ANALYSIS OF THE AVERAGE CROP REVENUE ELECTION PROGRAM, A REPRESENTATIVE FARM APPROACH

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by
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The undersigned, appointed by the Dean of the Graduate School, have examined the thesis entitled

ANALYZING THE AVERAGE CROP REVENUE ELECTION PROGRAM, A REPRESENTATIVE FARM APPROACH

Presented by Scott Gerlt

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And hereby certify that in their opinion it is worthy of acceptance.

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All credit for this work is due to God. This accomplishment is only possible by His will. Additionally, I would like to thank my wife, Claycie, for her support. She was a source of encouragement and strength in words and actions as I completed this thesis. I look forward to the next stage of our lives together. Finally, thank you to my family who has laughed with me in the good times and encouraged me in the bad.

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ABSTRACT

The Average Crop Revenue Election (ACRE) program was created in the Food, Conservation and Energy Act of 2008. The program is intended to help offset years of low market revenues for agricultural producers. However, those who enroll in ACRE must forego portions of traditional payments. This study was conducted to determine what types of farms are good candidates for the ACRE program and the sensitivity of those results to input parameters and program provisions.

These objectives were accomplished by creating four model farms representing typical, full-time operations. This resulted in representative farms in the following counties: McLean, Illinois; Sumner, Kansas; Hale, Texas; and Boliver, Mississippi. One thousand stochastic prices and yields were generated for each crop on each representative farm. Correlations were imposed on the variables to create the appropriate interactions between prices and yields.

The results of the Monte Carlo simulations show that cotton producers are unlikely to benefit from the ACRE program, as the payments foregone to enroll in this new program are very high. Additionally, states with lower price/yield correlation tend to receive ACRE payments more often. Furthermore, 2009 is shown to be the best year to enroll under the assumed price path. Altering the price path can change the ACRE enrollment decision as demonstrated in the analysis. Likewise, the optimal producer decision is shown to be sensitive to the base acres on each representative farm. Finally, the analysis reveals that ACRE benefits are dependent on the program's payment rate restrictions.

CHAPTER 1: INTRODUCTION

The Food, Conservation and Energy Act of 2008 (2008 Farm Bill) became public law on June 18, 2008 after Congress overrode President Bush's veto ("Food, Conservation, and Energy Act of 2008," 2008). Included in the 2008 Farm Bill was a new program titled the Average Crop Revenue Election (ACRE) program designed to combat revenue risk for agricultural producers. Supporters of some type of counter-cyclical revenue program included the National Corn Growers; American Farm Bureau Federation; American Farmland Trust; Senate Committee on Agriculture, Nutrition and Forestry; USDA; and House Committee on Agriculture (Coble & Barnett). However, the resulting ACRE program contained significant differences from many of the proposals.

The idea for a revenue based program is not new. Proposals can be traced back to at least 1983 and have routinely arisen since (Coble & Barnett). With the current set of high crop prices and forecasts predicting more of the same (FAPRI, 2009), traditional Loan Deficiency Payments (LDPs) and Counter-Cyclical Payments (CCPs) may never trigger payments to grain and oilseed producers during the life of the 2008 Farm Bill. ACRE spans the problem of potentially low federal payments due to high prices to create a way for farmers to continue to receive counter-cyclical subsidies. By having moving benchmarks and tying payments to recent prices and yields, ACRE can pay when current programs would not.

Additionally, traditional commodity programs have focused on price risk. Yield and revenue risk have been addressed by federally subsidized crop insurance. ACRE is a new direction for farm programs as producers can now receive subsidies based on revenue risk.

Even though ACRE is potentially beneficial, it is not free to farmers. Producers on each Farm Service Agency (FSA) farm must decide whether to enroll or remain in the traditional Direct and Counter-cyclical Program (DCP). Portions of traditional payments must be foregone to enroll in ACRE. As a result, timely analysis of the program is crucial for agricultural producers.

1.1 Objectives

This study focuses on determining the types of farms most likely to gain from ACRE. Payments will likely vary by state and crop. Some states will have yields that are more variable and less correlated to national price thereby inducing more payments. However, states with higher yields could receive larger payments. Furthermore, foregone payments under ACRE will vary depending on the amount and composition of base acres on the farm. This study will attempt to analyze these effects to see how they influence the optimal ACRE enrollment decision.

Additionally, this study will consider the importance of various provisions of the ACRE program. After the baseline results are achieved, input parameters and program components will be altered to determine if the optimal decision changes for different types of farms in different states. This should shed light on the significance of various components of the program and sensitivity of results to input parameters.

CHAPTER 2: AN OVERVIEW OF THE ACRE PROGRAM

ACRE is an optional program available to producers of the major field crops. To enroll, producers on a farm must first elect the ACRE option. This irrevocable step puts the farm in the program for the life of the farm bill (through 2012). If no decision is made, the farm stays in the traditional DCP. However, producers can elect into the program in any year of the farm bill. Following election, producers will have to make a decision annually whether to enroll in the current year's contract. If a farm is enrolled in ACRE, it must forego all CCPs, 20% of Direct Payments (DPs), and accept a 30% reduction in loan rates[1].

The decision to enroll is made on an FSA farm unit basis. The entire farm unit is either in or out. In other words, producers cannot selectively enroll crops. However, the decision is independent for each farm unit. A producer can selectively choose which of his or her farms he or she wants (or does not want) to enroll.

Two criteria must be met to trigger ACRE payments for a crop.

1) State revenue must be below the ACRE state revenue guarantee and
2) Farm revenue must be below the ACRE farm benchmark revenue.

[1] If a farm elects into ACRE and does not enroll in the current year's contract, it will not receive ACRE payments, CCPs, or DPs. The farm is eligible for LDPs, but it is not clear at this point if the loan rate will be reduced by 30%.

The ACRE state guarantee is calculated as the:

(1) (average of the national marketing year average price for the past two years)
× (five year Olympic average[2] yield per planted acre[3])
× .9

The ACRE farm benchmark revenue is calculated as the:

(2) (average of the national marketing year average price for the past two years)
× (five year Olympic average yield per planted acre on the farm)
+ (the crop insurance premium paid)

The state revenue is calculated as the:

(3) higher of:
(average of the national marketing year average price during the year) or
(70% of the loan rate)
× (average state yield per planted acre)

The farm revenue is calculated as the:

(4) higher of:
(average of the national marketing year average price during the year) and
(70% of the loan rate)
× (average farm yield per planted acre)

If both criteria are met, payments are triggered for the farm. Payments are calculated as:

(5) The lesser of:
(25% of the ACRE state revenue guarantee) or
((the ACRE state revenue guarantee) – (the state revenue))
× (five year Olympic average yield per planted acre on the farm)
÷ (five year Olympic average yield per planted acre in the state)
× (payment acres)

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[2] An Olympic average is an average excluding the minimum and maximum values. In this case, the high and low yields are dropped and the other three are averaged.

[3] Yield per planted acre is defined as total production divided by the sum of harvested and failed acres. It does not account for silage production. Thus acres devoted to silage production are not defined as planted acres for purposes of ACRE.

Payments for each crop are calculated separately. As a result, some crops may trigger payments while others do not. Payment acres are 83.3% of planted acres for 2009-2011, 85% in 2012. Total payment acres cannot exceed total base acres for the farm. If this should occur, producers will have to specify which crops should have payment acres reduced so that payment acres do not exceed base acres. Total ACRE and CCP payments per person or legal entity cannot exceed $65,000 plus the amount that DPs are reduced. Last of all, the state ACRE revenue guarantee is not allowed to change by more than 10% per year in 2010, 2011, and 2012.

Counter-cyclical payments for a crop *i* are calculated as:

(6) Max(0, Target price$_i$ – Direct payment rate$_i$ – Max(Loan rate$_i$, National marketing year average price$_i$))
× Base acres$_i$
× CCP yield$_i$
× (83.3% in 2009 through 2011, 85% in 2012)

Direct payments for a crop *i* are calculated as:

(7) DP yield$_i$
× DP rate$_i$
× Base acres$_i$
× (83.3% in 2009 through 2011, 85% in 2012)

Loan deficiency payments for a crop *i* are calculated as:

(8) Max(0, Loan rate$_i$ – (Posted county price$_i$ for wheat, feedgrains, and soybeans, Average world price for cotton and rice))
× Production$_i$

Base acres, DP yields, and CCP yields are determined by historical production on an FSA farm unit. They are unique to each farm and remain constant between years unless Congress legislates updates. Loan rates, DP rates, and CCP rates are set by the farm bill and are common to all farms. The Posted County Price (PCP) is posted daily by the FSA to reflect the county market price. The PCPs tend to average less than the marketing year average price. Cotton and rice use an Average World Price (AWP) to calculate loan benefits. Like the PCPs, the AWPs tend to average less than the marketing year average price.

Table 1: Commodity program parameters for 2009 through 2012

Crop	**Loan rate**	**Target price**	**DP rate**
Corn (per bushel)	$1.95	$2.63	$0.28
Soybeans (per bushel)	$5.00	$5.80 in 2009 $6.00 in 2010-2012	$0.44
Cotton (per pound)	$0.52	$0.7125	$0.0667
Rice (per pound)	$0.065	$0.1050	$0.0235
Wheat (per bushel)	$2.75	$3.92 in 2009 $4.17 in 2010-2012	$0.52
Sorghum (per bushel)	$1.95	$2.57 in 2009 $2.63 in 2010-2012	$0.35

Source: USDA FSA

Given the ACRE costs and benefits, several hypotheses can be conjectured. First, crops with expected prices above target prices minus direct payment rates may want to participate in ACRE. The reduction in loan rates and surrender of CCPs has no effect if neither payment is triggered. Conversely, crops with prices below loan rates may not want to participate. Enrollment in ACRE would come at a steep cost that may outweigh the benefits.

Second, land that is not actively involved in production agriculture should not be enrolled in ACRE. Idle land with base acres can still collect CCP and DPs. However, since ACRE is tied to production, there would be no benefits to offset the cost of enrollment.

Third, small production states with high yield variability should trigger ACRE payments more often than states with large production and small yield variability. Yields in large production states should be highly correlated with national prices. The result is a natural hedge that decreases the chances of those states receiving a payment. Furthermore, yield stability would result in relatively stable revenues which would also reduce ACRE payment frequency.

While these conjectures should follow from the ACRE structure, empirical analysis would be able to provide stronger statements about the first and third statement. The second is trivial. The rest of this study will focus on testing these assumptions.

CHAPTER 3: LITERATURE REVIEW

This literature review contains two parts. The first examines current literature regarding revenue programs. The relative infancy of the Average Crop Revenue Election program limits the quantity of analysis in the literature. The second is literature regarding yield distributions. Crop yield distribution modeling, which is of paramount importance in ACRE analysis, has received much attention in the crop insurance literature. This study will benefit from the parallel work.

2.1 Review of commodity revenue program analysis

Zulauf, Dicks, and Vitale (2008) reported analysis of ACRE based on Zulauf's work (2008). 26 states were considered over a period of 30 historical years for corn, soybeans, and wheat.

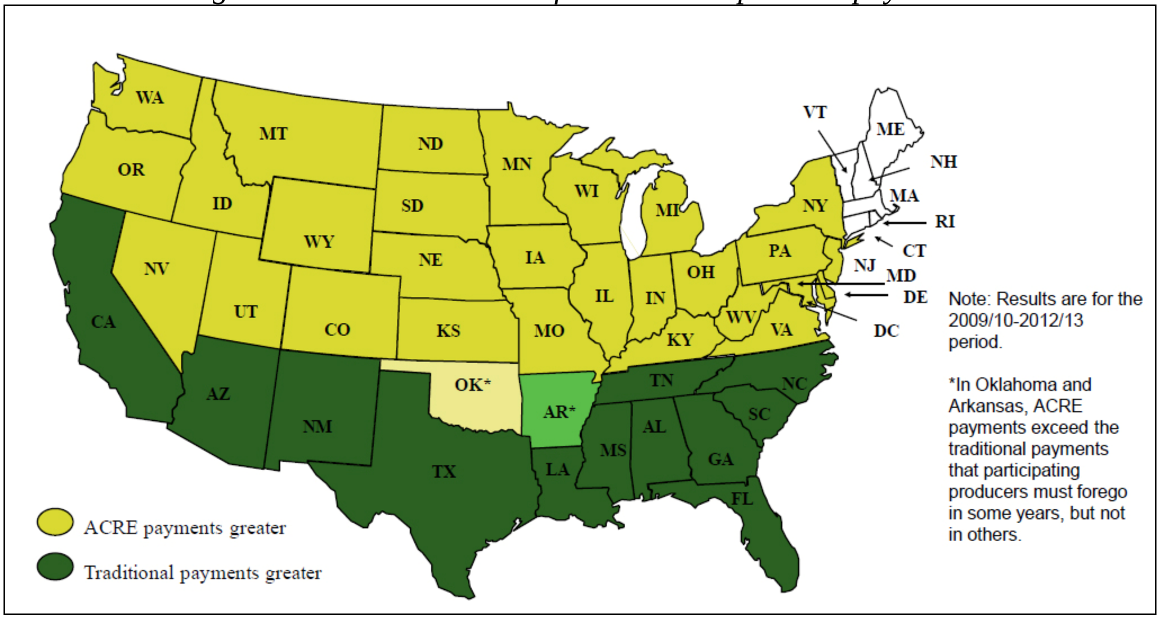
> The analysis uses (1) historic variability in county level yields adjusted to current levels of yield as a proxy for future yield variability and (2) the historic relationship between state yield and national price to predict the variability of future price at the U.S. Department of Agriculture average annual forecasted price for 2009-12 (Zulauf et al., 2008, p. 31).

The authors found that the state trigger would have been met in 5 to 15 of the historical years for each commodity/state combination. On average, payments occurred in slightly over one-third of the years for corn, soybeans, and wheat. The farm loss criterion is not very restrictive in the analysis as it prevents payments only 10 to 20% of the time when the state triggers payments. Zulauf notes that 75 to 80% of ACRE payments occurred in consecutive years (2008). This is partially due to the 10% limit on benchmark state revenue adjustments applying nearly 50% of the time in the analysis.

The authors' review of the analysis led them to conclude that ACRE becomes the better option as state yields and national prices become less correlated and as actual yields increase relative to program yields. Furthermore, the addition of the crop insurance premium to the farm benchmark revenue has minimal impact. They conclude that "ACRE addresses a risk associated with a market at or near equilibrium while traditional price programs address a risk associated with a market out of equilibrium" (Zulauf et al., 2008, p. 33).

Similarly, FAPRI (2009) analyzed ACRE by state for most of the U.S. The authors' analysis agrees with Zulauf that ACRE payments for each crop and year will likely be zero. The analysis, which uses the stochastic FAPRI baseline, projects that over the next ten years ACRE payments should exceed foregone payments for corn, soybeans, and wheat but not for upland cotton, rice, and peanuts. For Northern states, average expected ACRE payments exceed the payments producers must forego to participate in the program. For cotton and peanut producing Southern states, the reverse is true. This suggests ACRE is much more likely to be attractive to producers in the North than the South (Figure 1).

Figure 1: FAPRI estimates of net ACRE impacts on payments



Source: (FAPRI, 2009, p. 65)

Coble and Dismukes[4] (2008) studied several theoretical revenue programs. Their work encompasses multiple crops and regions. County, state, and national yield data were obtained from the National Agricultural Statistics Service (NASS) of the USDA for the years 1975 through 2004 and detrended. Each county in the study was assumed to be a representative farm. In order to overcome the problem of county yields having less variation than farm yields, the authors used crop insurance data to estimate the standard deviation of farm yields. Price paths were created by drawing from the distribution of historical annual percent changes in prices. Prices were based on the Marketing Year Average (MYA) prices for the years 1974-2005 and were adjusted for local basis. Five-hundred random draws for five years were made "simultaneously to maintain empirical correlations between prices and yields and between yields at different levels of aggregation" (Coble & Dismukes, 2008, p. 545).

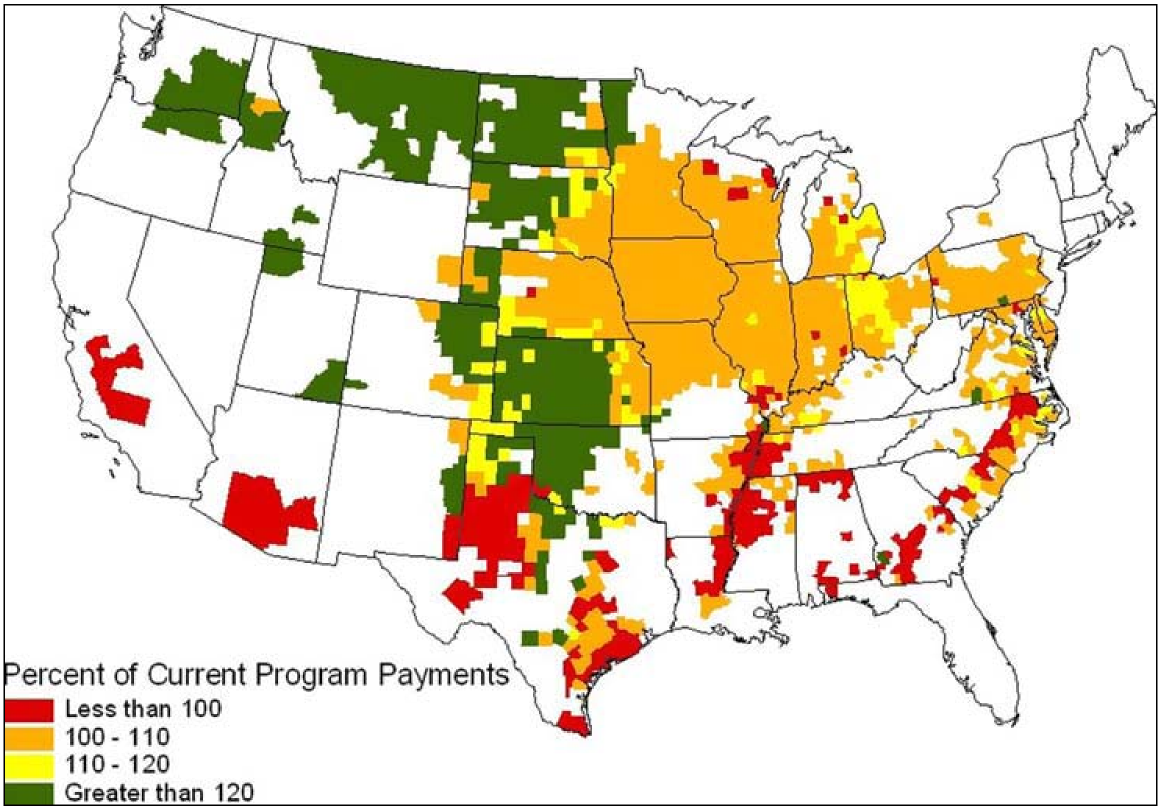
[4] (Coble & Barnett) conduct a very similar analysis. As a result, only this study will be discussed.

Four revenue scenarios were created from the data. The first was a baseline with 2002 Farm Bill programs. The other three replaced the CCP program with a revenue program with targets at the national, state, and county levels. Revenue targets were set at preplanting time using futures prices. Revenue insurance was included in each scenario and was wrapped around the revenue programs. To accomplish this, crop insurance indemnities were reduced by revenue program payments and premiums were reduced to reflect the change[5].

The results of Coble and Dismuke's analysis indicate that corn, soybeans, and wheat producers would benefit from the revenue program while cotton producers lose considerable payments. The revenue program reduced risk and insurance rates for all crops. Results for every crop were more favorable the smaller the level of aggregation. With the revenue trigger at the state level, the Southern U.S. would lose government payments relative to 2002 Farm Bill programs, the Plains states would gain, and the Corn Belt states would remain approximately unchanged (Figure 2).

