowed for sample selection, meaning farmers who buy supplemental area plans may behave differently from an average farmer with identical characteristics (X, Z) due to unobserved factors. (Maddala 1983; Fuglie and Bosch 1995; Abdulai and Huffman 2014) The expected value for the same farmer if he/she had not bought SCO is,

$$E(Y_{jN}|I=0) = X\beta_{jN} - \sigma_{Nu}\lambda_E \tag{3.7}$$

The difference in equation (3.6) and (3.7) can be referred to as the change in weighted average RP coverage level between buyers and non-buyers due to enrollment of SCO. The unbiased estimates of Average Treatment effect on the Treated can then be obtained as follow(Lokshin and Sajaia 2004),

$$ATT = E(Y_{jE}|I=1) - E(Y_{jN}|I=0) = (\beta_{jE} - \beta_{jN}) + (\sigma_{Eu} - \sigma_{Nu})\lambda_E \tag{3.8}$$

ATT in Equation (3.8) shows the difference between the expected value of weighted average RP coverage level for SCO buyers and if they had not bought. In this study we estimate the models at county level with year fixed effect.

Empirical Results

Basis Risk Not Include in Outcome Equations

The results of endogenous switching regression for corn and soybeans are presented in table 3.3. and 3.4., respectively. Column (1), (2), and (3) report results from selection equation while column (4) and (5) report the results from outcome equation. As we mentioned in previous section, the proper identification requires at least one variable in selection model does not include in outcome equations.

Variables in selection equation, representing determinants of RP-SCO enrollment, include reference rate, lagged loss ratio, RP-80+SCO+ECO-90 false negative probability (FNP), RP-80+SCO+ECO-90 false positive probability (FPP), and the proportion acres of Price Loss Coverage Program (PLC). For the variables in outcome equations, we do not include basis risk (FNP, FPP) and PLC acres because PLC are the eligibility for farmers to enroll in SCO, but does not tie to how farmers choose their coverage level. Since SCO is a rather new crop insurance option, it is assumed that farmers tend to make the decision about whether to buy SCO and how much coverage level of individual plans separately. Farmers may just buy SCO to add on top of their individual plans without considering overall basis risk.

Marginal effects in column (2) indicate the change in the probability of RP-SCO enrollment given a one standard deviation change in the explanatory variable. These are average marginal effects obtained by calculating average over the marginal effect of each variable for all observations in Z. Since all the measurement unit of our variables are in percentage, we multiply the marginal effect by one standard deviation based on summary statistics in previous section. The coefficient of marginal probability will then become the probability of RP-SCO enrollment given one-standard deviation change in the explanatory variable. Here we will discuss the results of corn and soybeans in table 3.3. and 3.4. together.

The coefficients of the reference rate which captures the crop yield risk in each county are significantly positive, suggesting counties with higher reference rate (higher yield risk) are more likely to buy supplemental area plan. Increasing one standard deviation of reference rate will increase probability of corn counties buying RP-SCO by 3.4%, and 5.1% for soybeans counties. Loss ratio of average COMBO policy with supplemental area plans in previous year shows negative sign on likelihood of enrollment; however, the coefficients are not significantly different from zero. Since farmers are eligible to buy SCO only when he/she chose PLC not ARC program, the positive impacts on likelihood of enrolling in RP-SCO are therefore reasonable and as what we expected. However, the proportion acres enrolled in PLC program only shows significance under corn specification. This may be due to the fact that the majority counties in soybeans producing states did not choose PLC programs from 2019 to 2021. (Paulson et al. 2020; Schnitkey, Swanson, et al. 2020)

The under-compensation probability when buying RP-80+SCO+ECO-90 policy, the false negative probability (FNP) of RP-80+SCO+ECO-90, suggests significantly negative effect on likelihood of buying

RP-SCO. When probability of under-compensation raises one standard deviation, probability of RP-SCO enrollment for corn tends to decrease 4.1%, and probability of RP-SCO enrollment for soybeans tends to decrease 4.2%. On the contrary to under-compensation cases, over-compensation probability of RP-80+SCO+ECO-90 policy significantly increases the likelihood of buying RP-SCO. Counties with higher chances of being over-compensated are more likely to buy RP-SCO. The likelihood of buying revenue protection with supplemental area plan increases 6.7% for corn and 8.7% for soybeans when basis risk of receiving more indemnity than what is needed at farm-level raises by one standard deviation.

The results regarding the impact of buying RP-SCO on weighted RP-coverage level are presented in fourth and fifth columns of table 3.3. and 3.4., for counties enrolled in RP-SCO and counties not enrolled in RP-SCO, respectively. As pointed out in previous section, the proper identification requires there is at least one variable in the selection model but not in the outcome equations. In table 3.3. and 3.4., variables such as basis risk and PLC enrolled acres are not included in the outcome specification.

The negative and significant coefficients of reference rate in column (4) and (5) in table 3.3. and 3.4. indicate that for counties buying RP-SCO and not buying RP-SCO in corn and soybeans major producing regions, areas with higher yield risk result in significantly lower weighted RP coverage level than areas with lower yield risk. For corn counties not enrolled in RP-SCO, previous-year average loss ratio significantly increase weighted RP coverage level at 5% significance level. However, it does not significantly influence weighted RP coverage level for corn counties with RP-SCO and other soybeans counties. This finding is consistent with Glauber (2004)'s argument that historical loss ratio may provide little information about future loss expectation because of rating adjustments in crop insurance program, the growth in participation, and shift to higher coverage levels.

