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# **ACRE: A Revenue-Based Alternative to Price-Based Commodity Payment Programs**

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# **ACRE: A Revenue-Based Alternative to Price-Based Commodity Payment Programs**

## **Abstract**

This paper develops a stochastic model for estimating the probability density function of the Average Crop Revenue Election (ACRE), a revenue-based commodity support payment that is offered under the 2008 Farm Act as an alternative to the traditional suite of price-based commodity payments, that is, marketing loan benefits and counter-cyclical payments. We minimize the potential for miss-specification bias in the model by using nonparametric and semi-nonparametric approaches as specification checks in the model. Our simulation results show that adding ACRE revenue payments to gross revenue reduced the downside risk in revenue for corn, wheat, and soybean farmers in 2009 in the four locations examined, with reductions ranging from 4% to 25%. Integrating Federal crop insurance with ACRE lowered insurance premiums from 10% to 40%, depending on the crop and location. A utility maximization approach is used to assess potential moral hazard effects of ACRE, and suggest little potential impact on acreage in the Heartland.

## **Key words**

Domestic support, average crop revenue election, loan deficiency payments, counter-cyclical payments, revenue, price, corn, yield, pairs bootstrap, kernel density, semi-nonparametric, combinatorial optimization, negative exponential utility function

## **A Revenue-Based Alternative to the Counter-Cyclical Payment Program**

### **Introduction**

Interest in revenue-based commodity support is evident in the Food, Conservation and Energy Act of 2008 (the 2008 Farm Act), which gives eligible producers the option of participating in the Average Crop Revenue Election (ACRE) program rather than in the traditional programs. ACRE differs in important ways from traditional commodity programs. The latter — that is, marketing loan benefits or counter cyclical payments — are triggered when market prices fall below statutory price floors (loan rates and target prices). These prices are fixed for the life of the Farm Act legislation (ERS, 2008).

In contrast, ACRE makes payments based on State gross crop revenue per acre (price times yield per acre) and, thus, provides a degree of yield as well as price protection. In particular, ACRE is designed as an income safety net that covers a portion of the shortfall in State-level revenue losses relative to a State level expected revenue (a “guarantee revenue” in the parlance of the ACRE program). With some limitations on how much it can change from year-to-year, the ACRE revenue guarantee also uses recent market prices, rather than fixed target prices, to set the level of protection, which makes the program relatively flexible in being able to address contemporary market conditions.

While a fair number of studies have been published that empirically examine the impacts of commodity-support on production (e.g., Sckokai and Moro, 2006; Goodwin and Mishra, 2006; Anton and Le Mouel, 2004; and Hennessy, 1998), the academic literature is thin on examinations of the implication of the empirical distribution of

commodity support payments for both government policy and for producer preferences.

However, there are a variety of policy-relevant reasons to examine the probability density function of commodity support payment. For example, under the rather broad aegis of “income safety net”, to what extent do the ACRE payments offset the farmer’s downside revenue risks? To what extent does ACRE cover revenue risk that is addressed by Federal crop insurance? In particular, to what extent could crop insurance premiums be decreased if ACRE payments are considered part of farm revenue for the purposes of calculating actuarially correct crop insurance premiums? Since farmers are generally considered to be non-neutral in their risk preferences, and risk averse in particular, if ACRE payments reduce risk, what impacts might ACRE have on crop production?

The goal of this paper is to develop and estimate a stochastic model for estimating potential ACRE revenue support payments to corn, soybean, and wheat producers in a variety of locations that will be used to address policy issues raised above. Before turning to the model, we provide a brief background on the ACRE program as well the as traditional suite of commodity support programs.

## **Background**

The eligible producer of a covered commodity can choose to elect to receive ACRE revenue payments in lieu of receiving counter-cyclical payments and in exchange for a 20-percent reduction in direct payments (a fixed annual payment) and a 30-percent reduction in marketing assistance loan rates. The grower can make this irrevocable election for the 2009-2012, 2010-2012, 2011-2012, or the 2012 crop years.

Average Crop Revenue Election (ACRE) is a State-based revenue guarantee for participants based on the 5-year State average yield and the 2-year national average price. ACRE provides producers with payments for a commodity when for the crop year: 1) the actual state revenue for the commodity is less than the revenue guarantee; and 2) the farmer's actual revenue is less than the farmer's expected revenue for the eligible crop.

The ACRE revenue payment (denoted as ACRE) to producer  $i$  of crop  $j$  in period  $t$  is (leaving out the State subscript):

$$1) \quad ACRE_{ijt} = \Phi_{ijt} \cdot \max \{ 0, \min[(0.25 \cdot PGR_{tj}), (PGR_{tj} - ASR_{tj})] \} \cdot \frac{E(Y_{ij})}{E(YS_{jt})} \cdot \{0.85$$

or 0.83 depending on the year\} \cdot (A\_{ij}),

where the ACRE Program Guarantee Revenue ( $PGR$ ) for a crop for a crop year =  $90\% \times$  (*Benchmark State Yield* per planted acre for the crop year)  $\times$  (*ACRE Program Guarantee Price* for the crop year). *Actual State Revenue* ( $ASR$ ) for a crop for a crop year = (Actual State yield per planted acre)  $\times$  (*National Average Market Price*). Acres planted to the crop in  $t$  is  $A_{ij}$ .

The *Benchmark State Yield* per planted acre  $E(YS_{jt})$  is the Olympic average of the State's yield per planted acre for 5 most recent crop years, removing the highest and lowest yield from the calculation. The *ACRE Program Guarantee Price* for the crop year is the simple average of the national average market price received by producers of the covered commodity or peanuts for the most recent 2 crop years. The *National Average Market Price* for the purpose of calculating *Actual State Revenue* is equal to the higher of the U.S. average cash price for the marketing year or 70 percent of crop's marketing assistance loan rate.

Indicator variable  $\Phi_{ijt}$  equals 1 when the farm's actual revenue for the crop is less than the farm's benchmark revenue for that crop year, and 0 otherwise. The farm's actual and ACRE benchmark revenues are calculated using formulas similar to the *Actual State Revenue* and ACRE Program Guarantee revenue, respectively, except that farm level yields are used. In addition, the farm's ACRE benchmark revenue includes the farm's Federal crop insurance premiums paid for the crop, but the ACRE program is not integrated with crop insurance in any other way.