[5] Crop insurance is not wrapped around the ACRE program.

Figure 2: Payments under alternative set of programs including state-level revenue counter-cyclical programs relative to current programs, corn, soybeans, wheat, and cotton



Source: (Coble & Dismukes, 2008, p. 550)

Vedenov and Power study the choice of yield versus revenue insurance under versions of the House and Senate's 2008 Farm Bill. The House proposed Revenue Counter-Cyclical Payments (RCCPs) were an optional, irrevocable choice that replaces CCPs and were supposed to be triggered by national revenue. The Senate Average Crop Revenue (ACR) proposal was essentially the same except that payments were triggered at the state level. Additionally, DPs were to be replaced with a slightly altered fixed payment.

The analysis was performed using copulas, a relatively new concept in the Agricultural economics literature. Copulas are functions that create a multivariate distribution from independent marginals. The authors argue that copulas impose less restrictive assumptions than other methods such as a multivariate normal distribution. Vedenov and Power elect to use a Gaussian copula and a nonparametric empirical kernel copula.

For the simulation, 20,000 random draws were made for prices and yields. Two representative farms were used for the analysis, one in Kossuth County, Iowa and the other in Jackson County, Texas. Crop Revenue Coverage (CRC) insurance was used as the revenue insurance and Multiple-Peril Crop Insurance (MPCI) was used as yield insurance. A Constant Relative Risk Aversion (CRRA) power utility function was used to calculate Certainty Equivalents (CE).

The results of the simulation indicate that RCCP "improve[s] the risk-reducing effectiveness of both APH and CRC contracts [on revenue]" (Vedenov & Power, 2008, p. 458). ACR, on the other hand, improves both insurance types in areas with low price/yield correlation (Texas), but decreases their effectiveness in areas of strong negative correlation (Iowa). The authors attribute this to the overlap of the government program with insurance policies in the presence of strong negative price/yield correlation.

2.2 Yield distributions

Yield distributions have received much attention in the Agricultural economics literature. The stochastic assumptions surrounding yields determine the rating of crop insurance policies. Even so, there is not a clear consensus on the correct distribution of yields. The following is a chronological discussion of the recent, relevant literature.

Nelson and Preckel (1989) propose a conditional beta distribution. They argue that a parametric distribution, if correct, is more efficient than a nonparametric distribution. Three properties of the beta distribution make it superior to others. First, crop yields are bounded between zero and some upper potential yield. Second, the beta allows for negative and positive skewness. Last of all, the beta is well known and its moments easily calculated.

The authors test their proposal with corn yields in five Iowa counties. The data was collected over ten years on Iowa Agricultural Experiment stations. The specification is tested with an information matrix test. The results fail "to reject the null hypothesis of correct specification of the likelihood function at a significance level of 0.05" for all five counties (Nelson & Preckel, 1989, p. 377). However, it is worth noting that four of the five counties would reject the null at the 0.10 level.

Goodwin and Ker (1998) take a nonparametric approach. They contend that parametric stochastic yield models rely on assumptions that, if wrong, result in "inaccurate predictions and misleading inferences" (Goodwin & Ker, 1998, p. 140). On the other hand, nonparametric procedures are more flexible and "essentially 'nest' parametric specifications" (Goodwin & Ker, 1998, p. 140). Additionally, nonparametric procedures capture idiosyncrasies that could be lost in a parametric specification. However, the Kernel Density Estimators (KDEs), which are commonly used to build nonparametric distributions, have a slow rate of convergence and are less efficient if the true parametric distribution is known.

The authors note that the normal distribution is sometimes used to model average yields with the support of the Central Limit Theorem (CLT). However, the underlying yields are likely to be spatially correlated, which violates the classical CLT.

Additionally, Goodwin and Ker examine the heteroskedasticity of crop yields. The authors use the Goldfeld-Quandt test to conclude that the absolute errors are heteroskedastic, but the proportional errors are not. This seems to be a common view in the Agricultural economics field (Goodwin & Ker, 1998; Paulson & Babcock, 2008; Richardson, Klose, & Gray, 2000).

Just and Weninger (1999) reopen the debate on normality of crop yields. Skewness of yield data is often cited to reject the normal distribution. However, studies differ on the direction of the skewness. Furthermore, alternative parametric distributions have not been thoroughly tested. The authors attempt to show that studies rejecting normality have fallen victim to at least one of three errors.

The first error is "misspecification of the nonrandom components of yield distributions" (Just & Weninger, 1999, p. 287). Many studies assume the mean yield can be modeled by a polynomial time trend. If this assumption does not hold, the true model error will be misrepresented with incorrect error estimates. Additionally, failing to account for heteroskedasticity can cause similar problems.

The second error is "misreporting of statistical significance" (Just & Weninger, 1999, p. 287). One cause of this is performing multiple tests on the same time series without considering the impact of double jeopardy. Another source of the error is performing tests at an α level of significance on k time series. "Bonferroni's theorem implies that, in the absence of multivariate analysis, each marginal distribution must be tested at significance level α/k to assure an overall significance level of α" (Just & Weninger, 1999, p. 295). Furthermore, the k time series are potentially correlated which inflates the results.

The last problem is the "use of aggregate time-series (ATS) data to represent farm-level yield distributions" (Just & Weninger, 1999, p. 287). The pooling of regional data captures systemic variability but fails to capture idiosyncratic deviations. Tests that use ATS data are not actually testing the normality of farm yield distributions.

Just and Weninger note that crop yields at all levels are averages. The CLT states that averages are asymptotically normally distributed for observations from an independent, identically distributed random sample. Using the Liapounov CLT, the identical distribution assumption can be relaxed if the deterministic and heteroskedastic components of yields are accurately modeled. Furthermore, other versions developed by Serfling and by White and Domowitz show that the independence assumption need not hold if "observations [are] sufficiently far apart in time or space are either independent or approach independence asymptotically…, then the basic assertion of CLT hold" (Just & Weninger, 1999, p. 302). As a result, distributions of yields for large regions should be normally distributed. The authors believe the lack of empirical evidence for this theoretical conclusion is due to the misspecification of the "deterministic and heteroskedastic components of yield distributions" (Just & Weninger, 1999, p. 302).

Ker and Coble (2003) introduce a new distribution to the Agricultural economics literature. They argue that yield data is not sufficient to reject many candidate parametric models. Using corn yield data for 87 Illinois counties from 1956-2000, Ker and Coble tested the Beta and Normal specifications and rejected both. They propose filling the void left by rejecting the two common parametric specifications with a semi-parametric model.

The semiparametric estimator is a Kernel Density Estimator with a correction factor based on a parametric distribution. If the parametric distribution is the correct underlying distribution, the estimator will tend to it. However, even if the parametric estimator is incorrect, efficiency can still be gained. The correction factor provides guidance to the curvature of the data. “The standard kernel estimator is equivalent to the semiparametric estimator using the Uniform distribution for the parametric component” (Ker & Coble, 2003, p. 297). In reality, crop yield distributions are likely closer to the Normal or Beta. As a result, using the distributions in the correction factor should increase the efficiency of the estimator over the standard KDE.

Ker and Coble tested this on the 87 Illinois counties. The semiparametric Normal performed the best, followed by the semiparametric Beta and nonparametric kernel. The Beta and Normal performed the worst.

Table 2 summarizes different yield distributions either used in studies or advocated in literature. Based on quantity, the KDE has been quite popular. However, yield distribution specification varies widely.

Table 2: Crop yield distributions used in empirical studies

Distribution	Study	Notes
Beta	(Mason, Hayes, & Lence, 2003)	
Beta*	(Nelson & Preckel, 1989)	
Beta*	(Tirupattur, Hauser, & Chaherli, 1996)	
Empirical	(Gray & et al., 2004)	
Empirical	(Paulson & Babcock, 2008)	
KDE	(Ker & Goodwin, 2000)	Variable smoothing approach with KDE variance equal to sample variance
KDE	(Deng, Barnett, &	

	Vedenov, 2007)	
KDE	(Nadolnyak, Vedenov, & Novak, 2008)	
KDE	(Racine & Ker, 2006)	
KDE	(Vedenov & Power, 2008)	
KDE	(Goodwin & Ker, 1998)	
Multivariate parametric model	(Field, Misra, & Ramirez, 2003)	
No assumption	(Coble, Heifner, & Zuniga, 2000)	Uses hyperbolic tangent transformation to normalize yields
Normal	(Coble & Dismukes, 2008)	Distribution of farm idiosyncratic risk only
Normal	(Coble & Barnett)	Distribution of farm idiosyncratic risk only
Semiparametric*	(Ker & Coble, 2003)	
Weibull	(Schnitkey, Sherrick, & Irwin, 2003)	

*Indicates the study tested the fit of the distribution

CHAPTER 4: METHODS

Analyzing the ACRE program is a non-trivial problem. Given its structure, which is based on national, state, and farm level results, analysis using high levels of aggregation can provide useful but limited insight. Alternatively, a representative farm approach can provide insight into nuances of the program.

Four states were chosen to represent different regions of U.S. agriculture. Illinois represents the Corn Belt, Kansas the Great Plains, Texas the large cotton producers, and Mississippi the small production states. Within each state, a county with significant agricultural production was selected to represent the farm. Two to three of the largest crops by acres for each county were selected to be grown on the representative farm. The following representative farms resulted: corn and soybeans in McLean County, Illinois; wheat and grain sorghum in Sumner County, Kansas; cotton and grain sorghum Hale County, Texas; and cotton, rice, and soybeans in Boliver County, Mississippi. Each constructed farm was assumed to be one FSA farm unit.

The ACRE analysis compared enrollment versus non-enrollment (DCP) for each of these farms over the years 2009 through 2012. To do this, 1,000 prices, farm yields, and state yields for each crop and year on each representative farm were used to obtain a distribution of results. The stochastic approach provides stronger results than a deterministic approach. If average prices are not expected to decline, deterministic analysis would likely show that ACRE never makes payments. In reality, there is a distribution around the expected prices and yields. Therefore, the expected value of ACRE payments is not truly zero.

4.1 Yield modeling

County yield data were obtained from the National Agricultural Statistics Service (NASS) of the USDA. Thirty years were used for each crop on each representative farm. For corn, soybeans, and sorghum this was the years 1979 through 2008. For wheat, rice, and cotton this was the years 1978 through 2007. Corn, soybean, wheat, and sorghum yields are reported on a per bushel basis. Cotton yields are reported on a per pound basis, and rice yields are per hundredweight.

NASS yields are reported per harvested acre. The following adjustment was used to convert the yields to a per planted acre basis:

$$\text{(9)} \qquad Yield\ \ per\ \ planted\ \ acre = \frac{Total\ \ production}{Planted\ acres - Silage\ acres}$$

Only corn and sorghum have silage acres. Each series was regressed on a linear time trend (Table 3). A second-order polynomial trend was tested for several crops and was not found to have any additional explanatory power. As a result, the extra term was dropped.

Table 3: Trend results for county yield per planted acre

County/crop	Intercept	Trend	p-value
McLean, IL corn	105.22	2.46	0.000
McLean, IL soybeans	38.38	0.46	0.000
Sumner, KS wheat	29.04	0.11	0.561
Sumner, KS sorghum	32.58	0.89	0.008
Hale, TX cotton	284.07	17.91	0.000
Hale, TX sorghum	84.32	-0.40	0.139
Boliver, MS cotton	507.47	10.68	0.001
Boliver, MS rice	3963.84	104.27	0.000
Boliver, MS soybeans	19.70	0.67	0.000

All of the yields have a positive trend with the exception of Hale, Texas sorghum. The latter's trend term was set to 0 and the average used for the expected value. Sorghum farmers in Hale, Texas are likely not becoming less productive but are probably facing other issues such as drought or adding less fertile acres to sorghum production. Setting the slope equal to zero assumes that this trend will not continue.

A Breusch-Pagan-Godfrey (BPG) test was conducted to check the yields for heteroskedasticity[6]. None of the tests were significant at the 0.05 level. As a result, the deviations from trend were used to estimate the county yield variance.

However, the county yield variance may not accurately represent the farm yield variance. If the inter-farm correlation is less than one, then the farm yield variance must be greater than the county yield variance. Consider a county, c, with farms $\{x_1,\ldots,x_n\}$ each with a w_i fraction of acres in the crop for the county.

$$\sigma_c^2 = \mathrm{Var}\left(\sum_{i=1}^{n} w_i x_i\right) = \sum_{i=1}^{n} w_i^2 \sigma_i^2 + \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} \rho_{i,j} w_i w_j \sigma_i \sigma_j \tag{10}$$

While it is not true that every farm within a county has the same variance and is the same size, farms within close spatial proximity should be highly homogenous. The soil type and weather conditions should be very similar which produces approximately identical yield distributions. Therefore, assume that farm yields are homoskedastic such that $\sigma_i^2 = \sigma_j^2 = \sigma_f^2 \ \forall\, i, j$. Then:

$$\sigma_c^2 = \sigma_f^2 \sum_{i=1}^{n} w_i^2 + \sigma_f^2 \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} \rho_{i,j} w_i w_j \tag{11}$$

[6]The BPG test for Hale, Texas sorghum was based on deviations from the mean instead of the trend.

Now, consider the average intra-county farm correlation ρ_c. This would be calculated as:

(12a)
$$\rho_c = \frac{\sum_{i=1}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n} \rho_{i,j} w_i w_j}{\sum_{i=1}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n} w_i w_j}$$

Each element of the correlation matrix is weighted by the product of the weights for each farm. Since all the diagonal elements of the correlation matrix are 1, they are not included in the sum. The products of the weights in the numerator do not sum to one, so the numerator is divided by the sum of the weights. Rearranging this:

(12b)
$$\rho_c = \frac{\sum_{i=1}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n} \rho_{i,j} w_i w_j}{\sum_{i=1}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n} w_i w_j}$$

(12c)
$$\rho_c = \frac{\sum_{i=1}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n} \rho_{i,j} w_i w_j}{\sum_{i=1}^{n} w_i \sum_{\substack{j=1 \\ j\neq i}}^{n} w_j}$$

(12d)
$$\rho_c = \frac{\sum_{i=1}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n} \rho_{i,j} w_i w_j}{\sum_{i=1}^{n} w_i \left(1 - w_i\right)}$$

(12e)
$$\rho_c = \frac{\sum_{i=1}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n} \rho_{i,j} w_i w_j}{\sum_{i=1}^{n} w_i - \sum_{i=1}^{n} w_i^2}$$

(12f) $$\rho_c\left(1-\sum_{i=1}^{n} w_i^2\right)=\sum_{i=1}^{n}\sum_{\substack{j=1\\ j\neq i}}^{n}\rho_{i,j}w_i w_j$$

Substituting Equation 12f into Equation **Error! Reference source not found.**:

(13) $$\begin{aligned}\sigma_c^2 &= \sigma_f^2\sum_{i=1}^{n} w_i^2+\sigma_f^2\rho_c\left(1-\sum_{i=1}^{n} w_i^2\right)\\ &= \sigma_f^2\sum_{i=1}^{n} w_i^2+\sigma_f^2\rho_c-\sigma_f^2\rho_c\sum_{i=1}^{n} w_i^2\\ &= \rho_c\sigma_f^2+(1-\rho_c)\sigma_f^2\sum_{i=1}^{n} w_i^2\end{aligned}$$

By definition, $w_i \in (0,1]$ and $\sum_{i=1}^{n} w_i^2 \in \left[\frac{1}{n},1\right]$. If one farm accounted for all the production in the county, then the county variance would equal the average farm variance. Most likely, the true w_i's are closer to $1/n$ as the farms in the county face similar economic conditions. Therefore, while most farms are certainly not equal in size, such an assumption is likely more realistic than the converse. This analysis will assume that all farms are of equal size such that $w_i=\frac{1}{n}$ while acknowledging that this maximizes the estimated average farm variance. With the assumption:

(14) $$\sigma_c^2=\rho_c\sigma_f^2+(1-\rho_c)\frac{1}{n}\sigma_f^2$$

If the cross farm correlation equals one, then county $\sigma_c^2=\sigma_f^2$ which is a logical result. On the other hand, if the cross farm correlation equals zero, then $\sigma_c^2=\frac{1}{n}\sigma_f^2$. This result is consistent with the central limit theorem. If there is only one farm in the county, $\sigma_c^2=\sigma_f^2$. As the number of farms in the county tends to infinity:

(15) $$\sigma_c^2 \xrightarrow{a} \rho_c\sigma_f^2$$

The implications of equation 13 are very powerful. Only the county variance and the average county inter-farm correlation are needed to calculate the farm variance. However, the correlation is still an unknown. It is quite safe to assume that the correlation is non-negative. Additionally, it is very unlikely that it is close to zero as the county variance would approach zero. It would not be unreasonable to expect the correlation to be between 0.5 and 0.9. As a result, this study will consider scenarios with the correlation at 0.5, 0.7, and 0.9.

The county yields errors are adjusted by the following formulation to produce the inflated variance:

(16) $$\tilde{\varepsilon}_i = \frac{\varepsilon_i}{\sqrt{\tilde{\rho}_c}}$$

where ε_i is the deviation from trend for the i^{th} observation, $\tilde{\rho}_c$ is the assumed inter-farm correlation within the county, and $\tilde{\varepsilon}_i$ is the new residual with the inflated variance.

The correlations along with the number of farms in each county for each crop (Table 4) support the use of asymptotics. The smallest number of farms is for Boliver, Mississippi cotton. Using equation 14, the county error is inflated by a factor of 1.40. With equation 15, the inflation factor is 1.41. Since 0.5 is the correlation used that would most affect the difference and even it hardly shows any difference, assuming asymptotics has hardly any discernible effect on the error adjustments.

Table 4: Number of farms harvesting crop in county during 2007

County/crop	Farms
McLean, IL corn	960
McLean, IL soybeans	813
Sumner, KS wheat	490
Sumner, KS sorghum	212
Hale, TX cotton	331
Hale, TX sorghum	188
Boliver, MS cotton	54
Boliver, MS rice	86
Boliver, MS soybeans	274

Source: USDA Census of Agriculture

State yields were also obtained from NASS. Each was regressed on a trend variable and checked for heteroskedasticity. The results of the regressions are in Table 5. Like Hale, Texas sorghum, Texas sorghum had a negative but not significant trend. Therefore, the trend was set to zero for the reasons mentioned for Hale, Texas sorghum.

Table 5: Trend results for state yields per planted acre

State/crop	Intercept	Trend	p-value
Illinois corn	101.49	2.09	0.000
Illinois soybeans	33.78	0.42	0.000
Kansas wheat	27.22	0.28	0.074
Kansas sorghum	53.09	0.44	0.110
Texas cotton	299.22	16.18	0.000*
Texas sorghum	51.97	-0.16	0.361
Mississippi cotton	580.12	6.65	0.007
Mississippi rice	3859.22	104.06	0.000
Mississippi soybeans	17.48	0.56	0.000

*Estimated using White's estimator

A BPG test of state yields for heteroskedasticity failed to reject the null hypothesis of homoskedasticity for all crops at the 0.05 significance level except Texas cotton which had a p-value of 0.028. A common approach in the Agricultural economics literature to deal with the heteroskedasticity of yields is to assume the error variance divided by the expected yield is constant (Goodwin & Ker, 1998; Gray & et al., 2004; Paulson & Babcock, 2008). This approach assumes the standard deviation of the adjusted residuals is the coefficient of variation which remains temporally constant.