The estimates for the average treatments effects (ATT) under specifications in table 3.3. and 3.4. are reported in table 3.5. The results of ATT show the impact of RP-SCO enrollment on weighted RP coverage level. Different from the descriptive summary mean difference in table 3.2., the ATT estimates account for selection bias based on the fact that counties who buy RP-SCO and counties who don't buy RP-SCO may be systematically different. (Abdulai and Huffman 2014) The results in table 3.5. suggest there is no buydown behavior for corn and soybeans counties from 2019 to 2021. For counties in major corn producing regions with RP-SCO, the expected weighted RP coverage level will increase approximately 5% after enrolling in RP-SCO. For counties in major soybeans producing areas, weighted RP coverage level increases about 6.7% after RP-SCO enrollment. These findings are contradict to the simulation results from (Bulut and J. Collins 2014).

Basis Risk Include in Outcome Equations

Since basis risk indicates the likelihood of famers' losses being covered sufficiently or not, farmers may change their decisions on individual plans while considering overall risk management. The choices about how much coverage level under revenue protection becomes the decision of overall coverage level. In this subsection, we therefore include basis risk in the outcome equations, assuming farmers accounts for their basis risk while deciding whether to buy RP-SCO; at the same time, choose their revenue protection coverage level. The reports of these specifications are presented in table 3.6 and 3.7.

From column (1), (2), and (3) in table 3.6. and 3.7., we find similar direction of the coefficients in selection equation compared to table 3.3. and 3.4. Compared to table 3.3. and 3.4., the average loss ratio in previous year becomes significantly negative impact on whether farmers in a county will buy RP-SCO. Higher loss ratio in previous years reduces the probability for farmers to buy RP-SCO. Increase in one standard deviation of loss ratio, counties in corn producing regions reduce 1.8% probability of buying RP-SCO, and counties in soybeans regions reduce 1.6% probability. The probability of corn farmers choosing RP-SCO decreases 8% and increases 8.7% when under-compensated likelihood and over-compensated likelihood increase by one standard deviation, respectively. For soybeans counties, the probability of buying RP-SCO decreases 2.6% and increases 5.7% when likelihood of under-compensation and over-compensation raises by one standard deviation.

The impact of buying RP-SCO on weighted RP coverage level after incorporating basis risk into outcome equations are presented in column (4) and (5) in table 3.6. and 3.7. For corn and soybeans counties with and without RP-SCO, higher reference rate (higher production risk) areas reduces the weighted RP coverage level. We also notice previous loss ratio do not have significant impact on how much coverage level farmers would choose. This is similar to what we find in previous subsection.

For basis risk, we find both under-compensated and over-compensated basis risk provide significant impacts on coverage level of revenue protection. No matter whether counties have RP-SCO enrollment, false negative probability of RP-80+SCO+ECO-90, under-compensated likelihood, decreases the weighted coverage level farmers would choose. On the other hand, false positive probability of RP-80+SCO+ECO-90, over-compensated likelihood, increases farmers coverage level choices on revenue protection. These findings are consistent with our findings in previous chapter that adding higher coverage level with supplemental area plans results in lower under-compensation basis risk while higher over-compensation likelihood. The results in table 3.6. and 3.7. suggest farmers tend to choose the coverage level which allows them to reduce under-compensation probability and increase over-compensation probability.

Table 3.8. shows the estimates of the average treatment effects after including basis risk in the decision of coverage level. It is found that counties with corn major producing states reduce their coverage level of revenue protection by 3.7% after considering basis risk when making their decisions on coverage choices. There is buydown behaviors for corn farmers after enrollment of RP-SCO. However, we still do not find buydown effect for soybeans counties. For counties who enrolled in RP-SCO, the expected value of weighted RP coverage level drops from 77% to 74% if they decide not to enroll in RP-SCO.

Conclusion and Implications

While the new supplemental area plans are designed to provide more coverage levels for farmers, the subsidy rate which allows farmers to pay less than the similar coverage level of individual plan may incentivize farmers to lower their individual plan coverage and cover the overlapped band of coverage by supplemental area plans. Potential issues related to buy down effect include whether lowering coverage levels with SCO provides enough risk reduction compared to individual plan, and increased costs to taxpayers to deliver inferior insurance coverage to farmers based on marginal subsidy rate differences.

In this analysis we apply endogenous switching regression with the Full Information Maximum Likelihood (FIML) method to test whether there is crowd out effect on individual RP policy empirically using USDA RMA and FSA public data. In contrast to existing literatures using simulation analysis, we do not find compelling evidence of buy-down behavior among farmers using SCO with individual coverage relative to those who insure with an individual plan only.