Several limitations apply to the ACRE payments. For 2010-12, *PGR* cannot increase or decrease more than 10 percent from its value the previous year. Further, the total number of planted acres a producer may receive ACRE payments for may not exceed the total base acreage for all covered commodities and peanuts on the farm. If the total number of planted acres to all covered commodities and peanuts of the producers on a farm exceeds the total base acreage (a fixed level of acreage for certain commodity payment purposes) of the farm, the producers on the farm may choose which planted acres to enroll in ACRE.

Separate ACRE Program Guarantees are created for irrigated and non-irrigated land if a state's planted acres are at least 25 percent irrigated and at least 25 percent non-irrigated. Total payments to a person or legal entities are limited under ACRE. Direct payments are limited per year to \$40,000 less the amount of the individual's 20 percent reduction in direct payments. Total ACRE revenue payments are limited per year to \$65,000 per person or legal entity. See ERS (2008) for additional details of ACRE.

In contrast to the ACRE revenue payment, the traditional counter-cyclical payments (CCP) are established using a payment rate determined by shortfalls in an “effective” price with respect to a statutory target price, multiplied by the fixed base acreage and base yield, and carries over from the 2002 Farm Act legislation. In other words, current production of the commodity is not required for the producer to receive a CCP payment. The total CCP option for a producer  $i$  of crop  $j$  in year  $t$  would be calculated over 2009 to 2012 as:

$$(1b) \text{ P-CCP}_{ijt} = 0.85 \cdot \max \{ 0, (TP_j - (\text{Max}(NP_{jt}, LR_j)) - Dj) \} \cdot (\bar{A}_{ij}^B \cdot \bar{Y}_{ij}^B),$$

where  $TP_j$ ,  $LR_j$ , and  $Dj$  are the statutory per bushel target price, national average loan rate, and direct payment rate, respectively, for a covered crop as specified in the farm legislation.<sup>1</sup> For each covered crop,  $NP_{jt}$  is a national market price (season average price for the marketing year),  $\bar{A}_{ij}^B$  and  $\bar{Y}_{ij}^B$  are farm-specific base acreage and base yield, respectively, i.e., where the latter is historic and fixed yield calculated as per government rules (FSA, 2006a). While the acreage and yield values in equation (1b) are fixed, the payment rate itself is a function of contemporary season prices.

For farmer  $i$  of a crop in region  $j$  in time  $t$ , the existing price-based marketing loan benefit, the price-based marketing loan benefit, or equivalently in terms of value, the loan deficiency payment, is calculated as:

$$(1c) \text{ LDP}_{ijt} = \max \{ 0, LLR_{jt} - ALR_{jt} \} \cdot A_{ijt} \cdot Y_{ijt},$$

where the statutorily-set local loan rates ( $LLR$ ) is the national loan rate ( $LR$ ) adjusted by various region-specific (county or other region) and quality factors. The alternative loan repayment rate, or  $ALR$ , is essentially a USDA-determined market price that varies according to market conditions, and is adjusted to reflect quality of the product.



Depending on the crop, the *ALR* may be a county (wheat, feed grains, oilseeds), national (peanuts), or world (upland cotton and rice) “posted” price. The payments are applied to current production on each farm, which equals harvested area, *A*, times harvested yield, *Y*. For farmers enrolled in ACRE, the loan rate *LR* is decreased by 30%.

From the producer’s perspective, a potential benefit, or liability, of ACRE over the LDP and the CCP is that the ACRE’s guarantee revenue automatically rebalances itself to relatively recent market prices. Therefore, it can provide payments in situations in which market prices are well above statutory loan rates and target prices. Of course, when market prices are low relative to loan rates and target prices, the ACRE can be expected to provide lower mean benefits than the LDP plus the CCP (albeit leaving differences in the fixed payments out of the analysis). However, under current market prices, loan rates, and target prices, feed grain and oilseed producers have a statistically insignificant chance of receiving CCPs or LDPs. For these producers, the decision to participate in ACRE is likely to be based on the producer’s perceived trade-off between the 20 percent of direct payments forgone when participating in ACRE and the ACRE revenue payment, and not on forgone price-based support.

### **Methodology for estimating the density function for ACRE payments**

The only two stochastic variables that we explicitly need for calculating ACRE payments at the national level are realized yield and season average price, although other variables can usefully feed into the econometric analysis, both to reduce omitted variable bias, and as intercept shifting terms that can be useful for policy simulations. For the simulation of payments then, we need to generate the distributions of price and yield.

However, the procedure for doing so is considerably complicated by the fact that price and yield are correlated, and hence the estimated distributions must take this correlation into account. We estimate the density function for payments given: 1) econometric estimates of the historic relationship between national price and national average yield; 2) estimates of the distribution of yield density for a particular base year; and 3), a bootstrap approach that links 1) and 2).

### **Modeling the price-yield relationship using price and yield deviates**

Our focus is on estimating the distribution of payments for a given reference crop year  $t$ , given that at pre-planting time in  $t$ , season average prices and realized yield are stochastic. As such, sector level modeling that separately identifies supply, demand, and storage is unnecessarily complex to service our needs and diverts attention away from focus of the paper. A convenient way to address our questions is to model prices and yield as percentage deviations of realized prices and yields at the end of the season from the expected values at the beginning of the season when planting decisions are made. If one accepts that the observed distribution of percentage changes in price and yield between pre-planting and harvest are representative of their future distribution, then our econometric specification of the price-yield relationship can be reduced to one equation.

While the academic literature is rich with papers on price estimation for commodities (e.g., Goodwin, 2002, for an overview), few express prices in deviation form. One example that does is Lapp and Smith (1992), albeit as the difference in price between crop years rather than between pre-planting time and harvest within the same crop year. As price deviation in their paper was measured between years, yield change

was not included in that analysis. Paulson and Babcock (2008) provide a rare example of the examination of the price-yield relationship within a season in an examination of crop insurance. Like them, for the purposes of estimating the relationship between price and yield, we re-express the historic price and yield data as proportional changes between expected and realized price and expected and realized yield within each period, respectively. However, among the differences in our approach from that in Babcock and Paulson is that ours uses a modeling approach that easily permits multiple explanatory variables, thereby decreasing the chance of misspecification of the price-yield relationship, and permitting sensitivity analysis with respect to parameters of policy interest.