(17)
$$y_i \sim \left(\mathrm{E}[y_i], \sigma_i^2\right)$$
$$\frac{y_i - \mathrm{E}[y_i]}{\mathrm{E}[y_i]} \sim \left(0, \frac{\sigma_i^2}{\mathrm{E}[y_i]^2}\right)$$

After adjusting the errors accordingly, the BPG test for Texas cotton yields had a p-value of 0.740. The transformation appears to correct the heteroskedasticity.

Thus far, no parametric distribution has been imposed for yields. As discussed in Chapter 3, there is no consensus for the correct specification. As a result, this study will avoid using a potentially wrong parametric distribution. Instead, a nonparametric Kernel Density Estimator (KDE) as described by Silverman (1986) will be used. This approach creates a marginal distribution while avoiding distributional assumptions by forming a distribution based on the observed data. The KDE is formally defined as:

(18)
$$f(x) = \frac{1}{nh} \sum_{t=1}^{T} K\left(\frac{x - X_t}{h}\right)$$

where h is smoothing parameter or bandwidth and K is a kernel function such that:

(19)
$$\int_{-\infty}^{\infty} K(x)\,dx = 1$$

KDEs are essentially a smoothed, continuous histogram. Kernels are created at each data point and each kernel is summed at x. h determines the width of the effect of each data point. A small h creates a local effect for each data point whereas a large h stretches the effect of each data point across much of the distribution. A small h creates a lumpy distribution while a large h creates a smooth distribution.

The selection of the bandwidth is a nontrivial problem. Choose one too large and the details of the distribution are lost. Conversely, choose one too small and the individual data points are overemphasized. Rather advanced methods such as least-squares cross-validation and likelihood cross-validation can estimate an appropriate bandwidth. Silverman (1986) shows that for normally distributed data the ideal bandwidth is:

(20) $$h = \left(\frac{4}{3}\right)^{1/5} \sigma n^{-1/5}$$

Silverman creates a more general rule of thumb that works well for any distribution:

(21) A = min(standard deviation, interquartile range/1.34)

(22) $$h = .9An^{-1/5}$$

In addition to bandwidth, a kernel function must be selected to use a KDE. A Gaussian function is commonly used in the Agricultural economics literature. While the Gaussian function is highly efficient, the Epanechnikov kernel is the most efficient. The Epanechnikov kernel is defined as:

(23) $$K(t) = \begin{cases} \frac{3}{4}\left(1 - \frac{1}{5}t^2\right) \Big/ \sqrt{5} & \textit{for } |t| < \sqrt{5} \\ 0 & \textit{otherwise} \end{cases}$$

In addition to efficiency, the Epanechnikov kernel has several other useful properties. It is not continuous over all reals. Yields must be greater than 0 and ideally less than some theoretical upper limit. The Gaussian kernel is continuous over all reals. This creates the potential for both negative yields and unrealistically high yields. Additionally, the Epanechnikov kernel is easily tractable. The moments can easily be derived.

Yields were forecasted for the period 2009 through 2012 for the state and county with the trend equations. Deviations from trend were generated from the KDE with the residuals by the following algorithm from Silverman (1986):

Step 1) Choose t uniformly with replacement from $\{\tilde{x}_1, \ldots, \tilde{x}_T\}$

Step 2) Generate e to have probability density function K

Step3) Set $Y = \mu + (\hat{x}_t - \mu + he) \big/ \sqrt{1 + h^2 \sigma_K^2 / \sigma_{\hat{x}}^2}$

where σ_K^2 is the variance of the kernel and $\sigma_{\hat{x}}^2$ is the variance of the data. The Y's will be distributed with mean μ and variance $\sigma_{\hat{x}}^2$.

Additionally, Silverman (1986) describes a very fast algorithm for generating e from the rescaled Epanechnikov kernel:

(24) $$K(x) = \frac{3}{4}\left(1 - x^2\right) \; for \; |x| \leq 1.$$

Step 2a) Generate three uniform [-1, 1] random variates V_1, V_2, V_3.

Step 2b) If $|V_3| \geq |V_2|$ and $|V_3| \geq |V_1|$, set $e = V_2$
otherwise set $e = V_3$

The variance of the rescaled Epanechnikov kernel is:

(25) $$\sigma_K^2 = \int_{-1}^{1} x^2 K(x) dx = \frac{1}{5}$$

Each crop and yield deviation was iterated 1,000 times at the county/farm and state level. The deviation was added to the trend[7]. The result was 1,000 uncorrelated random draws for the yields.

[7] Texas cotton instead is multiplied the trend yield by (1+random draw).

4.2 Price and yield correlation

One of the keys to analyzing the ACRE program is maintaining the interactions between prices and yields. This has often been done in the Agricultural economics literature by imposing correlation among simulated variables. The following provides the theoretical foundation for the methodology.

Let *C* be an *n*x*n* correlation matrix, *P* be an *n*x*n* matrix such that $PP^T = C$, and ε be an nx1 vector of standard normal random variables. Richardson and Condra (1978) and RiskMetrics™ (*RiskMetrics(TM) Technical Document*, 1996) show that:

(26) $$P\varepsilon \sim N(0_{n\text{x}1}, C)$$

This follows from the fact that:

(27) $$\mathrm{E}[P\varepsilon] = P\,\mathrm{E}[\varepsilon] = 0_{n\text{x}1}$$

and:

(28) $$\begin{aligned}\mathrm{Var}(P\varepsilon) &= \mathrm{E}\left[P\varepsilon\varepsilon^T P^T\right] - \mathrm{E}[P\varepsilon]\mathrm{E}[P\varepsilon]^T \\ &= P\,\mathrm{E}\left[\varepsilon\varepsilon^T\right]P^T - 0_{n\text{x}1}0_{n\text{x}1}^T \\ &= P\,\mathrm{E}\left[\varepsilon\varepsilon^T\right]P^T\end{aligned}$$

Note that $E\left[\varepsilon\varepsilon^T\right] = Var(\varepsilon) = I_n$, so:

(29) $$\begin{aligned}\mathrm{Var}(P\varepsilon) &= PI_nP^T \\ &= PP^T \\ &= C\end{aligned}$$

Since a correlation matrix is just a covariance matrix with all standard deviations equal to one, the method provides a way of generating correlated standard normal deviates (CSND) with correlation preserved. Richardson and Condra propose inserting the CSNDs into the normal distribution to obtain correlated uniform standard deviates

(CUSD). The inverse probability integral transform can then be used to create correlated observations from non-normal distributions.

Iman and Conover (1982) use a similar method. However, they argue that Pearson's correlation coefficient is dependent upon linear correlation and is tied to normal distributions. Instead, they propose a method using Spearman's rank correlation coefficient. Suppose R is an ixk matrix of standard normal random variables where i is the number of iterations and k is the number of variables. RP^T creates a matrix where the variables have a correlation matrix with expected value equal to C. Let M be an ixk matrix where each column is a variable with i observations generated from a distribution. Reorder the entries in each column of M to create M^* so that the rank of each entry within the column is the same as the rank of the entry in the corresponding row and column in RP^T. M^* now has rank correlation matrix approximately equal to C.

Iman and Conover proceed to show that M^* can be constructed to ensure a correlation matrix nearly equal to C, even with just a few iterations. Let T be the correlation matrix of R and S be a correction matrix such that:

(30) $$STS^T = C$$

Let Q be a matrix such that $QQ^T = T$. Then:

(31) $$SQQ^TS^T = C$$

Since $C = PP^T$:

(32) $$\begin{aligned} SQQ^TS^T &= PP^T \\ SQ &= P \\ S &= PQ^{-1} \end{aligned}$$

In this case, $R^* = RS^T$ and should have a correlation matrix nearly identical to C.

For the ACRE analysis, Iman and Conover's method with correlation correction was employed for two reasons. First, Silverman's simple algorithm for generating observations could easily be employed. Additionally, the method is robust. Nonlinear interactions among prices and yields can be captured.

In order to employ the procedure, the matrix C must be factored such that $PP^T = C$. This is typically done with the Cholesky decomposition. The Cholesky decomposition produces a lower triangular matrix that satisfies the aforementioned requirement. In order to find a solution, C must be positive definite (PD) (*RiskMetrics(TM) Technical Document*, 1996). For a true correlation matrix, this is not often a restrictive assumption as "all variance-covariance matrices are positive semi-definite"(Hogg, McKean, & Craig, 2005, p. 122).

However, the PD requirement can fail, particularly for synthesized correlation matrices. Additionally, correlations from different time periods can also cause problems ("Monte Carlo Simulation by Cholesky or PCA?," 2006). This issue has rarely been discussed in the Agricultural economics literature. For matrices that fail the PD requirement, eigenvalue decomposition can provide a feasible alternative to the Cholesky decomposition. The correlation matrix C can be written as:

(33) $$C = E\Omega E^T$$

where E is the matrix of eigenvectors and Ω is a diagonal matrix of eigenvalues. By definition, a symmetric PD matrix will have eigenvalues greater than zero, and a positive semi-definite (PSD) matrix will have eigenvalues greater than or equal to zero. The decomposition can be further decomposed to:

(34) $$C = E\Omega^{1/2}\Omega^{1/2}E^T$$

where $\Omega^{1/2}$ is a diagonal matrix of the square root of the eigenvalues. Under eigenvalue decomposition, $P = E\Omega^{1/2}$. The relative advantage is that PSD matrices can be decomposed. Even if a matrix is not PSD, the negative eigenvalue(s) can often be set to zero and the matrix decomposed with little effect on the correlation matrix ("Monte Carlo Simulation by Cholesky or PCA?," 2006).

The correlation matrix for each representative farm contains the rank correlations of farm yield deviations, state yield deviations, and national price deviations for each crop grown on the representative farm. The farm and state yield rank correlations were calculated from the deviations from trend yields. State yield and national price rank correlations were obtained from the FAPRI ACRE model. These correlations are based on future expectations. Therefore, they can differ from historical correlations since they account for structural changes in the industry. The county yield and national price correlations were obtained by multiplying correlation between the farm and the state for the crop by the correlation between the state for the crop and the national price.

Table 6: McLean, Illinois rank correlation matrix

		County yields		**State yields**		**Prices**	
		Corn	**Soybeans**	**Corn**	**Soybeans**	**Corn**	**Soybeans**
County yields	**Corn**	1.00	0.54	0.93	0.67	-0.41	-0.26
	Soybeans	0.54	1.00	0.44	0.68	-0.23	-0.27
State yields	**Corn**	0.93	0.44	1.00	0.71	-0.45	-0.33
	Soybeans	0.67	0.68	0.71	1.00	-0.34	-0.40
Prices	**Corn**	-0.41	-0.23	-0.45	-0.34	1.00	0.63
	Soybeans	-0.26	-0.27	-0.33	-0.40	0.63	1.00

Table 7: Sumner, Kansas rank correlation matrix

		County yields		**State yields**		**Prices**	
		Wheat	**Sorghum**	**Wheat**	**Sorghum**	**Wheat**	**Sorghum**
County yields	**Wheat**	1.00	0.13	0.79	0.09	-0.16	-0.12
	Sorghum	0.13	1.00	0.02	0.09	-0.01	-0.03
State yields	**Wheat**	0.79	0.02	1.00	0.08	-0.21	-0.15
	Sorghum	0.09	0.09	0.08	1.00	-0.16	-0.36
Prices	**Wheat**	-0.16	-0.01	-0.21	-0.16	1.00	0.83
	Sorghum	-0.12	-0.03	-0.15	-0.36	0.83	1.00

Table 8: Hale, Texas rank correlation matrix

		County yields		State yields		Prices	
		Cotton	**Sorghum**	**Cotton**	**Sorghum**	**Cotton**	**Sorghum**
County yields	**Cotton**	1.00	0.64	0.83	0.00	-0.15	-0.12
	Sorghum	0.64	1.00	0.73	0.45	-0.02	-0.08
State yields	**Cotton**	0.83	0.73	1.00	0.22	-0.18	-0.14
	Sorghum	0.00	0.45	0.22	1.00	-0.04	-0.18
Prices	**Cotton**	-0.15	-0.02	-0.18	-0.04	1.00	0.49
	Sorghum	-0.12	-0.08	-0.14	-0.18	0.49	1.00

Table 9: Boliver, Mississippi rank correlation matrix

		County yields			State yields			Prices		
		Cotton	**Rice**	**Soybeans**	**Cotton**	**Rice**	**Soybeans**	**Cotton**	**Rice**	**Soybeans**
County yields	**Cotton**	1.00	0.00	0.73	0.85	0.09	0.73	-0.16	-0.03	-0.14
	Rice	0.00	1.00	0.17	0.20	0.95	0.17	-0.06	-0.10	-0.08
	Soybeans	0.73	0.17	1.00	0.75	0.28	0.91	0.00	-0.02	-0.10
State yields	**Cotton**	0.85	0.20	0.75	1.00	0.29	0.76	-0.18	-0.03	-0.16
	Rice	0.09	0.95	0.28	0.29	1.00	0.27	-0.07	-0.10	-0.08
	Soybeans	0.73	0.17	0.91	0.76	0.27	1.00	0.00	-0.03	-0.11
Prices	**Cotton**	-0.16	-0.06	0.00	-0.18	-0.07	0.00	1.00	0.56	0.17
	Rice	-0.03	-0.10	-0.02	-0.03	-0.10	-0.03	0.56	1.00	0.25
	Soybeans	-0.14	-0.08	-0.10	-0.16	-0.08	-0.11	0.17	0.25	1.00

Prices for the analysis were obtained from the January 2009 FAPRI Stochastic Baseline. However, the baseline only generates 500 outcomes while this analysis uses 1,000. To increase the price outcomes, the 500 prices for each crop from the FAPRI baseline were sorted into an empirical distribution. One thousand draws were then made from that distribution using Latin Hypercube. The result is 1,000 price outcomes nearly identical in distribution to the FAPRI baseline.

Table 10: Mean values of forecasts

	2009	**2010**	**2011**	**2012**
McLean, IL corn yield, bu	181.6	184.1	186.5	189.0
McLean, IL soybean yield, bu	52.6	53.0	53.5	54.0
Sumner, KS wheat yield, bu	32.5	32.6	32.7	32.8
Sumner, KS sorghum yield, bu	60.3	61.2	62.1	63.0
Hale, TX cotton yield, lbs	857.3	875.3	893.2	911.1
Hale, TX sorghum yield, bu	78.1	78.1	78.1	78.1
Boliver, MS soybean yield, bu	40.5	41.2	41.8	42.5
Boliver, MS cotton yield, lbs	849.3	860.0	870.7	881.4
Boliver, MS rice yield, lbs	7,300.4	7,404.6	7,508.9	7,613.2
Illinois corn yield, bu	166.4	168.5	170.5	172.6
Illinois soybean yield, bu	46.8	47.2	47.6	48.0
Kansas wheat yield, bu	36.3	36.6	36.9	37.2
Kansas sorghum yield, bu	66.9	67.3	67.7	68.2
Texas cotton yield, lb	817.0	833.2	849.4	865.6
Texas sorghum yield, bu	49.4	49.4	49.4	49.4
Mississippi soybean yield, bu	34.9	35.5	36.0	36.6
Mississippi cotton yield, lbs	792.8	799.5	806.1	812.8
Mississippi rice yield, lbs	7,189.1	7,293.2	7,397.2	7,501.3
Corn price, $ per bu	3.74	3.78	3.80	3.91
Soybean price, $ per bu	8.76	8.81	9.17	9.22
Wheat price, $ per bu	5.30	5.33	5.42	5.50
Sorghum price, $ per bu	3.25	3.29	3.37	3.50
Cotton price, $ per lb	0.52	0.55	0.56	0.56
Rice price, $ per cwt	12.87	11.90	12.03	12.48

Each year for each farm has a matrix *M* with 1,000 rows and (crops x 3) columns. The first third of the columns are farm yield deviates plus trend yield for each crop generated from the KDEs. The second third are state yield deviates plus the trend yield[8] for each crop generated from the KDEs. The last third are the 1,000 price outcomes based on the FAPRI baseline. Correlation among the variables is obtained by using Iman and Conover's algorithm. *C* is a synthetic correlation matrix so *P* is derived by eigenvalue decomposition. Negative eigenvalues are set to zero. On the other hand, *T* is a "true" correlation matrix so *Q* is derived by the Cholesky decomposition which is computationally less taxing. The result is a matrix for every representative farm for every year of 1,000 iterations of all yields and prices.

4.3 Estimating representative farm parameters

The ACRE program is dependent upon several farm parameters. One of the most important is planted acres for each crop. The total farm size was determined by the 2007 Ag Census. The representative farm was assumed to have planted acres equal to the average harvested acres for farms of at least 2,000 acres in the county to preclude part-time operations. The five year average of planted acres in the county was calculated for each crop on the farm. The average of each crop divided by the sum of the averages for each crop on the representative farm was multiplied by the total planted acres to allocate acres to each crop on the farm. These were assumed to remain constant in all years of the analysis (Table 11). Base acres were assumed to equal planted acres for purposes of the baseline, but this was allowed to vary in the scenarios.

[8] Except Texas cotton which is trend yield x (1 + percent deviate).

Table 11: Acres of each crop

County/crop	Acres
McLean, IL corn	986
McLean, IL soybeans	697
Sumner, KS wheat	1,275
Sumner, KS sorghum	255
Hale, TX cotton	1,926
Hale, TX sorghum	216
Boliver, MS soybeans	2,571
Boliver, MS cotton	323
Boliver, MS rice	827

As previously mentioned, NASS county yields are not yet available for cotton, rice, and wheat for 2008. A linear model was used to estimate the 2008 county yield based on the state yield for those crops. Mississippi cotton is split into irrigated and non-irrigated for the ACRE program. Only the combined state yield has been reported for 2008. Therefore, 100 pounds was subtracted off the combined yield to estimate the non-irrigated yield. This correction was consistent with the differences in the yields in the previous years. Additionally, NASS has not yet reported 2008 rice yields in Mississippi so the data was taken from the reported FSA ACRE yields.

County CCP and DP yields could not be obtained so they were estimated. CCP yields were created in 2002 based on 1998 through 2001 farm yields. Therefore, state CCP and DP yields were multiplied by the ratio of the average 1998 to 2001 county yield to the average 1998 to 2001 state yield to obtain an estimate of the county CCP and DP yields.

Table 12: Program yields

County/crop	CCP yield	DP yield
McLean, IL corn	136	123
McLean, IL soybeans	44	39
Sumner, KS wheat	34	33
Sumner, KS sorghum	43	41
Hale, TX cotton	562	525
Hale, TX sorghum	53	53
Boliver, MS soybeans	26	25
Boliver, MS cotton	714	701
Boliver, MS rice	4,474	4,223

Yields in bushels except cotton and rice which are in pounds

2009 crop insurance premiums were obtained from the Risk Management Agency (RMA) of the USDA. Actual Production History (APH) yields are calculated as the minimum of four and maximum of ten years average yield. Once established, the APH yield cannot decrease by more than 10% nor increase by more than 20% per year (Edwards, 2009). 2009 APH yields for each farm were calculated as the average of the last 10 years of yield per planted acre for the county. Each crop was assumed to be insured with a 75% Crop Revenue Coverage (CRC) policy on the basic unit. Premiums were projected through 2012 by the following formula:

(35) $$\text{Premium}_t = \text{Premium}_{t-1} \frac{E[\text{Revenue}_t]}{\text{Revenue}_{t-1}}$$

where:

(36) $$E[\text{Revenue}_t] = \text{Trend yield}_t * E[\text{price}_t]$$

(37) $$E[\text{price}_t] = \text{price}_{t-1}$$

The insurance premium calculations simply inflate the lag premium by the ratio of expected revenues to lag revenues. This model assumes that the farm will keep the same type of insurance over the next four years. Additionally, price expectations are assumed to be naïve.