We find higher production risk, captured by insurance reference rate for the county, increases the likelihood of purchasing SCO and lowers average individual coverage levels. The “false-negative” measure of basis risk is associated with a lower likelihood of SCO enrollment and reduced average coverage levels for RP in the county. The “false-positive” measure of basis risk, on the other hand, increases the likelihood of SCO adoption and is associated with higher average coverage levels for RP in a county.

For corn, a crowd out effect is observed when the basis risk measures are included as one of determinants for crop insurance and coverage level simultaneously. The buy down RP coverage level is around 4% after adding SCO on top of RP policy. For soybeans, counties with RP+SCO tend to have average RP coverage levels that are 3% to 6% higher than those for acres covered by RP alone.

The lack of empirical evidence for buy-down, despite the predictions from simulation-based analysis, could be due to the fact that farmers just want to buy higher coverage level of crop insurance. Since most SCO is used in the regions where individual coverage is already high (RP with 80% or RP with 85%), SCO relaxes the coverage constraints for farmers who prefer even higher coverage level. Subsidized premium rates of SCO also allows these farmers to buy SCO in addition to their individual plans without adjusting individual coverage levels. Another reason why we didn’t observe empirical buy-down behavior may be explained by a number of limiting factors associated with our approach. We are limited to data aggregated at the county-level, meaning the results may not fully exhibit the real patterns of producer’s behaviors in every county.

Since our data is an average effect across states of corn and soybeans production, examining the buy-down effect among different regions would be interesting for future research. Data on farm-level insurance decisions may be also useful in the extension of this paper to evaluate farmers' behaviors when choosing combinations of individual plans with supplemental area plans. Our data is observational and thus lacks true counterfactual observations of insurance choices. While the switching regression method attempts to estimate the treatment effect of SCO enrollment on individual insurance coverage choice, restrictive assumptions are needed to interpret our estimates in this way.

Tables and Figure

Figure 3.1. Difference in Weighted RP Coverage Level under RP vs. RP+SCO from 2019 to 2021