For the model, the realized national average yield,  $Y_t$ , is transformed to the yield deviation  $\Delta Y_t$  according to  $\Delta Y_t = (Y_t - E(Y_t)) / E(Y_t)$ . To generate a distribution for  $Y_{2008}$  based on historic yield shocks, the historic yields must be detrended to reflect the proportional change in the state of technology between that in 2008 and that in time  $t$ , i.e.,  $Y_{it}$  is detrended to 2008 terms as

$$(2) Y_{it}^d = E(Y_{i2008})(\Delta Y_{it} + 1), \forall i \text{ counties}, t \text{ periods}, t \neq 2008.$$

It is convenient to specify the yield deviate as the deviation of detrended yield from expected yield in the base year used for detrending, which we denote as  $\Delta Y_t^d$ . We detrend yield based on the standard practice of using a linear trend regression of  $Y_t = f(t)$ . The expected value of  $Y_t$ , or  $E(Y_t)$ , is calculated from the fitted trend equation.

As with yield, price is transformed into deviation form, i.e., the realized price at harvest,  $P_t$ , is the difference between the expected and realized (harvest time) price, or

$$\Delta P_t = \frac{(P_t - E(P_t))}{E(P_t)}.$$

Given the estimated trend yields as the predictions of  $E(Y_t)$ , we can construct  $\Delta Y_t^d$  and estimate the relationship between  $\Delta P_t$  and  $\Delta Y_t^d$ . In particular, we assume that  $\Delta P_t$  can only be partially explained by  $\Delta Y_t^d$ , and that the uncertainty in this relationship can be incorporated into the empirical distribution. We do so by specifying  $\Delta P_t$  as

$$(3) \Delta P_t = g(\Delta Y_t^d, z_t) + \varepsilon_t,$$

where  $z_t$  is a vector of other variables that may explain the price deviation and  $\varepsilon_t$  is the error term. We expect that  $\frac{d\Delta P_t}{d\Delta Y_t^d} < 0$ , i.e., the greater the realization of national average yield over the expected level, the more likely harvest time price will be lower than expected price.

### **Generating the empirical distribution of payments – overview**

To generalize our empirical distribution of payments, we use a bootstrap method that allows for flexible right-hand-side regression modeling and for modeling interactions between variables. In particular, we use a paired bootstrap approach in a resampling methodology that involves drawing *i.i.d.* observations with replacement from the original data set (Efron, 1979; Yatchew, 1998), maintaining the pair wise relationship in each observation between the variables, e.g., variable values  $y_i$  and  $x_i$  are always kept together as a row. The bootstrap data-generating mechanism is to treat the existing data set of size  $T$  as a population from which  $G$  samples of size  $T$  are drawn. Equation (3) is re-estimated

for each of these bootstrapped data sets. Variation in estimates results from the fact that upon selection, each data point is replaced within the population. We can use this standard bootstrap to generate a distribution of  $\Delta P$  given  $\Delta Y^d$ .

However, while can directly estimate  $\Delta \hat{P}_{gt}$ ,  $g = 1, \dots, G$ , by substituting the  $G$  sets of bootstrapped coefficients and the  $(T \times 1)$  vector  $\Delta Y_t^d$  into equation (3), to compensate for the limited sample size, we can increase the smoothness of the bootstrapped distribution of  $\Delta P$  by substituting  $\Delta Y_t^d$  with yield deviations – denoted as  $\Delta Y^{d*}$  – that are generated from a random sample drawn from an estimated yield distribution using a kernel approach described in the next section. Doing so will allow us to estimate a set of price shocks associated with an arbitrarily large set of yield shocks, albeit defined by the actual data. Our approach to smoothing the distribution of yield maintains the coefficient of variation of yield of the actual yield data.

### **Generating the distribution of yield**

Like Deng, Barnett, and Vedenov (2007) and Goodwin and Kerr (1998), we utilize the nonparametric kernel-based probability density function (Hardle, 1990; Silverman, 1986) for generating a smoother yield density than that which would be supplied by the bootstrap of equation (3). This function, as applied to our notation, is

$$\hat{f}(y_j^d) = \frac{1}{Th} \sum_{t=1}^T K\left(\frac{y_j^d - Y_t^d}{h}\right), j = 1, \dots, J. \text{ This function allows us to generate values of}$$

$\Delta Y^d$  from a distribution that approaches a continuous function as  $J$  approaches infinity.

This function gives support to generating yield values over the observed range of

detrended yields, i.e., the  $(J \times 1)$  vector  $y^d$  is drawn over the range

$\{\min(Y_t^d) \dots \max(Y_t^d)\}$ ,  $t = 1 \dots T$ , where  $y_i^d$  are the yield points for which the density function is estimated. The function  $K(\cdot)$  is a Gaussian kernel (*ibid.*).<sup>2</sup> The optimal bandwidth  $h$  for smoothing the density is calculated according to equation 3.31 in Silverman (1986), which is a common choice for single mode densities such as those being evaluated here. We simulate the yield distribution by taking  $N$  draws of yield values, denoted as,  $Y_n^{d*}$ , from the estimated kernel density. Given the expected (trend) yield for a reference year, the yield deviate  $\Delta Y_n^{d*}$  is calculated for each  $Y_n^{d*}$ .

Yields generated from a kernel-based density function can be expected to have a lower standard error than the actual data given the smoothing of the density. We bring the standard error of the kernel generated yields back to the level of the actual data by assuming that any difference between the kernel yield and the actual yield is normally generated noise with mean zero, and add this noise to each  $Y_n^{d*}$ . This approach is discussed in more detail below in its application to generating farm level yields.

Prices are decided based on national-level yield shocks. ACRE payments are a function of State level yield shocks. County level yields are the lowest aggregation of yield data available from the USDA that has the same time series as the State and national data. We build our farm level yields off the county level. Hence, in addition to simulating national yield  $Y^{d*}$ , we simulate State ( $Y^{Sd*}$ ) and county yields ( $Y^{Cd*}$ ) using the same kernel approach.

### **Imposing estimated yield correlations on simulated yield data**

Of course, as drawn, the simulated national, State, and county yields, being *i.i.d.*, do not have the same Pearson correlation matrix as the original actual yield data, even if they have the correct mean and variances. The historic correlations between the national, State, and County level yields needs to be imposed on their simulated counterparts, but without changing the mean and variance of each yield vector. This is done by applying nonparametric Monte Carlo techniques to the three simulated yield in order to induce them to have the same correlation as the actual yield data.