Historical state yields per planted acre for the ACRE program for the past five years are reported by the FSA. Those were used instead of the historical state yields calculated from the NASS data if there was a conflict[9]. The 1,000 price and yield outcomes along with the representative farm parameters were run through the government program equations described in Chapter 3 with the exception of LDPs. Cotton and rice LDPs are determined by Average World Prices (AWP) which is usually below the MYA farm price. The AWP rice price is determined by adjusting the MYA price down by \$2.00 per cwt, and the AWP cotton price is determined by adjusting the MYA price down by \$0.03 per pound. For the other crops, the PCP is a reflection of the daily local county price. The MYA price does not capture the intra-year price variation. The MYA price could be above the loan rate while PCPs dip below during the year. As a result, the LDPs for corn, soybeans, wheat, and sorghum were calculated based upon the following FAPRI U.S. Crops Model equation:

$$\text{(38)} \qquad \text{LDP per bushel} = \text{Max}\begin{pmatrix} 0, .25 * \text{Max}(0, \text{Loan rate} + \alpha_0 - \text{MYA Price}) \\ + .50 * \text{Max}(0, \text{Loan rate} + \alpha_1 - \text{MYA Price}) \\ + .25 * \text{Max}(0, \text{Loan rate} - \text{MYA Price}) \end{pmatrix}$$

where:

[9] The only crop/state where the conflict was consistently significantly different was Texas sorghum due to the high number of failed acres for the crop. This potentially explains why the trend was negative for the crop/state. Using the errors from the NASS data will likely inflate the true variance for the crop/state.

Table 13: LDP equation parameters

Crop	α_0	α_1
Corn	0.40	0.20
Soy	0.44	0.22
Wheat	0.60	0.30
Sorghum	0.28	0.14

The specification allows LDPs to be triggered even if the MYA price is above the loan rate. Furthermore, as the MYA price approaches the loan rate, LDPs will increase disproportionally faster. This reflects the fact that PCPs are often below the MYA price. This equation captures the price differential and the price intra-year price variation of PCPs.

CHAPTER 5: BASELINE RESULTS

The following chapter describes the results of the 1,000 iterations of the representative farm ACRE model. One of the challenges of analyzing the program is reducing output to a few key variables that convey the intricacies and possibilities of the program. This study attempts to use the smallest combination of metrics that provides complete analysis. Additional output is available upon request.

The initial comparison to be made is the sensitivity of results to the assumed average county inter-farm correlation. Table 14 shows the average ACRE participation payments minus the average ACRE non-participation payments for each correlation and farm. The table indicates that the analysis is fairly insensitive to the correlation (within the assumed range). As a result, an average county inter-farm correlation of 0.7 will henceforth be assumed for the sake of brevity.

Table 14: Average ACRE participation payments minus average ACRE non-participation payments, dollars

Farm	Average county interfarm correlation	Year 2009	2010	2011	2012
McLean, Illinois	**0.5**	48,524	25,092	16,035	12,566
	0.7	48,524	25,087	16,035	12,567
	0.9	48,525	25,088	16,026	12,561
Sumner, Kansas	**0.5**	25,805	13,908	6,838	4,209
	0.7	25,805	13,908	6,838	4,209
	0.9	26,081	14,184	6,964	4,288
Hale, Texas	**0.5**	-119,169	-107,612	-102,268	-98,188
	0.7	-117,215	-106,201	-101,857	-97,463
	0.9	-115,837	-105,847	-101,821	-97,370
Boliver, Mississippi	**0.5**	53,188	45,263	15,510	9,905
	0.7	53,184	45,247	15,498	9,907
	0.9	53,371	46,031	15,881	9,950

The following four tables (Table 15, Table 16, Table 17, and Table 18) display the per acre results of the ACRE participation decision. Corn, soybeans, sorghum, rice, and wheat rarely trigger CCPs or LDPs under the DCP option during the next four years. The main cost for enrolling these crops in ACRE is the 20% reduction in DPs. The ACRE enrollment decision for producers with only these crops essentially reduces to whether ACRE benefits exceed 20% of DPs.

On the other hand, farms with cotton face a more complex decision. Cotton frequently triggers CCPs and LDPs under the DCP option. Under the ACRE option, the crop rarely triggers LDPs and ACRE precludes CCPs. Producers of this crop face a very steep opportunity cost of enrolling in ACRE. However, ACRE may still make sense for cotton producers if they have sufficient acreage of other crops on the FSA farm.

Table 15: Average payments per planted acre for McLean, Illinois

ACRE participation					ACRE non-participation				
	2009	2010	2011	2012		2009	2010	2011	2012
ACRE Payments					Counter-cyclical payments				
Corn	38.67	22.50	17.16	13.52	Corn	0.00	0.01	0.00	0.00
Soybeans	25.87	15.59	10.14	10.73	Soybeans	0.00	0.21	0.22	0.24
Loan deficiency payments					Loan deficiency payments				
Corn	0.00	0.00	0.00	0.00	Corn	0.00	0.00	0.00	0.00
Soybeans	0.00	0.00	0.00	0.01	Soybeans	0.00	0.24	0.23	0.42
Direct payments					Direct payments				
Corn	22.91	22.91	22.91	23.38	Corn	28.64	28.64	28.64	29.23
Soybeans	11.41	11.41	11.41	11.64	Soybeans	14.26	14.26	14.26	14.55

Table 16: Average payments per planted acre for Sumner, Kansas

ACRE participation					ACRE non-participation				
	2009	2010	2011	2012		2009	2010	2011	2012
ACRE Payments					Counter-cyclical payments				
Wheat	20.30	12.62	7.81	5.53	Wheat	0.02	0.10	0.14	0.11
Sorghum	16.61	9.20	5.60	6.81	Sorghum	0.05	0.24	0.11	0.14
Loan deficiency payments					Loan deficiency payments				
Wheat	0.00	0.00	0.00	0.00	Wheat	0.00	0.02	0.05	0.01
Sorghum	0.00	0.00	0.00	0.00	Sorghum	0.03	0.18	0.04	0.13
Direct payments					Direct payments				
Wheat	11.45	11.45	11.45	11.68	Wheat	14.31	14.31	14.31	14.60
Sorghum	9.58	9.58	9.58	9.77	Sorghum	11.97	11.97	11.97	12.22

Table 17: Average payments per planted acre for Hale, Texas

ACRE participation					ACRE non-participation				
	2009	2010	2011	2012		2009	2010	2011	2012
ACRE Payments					Counter-cyclical payments				
Cotton	26.38	14.06	13.10	13.06	Cotton	45.70	36.06	34.19	32.25
Sorghum	29.01	17.71	10.84	9.26	Sorghum	0.05	0.30	0.13	0.17
Loan deficiency payments					Loan deficiency payments				
Cotton	2.90	2.15	2.90	3.73	Cotton	41.51	31.03	29.70	29.84
Sorghum	0.00	0.00	0.00	0.00	Sorghum	0.04	0.24	0.05	0.14
Direct payments					Direct payments				
Cotton	23.35	23.35	23.35	23.82	Cotton	29.18	29.18	29.18	29.78
Sorghum	12.29	12.29	12.29	12.54	Sorghum	15.36	15.36	15.36	15.68

Table 18: Average payments per planted acre for Boliver, Mississippi

ACRE participation					ACRE non-participation				
	2009	2010	2011	2012		2009	2010	2011	2012
ACRE Payments					Counter-cyclical payments				
Soybeans	31.12	19.70	13.70	14.13	Soybeans	0.00	0.13	0.13	0.14
Cotton	16.41	6.61	7.56	11.41	Cotton	57.99	45.76	43.39	40.93
Rice	24.55	50.29	29.69	18.64	Rice	0.03	0.77	0.53	0.41
Loan deficiency payments					Loan deficiency payments				
Soybeans	0.00	0.00	0.00	0.00	Soybeans	0.00	0.19	0.19	0.28
Cotton	2.99	2.16	2.93	3.85	Cotton	41.85	31.91	30.35	30.14
Rice	0.00	0.00	0.02	0.00	Rice	0.29	2.89	2.06	1.64
Direct payments					Direct payments				
Soybeans	7.30	7.30	7.30	7.45	Soybeans	9.13	9.13	9.13	9.32
Cotton	31.15	31.15	31.15	31.79	Cotton	38.94	38.94	38.94	39.74
Rice	66.14	66.14	66.14	66.14	Rice	82.67	82.67	82.67	82.67

The next four tables (Table 19, Table 20, Table 21, and Table 22) of total payments for the farm help to determine whether the benefits exceed the cost of ACRE. McLean, Illinois; Sumner, Kansas; and Boliver, Mississippi tend to benefit on average with ACRE. In a typical year, DCP clearly provides more payments than ACRE for Hale, Texas. The opportunity cost of enrolling cotton base acres is very high and the few sorghum acres can't make up the difference. As a result, the farm earns about $100,000 less per year in average payments if it is enrolled in ACRE. This does not take payment limits into account though.

Perhaps the most interesting farm is Boliver, Mississippi. While it does have cotton and rice, the farm has about twice as many soybean acres as the two other crops combined. The result is that on average the farm receives higher payments by enrolling in ACRE.

Table 19: Average payments for McLean, Illinois

ACRE participation				
	2009	2010	2011	2012
ACRE Payments				
Corn	38,125	22,187	16,918	13,329
Soybeans	18,034	10,864	7,066	7,481
Total	56,159	33,050	23,984	20,810
Loan deficiency payments				
Corn	0	0	0	0
Soybeans	0	0	0	4
Total	0	0	0	4
Direct payments				
Corn	22,593	22,593	22,593	23,054
Soybeans	7,950	7,950	7,950	8,112
Total	30,543	30,543	30,543	31,166
Total payments (ACRE)	86,702	63,593	54,527	51,980
Net change (ACRE-DCP)	48,524	25,087	16,035	12,567

ACRE non-participation (DCP)				
	2009	2010	2011	2012
Counter-cyclical payments				
Corn	0	9	0	0
Soybeans	0	148	150	166
Total	0	158	150	166
Loan deficiency payments				
Corn	0	4	0	0
Soybeans	0	166	164	289
Total	0	170	164	289
Direct payments				
Corn	28,241	28,241	28,241	28,817
Soybeans	9,938	9,938	9,938	10,140
Total	38,178	38,178	38,178	38,958
Total payments (DCP)	38,178	38,506	38,492	39,413

Table 20: Average payments for Sumner, Kansas

ACRE participation	2009	2010	2011	2012
ACRE Payments				
Wheat	25,882	16,088	9,954	7,047
Sorghum	4,235	2,345	1,427	1,736
Total	30,117	18,433	11,381	8,783
Loan deficiency payments				
Wheat	0	0	0	0
Sorghum	0	0	0	0
Total	0	0	0	0
Direct payments				
Wheat	14,595	14,595	14,595	14,893
Sorghum	2,442	2,442	2,442	2,492
Total	17,038	17,038	17,038	17,385
Total payments (ACRE)	47,155	35,471	28,419	26,168
Net change (ACRE-DCP)	25,805	13,908	6,838	4,209

ACRE non-participation (DCP)	2009	2010	2011	2012
Counter-cyclical payments				
Wheat	28	132	178	139
Sorghum	12	62	27	36
Total	40	193	205	175
Loan deficiency payments				
Wheat	6	27	69	19
Sorghum	7	45	10	33
Total	13	73	79	52
Direct payments				
Wheat	18,244	18,244	18,244	18,617
Sorghum	3,053	3,053	3,053	3,115
Total	21,297	21,297	21,297	21,732
Total payments (DCP)	21,350	21,563	21,581	21,959

Table 21: Average payments for Hale, Texas

ACRE participation	2009	2010	2011	2012
ACRE Payments				
Cotton	50,817	27,081	25,225	25,155
Sorghum	6,266	3,826	2,342	2,000
Total	57,083	30,907	27,567	27,155
Loan deficiency payments				
Cotton	5,593	4,132	5,577	7,188
Sorghum	0	0	0	0
Total	5,593	4,132	5,577	7,188
Direct payments				
Cotton	44,967	44,967	44,967	45,885
Sorghum	2,655	2,655	2,655	2,709
Total	47,622	47,622	47,622	48,594
Total payments (ACRE)	110,299	82,662	80,767	82,938
Net change (ACRE-DCP)	-117,215	-106,201	-101,857	-97,463

ACRE non-participation (DCP)	2009	2010	2011	2012
Counter-cyclical payments				
Cotton	88,021	69,459	65,858	62,120
Sorghum	11	64	29	38
Total	88,033	69,523	65,887	62,158
Loan deficiency payments				
Cotton	79,945	59,760	57,198	57,470
Sorghum	8	52	11	30
Total	79,953	59,812	57,209	57,500
Direct payments				
Cotton	56,209	56,209	56,209	57,356
Sorghum	3,319	3,319	3,319	3,386
Total	59,528	59,528	59,528	60,743
Total payments (DCP)	227,514	188,863	182,624	180,401

Table 22: Average payments for Boliver, Mississippi

ACRE participation	2009	2010	2011	2012
ACRE Payments				
Soybeans	80,014	50,643	35,213	36,333
Cotton	5,302	2,136	2,442	3,685
Rice	20,301	41,591	24,556	15,412
Total	105,617	94,371	62,211	55,430
Loan deficiency payments				
Soybeans	0	0	0	9
Cotton	967	699	948	1,243
Rice	0	0	19	0
Total	967	699	966	1,252
Direct payments				
Soybeans	18,779	18,779	18,779	19,162
Cotton	10,062	10,062	10,062	10,268
Rice	54,697	54,697	54,697	54,697
Total	83,539	83,539	83,539	84,127
Total payments (ACRE)	190,123	178,608	146,716	140,809
Net change (ACRE-DCP)	53,184	45,247	15,498	9,907

ACRE non-participation (DCP)	2009	2010	2011	2012
Counter-cyclical payments				
Soybeans	0	331	334	370
Cotton	18,732	14,782	14,015	13,220
Rice	28	637	440	339
Total	18,760	15,749	14,790	13,928
Loan deficiency payments				
Soybeans	0	487	497	720
Cotton	13,516	10,309	9,803	9,734
Rice	240	2,394	1,706	1,360
Total	13,756	13,189	12,005	11,815
Direct payments				
Soybeans	23,474	23,474	23,474	23,953
Cotton	12,578	12,578	12,578	12,835
Rice	68,372	68,372	68,372	68,372
Total	104,423	104,423	104,423	105,159
Total payments (DCP)	136,939	133,361	131,218	130,902

Although average payments are useful, they hide important information. A producer may also be concerned about the frequency of payments. The following four tables (Table 23, Table 24, Table 25, and Table 26) summarize the frequency of payments for the simulation. About 90% of the outcomes received an ACRE payment in at least one of the four years. Cotton was the crop that triggered the least with less than 80% for both farms that had the crop.

Additionally, the Boliver, Mississippi farm provides some interesting results. County soybean yields are highly correlated with state soybean yields while both are weakly correlated to national soy prices. The result is a higher percent of outcomes triggering ACRE payments for soybeans than for the McLean, Illinois farm, where prices and yields have a much stronger negative correlation. This creates a natural hedge reducing the probability of triggering ACRE payments. Boliver, Mississippi cotton had high yields in four of the five years between 2004 and 2008 which helps explain the low percent of outcomes where cotton triggers ACRE payments.

Furthermore, one other observation is quickly apparent. The percent of outcomes triggering ACRE payments tends to decrease through time. The primary reason for this is that FAPRI baseline prices generally fall in 2009 from the high levels of 2007 and 2008. Therefore, the 2009 benchmark is quite high. Since the state benchmark cannot move by more than 10% per year, the state benchmark is slowly expected to decline through time. The effect is that payments become less frequent.

Table 23: Percent of outcomes where an ACRE payment is triggered for each crop/year in McLean, Illinois

Crop	**2009**	**2010**	**2011**	**2012**	**Total**
Corn	61.7%	38.2%	29.1%	24.3%	92.8%
Soybeans	57.3%	35.9%	23.0%	22.3%	91.6%
Total	70.4%	50.8%	40.0%	33.6%	

Table 24: Percent of outcomes where an ACRE payment is triggered for each crop/year in Sumner, Kansas

Crop	2009	2010	2011	2012	Total
Wheat	70.8%	52.5%	34.7%	26.8%	98.0%
Sorghum	54.6%	37.4%	24.7%	27.4%	91.4%
Total	81.2%	64.2%	46.2%	40.8%	

Table 25: Percent of outcomes where an ACRE payment is triggered for each crop/year in Hale, Texas

Crop	2009	2010	2011	2012	Total
Cotton	40.8%	24.4%	21.2%	19.9%	77.6%
Sorghum	70.9%	48.7%	33.6%	28.5%	97.4%
Total	80.2%	65.2%	47.8%	41.0%	

Table 26: Percent of outcomes where an ACRE payment is triggered for each crop/year in Boliver, Mississippi

Crop	2009	2010	2011	2012	Total
Soybeans	65.2%	44.6%	33.4%	33.8%	97.8%
Cotton	37.2%	19.2%	19.1%	24.1%	77.8%
Rice	28.9%	49.5%	31.6%	20.9%	87.8%
Total	76.6%	70.4%	56.6%	52.6%	

Similarly, the percent of outcomes where total payments under ACRE participation exceeds those under DCP participation are presented in the following next four tables (Table 27, Table 28, Table 29, and Table 30). The total column compares the sum of the payments over the four years for both participation options. The McLean, Illinois and Sumner, Kansas farms both receive larger payments under ACRE participation in over 90% of the outcomes. Unsurprisingly, the Hale, Texas farm has very few outcomes that favor ACRE participation. Most outcomes for Boliver, Mississippi favor ACRE participation, but not as strongly as for the McLean, Illinois and Sumner, Kansas farms.

The cumulative proportions in the total column for the Hale, Texas farm is much smaller than the proportion for any individual year. Conversely, the cumulative proportions in the total columns for the other farms are much larger than any individual year. The benchmark state revenue cannot move by more than 10% per year, so a low or high benchmark is temporally persistent. These results indicate that there is serial correlation, although not perfect, as the cumulative effect is often more extreme than any individual year.

Table 27: Percent of outcomes where ACRE participation payments exceeds DCP participation payments for McLean, Illinois

2009	2010	2011	2012	Total
68.5%	45.5%	34.9%	30.5%	91.0%

Table 28: Percent of outcomes where ACRE participation payments exceeds DCP participation payments for Sumner, Kansas

2009	2010	2011	2012	Total
79.2%	58.5%	38.2%	34.3%	93.8%

Table 29: Percent of outcomes where ACRE participation payments exceeds DCP participation payments for Hale, Texas

2009	2010	2011	2012	Total
6.9%	5.1%	5.0%	4.2%	1.4%

Table 30: Percent of outcomes where ACRE participation payments exceeds DCP participation payments for Boliver, Mississippi

2009	2010	2011	2012	Total
62.0%	55.7%	39.0%	33.2%	82.0%

Thus far the analysis has only considered the total probability of receiving an ACRE payment. However, both the farm and state must show a loss to receive the payment. Table 31, Table 32, Table 33, and Table 34 display the percent of outcomes where the farm received a payment if the state triggered a payment, i.e. $\mathrm{P}\left(\textit{farm revenue} < \textit{farm benchmark} \mid \textit{state revenue} < \textit{state guarantee} \right)$. For every crop and year, the result is about 90% or more with the exception of Sumner, Kansas sorghum.

This is likely due to the weak correlation between farm and state sorghum yields and the low yields for the farm during 2004 to 2008.