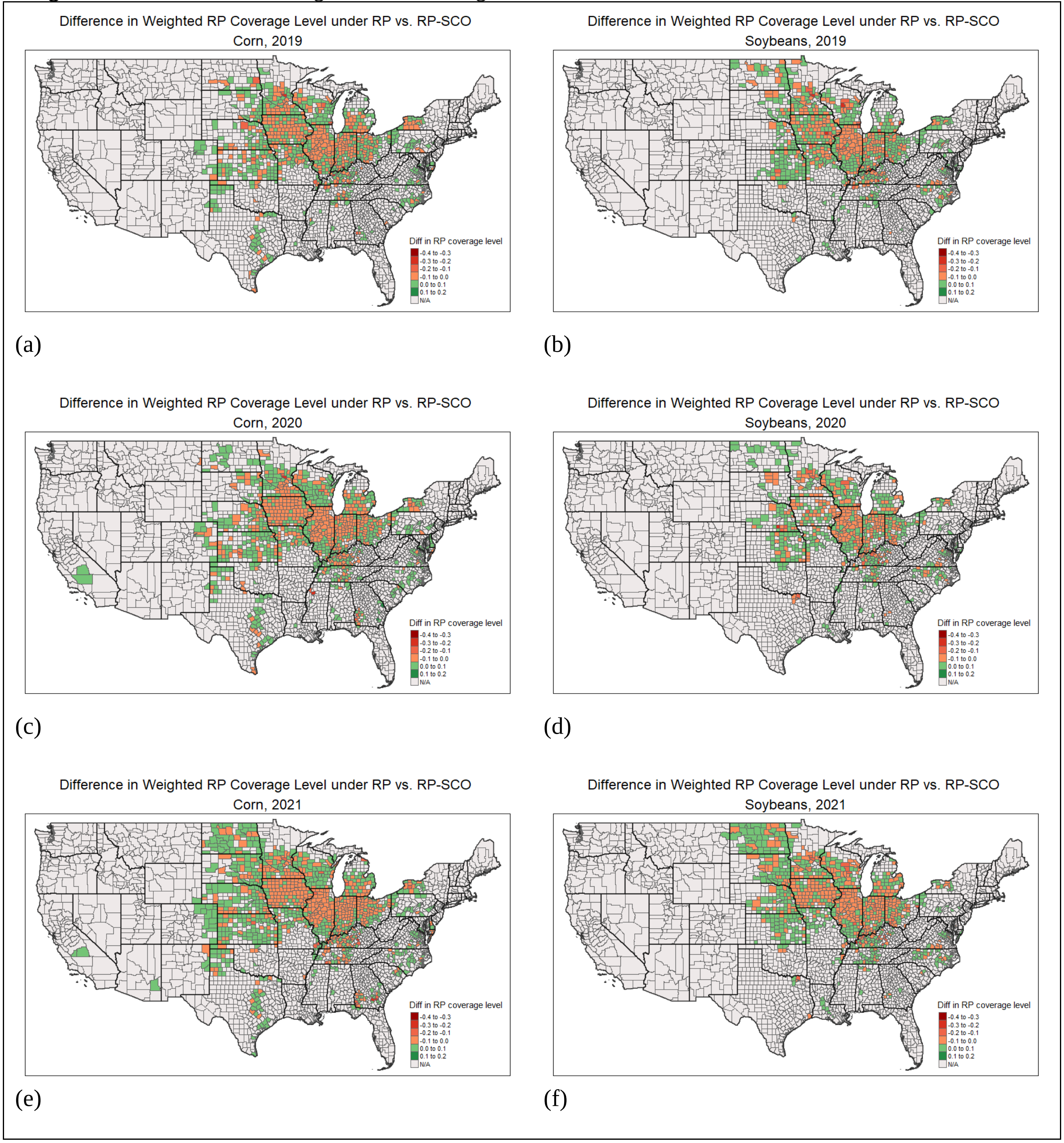


Table 3.1. Summary Statistics of variables used in estimations

Corn			
	Observations	**Mean**	**Standard Deviation**
Dependent Variables			
RP+SCO dummy (1=buy SCO)	3,489	0.758	0.428
Weighted RP coverage level	3,489	0.758	0.044
Explanatory Variables			
Reference rate	3,489	0.074	0.068
Loss ratio t-1	3,489	0.729	0.973
PLC enrolled acres proportion	3,489	0.669	0.278
RP-80+SCO+ECO-90 FNP	3,489	0.266	0.090
RP-80+SCO+ECO-90 FPP	3,489	0.178	0.032

Soybeans			
	Observations	**Mean**	**Standard Deviation**
Dependent Variables			
RP+SCO dummy (1=buy SCO)	2,710	0.719	0.449
Weighted RP coverage level	2,710	0.759	0.050
Explanatory Variables			
Reference rate	2,710	0.049	0.046
Loss ratio t-1	2,710	0.683	0.732
PLC enrolled acres proportion	2,710	0.182	0.189
RP-80+SCO+ECO-90 FNP	2,710	0.413	0.078
RP-80+SCO+ECO-90 FPP	2,710	0.126	0.028

Table 3.2. Descriptive Summary of Variables for Non-SCO buyers vs. SCO buyers

Corn			
	Non-SCO buyers	**SCO buyers**	**Difference**
Number of Observations	864	2,625	
Dependent Variable			
Weighted RP coverage level	0.727	0.768	-0.040***
Explanatory Variables			
Reference rate	0.115	0.061	0.054***
Loss ratio t-1	0.791	0.685	0.106***
PLC enrolled acres proportion	0.632	0.683	-0.050***
RP-80+SCO+ECO-90 FNP	0.322	0.249	0.073***
RP-80+SCO+ECO-90 FPP	0.156	0.184	-0.029***

Soybeans			
	Non-SCO buyers	**SCO buyers**	**Difference**
Number of Observations	767	1,943	
Dependent Variable			
Weighted RP coverage level	0.730	0.770	-0.040***
Explanatory Variables			
Reference rate	0.079	0.037	0.042***
Loss ratio t-1	0.843	0.616	0.227***
PLC enrolled acres proportion	0.226	0.167	0.059***
RP-80+SCO+ECO-90 FNP	0.387	0.314	0.073***
RP-80+SCO+ECO-90 FPP	0.111	0.132	-0.022***

*0.1 significance level, **0.5 significance level, ***0.01 significance level

Table 3.3. Endogenous Switching Regression Results for Corn SCO enrollment and Impact of RP+SCO enrollment on weighted RP coverage level

Corn	**Selection Equation**			**Outcome Equation**	
				Weighted RP coverage Level	
Variables	**Coefficients (1)**	**Marginal Probability (2)**	**Marginal Probability by one Standard Deviation (3)**	**Enrolled in RP+SCO (4)**	**Not Enrolled in RP+SCO (5)**
Constant	-0.393***			0.790***	0.723***
	(0.191)			(0.009)	(0.003)
Reference rate	1.761***	0.507***	0.034	-0.370***	-0.134***
	(0.666)	(0.192)		(0.076)	(0.014)
Loss ratio t-1	-0.013	-0.004	-0.004	-0.002	0.003**
	(0.023)	(0.007)		(0.005)	(0.001)
RP-80+SCO+ECO-90 FNP	-1.493***	-0.461***	-0.041		
	(0.395)	(0.122)			
RP-80+SCO+ECO-90 FPP	6.797***	2.099***	0.067		
	(0.725)	(0.221)			
PLC enrolled acres proportion	0.162***	0.050***	0.014		
	(0.057)	(0.016)			
Year fixed effect	yes			yes	yes

*0.1 significance level, **0.5 significance level, ***0.01 significance level

Table 3.4. Endogenous Switching Regression Results for Soybeans SCO enrollment and Impact of RP+SCO enrollment on weighted RP coverage level

Soybeans	**Selection Equation**			**Outcome Equation**	
				Weighted RP coverage Level	
Variables	**Coefficients (1)**	**Marginal Probability (2)**	**Marginal Probability by one Standard Deviation (3)**	**Enrolled in RP+SCO (4)**	**Not Enrolled in RP+SCO (5)**
Constant	0.170*** (0.005)			0.767*** (0.010)	0.711*** (0.005)
Reference rate	2.766*** (0.935)	0.756*** (0.252)	0.051	-1.937*** (0.163)	-0.192*** (0.028)
Loss ratio t-1	-0.013 (0.023)	-0.010 (0.010)	-0.010	-0.005 (0.008)	-0.002 (0.002)
RP-80+SCO+ECO-90 FNP	-1.982*** (0.067)	-0.541*** (0.181)	-0.042		
RP-80+SCO+ECO-90 FPP	11.423*** (1.778)	3.120*** (0.475)	0.087		
PLC enrolled acres proportion	-0.038 (0.038)	-0.006 (0.043)	-0.001		
Year fixed effect	yes			yes	yes