Specifically, heuristic combinatorial optimization (Charnpis and Pantelli, 2004) is used to rearrange the generated univariate *i.i.d.* yield samples, in order to obtain the desired Pearson's correlation between them while leaving the yield values unchanged. What this approach amounts to in this application is that pairs of values in  $Y^{Sd*}$  are randomly interchanged until  $\text{abs}\{\text{corr}(Y^{d*}, Y^{Sd*}) - \text{corr}(Y^d, Y^{Sd})\}$  achieve a minimum tolerance  $tol$ , and where  $\text{corr}(Y^d, Y^{Sd})$  is the correlation coefficient of the actual (historic) detrended data. Next, pairs of values in  $Y^{Cd*}$  are randomly interchanged until  $\text{abs}\{\text{corr}(Y^{d*}, Y^{Cd*}) - \text{corr}(Y^d, Y^{Cd})\} \leq tol$  and  $\text{abs}\{\text{corr}(Y^{Sd*}, Y^{Cd*}) - \text{corr}(Y^{Sd}, Y^{Cd})\} \leq tol$ . The tolerance  $tol$  was set equal to 0.0005 for all yield simulations, except for one county, for which the minimum achievable  $tol$  was 0.009.

As an alternative to the kernel approach for generating the yield density vectors and imposing the historical correlations between them, we also use the block bootstrap approach to generating yield distributions. This approach makes minimal assumptions for the distribution of yield, and maintains the historical relationships between the yield

values, but at the cost of lower smoothness in the yield density function. We found the payment simulations to be relatively unaffected by the choice of approach.<sup>3</sup>

### **Generating the farm level yield distribution**

In general, farm level yields with adequate times series and relevance to specific regions are not available from the USDA. One approach to developing farm level yield is infer it from Federal crop insurance premiums, using the assumption that the premiums are actuarially correct and that the difference between county and farm level yield is distributed normally with mean zero (Coble and Dismukes, 2008). Another approach is to make use the analysis by Cooper, Langemeier, Schnitkey, and Zulauf (2009) – herein denoted as CLSZ – of the longitudinal farm level data sets provided by the Kansas Farm Management Association and Illinois’ Farm Business and Farm Management Association (FBFM). Each approach has its merits and disadvantages. The former approach covers more regions but only for farming units that purchase crop insurance and also assumes that the insurance premiums are actuarially correct, while the latter approach compares actual farm level yield to county yield, albeit for farmers who are long term members of the farm associations. We use the former to assess the integration of crop insurance with ACRE, thus maintaining consistency with crop insurance premiums, and the latter to assess the impacts of ACRE on farm revenue.

Looking at both 10 year and 17 year datasets of farm level data for counties with at least 10 farms for corn, soybeans, and wheat, CLSZ find that the difference between farm level yield and county level yield (where for consistency, the county level yield is constructed from the farm level yields, and not NASS data) is distributed normally with



mean zero. They also found that the relationship between the coefficient of variation of yield at the farm level and at the county level tends to follow a simple double log relationship. Hence, it becomes relatively simple to convert the detrended county level yield density into a detrended farm level density.

Let  $Y_j^{Cd*}$  = yield for county  $j$ ,  $Y_{ij}^{Fd*}$  = yield for farmer  $i$  in county  $j$ , and  $\lambda_{ij} = Y_{ij}^{Fd*} - Y_j^{Cd*}$ ,  $\forall i, j$  (we omit time subscript  $t$  for clarity). Based on this notation,  $Y_j^{Cd*} + \lambda_{ij} = Y_{ij}^{Fd*}$ , and it follows that  $\text{var}(Y_j^{Cd*} + \lambda_{ij}) = \text{var}(Y_{ij}^{Fd*})$ . Since CLSZ found for their data that  $\text{cov}(Y_j^{Cd*}, \lambda_{ij}) = 0$ , the variance function simplifies to  $\text{var}(Y_j^{Cd*}) + \text{var}(\lambda_{ij}) = \text{var}(Y_{ij}^{Fd*})$ , or  $\text{var}(\lambda_{ij}) = \text{var}(Y_{ij}^{Fd*}) - \text{var}(Y_j^{Cd*})$ . CLSZ found that a good rule of thumb for the ratio of farm level standard deviation to county level standard deviation of yield is 1.3. We describe our application of the Coble and Dismukes approach to generating farm level yield in the section on insurance.

#### *Generating the empirical distribution of payments given the estimated yield distribution*

The estimated price shocks given  $\Delta Y^{d*}$  and the coefficient estimates from the bootstraps of equation (3) and are calculated as:

$$(4) \Delta \hat{P}^* = \hat{\beta}_0 + \hat{\beta}_1 \Delta Y^{d*}$$

where  $\Delta Y^{d*}$  is the  $N \times 1$  vector of yield shocks derived from the kernel yield distribution,

$\hat{\beta}_1$  is the  $(1 \times G)$  vector of draws of the coefficient on the yield deviate from the

regression bootstraps, and  $\hat{\beta}_0$  is the “grand mean”, i.e., the product of the bootstrap draws of the other bootstrapped coefficients times the assigned values of the explanatory

variables in  $z$ . The resulting  $\Delta\hat{P}^*$  is a  $(N \times G)$  matrix, i.e., every yield shock  $\Delta Y_n^{d*}$  is associated with a  $(1 \times G)$  distribution of price shocks. For our simulation,  $N = G = 1000$ .

To calculate the commodity payments and farm revenue, the  $\Delta\hat{P}^*$  must be transformed back to the price per bushel,  $\hat{P}^*$ . For a reference year, 2009 in this case, the simulated harvest time price per bushel is

$$5) \hat{P}_{gn}^{*2009} = E(P_{2009}) \cdot (\Delta\hat{P}_{gn}^{*2009} + 1),$$

for  $g = 1, \dots, G, n = 1, \dots, N$ . Finally, by substituting the vectors  $\Delta\hat{P}^{2009*}$  and  $\Delta Y^{2009d*}$  into Equations (1a) to (1c), we generate the probability density functions of 2009 payment and revenue density functions as seen from the beginning of the 2009 crop year.

## Data

Data on planted yields and acres for corn, wheat, and soybeans are supplied by the National Agricultural Statistics Service (NASS) of the U.S. Department of Agriculture. We assume that each farmer's APH yield for the insurance and ACRE calculations is simply the county Olympic average yields for 2004 to 2008.

For each crop, we follow RMA definitions of the expected and realized prices. For example, for realized price  $P_t$  for corn, we use the average of the daily October prices of the December CBOT corn future in period  $t$ . For the expected value of price  $P_t$ , or  $E(P_t)$ , we utilize a non-naive expectation, namely the average of the daily February prices of the December Chicago Board of Trade corn future (CBOT abbreviation CZ) in period  $t, t = 1975, \dots, 2007$ . For corn and soybeans, the value of  $E(P_{2009})$  using in equation (5) are the same as the official RMA base prices for the RA insurance products

for the 2009 crop year. However, the RMA base price for the 2009 calendar year harvest of winter wheat was established using August and September 2008 values of the 2009 KCBT July hard red winter wheat futures contract. This 2008 period exhibited significant commodity price spikes and is unlikely to reasonably reflect updated expected prices for the 2009 crop. Hence, we recalibrate the  $E(P_{2009})$  for winter wheat to \$5.85, which is the average of end-of-week closing prices in February 2009 for 2009 KCBT July hard red winter wheat.