Likewise, Table 35, Table 36, Table 37, and Table 38 show the percent of outcomes where the farm received a payment if farm revenue was less than the farm benchmark, i.e. $P(\textit{state revenue} < \textit{state guarantee} \mid \textit{farm revenue} < \textit{farm benchmark})$. Excepting Sumner, Kansas sorghum, these tables had lower values than the previous four. This is in response to two underlying effects. The first is that it is easier for the farm to meet its trigger criteria than the state. The farm benchmark adds the crop insurance premium while the state guarantee is docked 10%. In an average year, the farm will trigger while the state will not. The other effect is that farm yields should be more variable than state yields since state yields are an aggregation of many farms over a large geographical area. Therefore, local effects that could wipe out a farm's crop may only move state yields slightly.

Table 31: Percent of outcomes where the farm received an ACRE payment if state revenue was less than the state guarantee for McLean, Illinois

Crop	**2009**	**2010**	**2011**	**2012**
Corn	100.0%	98.7%	100.0%	99.2%
Soybeans	99.1%	97.3%	97.9%	98.2%

Table 32: Percent of outcomes where the farm received an ACRE payment if state revenue was less than the state guarantee for Sumner, Kansas

Crop	**2009**	**2010**	**2011**	**2012**
Wheat	99.7%	96.0%	88.3%	90.2%
Sorghum	60.6%	51.0%	48.0%	59.2%

Table 33: Percent of outcomes where the farm received an ACRE payment if state revenue was less than the state guarantee for Hale, Texas

Crop	**2009**	**2010**	**2011**	**2012**
Cotton	79.2%	68.0%	69.1%	67.7%
Sorghum	94.0%	80.8%	75.5%	80.7%

Table 34: Percent of outcomes where the farm received an ACRE payment if state revenue was less than the state guarantee for Boliver, Mississippi

Crop	**2009**	**2010**	**2011**	**2012**
Soybeans	99.2%	94.9%	96.8%	98.5%
Cotton	93.9%	89.7%	92.7%	95.6%
Rice	100.0%	100.0%	96.9%	98.1%

Table 35: Percent of outcomes where the farm received an ACRE payment if farm revenue was less than the farm benchmark for McLean, Illinois

Crop	**2009**	**2010**	**2011**	**2012**
Corn	75.6%	61.7%	52.5%	48.3%
Soybeans	69.5%	58.6%	49.0%	45.7%

Table 36: Percent of outcomes where the farm received an ACRE payment if farm revenue was less than the farm benchmark for Sumner, Kansas

Crop	**2009**	**2010**	**2011**	**2012**
Wheat	74.6%	66.7%	65.6%	56.3%
Sorghum	93.7%	84.8%	64.2%	58.4%

Table 37: Percent of outcomes where the farm received an ACRE payment if farm revenue was less than the farm benchmark for Hale, Texas

Crop	**2009**	**2010**	**2011**	**2012**
Cotton	55.7%	49.6%	42.2%	42.3%
Sorghum	79.7%	73.0%	57.2%	48.1%

Table 38: Percent of outcomes where the farm received an ACRE payment if farm revenue was less than the farm benchmark for Boliver, Mississippi

Crop	**2009**	**2010**	**2011**	**2012**
Soybeans	81.2%	72.4%	64.0%	59.1%
Cotton	62.4%	51.6%	46.5%	50.1%
Rice	51.4%	65.6%	60.1%	54.7%

Although average total payments under ACRE and DCP are an important part of the analysis, the insurance effect of farm bill programs is also important. Economic actors are often willing to invest in an asset with a negative expected value if the asset has an income smoothing effect on the actor's bundle of assets. For example, many people purchase insurance policies with a loss ratio less than one to decrease their liability. While some of the farms clearly had higher average payments under either ACRE or DCP, the consideration of income risk could change the optimal program for the farm.

Figure 3, Figure 4, Figure 5, and Figure 6 display three points of the distribution of the sum of market payments and government receipts for each year. McLean, Illinois and Sumner, Kansas have similar distributions. In a good revenue year, ACRE and DCP perform about the same. ACRE results in larger payments in an average revenue year. In the lower tail of the distributions, ACRE participation results in much higher revenue. This result is not surprising since ACRE is meant to combat years of low revenue. Boliver, Mississippi is similar except that revenue has a slightly higher potential under DCP. For this farm, ACRE narrows the revenue distribution. Hale, Texas' revenue distribution is drastically different than the other three farms. DCP outperforms ACRE at every level. LDPs and CCPs safeguard revenue more than ACRE for this farm.

Figure 3: Distribution of the sum of market revenues and government payments for McLean, Illinois

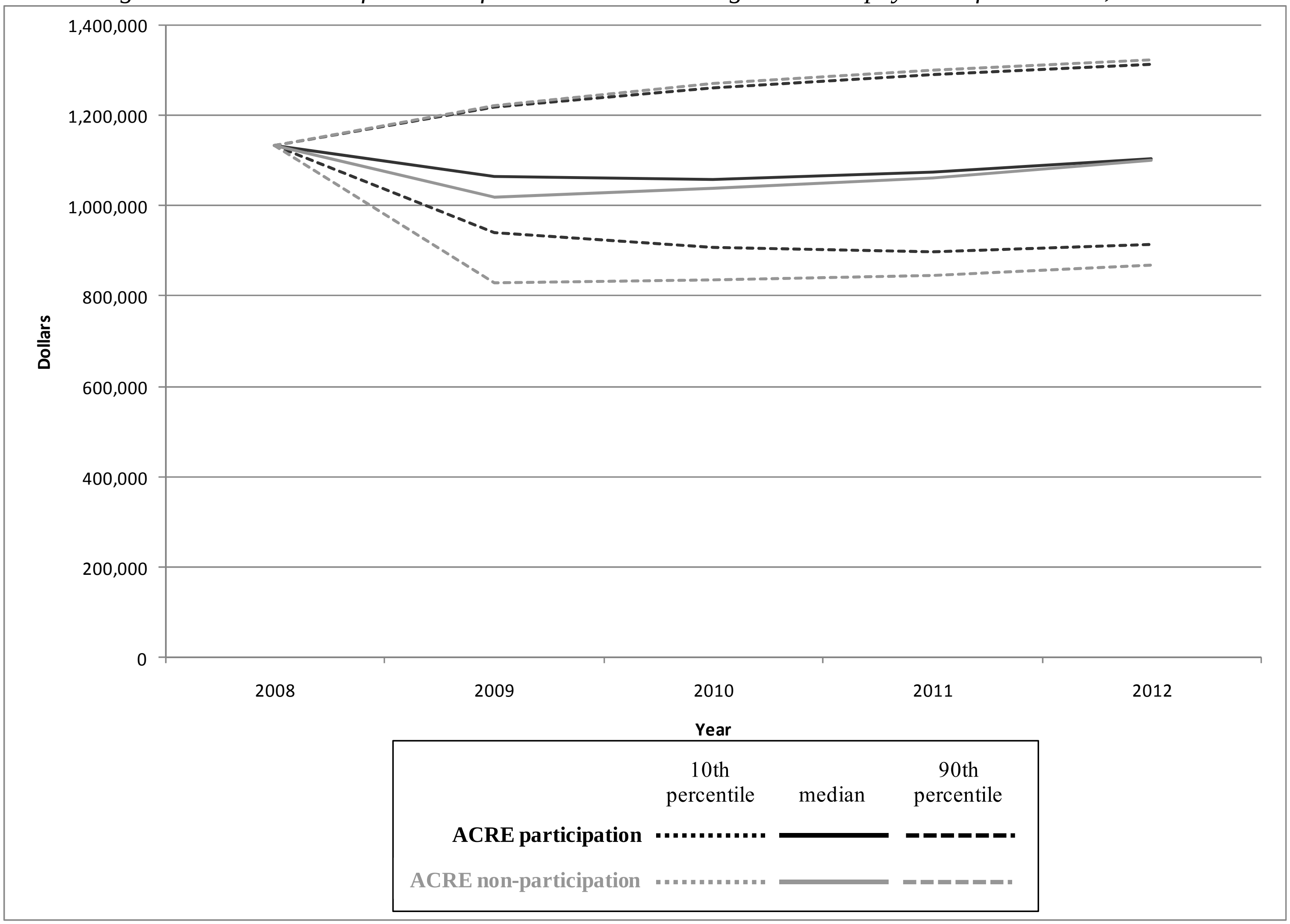


Figure 4: Distribution of the sum of market revenues and government payments for Sumner, Kansas

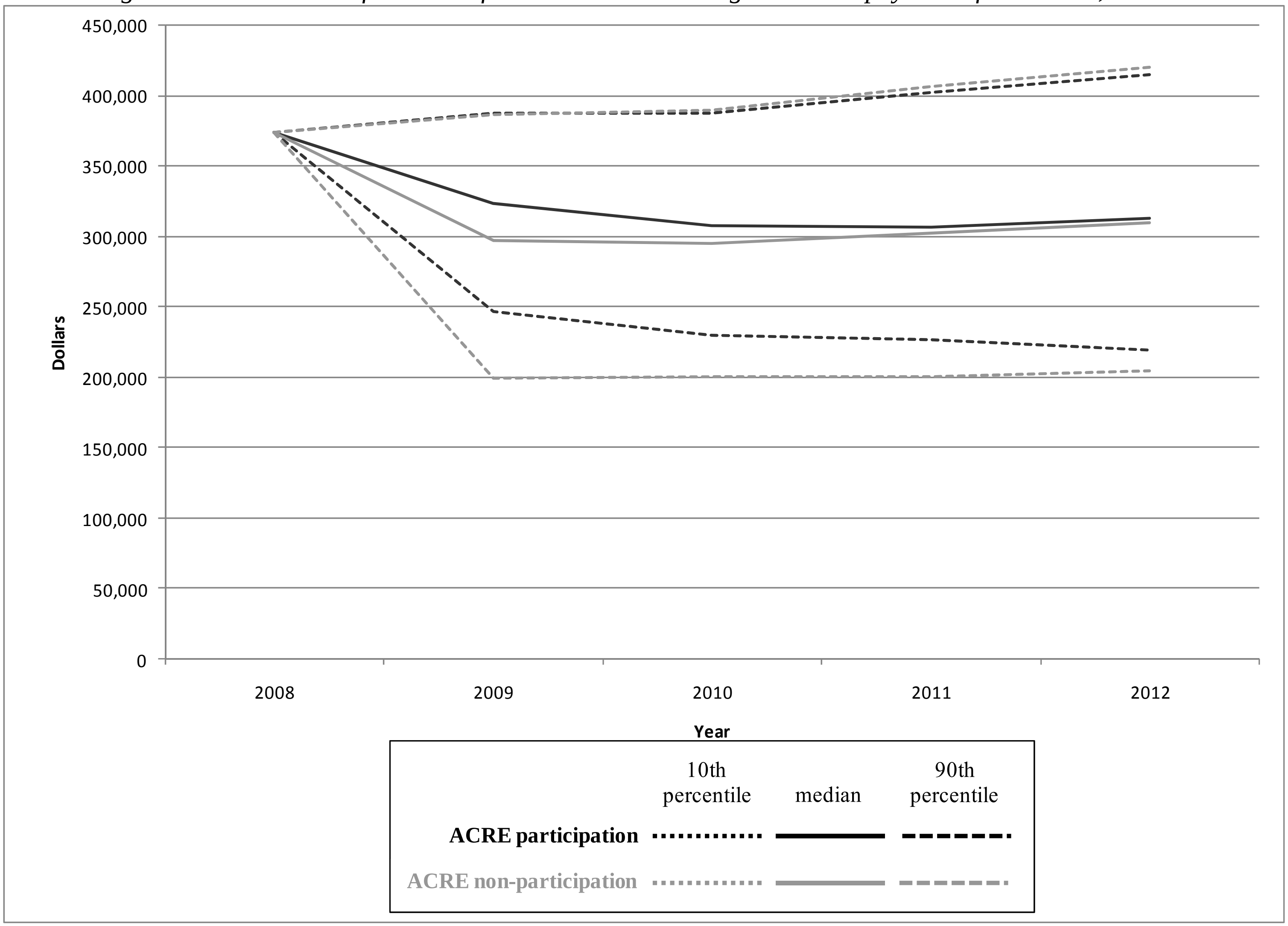


Figure 5: Distribution of the sum of market revenues and government payments for Hale, Texas

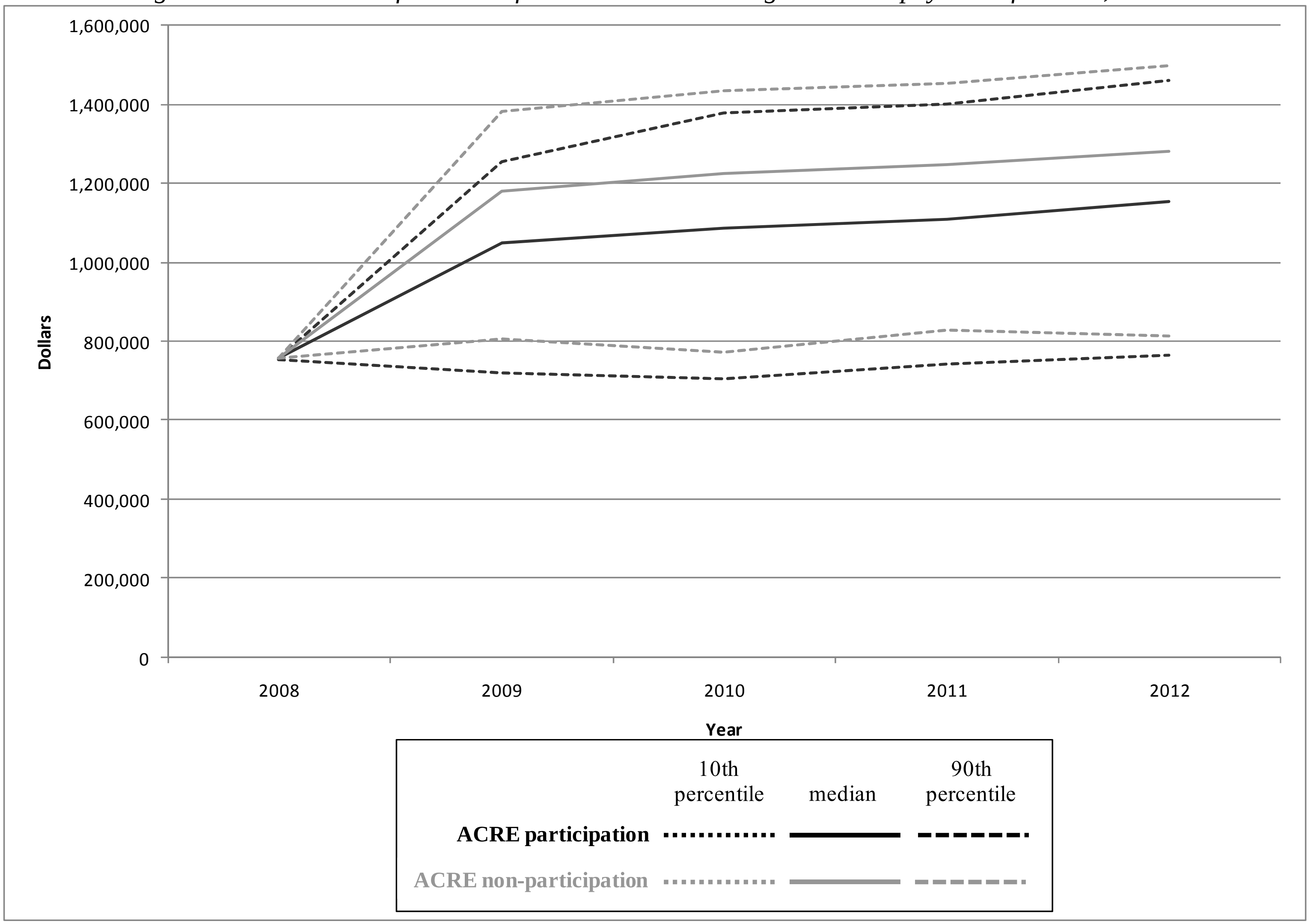
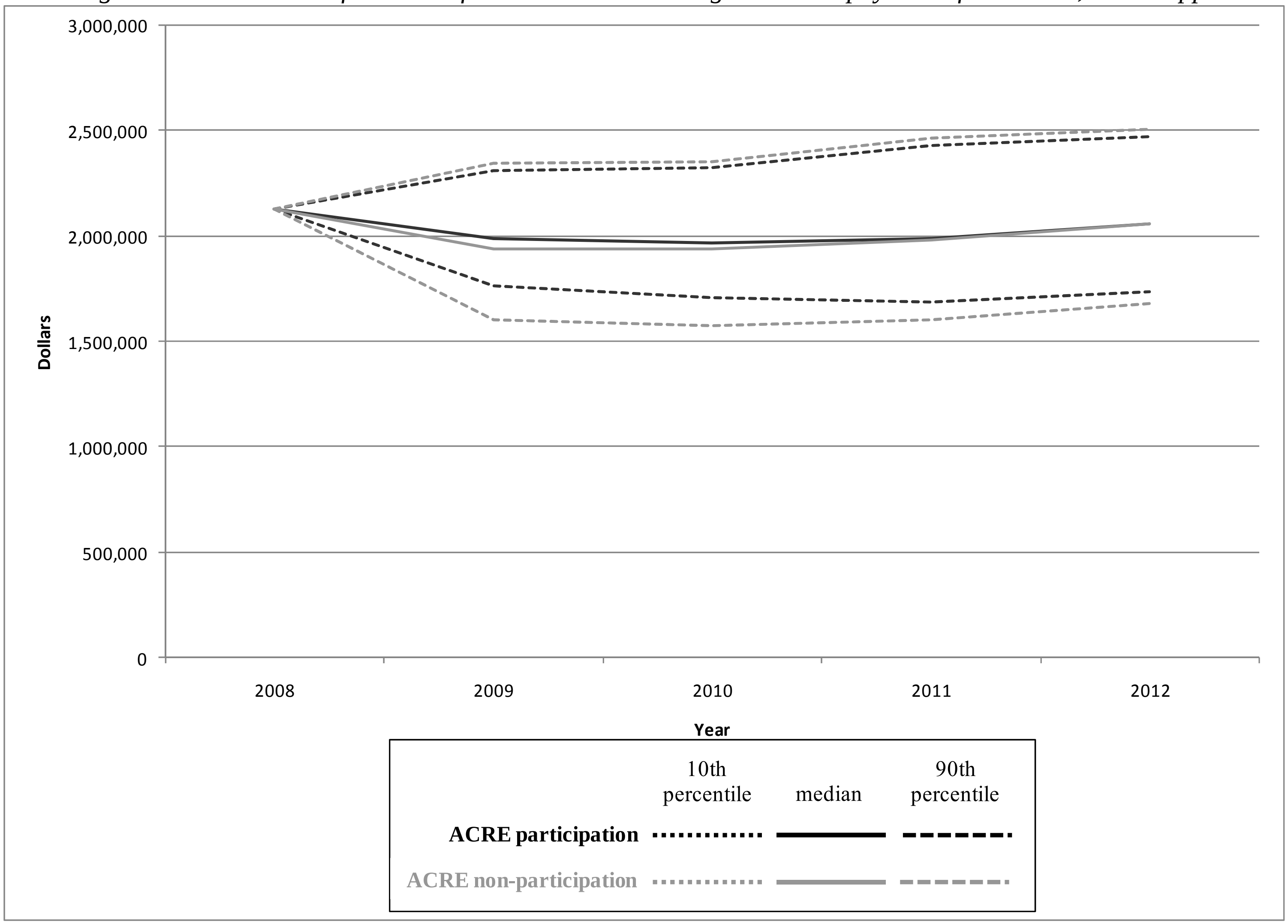


Figure 6: Distribution of the sum of market revenues and government payments for Boliver, Mississippi



Thus far, the expected value and distribution of ACRE participation and non-participation has been considered. For the McLean, Illinois; Sumner, Kansas; and Boliver, Mississippi farms ACRE participation has higher expected payments and a positive effect on the revenue distribution. ACRE is the obvious choice for those three farms under the current assumptions. On the other hand, Hale, Texas has higher expected payments and revenue distribution benefits under ACRE non-participation. Staying with DCP is the obvious choice for this farm under the current assumptions. Ideally, all this information would be combined into one metric to sort out ambiguities that could occur in scenarios. A more advanced technique is necessary to determine the optimal decision under potentially ambiguous conditions.