*0.1 significance level, **0.5 significance level, ***0.01 significance level

Table 3.5. Impact of buying RP+ SCO on weighted RP coverage level for Corn and Soybeans

	Mean Outcome		
Corn	**Enrolled in RP+SCO**	**Not Enrolled in RP+SCO**	**ATT**
Weighted RP coverage level	0.7651 (0.0148)	0.7138 (0.0105)	0.0513*** (0.0001)
Soybeans	**Enrolled in RP+SCO**	**Not Enrolled in RP+SCO**	**ATT**
Weighted RP coverage level	0.7657 (0.0107)	0.6980 (0.0143)	0.0677*** (0.0001)

*0.1 significance level, **0.5 significance level, ***0.01 significance level

Table 3.6. Endogenous Switching Regression Results for Corn SCO enrollment and Impact of RP+SCO enrollment on weighted RP coverage level

Corn	**Selection Equation**			**Outcome Equation**	
				Weighted RP coverage Level	
Variables	**Coefficients** (1)	**Marginal Probability** (2)	**Marginal Probability by one Standard Deviation** (3)	**Enrolled in RP+SCO** (4)	**Not Enrolled in RP+SCO** (5)
Constant	-0.488 (0.331)			0.786*** (0.011)	0.693*** (0.014)
Reference rate	0.349 (0.696)	0.092 (0.184)	0.006	-0.057* (0.032)	-0.102*** (0.030)
Loss ratio t-1	-0.074*** (0.027)	-0.019*** (0.007)	-0.018	0.015 (0.001)	0.001 (0.001)
RP-80+SCO+ECO-90 FNP	-3.358*** (0.650)	-0.886*** (0.172)	-0.080	-0.217*** (0.023)	-0.059* (0.033)
RP-80+SCO+ECO-90 FPP	10.367*** (1.263)	2.734*** (0.324)	0.087	0.172*** (0.044)	0.598*** (0.062)
PLC enrolled acres proportion	0.238*** (0.082)	0.063*** (0.022)	0.018		
Year fixed effect	yes			yes	yes

*0.1 significance level, **0.5 significance level, ***0.01 significance level

Table 3.7. Endogenous Switching Regression Results for Soybeans SCO enrollment and Impact of RP+SCO enrollment on weighted RP coverage level

Soybeans	**Selection Equation**			**Outcome Equation**	
				Weighted RP coverage Level	
Variables	**Coefficients** (1)	**Marginal Probability** (2)	**Marginal Probability by one Standard Deviation** (3)	**Enrolled in RP+SCO** (4)	**Not Enrolled in RP+SCO** (5)
Constant	0.565 (0.472)			0.854*** (0.021)	0.701*** (0.017)
Reference rate	7.904*** (1.203)	2.176*** (0.316)	0.100	-0.162** (0.065)	-0.108*** (0.031)
Loss ratio t-1	-0.081* (0.042)	-0.022* (0.011)	-0.016	0.002 (0.002)	0.001 (0.002)
RP-80+SCO+ECO-90 FNP	-1.201 (0.788)	-0.331 (0.217)	-0.026	-0.197*** (0.035)	-0.070** (0.031)
RP-80+SCO+ECO-90 FPP	7.441*** (2.046)	2.048*** (0.561)	0.057	0.158* (0.088)	0.473*** (0.070)
PLC enrolled acres proportion	0.015 (0.179)	0.004 (0.049)	0.001		
Year fixed effect	yes			yes	yes

*0.1 significance level, **0.5 significance level, ***0.01 significance level

Table 3.8. Impact of buying RP+ SCO on weighted RP coverage level for Corn and Soybeans

	Mean Outcome		
Corn	**Enrolled in RP+SCO**	**Not Enrolled in RP+SCO**	**ATT**
Weighted RP coverage level	0.7678 (0.0213)	0.8054 (0.0184)	-0.0376*** (0.0002)
Soybeans	**Enrolled in RP+SCO**	**Not Enrolled in RP+SCO**	**ATT**
Weighted RP coverage level	0.7695 (0.0179)	0.7374 (0.0233)	0.0322 (0.0002)

*0.1 significance level, **0.5 significance level, ***0.01 significance level

REFERENCES

CHAPTER 1

Bellemare, M. F., Masaki, T., & Pepinsky, T. B. (2017). Lagged Explanatory Variables and the Estimation of Causal Effect. *The Journal of Politics*, *79*(3), 949–963. https://doi.org/10.1086/690946

Goodwin, B. K., Mishra, A. K., & Ortalo-Magné, F. N. (2003). What's Wrong with Our Models of Agricultural Land Values? *American Journal of Agricultural Economics*, *85*(3), 744–752.