ACRE revenue payments are calculated using the NASS season average cash price. We convert  $P_{2009}$  to this price using the basis defined as the median difference between  $P_t$  and the NASS price in  $t$  over the ten years prior to 2009.

In addition to the yield shock  $\Delta Y$ , we include several other explanatory variables in our regression of Equation (3). We do not use these for any additional policy analysis, and the motivation for their inclusion is simply to reduce the potential effects of omitted variable bias on the yield shock coefficient and on the intercept coefficient. The dummy variable *FarmAct* takes the value of “1” for years 1996 and above (and 0 otherwise), reflecting the Federal government being out of the commodity storage business under recent Farm Acts.<sup>4</sup> As commodity storage may be expected to have a stabilizing influence on futures prices (Tomek and Grey, 1970), we include the corn stocks to use ratio, as measured at the beginning of the crop year in order to maintain Equation (3) in reduced form. As the inflation rate may impact price variability (e.g., Lapp and Smith, 1992), we include the inflation rate (CPI-U) over the quarter immediately prior to planting, the idea being that a lag may exist in the impact of near term inflation on the commodity price, with a higher rate increasing the price shock.

To model international linkages in a reduced form, we include deviation of actual yield from expected yield of corn in time  $t$  in the rest of the world, as calculated from FAOSTAT data. To account for the difference in the timing of seasons north and south of the equator, this variable is disaggregated into northern and southern hemispheres. The expectation is that a negative yield shock in the rest of the world will increase the U.S. corn harvest time price relative to the expected price. As exchange rate changes can be expected to have an impact on corn exports (Babula, Ruppel, and Bessler, 1995), we include the percent change in the nominal exchange rate between planting time and harvest, where the expectation is that an increase in this value lowers the export demand for U.S. corn, and therefore, its price. Several other variables are included, and are defined at the bottom of Table 1.

### **Econometric results**

Table 2 provides the econometric results for a linear specification of Equation 3 for each crop using OLS. We tested whether or not the error term  $\varepsilon_t$  is *i.i.d.* with mean 0 and variance  $\sigma_\varepsilon^2$ . In particular, we tested the regressions for evidence of heteroskedasticity with respect to the yield shock variable using the Breusch-Pagan Test (Greene, 2004), based on  $z = \{1, \Delta Y, \Delta Y^2\}$ . The test statistics of 4.04, 0.41, and 1.393 for the corn, wheat, and soybean regressions, respectively, were all under the critical value of 5.99 (chi-squared, two degrees of freedom, 5 percent significance), and homoskedasticity of  $\varepsilon_t$  is not rejected.

The coefficient on  $\Delta Y$  is significant at the 1 percent level for each crop. Of the additional explanatory variables, *stocks/use*,  $\pi$ ,  $\Delta r$ ,  $LRdiff_t$ , and *Acres Idled<sub>t</sub>* are each

significant to at least the 10 percent level in at least one of the three regressions. A specification of equation (3) that is semi-nonparametric (SNP) with respect to  $\Delta Y$  was also examined, and the relationship  $d\Delta P / d\Delta Y$  was found not to be statistically different than for the parametric specification in Table 1.<sup>5</sup>

### **Discussion of payment simulation results**

Table 2 presents the values of the price and yield parameters used in the simulations. The table also includes the average direct payment rates per acre per crop for the counties in which the farms are situated, but recall that these payment rates would be reduced by 20 percent if the farmer enrolls in ACRE.

Table 3 summarizes the results of the *ex ante* stochastic analysis that predicts at planting time the probability density of ACRE revenue payments per acre, gross revenue per acre, and total gross revenue (i.e., gross revenue  $t$  plus the ACRE payment in  $t$ ) given the distribution functions for price and yield.<sup>6</sup> Mean payments per commodity vary as much as several orders of magnitude between counties, from \$6.8/acre for the corn farmer in Butler, KS, to \$29/acre for the corn farmer in Logan county, IL, for example. For each farmer/crop combination, the probability of not receiving a payment is high enough that the lower bound of the 90% empirical confidence interval of payments is \$0. The Logan county corn and soybean farmers had the highest probability of receiving an ACRE payment, at 61 and 58 percent, respectively. The Butler and Finney County corn farmers had the lowest probability of receiving the ACRE payments, at 22 and 24 percent of the time, respectively. The differences in the probability of receiving a payment are based more on differences in farm level standard deviations of yield and revenue between

the farmers than on differences in the State-farm yield correlations between the farmers. However, as a number of interactions between prices, national, state, and farm level yields determine the payment densities, it is difficult to generalize as to the causes of the differences in the payment densities across the farms.

In all cases, receipt of the ACRE revenue payments lower the farmer's coefficient of variation of revenue (last column of table 3), ranging from approximately 4 percent for the Butler farmer to 25 percent for the Logan soybean farmer. The decrease in the coefficient of variation in the last column and the coefficient of variation of gross revenue (the last column of part B in the table) are negatively correlated, with a correlation coefficient of -0.52. The ACRE payment also raised the lower 90% bound of revenue for all farmers (third column from end). The upper 90% bound of total gross revenue is the same as the upper 90% bound of gross revenue without the payment, and is not shown in the table. Hence, with the double trigger, ACRE appears to address downside risk without contributing to upside "risk".

Figure 1 graphs a portion of the density function of revenue with and without the ACRE payment for the Logan and Barnes County corn farmers. The graphs clearly show the payment to reduce some of the downside risk of the farmer. The density functions with and without the payments converge in the upper tails (for the Barnes farmer outside the revenue per acre range shown on the graph). The Logan farmer's revenue density function with or without the ACRE payment is relatively symmetric. However, the density function of the Barnes corn farmer exhibits a spike at the low end of the revenue range given the relatively significant probability that this farmer can suffer a crop failure. The ACRE payment removes this spike at the lower tail of revenue for this farmer.