The tool employed for the task was Stochastic Efficiency with Respect to a Function (SERF) using Simulation and Econometrics To Analyze Risk (SIMETAR) software (2008). SERF analysis uses a utility function to find the Certainty Equivalent (CE) of payoffs. The Risk Aversion Coefficients (RACs) are allowed to vary within a range. The result is the same as stochastic efficiency analysis, only no assumptions are made about risk aversion. While such analysis is usually based on net income, revenues in this case should still provide reasonable analysis if we treat production costs in each year as sunk.

Risk aversion can be grouped into two types: absolute and relative. Absolute risk aversion is concerned with actual dollar amounts while relative risk aversion is concerned with the share of wealth. With absolute risk aversion, \$10 extra provides as much utility to actors whether they have \$100 or \$1,000 of wealth. On the other hand, with relative risk aversion \$10 extra provides as much utility to an actor with \$100 of wealth as \$100 extra would if the actor had $1,000 of wealth. Richardson (2008) recommends using the following Relative RACs (RRACs) based on Anderson and Dillon's work from 1992:

Table 39: Relative risk aversion coefficients

RRAC	**Corresponds to:**
0.0	Risk neutral
0.5	Hardly risk adverse
1.0	Normal or somewhat risk adverse
2.0	Rather risk adverse
3.0	Very risk adverse
4.0	Extremely risk adverse

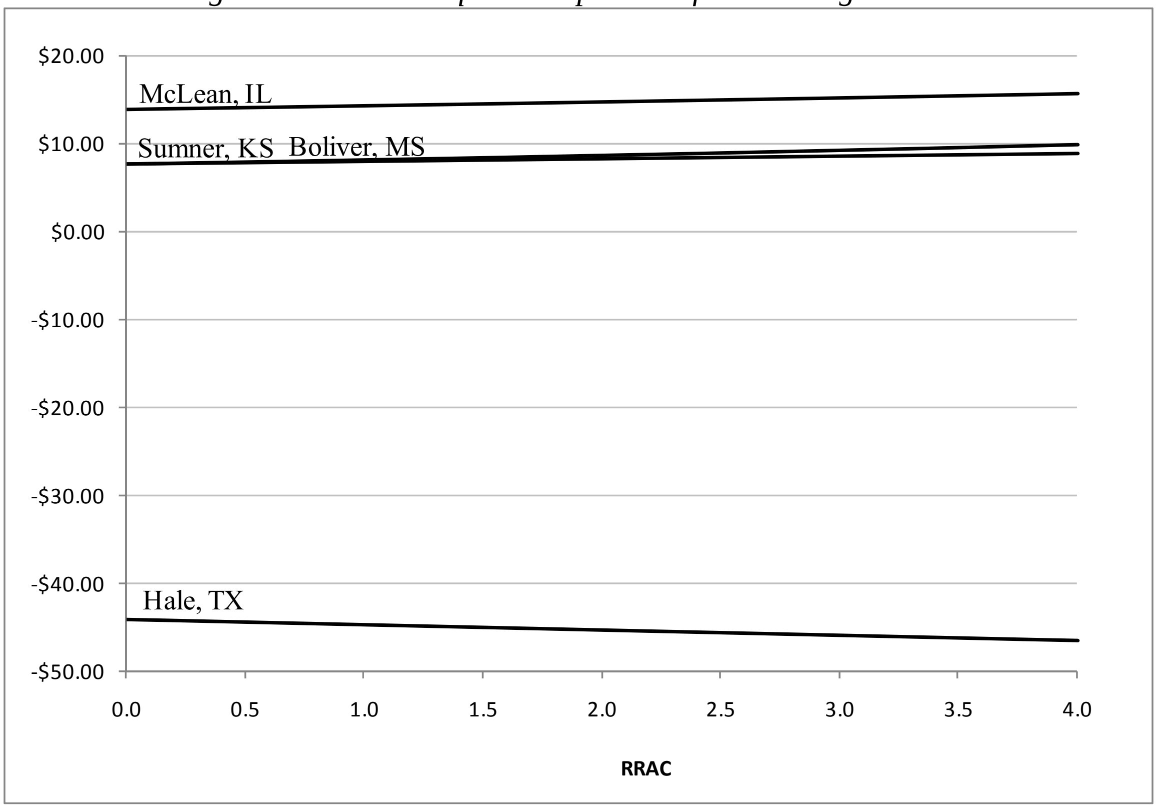
A power utility function with RRACs is used for the analysis. According to SIMETAR, for wealth, *w*, the function is defined as:

(39) $$\mathrm{U}(w) = \frac{w^{1-RRAC}}{1-RRAC}$$

An initial wealth of zero was assumed. While this should decrease the effect of risk on CEs, using revenues instead of net income has the opposite effect. They should be at least partially offsetting.

The four years of farm revenues were converted to a present value using an estimated current ag interest rate of 4.75% (T. Gerlt, personal communication, April 7, 2009). After a CE was calculated for each RRAC under ACRE participation and ACRE non-participation, the latter was subtracted from the former. This created a total risk premium that the producer would be willing to pay to enroll in ACRE over staying in DCP. The total risk premium was divided by the sum of planted acres over the four years. This result represents the premium per acre for enrolling in ACRE. The results are presented in Figure 7.

Figure 7: Premium equivalent per acre for enrolling in ACRE



Consistent with the prior analysis, the McLean, Illinois; Sumner, Kansas; and Boliver, Mississippi farms gain from ACRE enrollment while Hale, Texas would lose. The first three show that ACRE reduces risk as the premium equivalent increases with the level of risk aversion. On the other hand, ACRE enrollment increases risk for Hale, Texas as indicated by the curve that decreases with the level of risk aversion.

CHAPTER 6: ALTERNATIVE SCENARIOS

Although the Chapter 5 results are inherently useful, they can also be used to provide a benchmark against which to compare scenarios. The underlying assumptions about the farm can be altered to extract the sensitivity of the results. Furthermore, the program parameters can be adjusted to test their significance. This chapter reports results from undertaking such analysis to provide answers to some of the most relevant questions.

6.1 Scenario 1: Alternate enrollment years

For the previous analysis, it was assumed the farm was enrolled in ACRE in 2009. However, the farm can be enrolled in any year during the life of the program (2009 through 2012). Naturally, this provision begs the question, "How does waiting to enroll affect the farm's benefits?"

Figure 8, Figure 9, Figure 10, and Figure 11 display the SERF analysis for the enrollment timing scenarios. For each farm, the premium tends to zero as the enrollment delay is increased. This is expected since not enrolling in ACRE would be equivalent to a $0.00 premium. As a result, the influence of DCP increases with the delay of ACRE enrollment. This also forces the insurance effect of ACRE to decrease with delay. The SERF lines tend to flatten with the delay because of this effect.

The analysis in the next charts is heavily dependent on the chosen price path for crops for 2009 through 2012. Projected prices fall in 2009 from the 2007-2008 average of MYA prices which are used to set the 2009 ACRE benchmark. As a result, ACRE payments are expected to be highest in 2009 and decrease through 2012. Additionally, for most crops, prices increase after 2010. These price movements explain the decreasing marginal effect of enrollment delay. However, for the farms that favored ACRE under the baseline, ACRE benefits decrease with the enrollment delay. Given the price assumptions, the optimal behavior for the representative farms would be to enroll starting in 2009.

Figure 8: Premium equivalent per acre for McLean, Illinois for enrolling in ACRE starting in…

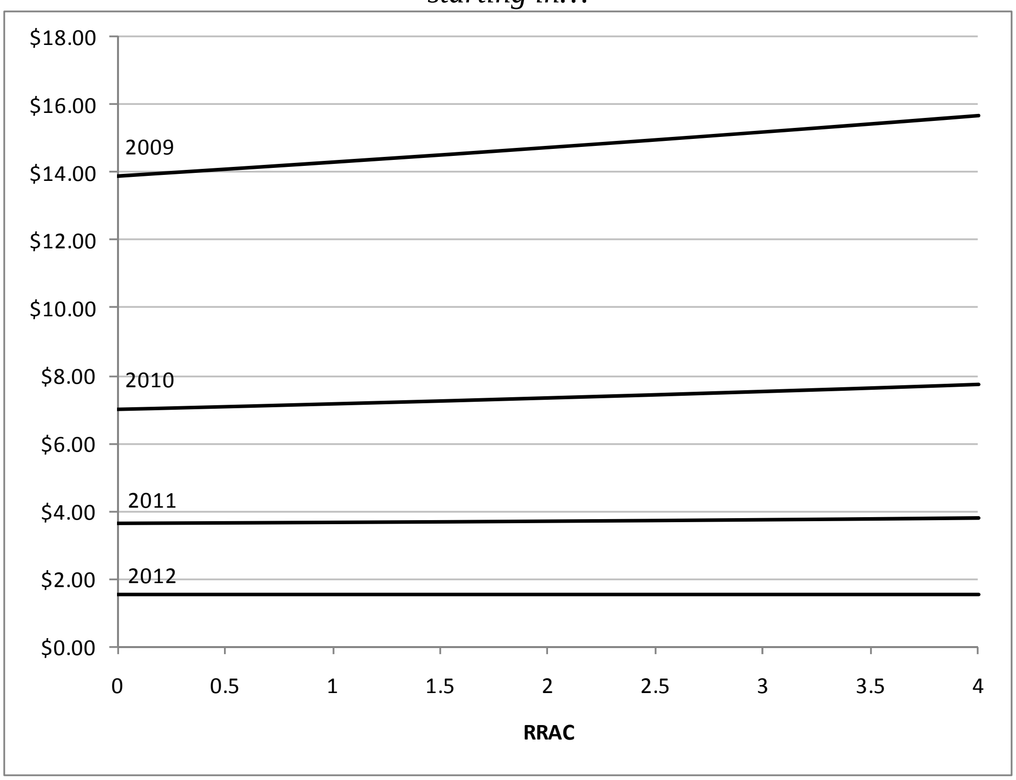


Figure 9: Premium equivalent per acre for Sumner, Kansas for enrolling in ACRE starting in…

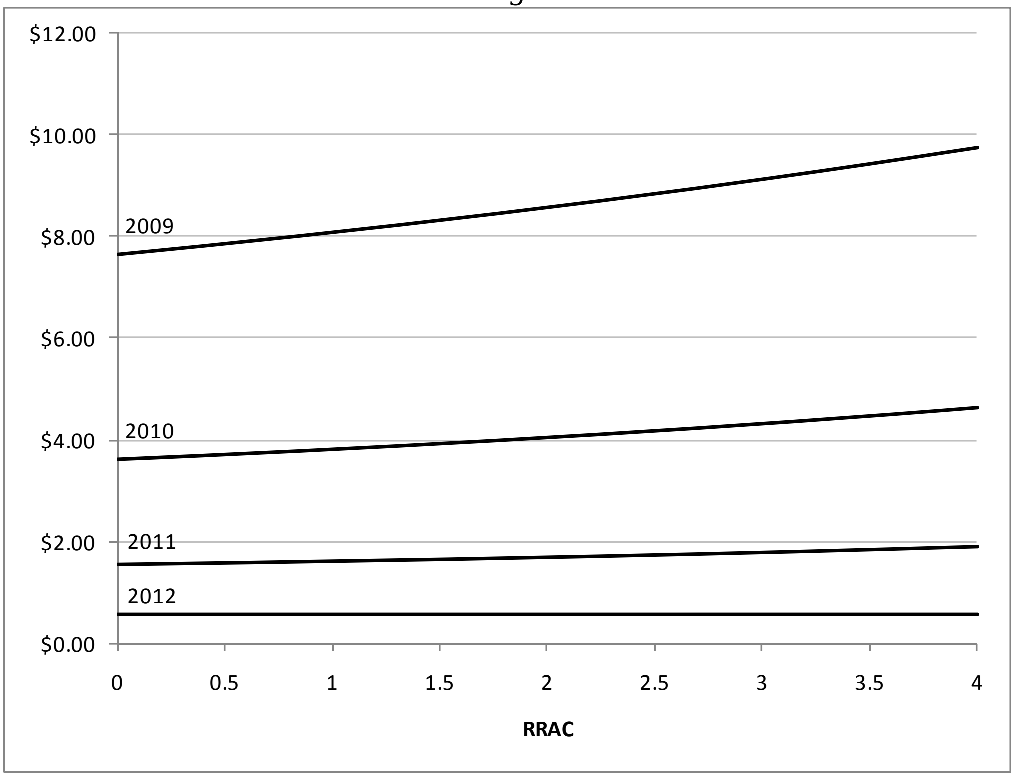


Figure 10: Premium equivalent per acre for Hale, Texas for enrolling in ACRE starting in…

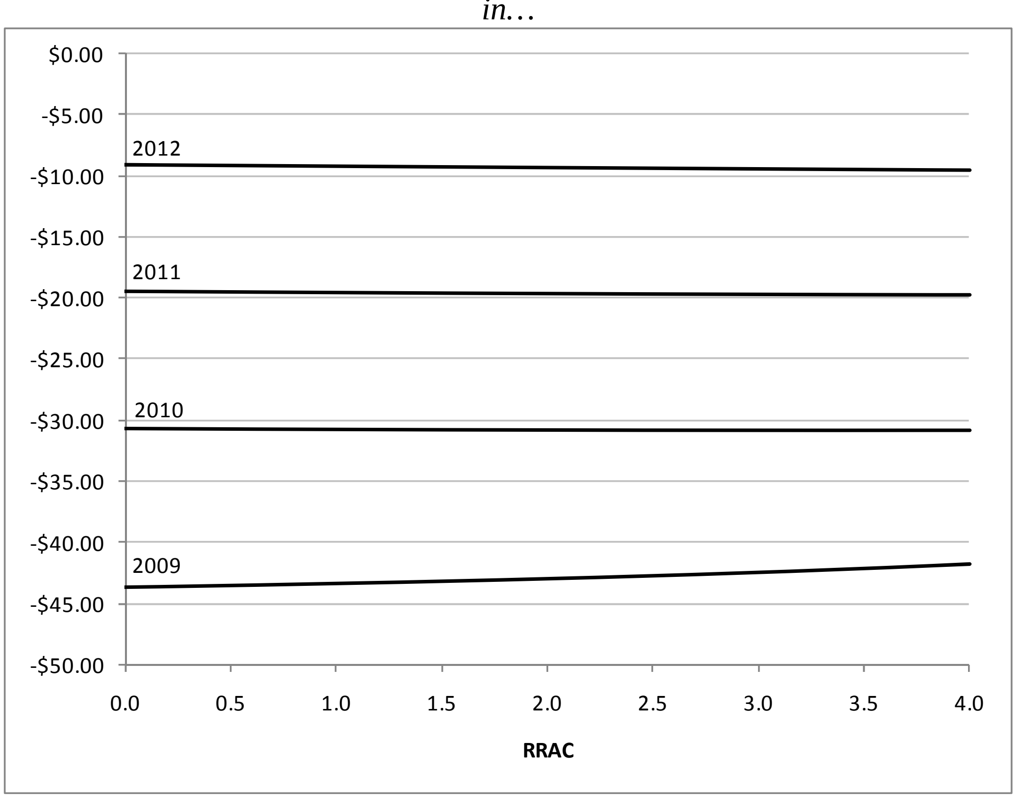
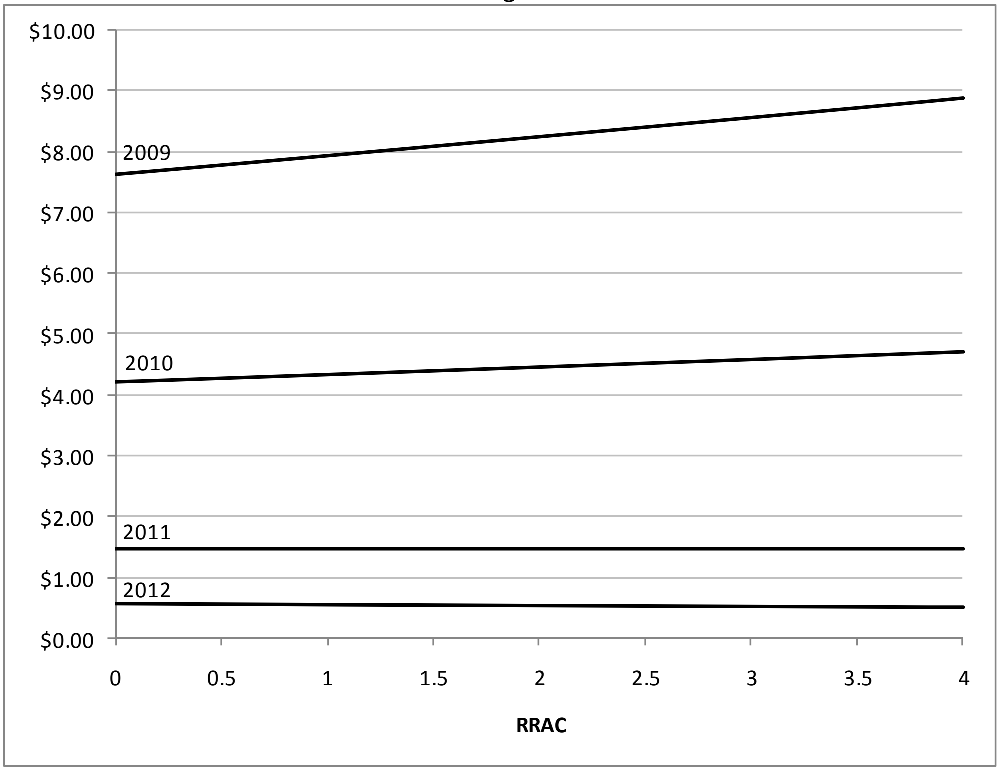


Figure 11: Premium equivalent per acre for Boliver, Mississippi for enrolling in ACRE starting in…

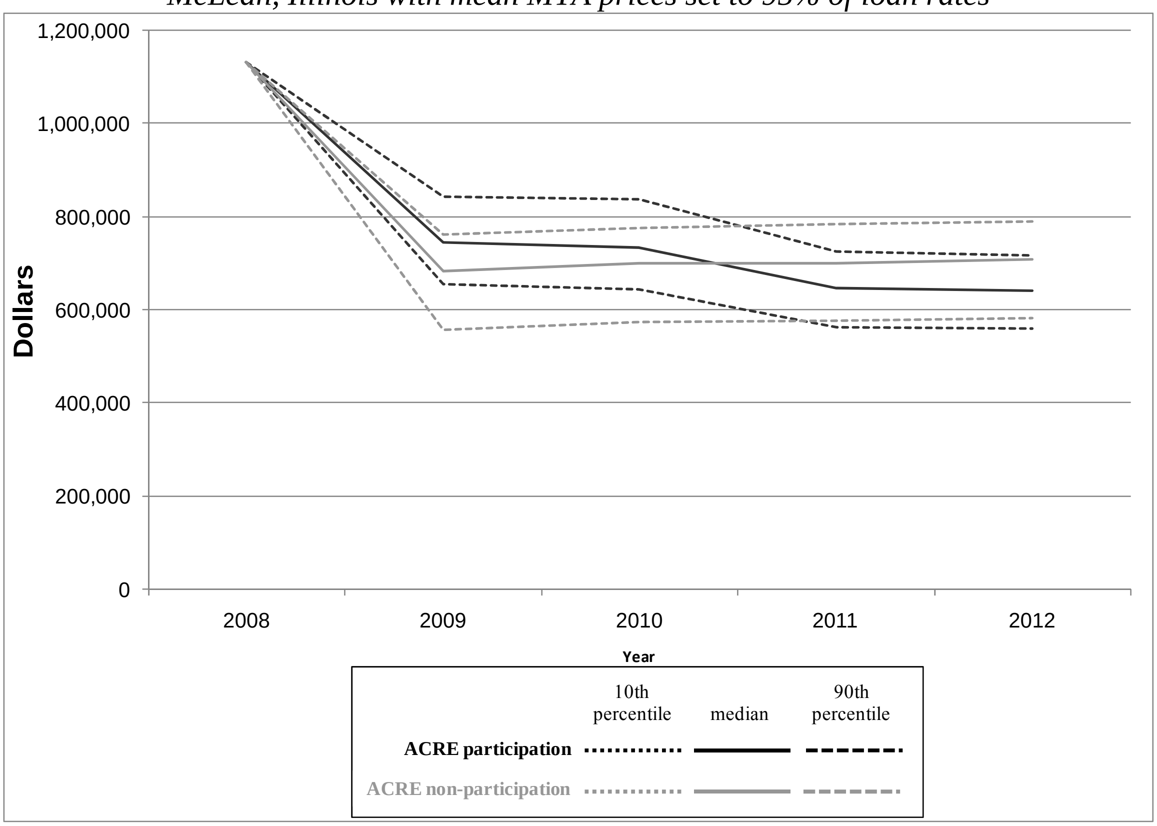


6.2 Scenario 2: Mean MYA prices below loan rate

A key assumption for all ACRE analysis is the MYA price path. With the exception of cotton, every crop in the analysis has had a mean price path well above loan rates and target prices. As a result, farms without much cotton base tend to earn more payments with ACRE enrollment. However, how are results affected if prices drop low enough to trigger loan program benefits and CCPs for non-participants in ACRE? The mean MYA price for each year was dropped to 95% of the loan rate. This was done by multiplying each of the 1,000 prices by the ratio of 95% of the loan rate to the old price mean. It is worth noting that this does decrease the variance of the price distributions. This price change will trigger LDPs and CCPs under DCP on average for the farm without triggering ACRE LDPs on average.