Goodwin, B. K., Mishra, A., & Ortalo-Magné, F. (2011). *The Buck Stops Where? The Distribution of Agricultural Subsidies* (No. w16693). National Bureau of Economic Research. https://doi.org/10.3386/w16693

Hendricks, N. P., Janzen, J. P., & Dhuyvetter, K. C. (2012). Subsidy Incidence and Inertia in Farmland Rental Markets: Estimates from a Dynamic Panel. *Journal of Agricultural and Resource Economics*, *37*(3), 361–378.

Kirwan, B. E. (2009). The Incidence of U.S. Agricultural Subsidies on Farmland Rental Rates. *Journal of Political Economy*, *117*(1), 138–164. https://doi.org/10.1086/598688

Kirwan, B. E., & Roberts, M. J. (2016). Who Really Benefits from Agricultural Subsidies? Evidence from Field-level Data. *American Journal of Agricultural Economics*, *98*(4), 1095–1113. https://doi.org/10.1093/ajae/aaw022

Lattz, D. (2017). Landowner's Adjusted Net-Share Rent as a Percent of Crop Returns, a Historic Review. *Farmdoc Daily*, *(7):17*((7):17). http://farmdocdaily.illinois.edu/2017/01/landowner-adjusted-net-share-rent-historic-review.html

Lence, S. H., & Mishra, A. K. (2003). The Impacts of Different Farm Programs on Cash Rents. *American Journal of Agricultural Economics*, *85*(3), 753–761.

Patton, M., Kostov, P., McErlean, S., & Moss, J. (2008). Assessing the influence of direct payments on the rental value of agricultural land. *Food Policy*, *33*(5), 397–405. https://doi.org/10.1016/j.foodpol.2008.01.001

Roberts, M. J., Kirwan, B., & Hopkins, J. (2003). The Incidence of Government Program Payments on Agricultural Land Rents: The Challenges of Identification. *American Journal of Agricultural Economics*, *85*(3), 762–769. https://doi.org/10.1111/1467-8276.00481

Uchtmann, D. L. (2006). October 31 is "Notice" Deadline for Many Farm Leases • farmdoc. *Farmdoc*. https://farmdoc.illinois.edu/publications/october-31-is-notice-deadline-for-many-farm-leases

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed). MIT Press.

CHAPTER 2

Barnett, Barry J., J. Roy Black, Yingyao Hu, and Jerry R. Skees. 2005. “Is Area Yield Insurance Competitive with Farm Yield Insurance?” *Journal of Agricultural and Resource Economics* 30(2):285–301.

Belasco, Eric J., Joseph Cooper, and Vincent H. Smith. 2020. “The Development of a Weather-based Crop Disaster Program.” *American Journal of Agricultural Economics* 102(1):240–58. doi: 10.1093/ajae/aaz021.

Binswanger-Mkhize, Hans P. 2012. “Is There Too Much Hype about Index-Based Agricultural Insurance?” *Journal of Development Studies* 48(2):187–200. doi: 10.1080/00220388.2011.625411.

Chambers, Robert G. 1989. “Insurability and Moral Hazard in Agricultural Insurance Markets.” *American Journal of Agricultural Economics* 71(3):604–16. doi: 10.2307/1242016.

Clarke, Daniel J. 2016. “A Theory of Rational Demand for Index Insurance.” *American Economic Journal: Microeconomics* 8(1):283–306. doi: 10.1257/mic.20140103.

Elabed, Ghada, Marc F. Bellemare, Michael R. Carter, and Catherine Guirkinger. 2013. “Managing Basis Risk with Multiscale Index Insurance.” *Agricultural Economics* 44(4–5):419–31. doi: 10.1111/agec.12025.

Elabed, Ghada, and Michael R. Carter. 2015. “Compound-Risk Aversion, Ambiguity and the Willingness to Pay for Microinsurance.” *Journal of Economic Behavior & Organization* 118:150–66. doi: 10.1016/j.jebo.2015.03.002.

Giné, Xavier, Robert Townsend, and James Vickery. 2008. “Patterns of Rainfall Insurance Participation in Rural India.” *The World Bank Economic Review* 22(3):539–66. doi: 10.1093/wber/lhn015.

Glauber, J. W. 2013. “The Growth Of The Federal Crop Insurance Program, 1990-2011.” *American Journal of Agricultural Economics* 95(2):482–88. doi: 10.1093/ajae/aas091.

Halcrow, Harold G. 1949. “Actuarial Structures for Crop Insurance.” *Journal of Farm Economics* 31(3):418. doi: 10.2307/1232330.

Iman, Ronald L., and W. J. Conover. 1982. “A Distribution-Free Approach to Inducing Rank Correlation among Input Variables.” *Communications in Statistics - Simulation and Computation* 11(3):311–34. doi: 10.1080/03610918208812265.

Keller, James B., and Tina L. Saitone. 2022. “Basis Risk in the Pasture, Rangeland, and Forage Insurance Program: Evidence from California.” *American Journal of Agricultural Economics* ajae.12282. doi: 10.1111/ajae.12282.