Table 4 shows the density function of pseudo-LDP and CCP payments and their impacts on gross revenue for corn farmers in two locations. The purpose of this exercise is to examine how these two payments approaches differ from ACRE in the higher moments of their payment density functions and in their impacts on revenue. These are “pseudo” payments as the loan rate and target price have to be increased over the actual values of \$1.95 and \$2.63/bu., respectively in order to produce non-zero probability of payments at February 2009 expected prices. For each farmer, the loan rate and target price were increase to the point where the mean LDP and CCP payment were the same as the farmer’s ACRE revenue payment, using multiplier values noted in Table 4.

For the Logan county farmer, the upper bound of the 90% confidence interval of the CCP payments is lower than for the ACRE payment as the CCP payment rate cannot exceed the target price less the sum of the loan rate plus the direct payment rate. The LDP payment rate has no such cap, and the upper bound on LDP payments per acre is higher than the ACRE payment for the Logan county farmer, suggesting that this price-based payment can over-pay relative to a revenue-based payment for farmers in the Heartland. This impact is also shown in a 90% upper bound on revenue with the payment being higher than revenue without the payment. However, the Finney corn farmer has a lower price-yield correlation than the Logan farmer, and the LDP underpays relative to ACRE for that farmer. For both farmers, receiving the CCP and LDP lowered the coefficient of variation of revenue, but not as much as did ACRE, even though the difference may not be dramatic for the Finney County farmer.

### **Integration of Federal Crop Insurance with ACRE**

We now examine to what extent crop insurance premiums could decrease if harvest time revenue used in the premium calculation include the ACRE revenue payment. If the ACRE and insurance programs were to be formally integrated in such a manner, the greater the percentage of the farmer's revenue risk covered by the ACRE revenue payment, the lower the actuarially correct crop insurance premium would need to be. Given that the government subsidizes on average 59 percent of the farmer's insurance premium, such an integration would likely result in Federal budgetary savings.

The previous section used data on difference between actual farm level yields and county yields to transform the county level yield density function into the farm level yield density function. In this section, for the sake of consistency with actual RMA insurance rates, we infer the difference between farm and county level yields from the RMA crop insurance premiums. In our application of the Coble and Dismukes approach to backing-out the farm level standard deviation of yield from crop insurance premiums from the Risk Management Agency (RMA) of the USDA, we assume that our representative farmers purchase revenue assurance (RA) with the base price option and 70 percent coverage (RMA, 2009). In our notation, the RA indemnity payment per acre for producer  $i$  of crop  $j$  in period  $t$  is

$$6) RA_{ijt} = \max \{0, (0.7 \cdot E(P_{jt}) \cdot Y_{ijt}^{APH} - P_{jt} \cdot Y_{ijt}^{Fd*})\},$$

where  $E(P_{jt})$  and  $P_{jt}$  are expected and harvest time futures prices, respectively, and

$Y_{ijt}^{APH}$  is the actual production history for the farm. In our simulation context, the

insurance premium,  $PREM_{ijt}$ , is actuarially correct if it is set equal to  $E(RA_{ijt})$ , where

$E(RA_{ijt})$  is mean of all outcomes of Equation (6) given our  $(N \times G)$  matrix of prices and



$(G \times 1)$  vector of farm yields. We assume that  $Y_{ijt}^{Fd*} = Y_{jt}^{Cd*} + z_t$ , where

$$z \sim N(0, \sigma(Y_{ijt}^{Fd*} - Y_{jt}^{Cd*})).$$

Using a quasi-Newton technique, we find the value of  $\sigma(Y_{ijt}^{Fd*} - Y_{jt}^{Cd*})$  that minimizes  $abs(PREM_{ijt} - E(RA_{ijt}))$ , where  $PREM_{ijt}$  is the full premium including the farmer paid portion and the portion subsidized by the government. The farmer paid premium is downloaded from the RMA website (RMA, 2009) using the price and yield values from Table 2, and divided by 0.41 to generate  $PREM_{ijt}$ . Generally, we find that  $\sigma(Y_{ijt}^{Fd*} - Y_{jt}^{Cd*})$  is higher when inferred from the RMA premiums than when calculated from the farm management data. For our farmer/crop combinations, the ratio of  $\sigma(Y_{ijt}^{Fd*})/\sigma(Y_{jt}^{Cd*})$  is on average 1.9 times higher based on the RMA data.

If  $RA$  was to explicitly consider ACRE revenue payments as part of harvest time revenue, the  $RA_{ijt}$  from Equation (6) would be rewritten as  $RA_{ijt} = \max\{0, 0.7 \cdot E(P_{jt}) \cdot Y_{ijt}^{APH} - (P_{jt} \cdot Y_{ijt}^{Fd*} + ACRE_{ijt})\}$ .<sup>7</sup> Table 5 shows that integration of the two programs decreases the full crop insurance premium from 10% to 41% depending on the farm/crop combination. If we had used the farm level yield densities based on the lower farm to county level noise in the farm management datasets, the decreases would have been larger in most of the farm/crop combinations.

### **Moral hazard implications of ACRE**

Since ACRE reduces downside revenue risk, it may have impacts on planted acres. As total U.S. acres planted to corn, wheat, and soybeans have been relatively stable over the last 20 years regardless of the agricultural policy changes occurring over the period, it

would be difficult to stage a convincing argument that ACRE would do much to change total acreage planted to these crops. But this is not to say that ACRE could motivate some shifting between crops, whether regionally or nationally. This section provides a preliminary examination of such impacts. As with Goodwin (2009) and Hennessy (1998), we assume that the farmer chooses acreage to maximize the expected value of a negative exponential utility function with respect to planted acreage  $A$  over our  $N \cdot G = 1,000,000$  simulated price, yield, and commodity payment combinations as

$$7) EU(\pi) = \frac{1}{N \cdot G} \sum_{i=1}^{N \cdot G} [-e^{-\lambda \pi_i(A)} + \beta \pi_i(A)]$$

According to Hennessy (1998), the  $\lambda$  and  $\beta$  imply a risk aversion coefficient of

$\rho(\pi) = (\lambda^2 e^{-\lambda \pi}) / (\lambda e^{-\lambda \pi} + \beta)$ . We use the same  $\lambda = 1 \times 10^{-4}$  and  $\beta = 1 \times 10^{-5}$  as Goodwin (2009) to reflect estimated value of absolute risk aversion in the literature, with  $\beta > 0$  implying decreasing absolute risk aversion (DARA).

As with Goodwin (2009), we assume a single-crop farm for tractability.