Inducing such a change to prices will trigger high ACRE payments initially. Since the state benchmark and farm guarantee are based on a moving two year average price, both will fall over time, but the 10% rule will ease the transition. The end result will be revenues declining with time. On the other hand, under DCP market revenues plus payments will fall to a level and stay there. While the two year price continues to fall under ACRE, DCP prices will remain level. As a result, in the beginning ACRE will probably yield larger payments, but after a couple of years DCP will become the higher paying program (Figure 12).

Figure 12: Distribution of the sum of market revenues and government payments for McLean, Illinois with mean MYA prices set to 95% of loan rates



The adjustments were made to prices and the analysis rerun. As expected, ACRE benefits decreased for each farm (

Figure 13, Figure 14, Figure 15, and Figure 16). In fact, DCP is now the optimal program for the Sumner, Kansas and Boliver, Mississippi farms. ACRE benefits dropped about 50% for Illinois but this is not enough to change the ACRE decision for the farm. Hale, Texas already favored DCP, so the optimal decision remains the same for it.

Figure 13: Premium equivalent per acre for McLean, Illinois for enrolling in ACRE under alternate mean prices

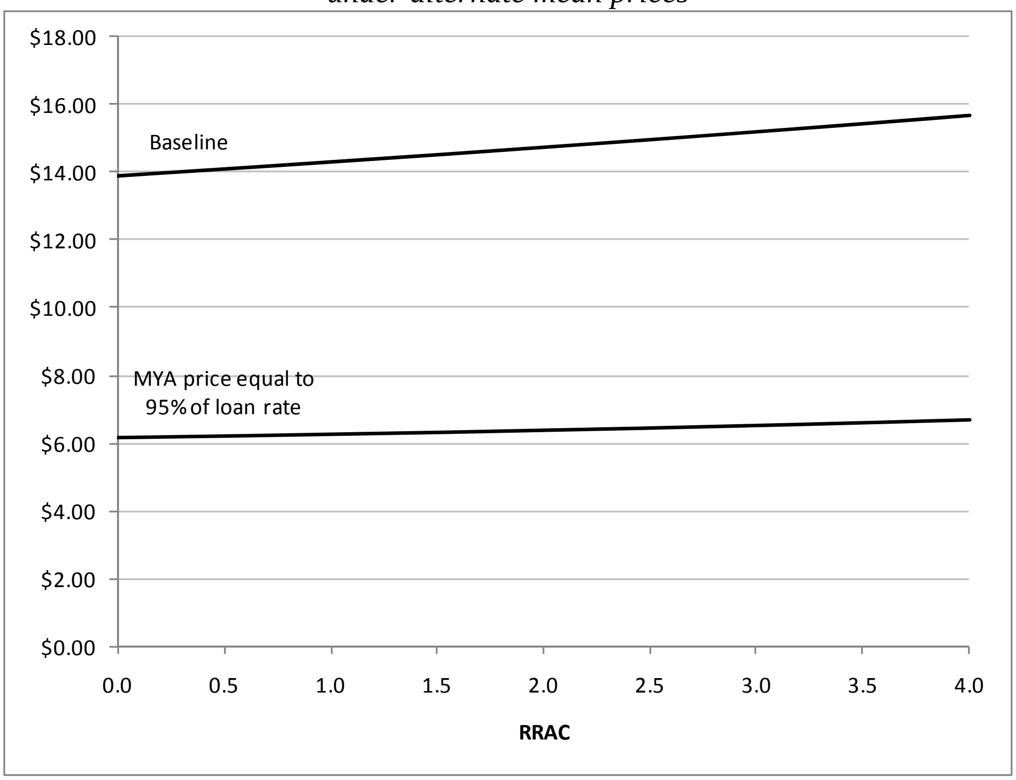


Figure 14: Premium equivalent per acre for Sumner, Kansas for enrolling in ACRE under alternate mean prices

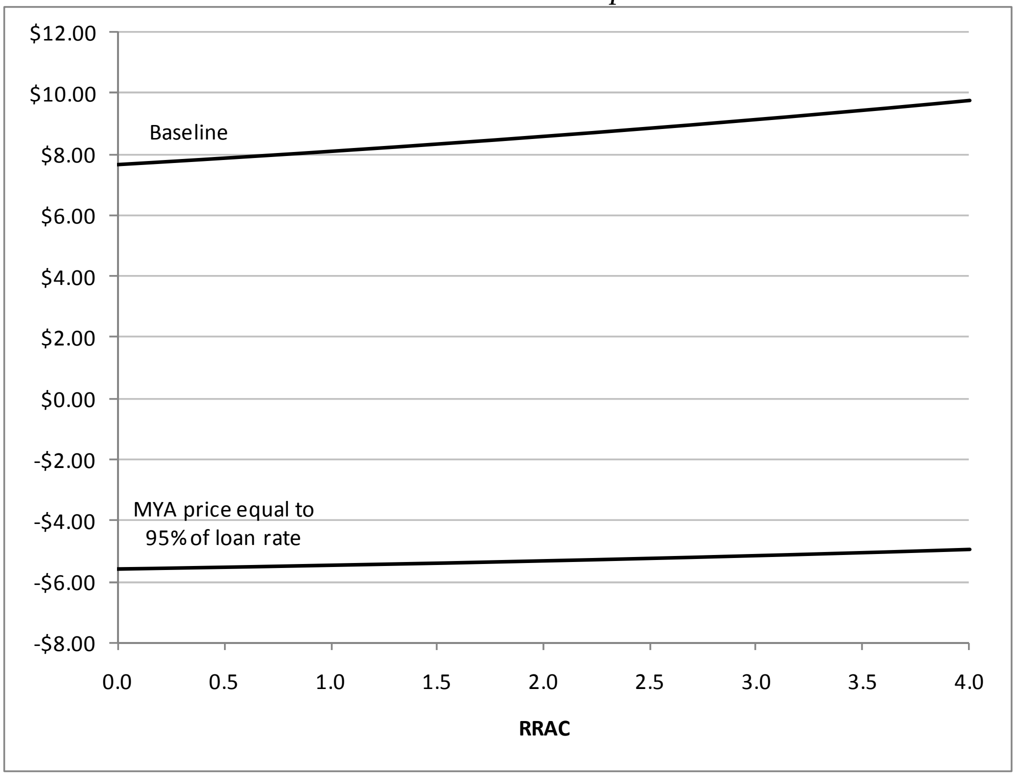


Figure 15: Premium equivalent per acre for Hale, Texas for enrolling in ACRE under alternate mean prices

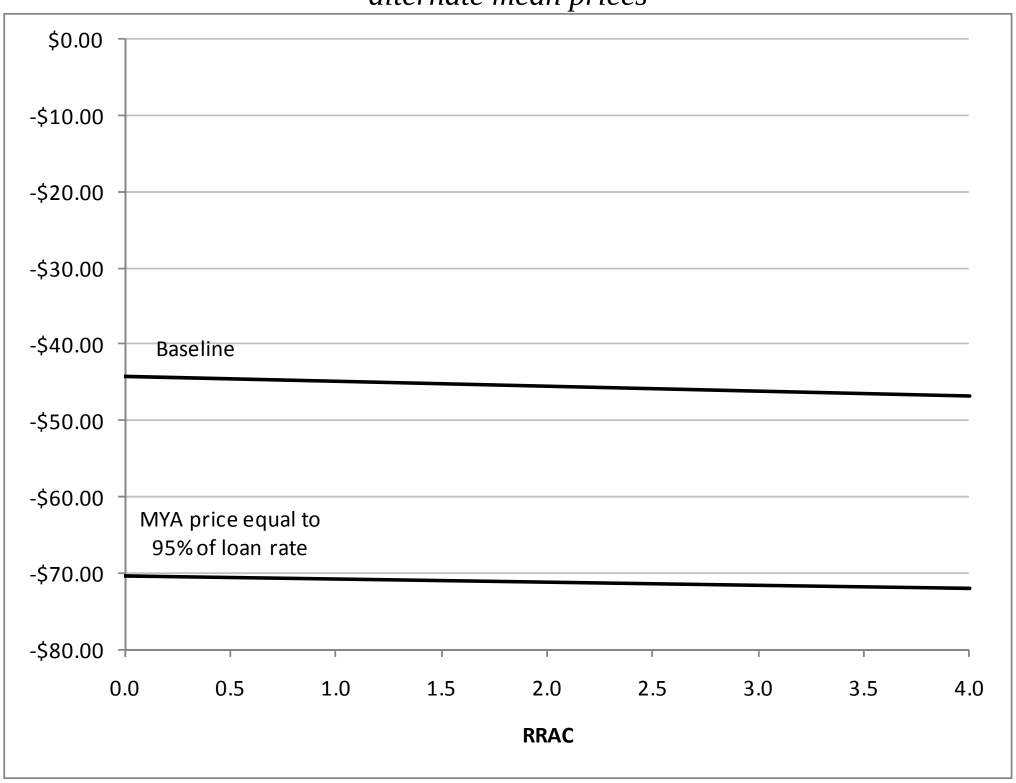
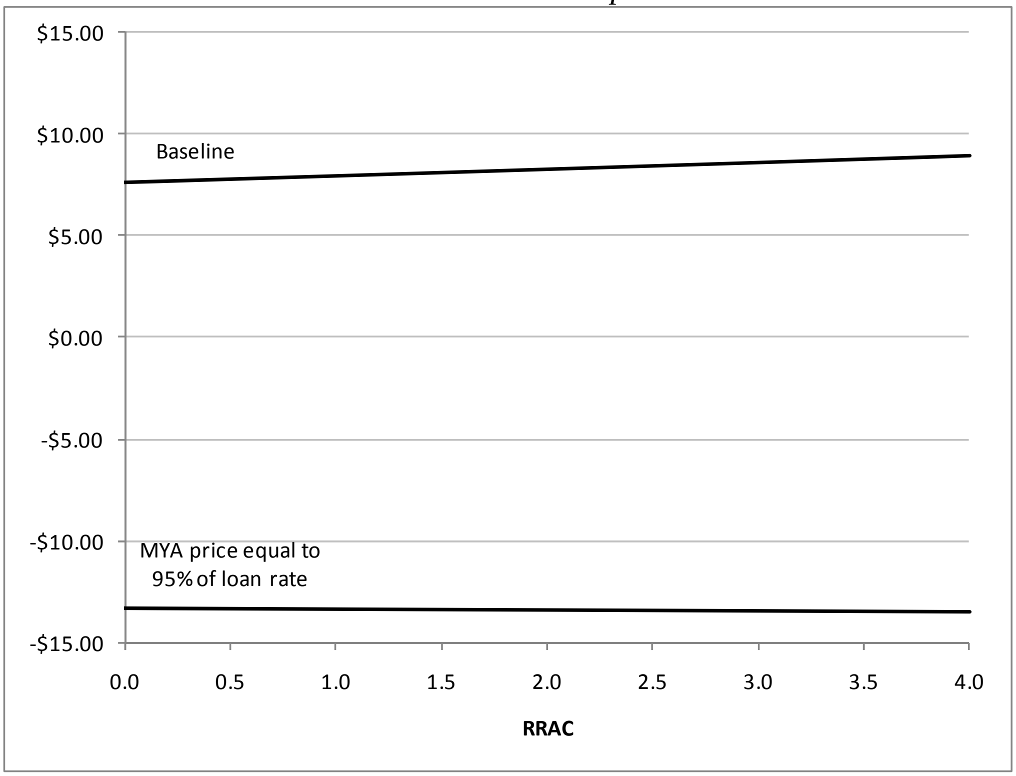


Figure 16: Premium equivalent per acre for Boliver, Mississippi for enrolling in ACRE under alternate mean prices



An important factor not considered in this scenario is payment limits. All payments have a limit per person involved on the farm except LDPs. Considering payment limitations would tend to make ACRE participation less attractive to producers as DCP would generate large, uncapped LDPs while ACRE would generate limited payments. This factor was omitted from the scenarios because the results are heavily dependent on assumptions about the number of people involved in the operation and the extent to which payment limits can be avoided through legal reorganization strategies.

6.3 Scenario 3: Alternate state payment limits

An important component of the ACRE payment formula is that the state payment rate cannot exceed 25% of the state benchmark revenue. This rule is in addition to the payment limits per entity. Those restrict total payments per individual whereas the 25% payment rate rule restricts the state ACRE payment rate. ACRE payments are still subject to payment limits.

Zulauf reports that the most commonly purchased crop insurance policies have a 75% coverage level (2008). The 25% payment rate rule is designed to prevent the overlap of the ACRE program and crop insurance. Yet, without empirical analysis it is hard to determine the importance of 25% payment rate rule. Furthermore, the rate could potentially be decreased to assist with World Trade Organization (WTO) compliance. Sensitivity of the results to the payment rate limit was observed by comparing the baseline against scenarios of a 10% payment rate limit and of no payment rate limit.

For every farm, removing the payment limit increases ACRE's benefits and lowering it decreases ACRE's net benefits to producers (
Figure 17, Figure 18, Figure 19, and Figure 20) which is consistent with expectations. Removing the limit seems to decrease the per acre premium equivalent by about $2.00. The exception is McLean, Illinois where there is hardly any change. This indicates that the state was hardly ever reaching the 25% limit. The natural revenue hedge for the Illinois likely creates this result. The only scenario where altering the limit would change the optimal program is the 10% limit for the Boliver, Mississippi farm. At that level DCP would be the optimal choice for the farm.

Figure 17: Premium equivalent per acre for McLean, Illinois for enrolling in ACRE under different state payment limits

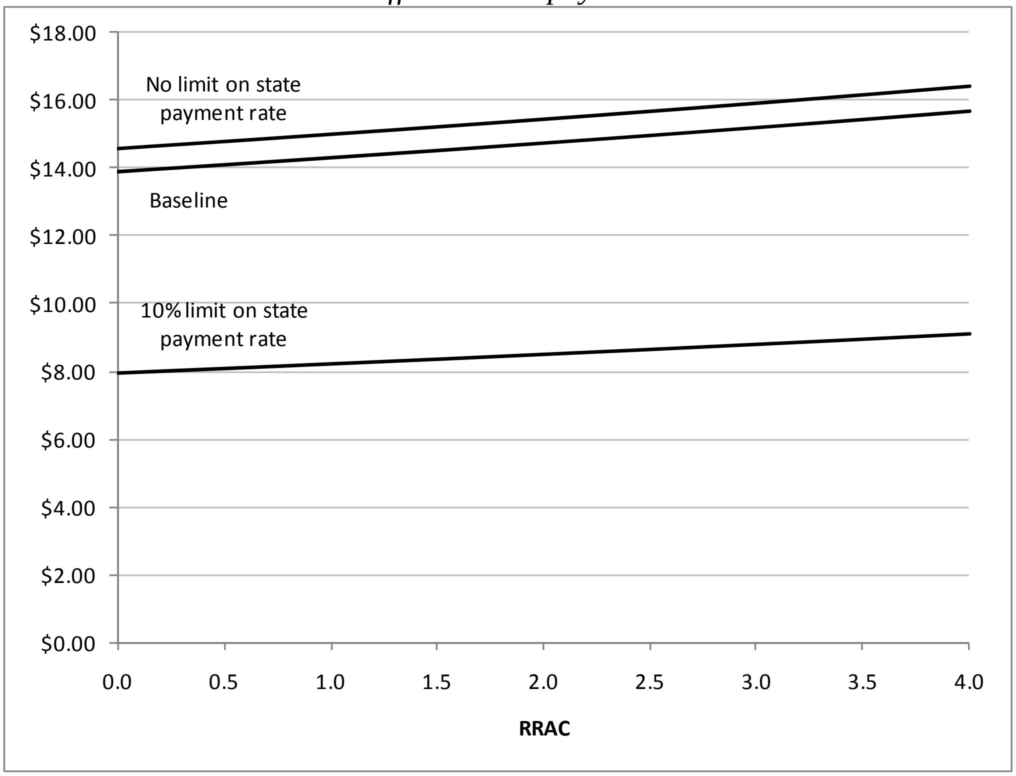


Figure 18: Premium equivalent per acre for Sumner, Kansas for enrolling in ACRE under different state payment limits