Maples, Joshua G., B. Wade Brorsen, and Jon T. Biermacher. 2016. “THE RAINFALL INDEX ANNUAL FORAGE PILOT PROGRAM AS A RISK MANAGEMENT TOOL FOR COOL-SEASON FORAGE.” *Journal of Agricultural and Applied Economics* 48(1):29–51. doi: 10.1017/aae.2016.3.

Miranda, Mario J. 1991. “Area-Yield Crop Insurance Reconsidered.” *American Journal of Agricultural Economics* 73(2):233–42. doi: 10.2307/1242708.

Paulson, Nicholas D., Bruce A. Babcock, Nicholas D. Paulson, and Bruce A. Babcock. 2008. “Get a Grip: Should Area Revenue Coverage Be Offered Through the Farm Bill or as a Crop Insurance Program?” doi: 10.22004/AG.ECON.42458.

Schnitkey, Gary, Nick Paulson, Krista Swanson, and and Carl Zulauf. 2021. “RP, ECO, and SCO Tradeoffs.” *Farmdoc Daily* 11(29).

Schnitkey, Gary, Nick Paulson, Carl Zulauf, and and Krista Swanson. 2021. “Crop Insurance Coverage Levels and ECO Use on Corn.” *Farmdoc Daily* 11(71).

Smith, Vincent H., Hayley H. Chouinard, and Alan E. Baquet. 1994. “Almost Ideal Area Yield Crop Insurance Contracts.” *Agricultural and Resource Economics Review* 23(1):75–83. doi: 10.1017/S1068280500000435.

Tsay, Juo-Han, Nick Paulson, and and Gary Schnitkey. 2021. “Supplemental Area Insurance and Basis Risk Measures: Part I.” *Farmdoc Daily* 11(72).

Vedenov, Dmitry V., Mario J. Miranda, Robert Dismukes, and Joseph W. Glauber. 2004. “Economic Analysis of the Standard Reinsurance Agreement.” *Agricultural Finance Review* 64(2):119–34. doi: 10.1108/00214660480001158.

Yu, Jisang, Monte Vandeveer, Jerry D. Volesky, Keith Harmoney, Jisang Yu, Monte Vandeveer, Jerry D. Volesky, and Keith Harmoney. 2019. “Estimating the Basis Risk of Rainfall Index Insurance for Pasture, Rangeland, and Forage.” doi: 10.22004/AG.ECON.281319.

CHAPTER 3

Abdulai, A., and W. Huffman. 2014. “The Adoption and Impact of Soil and Water Conservation Technology: An Endogenous Switching Regression Application.” *Land Economics* 90(1):26–43. doi: 10.3368/le.90.1.26.

Adela, F. A., J. Aurbacher, F. A. Adela, and J. Aurbacher. 2018. “Access to Irrigation Water-Poverty Nexus: Application of an Endogenous Switching Regression in Ethiopia.” doi: 10.22004/AG.ECON.277521.

Buchanan, James M. 1975. “The Samaritan’s Dilemma.” *Phelps, ES (Ed.): Altruism, Morality and Economic Theory, New York (Russell Sage Foundation)* 71–85.

Bulut, Harun. 2018. “US Farmers’ Insurance Choices under Budget Heuristics.” *Agricultural Finance Review* 78(1):152–72. doi: 10.1108/AFR-02-2017-0009.

Bulut, Harun, and Keith J. Collins. 2014. "Designing Farm Supplemental Revenue Coverage Options on Top of Crop Insurance Coverage." *Agricultural Finance Review* 74(3):397–426. doi: 10.1108/AFR-08-2013-0032.

Cooper, Joseph, Ashley Hungerford, Erik O'Donoghue, Joseph Cooper, Ashley Hungerford, and Erik O'Donoghue. 2015. "Interactions of Shallow Loss Support and Traditional Federal Crop Insurance: Building a Framework for Assessing Commodity Support Issues for the Next Farm Act." doi: 10.22004/AG.ECON.205310.

DeLay, Nathan. 2019. "The Impact of Federal Crop Insurance on the Conservation Reserve Program." *Agricultural and Resource Economics Review* 48(02):297–327. doi: 10.1017/age.2019.9.

Deryugina, Tatyana, and Barrett Kirwan. 2018. "DOES THE SAMARITAN'S DILEMMA MATTER? EVIDENCE FROM U.S. AGRICULTURE: DOES THE SAMARITAN'S DILEMMA MATTER?" *Economic Inquiry* 56(2):983–1006. doi: 10.1111/ecin.12527.

Du, Xiaodong, Hongli Feng, and David A. Hennessy. 2016. "Rationality of Choices in Subsidized Crop Insurance Markets." *American Journal of Agricultural Economics* aaw035. doi: 10.1093/ajae/aaw035.

Feng, Hongli, David A. Hennessy, and Ruiqing Miao. 2013. "The Effects Of Government Payments On Cropland Acreage, Conservation Reserve Program Enrollment, And Grassland Conversion In The Dakotas." *American Journal of Agricultural Economics* 95(2):412–18. doi: 10.1093/ajae/aas112.

Fuglie, Keith O., and Darrell J. Bosch. 1995. "Economic and Environmental Implications of Soil Nitrogen Testing: A Switching-Regression Analysis." *American Journal of Agricultural Economics* 77(4):891–900. doi: 10.2307/1243812.