Nonetheless, the relative magnitude of the acreage impacts of ACRE on each crop can still provide an indication of how the crop mix might change. Leaving out the subscripts denoting crop, farmer, and period, profits  $\pi$  are

$$8) \pi_i(A) = (P_i \cdot Y_i - c)A + \cdot PYMT(P_i, Y_i, A, \bar{A}^B)$$

for each simulated price and yield pair, where  $c$  = total cost per acre and  $PYMT(\cdot)$  is government payments. With the traditional programs under 2009 expected prices, the probability of price-based support payments is essentially zero for corn, wheat, and soybeans, and  $PYMT(\cdot)$  is simply the direct payment rate from Table 2 times the farm's bases acres, or  $PYMT(\cdot) = dpr \cdot \bar{A}^B$ . Under ACRE,  $PYMT(\cdot) =$

$0.8 \cdot dpr \cdot \bar{A}^B + ACRE_i \cdot \min\{\bar{A}^B, A\}$  as the ACRE revenue payments cannot be applied to planted acres exceeding the farm's base acres  $\bar{A}^B$ .

Estimating costs per acre  $c$  is like trying to hit a moving target. Rather than relying on cost estimates that may be out of date, we let the model infer them. In particular, we assume that the farmer's *EU* maximizing choice of  $A$  under the traditional support programs is  $A = 400$  acres. Given this assumption, we find the value of  $c$  for each crop/location that maximizes equation (7). Given this calibration of  $c$ , we re-maximize (7) under the ACRE program with respect to  $A$ . This approach gives us the change in acreage under ACRE relative to the traditional programs.

Table 6 presents the result of this simulation for 2009. For each crop/location combination, ACRE stimulates acreage relative to traditional support in the context of the *EU* model. Of course, these results are based on the assumption that the support payments are not passed through to the farmer in the form of higher rents. Nonetheless, the relative results between crops can still be taken as an indication of the differential effect of ACRE on crop mix. For the Logan county farmer, the percent increase in planted acreage under ACRE relative to the traditional programs is the same for corn and soybeans. This result is not surprising given that farmers in this region have a comparative advantage in the production of both crops even under the traditional programs. As per Table 3, ACRE did little to reduce the coefficient of variation of the corn farmer in Butler, KS, and is not surprising it produced a bigger acreage effect for soybeans and wheat. In Butler, Finney, and Barnes Counties, ACRE reduced the disadvantage of growing soybeans relative to wheat (spring wheat in the latter). For the Finney, KS, and Barnes farmers, it also

reduced the disadvantage of growing corn relative to wheat, and particularly so for the latter, which is in North Dakota.

As ACRE appears to have the same relative impact on planted acres for corn and soybeans for our farmer in Logan County, IL, which is part of the Heartland region that largely determines the price for corn and soybeans, and given the relatively stable total crop acreages in this region, it appears that ACRE does not have a strong impacts on prices for these crops under 2009 conditions.

We can also maximize *EU* under ACRE to find the payment pass-through in the form of higher rents that would not change acreage. For the Logan County corn farmer in 2009, costs would have to increase by \$56/acre under ACRE to induce no change in the *EU* maximizing acreage. As the increase in mean *PYMT* for this farmer under ACRE is \$23.74/acre (on acres not exceeding base), the additional costs the farmer is willing to bear reflects a certainty equivalent benefit of ACRE.

### **Concluding Remarks**

Our simulation results show that adding ACRE revenue payments to gross revenue reduced the downside risk in revenue for corn, wheat, and soybean farmers in 2009 in the four locations examined, with reductions ranging from 4% to 25%. The differences in the decrease in the coefficient of variation of revenue across the farmers was relatively large, suggesting the ACRE payments are sensitive to farm level yield densities, and differences in the correlations between prices and yields at the individual, State, and national levels of yield aggregation.

Of course, the decrease in the coefficient of variation of revenue under ACRE is sensitive its program parameters. For instance, a reduction in the ACRE guarantee price for corn by 10% from its 2009 value (Table 2) means the reduction in the coefficient of total gross revenue due to the ACRE payment falls from 17% (Table 3) to 7% for the Logan County, IL, farmer.

Based on a utility maximization exercise, single crop farmers for the crop and location combinations examined here clearly prefer the ACRE program to the traditional suite of price-based support. However, this analysis is for the 2009 crop year for an individual with a one period time horizon. Future analysis of farmer preferences for ACRE can benefit from being inter-temporal. In particular, the farmer's decision to enroll in ACRE should consider market conditions over the remaining life of the 2008 Farm Act for two primary reasons: 1) the farmer's enrollment decision is irrevocable through the rest of the 2008 Farm Act period; and 2) the ACRE program guarantee price cannot change more than 10 percent in either direction from the previous year. The latter means that the 2009 program guarantee price determines the bounds on this price through 2012.

The simulation results suggest that although the ACRE payment rate is determined at the State-level, it does cover a significant portion of the farm-level revenue risk. As such, integrating this program with Federal crop insurance to explicitly account for the overlap in risk coverage can result in significantly reduced crop insurance premiums for some of the crop and location combinations examined here. However, pragmatic issues would need to be addressed to implement such an integration. For example, the insurance indemnity payment cannot be determined until after the farm's ACRE revenue payment is calculated. Of course, institutional resistance to this

integration cannot be discounted. Over the relatively long history of price-based support, it is probable that the integration of it with Federal crop insurance would have lowered insurance premiums – even if with likely lower saving than integration with ACRE – but this integration was never attempted.

## Endnotes

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<sup>1</sup> An exception to the average national loan rates for the purposes of CCPs is made for rice and barley, for which the Secretary of Agriculture would determine the average loan rates.

<sup>2</sup> We found the estimated density of program payments for corn to be insensitive to the choice between Gaussian and biweight kernels.

<sup>3</sup> As a supplement to the modeling results based on the kernel density for yield we examined alternative results for Table 3 based on generating the yield densities without any smoothing. In particular, the block bootstrap (Lahiri, 1999) approach is used to randomly resample with replacement the national, State, and county yields from the actual yield dataset. Year-wise relationships among the yield values are maintained when resampling, thereby ensuring that the simulated dataset has the same correlation between the national, State, and county yields as the original data. Farm level yield is generated by adding the normally distributed noise to the county level yields, using the approach based on the farm management data.

<sup>4</sup> This variable might be interpreted as the change in the weather premium after the 2006 Farm Act. A negative sign on its coefficient would suggest an increase in the weather premium, which might be expected without the government holding significant reserve stocks after 1996.