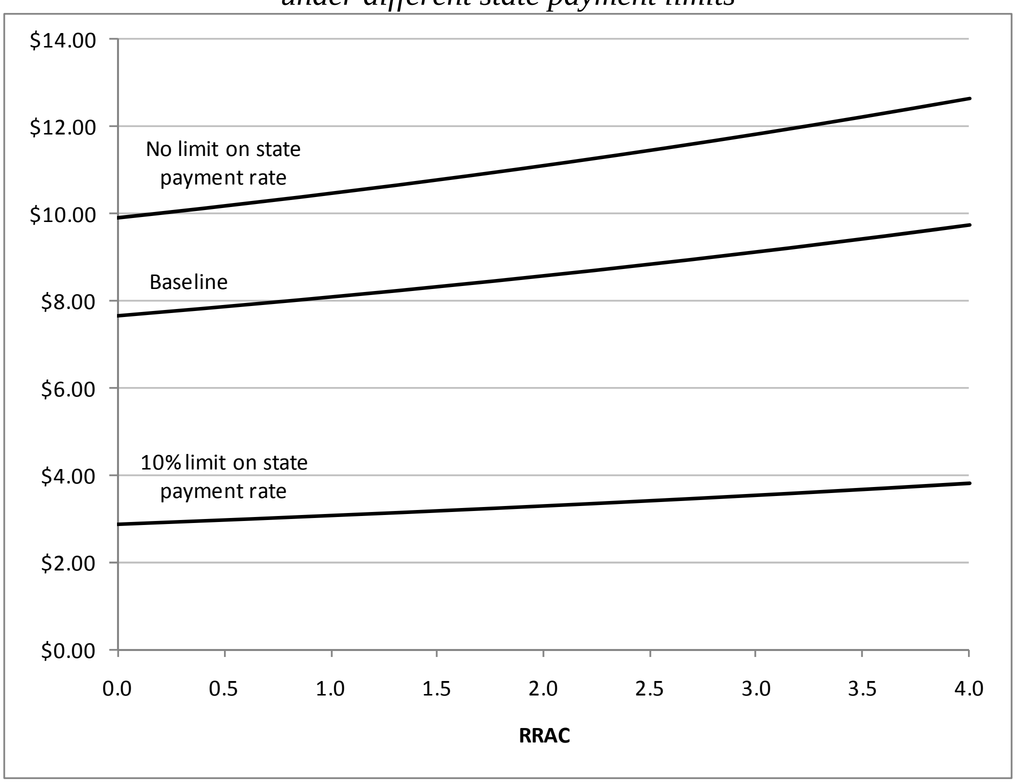


Figure 19: Premium equivalent per acre for Hale, Texas for enrolling in ACRE under different state payment limits

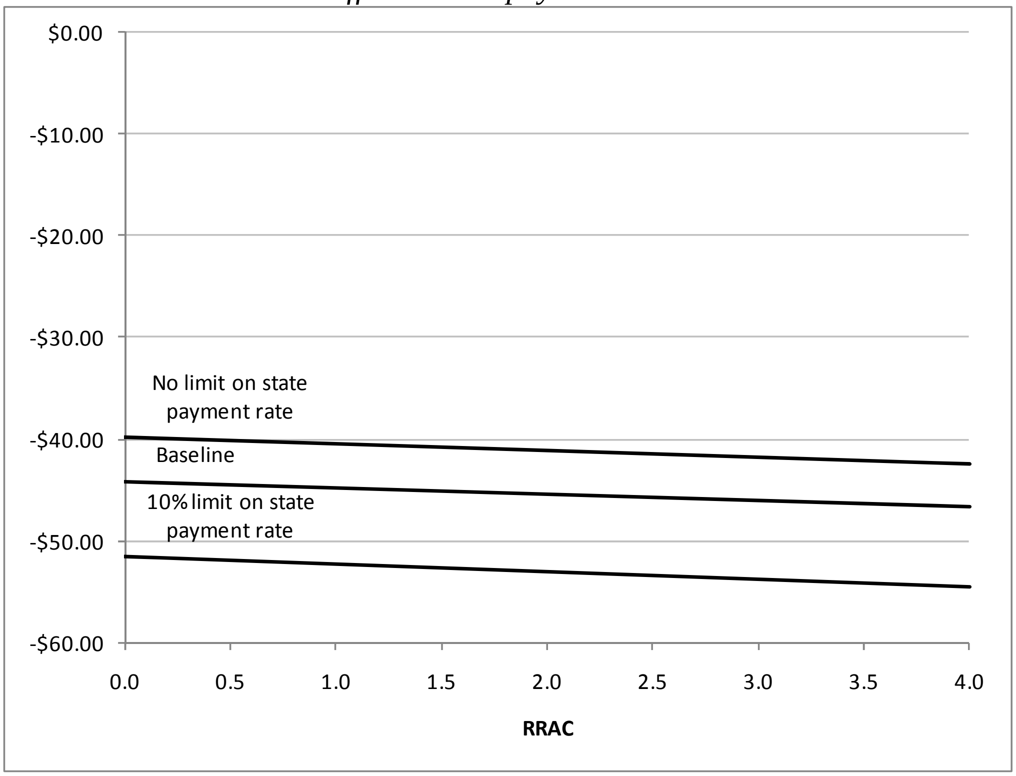
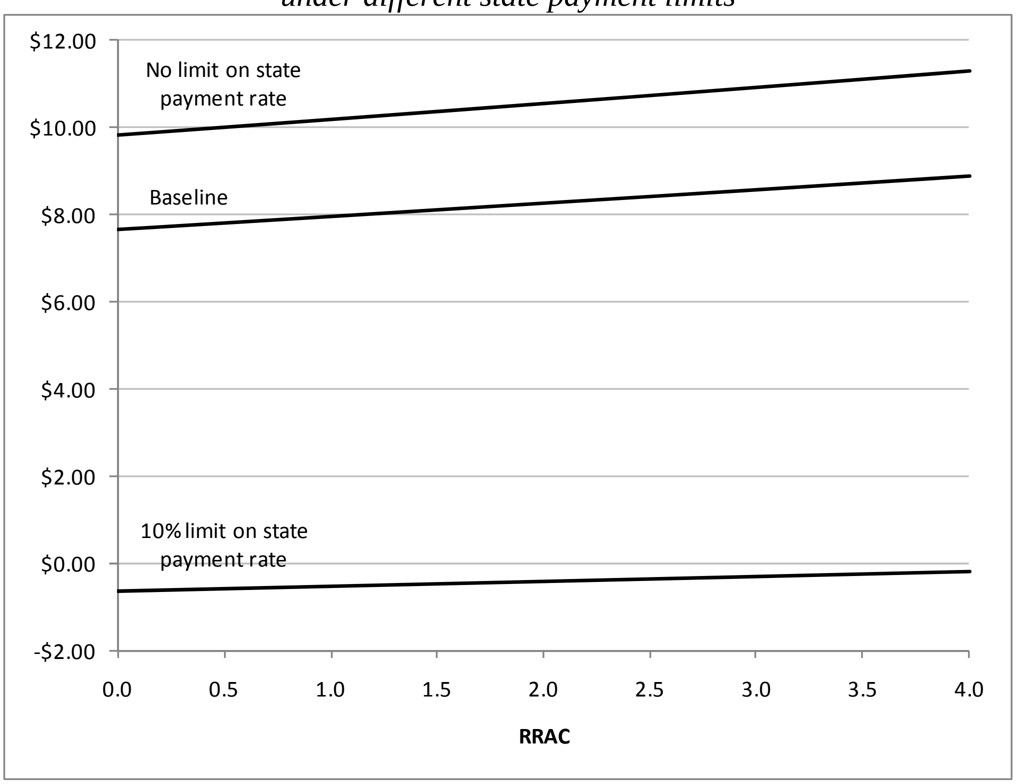


Figure 20: Premium equivalent per acre for Boliver, Mississippi for enrolling in ACRE under different state payment limits



6.4 Scenario 4: Alternate base acre allocations

The last scenario examines the effects of different levels of base acres. Planted acres are assumed to remain constant. In reality, this is not the case but it provides results that can easily be compared to the baseline. For example, if the Boliver, Mississippi farm substituted planted cotton acres into rice or soybeans, the results would favor ACRE participation more heavily.

An increase in base acres tips the scales in favor of ACRE as long as total planted acres do not exceed 83.3% (85% in 2012) of base acres. Beyond that point, only the reduced DPs are increasing under ACRE. However, the full DPs and CCPs are increasing under DCP.

Table 40, Table 41, Table 42, and Table 43 display the effects on the Net Present Value (NPV) of ACRE minus foregone payments of varying base acres as a percent of planted acres. McLean, Illinois and Sumner, Kansas have very similar results. Both slightly favor DCP when there are with zero base acres. This follows from the fact that LDPs are the only payment received with no base and LDPs must always be higher under DCP due to the higher loan rate under that program. The effects of increasing sorghum base relative to planted acres on the Sumner, Kansas farm are modest since it has so few planted acres of the crop.

For most crops on most farms, the NPV of ACRE minus foregone payments is maximized when base acres are 80% to 100% of planted acres. This is consistent with the aforementioned expectations. Beyond the 85% level, DCP payments are increasing faster than ACRE participation payments. Below that level, ACRE outperforms DCP per base acre on these two farms. Therefore, increasing base increases the total difference.

These two effects converge to form a maximum around 85%. Besides cotton, the notable exception to this is the McLean, Illinois farm. ACRE net benefits are maximized with soybean base equal to 200% of planted acres and no corn base. This is because neither crop triggers LDPs nor CCPs and soybean DPs are much less for the farm. 200% of soybean planted acres 83% of total planted acres. The net effect is still the proper amount of base but with lower foregone payments.

Hale, Texas presents a very different story from the first two farms. Sorghum base has a positive effect on ACRE up to the 85% level. Conversely, cotton only has a negative effect. Since this farm is predominately cotton, that crop dominates the outcomes. Even with zero cotton base acres, the LDPs foregone on cotton outweigh the ACRE benefits of sorghum. Within the range of base acres examined, DCP is always the optimal program for the Hale, Texas representative farm.

Perhaps the most interesting farm in this scenario is Boliver, Mississippi. Once again, cotton base only has a negative effect on ACRE participation while soybeans and rice have a positive effect. Therefore, the maximum benefit of ACRE is achieved with no cotton base acres and soybean and rice base acres that are 80% to 100% of planted acres. As cotton base increases and soybean and rice base move away from the 100% level, the ACRE benefits to producers over DCP diminish. In some cases, DCP becomes the optimal program. In reality, cotton base acres can be many times the amount of cotton planted acres further decreasing the ACRE advantages.

Table 40: Average NPV of ACRE minus foregone payments for McLean, Illinois, dollars

	Corn base acres as a percent of planted corn acres										
Soybean base acres as a percent of planted soybean acres	0%	20%	40%	60%	80%	100%	120%	140%	160%	180%	200%
0%	-538	12,450	25,438	38,426	51,413	64,401	77,389	90,377	88,531	84,481	80,431
20%	10,001	22,988	35,976	48,964	61,951	74,939	87,927	91,075	87,025	82,975	78,925
40%	20,539	33,526	46,514	59,502	72,490	85,477	93,619	89,569	85,519	81,470	77,420
60%	31,077	44,065	57,052	70,040	83,028	95,847	92,114	88,064	84,014	79,964	75,914
80%	41,615	54,603	67,590	80,578	93,566	94,658	90,608	86,558	82,508	78,458	74,408
100%	52,153	65,141	78,128	91,116	97,202	93,152	89,102	85,052	81,002	76,952	72,903
120%	62,691	75,679	88,667	99,715	95,696	91,646	87,596	83,547	79,497	75,447	71,397
140%	73,229	86,217	99,205	98,240	94,190	90,141	86,091	82,041	77,991	73,941	69,891
160%	83,767	96,755	100,784	96,735	92,685	88,635	84,585	80,535	76,485	72,435	68,385
180%	94,305	103,329	99,279	95,229	91,179	87,129	83,079	79,029	74,979	70,930	66,880
200%	104,844	101,823	97,773	93,723	89,673	85,623	81,574	77,524	73,474	69,424	65,374

Table 41: Average NPV of ACRE minus foregone payments for Sumner, Kansas, dollars

	Wheat base acres as a percent of planted wheat acres										
Sorghum base acres as a percent of planted sorghum acres	0%	20%	40%	60%	80%	100%	120%	140%	160%	180%	200%
0%	-192	9,601	19,394	29,187	38,979	48,750	46,193	43,494	40,795	38,096	35,397
20%	1,844	11,637	21,430	31,223	41,016	48,430	45,731	43,032	40,333	37,635	34,936
40%	3,881	13,674	23,467	33,259	43,052	47,969	45,270	42,571	39,872	37,173	34,474
60%	5,917	15,710	25,503	35,296	45,089	47,507	44,808	42,109	39,410	36,711	34,012
80%	7,954	17,747	27,540	37,332	47,125	47,045	44,346	41,647	38,948	36,249	33,550
100%	9,990	19,783	29,576	39,369	49,140	46,583	43,884	41,185	38,486	35,787	33,088
120%	12,027	21,820	31,612	41,405	48,820	46,121	43,422	40,723	38,024	35,325	32,626
140%	14,063	23,856	33,649	43,442	48,358	45,659	42,960	40,261	37,562	34,863	32,164
160%	16,100	25,892	35,685	45,478	47,896	45,197	42,498	39,799	37,100	34,401	31,702
180%	18,136	27,929	37,722	47,515	47,434	44,735	42,036	39,337	36,638	33,939	31,240
200%	20,172	29,965	39,758	49,529	46,972	44,273	41,574	38,875	36,176	33,477	30,778

Table 42: Average NPV of ACRE minus foregone payments for Hale, Texas, dollars

Sorghum base acres as a percent of planted sorghum acres	Cotton base acres as a percent of planted cotton acres: 0%	20%	40%	60%	80%	100%	120%	140%	160%	180%	200%
0%	-208,032	-239,539	-271,045	-302,551	-334,058	-375,334	-434,621	-493,908	-553,195	-612,481	-671,768
20%	-205,418	-236,924	-268,430	-299,937	-331,443	-375,835	-435,122	-494,409	-553,696	-612,982	-672,269
40%	-202,803	-234,309	-265,816	-297,322	-328,828	-376,336	-435,623	-494,910	-554,197	-613,483	-672,770
60%	-200,188	-231,695	-263,201	-294,707	-326,214	-376,837	-436,124	-495,411	-554,698	-613,984	-673,271
80%	-197,574	-229,080	-260,587	-292,093	-323,599	-377,338	-436,625	-495,912	-555,199	-614,485	-673,772
100%	-194,959	-226,466	-257,972	-289,478	-320,985	-377,839	-437,126	-496,413	-555,700	-614,986	-674,273
120%	-192,345	-223,851	-255,357	-286,864	-319,309	-378,340	-437,627	-496,914	-556,201	-615,487	-674,774
140%	-189,730	-221,236	-252,743	-284,249	-319,555	-378,841	-438,128	-497,415	-556,702	-615,988	-675,275
160%	-187,116	-218,622	-250,128	-281,635	-320,056	-379,342	-438,629	-497,916	-557,203	-616,489	-675,776
180%	-184,501	-216,007	-247,514	-279,020	-320,557	-379,843	-439,130	-498,417	-557,704	-616,990	-676,277
200%	-181,886	-213,393	-244,899	-276,405	-321,058	-380,344	-439,631	-498,918	-558,204	-617,491	-676,778

Table 43: Average NPV of ACRE minus foregone payments for Boliver, Mississippi, dollars

Cotton base acres as a percent of planted cotton acres	Soybean and rice base acres as a percent of respective planted acres: 0%	20%	40%	60%	80%	100%	120%	140%	160%	180%	200%
0%	-42,030	7,148	56,326	105,504	154,682	177,236	163,680	150,124	136,569	123,013	109,457
20%	-48,778	400	49,578	98,756	147,934	164,525	150,969	137,413	123,857	110,301	96,745
40%	-55,526	-6,348	42,830	92,008	141,186	151,813	138,257	124,701	111,145	97,590	84,034
60%	-62,275	-13,097	36,081	85,259	134,437	139,102	125,546	111,990	98,434	84,878	71,322
80%	-69,023	-19,845	29,333	78,511	127,689	126,390	112,834	99,278	85,722	72,167	58,611
100%	-75,771	-26,593	22,585	71,763	120,941	113,679	100,123	86,567	73,011	59,455	45,899
120%	-82,520	-33,342	15,836	65,015	113,694	100,967	87,411	73,855	60,299	46,743	33,188
140%	-89,268	-40,090	9,088	58,266	101,811	88,255	74,700	61,144	47,588	34,032	20,476
160%	-96,016	-46,838	2,340	51,518	89,100	75,544	61,988	48,432	34,876	21,320	7,765
180%	-102,764	-53,586	-4,408	44,770	76,388	62,832	49,277	35,721	22,165	8,609	-4,947
200%	-109,513	-60,335	-11,157	38,021	63,677	50,121	36,565	23,009	9,453	-4,103	-17,659

CHAPTER 7: SUMMARY AND CONCLUSIONS

This study used four representative farms to analyze the ACRE program created in the 2008 Farm Bill. The farms were based on the counties of McLean, Illinois; Sumner, Kansas; Hale, Texas; and Boliver, Mississippi. Each farm was chosen to represent a different region and crop production mixture.

Each farm required state and farm yield forecasts for every crop grown. These were projected using a trend yield based on 30 years of history. Errors from the trend yield were used to create 1,000 potential yields for every crop at the state and farm level. These yields were then correlated with the FAPRI stochastic prices to create a matrix of stochastic input variables to analyze ACRE for each farm.

The strongest conclusion drawn from the analysis is that cotton producers are unlikely to find ACRE participation attractive given the assumptions in this study. The Hale, Texas representative farm would forego large LDPs and CCPs to enroll in ACRE. Even under alternative scenarios, the farm earned larger payments participating in ACRE. The Boliver, Mississippi representative farm also had cotton but favored ACRE. The cotton acres were a small enough percentage of total acres that ACRE was the optimal program for the farm. However, under alternative scenarios, the farm does under some conditions earn more payments with DCP. All other crops considered (corn, soybeans, rice, wheat, and grain sorghum) favored ACRE. Given the regions where these crops are grown, these results are consistent with prior FAPRI analysis and Coble and Dismuke's analysis.

However, this conclusion assumes a price path that declines in 2009 but then increases for most crops. The analysis indicates that prices falling below the loan rate could change the optimal program. This was the case for the Sumner, Kansas and Boliver, Mississippi representative farms. ACRE benefits declined for the McLean, Illinois representative farm but did not change the optimal program. If prices should rise over time, ACRE may not be the optimal program for producers as it will not trigger payments except in the case of a sharp yield reduction larger than the increase in prices.

If the assumed FAPRI baseline price path where mean prices fall in 2009 and then increase is correct, then the optimal year to enroll in ACRE is 2009. 2009 should have the highest payments and succeeding years will face ever declining ACRE payments on average as the state benchmark decreases and/or actual revenues increase. Furthermore, the more years a farm is enrolled in ACRE the more likely it will trigger an ACRE payment during the life of the program.

However, even though these general conclusions seem to hold, the gains from ACRE are unique to each farm. Several of the farms had non-empty intersections of the sets of crops grown. These common crops had differing returns for different farms. This is largely due to non-identical correlations and farm program parameters. For instance, soybeans were grown on the Illinois and Mississippi farms. However, Mississippi received higher average ACRE payments than Illinois for soybeans. This can largely be explained by two correlations. The Boliver, Mississippi farm had a stronger yield correlation with its state yield than did the McLean, Illinois farm, and Mississippi had a weaker correlation between state yields and national prices. The result is that Mississippi had a weaker price/yield hedge than Illinois. This results in payments being triggered more often. Furthermore, since the Boliver farm and Mississippi state yields are more strongly correlated than McLean's and Illinois, the two trigger criterion of ACRE is less likely to be binding. This also results in higher payments.

Similarly, farm program parameters are a nontrivial component of determining the optimal farm program. The type and amount of base acres can change the results of the analysis. For example, adjusting the state payment rate limit changed the optimal program for the Boliver, Mississippi farm. Additionally, the amount of base acres was also shown to change the qualitative results in certain cases.

All of the above factors are important components of the ACRE enrollment decision. Farm specific analysis is appropriate to aide individual producers in making the choice, but this analysis does provide several generalities to help guide the decision. While ACRE is a complex program, this study does show that it can have large payoffs and deserves careful consideration.

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