Glauber, J. W. 2013. "The Growth Of The Federal Crop Insurance Program, 1990-2011." *American Journal of Agricultural Economics* 95(2):482–88. doi: 10.1093/ajae/aas091.

Glauber, Joseph W. 2004. "Crop Insurance Reconsidered." *American Journal of Agricultural Economics* 86(5):1179–95. doi: 10.1111/j.0002-9092.2004.00663.x.

Heckman, James J. 1979. "Sample Selection Bias as a Specification Error." *Econometrica* 47(1):153. doi: 10.2307/1912352.

Kahneman, Daniel, and Amos Tversky. 2013. "Prospect Theory: An Analysis of Decision Under Risk." Pp. 99–127 in *World Scientific Handbook in Financial Economics Series*. Vol. 4. WORLD SCIENTIFIC.

Kai, Li, and Nagpurnanand R. Prabhala. 2007. "Self-Selection Models in Corporate Finance**We Thank N.K. Chidambaran, Craig Doidge, Espen Eckbo, Andrew Karolyi, Gordon Phillips, Vojislav Maksimovic, Jeffrey Smith, and Xinlei Zhao without Implicating Them for Any Errors or Omissions, Which Remain Ours. Li Acknowledges the Financial Support from the Social Sciences and Humanities Research Council of Canada, and the W.M. Young Chair in Finance from the Sauder School of Business at UBC. Li Also Wishes to Thank the Support and Hospitality of the MIT Sloan School of Management Where She Completed Most of Her Work on This Chapter." Pp. 37–86 in *Handbook of Empirical Corporate Finance*. Elsevier.

Kunreuther, Howard, and Erwann Michel-Kerjan. 2013. “Managing Catastrophic Risks Through Redesigned Insurance: Challenges and Opportunities.” Pp. 517–46 in *Handbook of Insurance,* edited by G. Dionne. New York, NY: Springer New York.

Lee, Lung-Fei. 1982. “Some Approaches to the Correction of Selectivity Bias.” *The Review of Economic Studies* 49(3):355. doi: 10.2307/2297361.

Lokshin, Michael, and Zurab Sajaia. 2004. “Maximum Likelihood Estimation of Endogenous Switching Regression Models.” *The Stata Journal: Promoting Communications on Statistics and Stata* 4(3):282–89. doi: 10.1177/1536867X0400400306.

Maddala, G. S. 1983. *Limited-Dependent and Qualitative Variables in Econometrics*. Cambridge: Cambridge University Press.

Miao, Ruiqing, Hongli Feng, David A. Hennessy, and Xiaodong Du. 2016. “Assessing Cost-Effectiveness of the Conservation Reserve Program (CRP) and Interactions between the CRP and Crop Insurance.” *Land Economics* 92(4):593–617. doi: 10.3368/le.92.4.593.

Miglietta, Pier Paolo, Donatella Porrini, Giulio Fusco, and Fabian Capitanio. 2020. “Crowding out Agricultural Insurance and the Subsidy System in Italy: Empirical Evidence of the Charity Hazard Phenomenon.” *Agricultural Finance Review* 81(2):237–49. doi: 10.1108/AFR-04-2020-0061.

Paulson, Nick, Gary Schnitkey, Jonathan Coppess, Krista Swanson, and and Carl Zulauf. 2020. “2019 ARC-CO Payments for Corn and Soybeans in the United States.” *Farmdoc Daily* 10(187).

Ramirez, Octavio A., J. Scott Shonkwiler, Octavio A. Ramirez, and J. Scott Shonkwiler. 2017. “A Probabilistic Model of Crop Insurance Purchase Decision.” doi: 10.22004/AG.ECON.252751.

Ravallion, Martin. 2007. “Chapter 59 Evaluating Anti-Poverty Programs.” Pp. 3787–3846 in *Handbook of Development Economics*. Vol. 4. Elsevier.

Schnitkey, Gary, Nick Paulson, Carl Zulauf, and and Krista Swanson. 2020. “Revenue Protection: The Most Used Crop Insurance Product.” *Farmdoc Daily* 10(198).

Schnitkey, Gary, Nick Paulson, Carl Zulauf, and and Krista Swanson. 2021. “Crop Insurance Coverage Levels and ECO Use on Corn.” *Farmdoc Daily* 11(71).

Schnitkey, Gary, Krista Swanson, Nick Paulson, Carl Zulauf, and and Jonathan Coppess. 2020. “What We Know About Income Outlook for Crop Farms Given COVID-19.” *Farmdoc Daily* 10(54).

Thaler, Richard H. 2008. “Mental Accounting and Consumer Choice.” *Marketing Science* 27(1):15–25. doi: 10.1287/mksc.1070.0330.

Wu, JunJie. 1999. “Crop Insurance, Acreage Decisions, and Nonpoint-Source Pollution.” *American Journal of Agricultural Economics* 81(2):305–20. doi: 10.2307/1244583.

Yehouenou, Lauriane, Barry J. Barnett, Ardian Harri, and Keith H. Coble. 2018. “STAX Appeal?” *Applied Economic Perspectives and Policy* 40(4):563–84. doi: 10.1093/aepp/ppx060.