<sup>5</sup> To examine the potential for bias due to miss-specification in estimating equation (3), in addition to a linear parametric estimate of the equation, we also estimated the equation using a semi-nonparametric (SNP) econometric approach based on the Fourier transformation (Fenton and Gallant, 1996). The SNP regression is limited by degrees of

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freedom in the number of variables that can receive the SNP treatment, and as such, the SNP regression variables in our application are limited to  $\Delta Y$  and its first order sine and cosine transformations. Using the regression results in a bootstrap-based test (Efron, 1987), the hypotheses  $H_0: d\Delta P^{para} / d\Delta Y^{para} - d\Delta P_t^{snp} / d\Delta Y_t^{snp} = 0$  cannot be rejected at the 90 percent level or better for all  $j \neq k$ . This result suggests that the parametric model is adequate to the task of modeling the interaction between price and yield.

<sup>6</sup> The explanatory variables in  $z$  are evaluated at 0 or their most recent values.

<sup>7</sup> For this simulation, we assume that the farm's ACRE benchmark revenue does not include the farm's Federal crop insurance premiums in order to preclude a double subsidy.



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**Table 1. Parametric Regression Results for the Function Explaining  $\Delta P_t$** 

Variable	Corn		Soybeans		Wheat	
Constant	-0.231	<i>-2.94</i>	-0.120	<i>-1.05</i>	-0.039	<i>-0.28</i>
$\Delta Y_t$	-0.938	<i>-3.54</i>	-1.521	<i>-4.18</i>	-0.955	<i>-3.00</i>
FarmAct	-0.056	<i>-0.75</i>	0.057	<i>0.64</i>	0.081	<i>0.62</i>
Stocks/use	0.563	<i>1.89</i>	0.633	<i>1.01</i>	-0.520	<i>-2.16</i>
$\Delta Y_t^{SH}$	0.305	<i>0.49</i>	-0.372	<i>-0.88</i>	-0.401	<i>-0.67</i>
$\Delta Y_t^{NH}$	-0.387	<i>-1.39</i>	0.023	<i>0.98</i>	-0.003	<i>-0.01</i>
$\pi$	9.372	<i>2.08</i>	0.155	<i>0.03</i>	5.109	<i>0.56</i>
$\Delta r_t$	-0.364	<i>-1.37</i>	-0.671	<i>-2.11</i>	-0.319	<i>-0.84</i>
Ethanol use <sub>t</sub>	0.908	<i>1.50</i>	0.163	<i>0.18</i>	1.442	<i>1.19</i>
LRdiff <sub>t</sub>	0.473	<i>2.23</i>	-0.477	<i>-0.43</i>	-2.590	<i>-1.95</i>
Acres Idled <sub>t</sub>	-0.007	<i>-1.00</i>	—	—	0.015	<i>2.26</i>
$R^2$	0.68		0.55		0.58	
$Ln-L$	30.91		24.43		17.51	
$Ln-L^{SNPDF}$	31.75		24.52		18.62	

Notes:  $T$ -values are shown in italics.  $Ln-L^{SNPDF}$  is the log-likelihood value for the model that is semi-nonparametric distribution free in  $\Delta Y_t$ .

$\Delta Y_t$  is the percentage deviation in US corn yields from the expected (trend) yield. *Stocks/use* is the ratio of total U.S. corn stocks at the end of the previous crop year to total utilization of U.S. corn (source: ERS). *FarmAct* equals 1 for 1996 to 2005 and 0 otherwise.  $\Delta Y_t^{NH}$  is the percentage deviation in Northern

hemisphere corn yield (less the U.S.) from the trend yield in that world region, and  $\Delta Y_t^{SH}$  Southern

*Production* is the percent deviation in Southern hemisphere corn yield (less the U.S.) from the trend yield in that world region (data source: FAOSTAT).  $\pi$  is the inflation rate (CPI-U) over the quarter prior to

planting.  $\Delta r_t$  is the percentage change in the nominal exchange rate (Euro/\$) between planting and

harvest time. *Ethanol use<sub>t</sub>* is fraction of U.S. corn production used to producer ethanol. *LRdiff<sub>t</sub>* is  $(E(P_t) - basis_t - LR_t)/LR_t$  when  $(E(P_t) - basis_t - LR_t) > 0$ , and 0 otherwise, where  $E(P_t)$  is the planting time futures price, *basis<sub>t</sub>* is the rolling average basis over 10 years, and  $LR_t$  is commodity loan rate. *Acres Idled<sub>t</sub>* is the percent of the acreage idled under pre-1996 Farm Acts.

**Table 2. Policy and other parameters used in the simulations (ACRE and RA crop insurance)**

<b>National level parameters</b>	Corn			Soybeans			Wheat		
ACRE Guarantee Price, 2009 (\$/bu.)	\$4.15			\$9.73			\$6.64		
Revenue Assurance base price, 2009	\$4.05			\$8.80			\$8.77(\$6.20) <sup>d</sup>		
Expected price for simulation	\$4.05			\$8.80			\$5.85		
<b>State, county, and farm specific parameters</b>	ACRE State benchmark yield (bu./acre) <sup>a</sup>	Direct payment rate (\$/acre) <sup>b</sup>	Farm's APH yield (bu./ acre)	ACRE State benchmark yield (bu./acre) <sup>a</sup>	Direct payment rate (\$/acre) <sup>b</sup>	Farm's APH yield	ACRE State benchmark yield (bu./acre) <sup>a</sup>	Direct payment rate (\$/acre) <sup>b</sup>	Farm's APH yield
Logan County, Illinois	170	33	180	47	16	51	--	33	--
Butler County, Kansas <sup>c</sup>	128	17	100	35	6	34	33	17	34
Finney County, Kansas <sup>c</sup>	128	34	160	35	16	50	33	34	37
Barnes County, North Dakota	103	18	113	31	11	31	35	18	45 <sup>e</sup>

Notes:

<sup>a</sup> These ACRE yield values differ slightly from the official FSA benchmark yields. In some cases, FSA will calculate planted acres as NASS harvested acres plus FSA failed acres. However, the simulation uses yield data back to 1975, making the approach of using NASS planted acres more practical for the simulation.

<sup>b</sup> The direct payment rate per acre for crop *i* in county *j* is (direct payment rate for crop *i*)\*(average direct payment yield for crop *i* in county *j*). This payment rate per acre is then multiplied by 0.833 as direct payments are made for this percentage of base acres (for the 2009-2011 crop years). Note that ACRE enrollment requires a 20% reduction in the payment rates above.

<sup>c</sup> Actual ACRE benchmark corn yields for Kansas are calculated separately for irrigated and nonirrigated corn. Since the NASS county level yield data from which farm level yields are built is not continuous over 1975 to 2008 for irrigated and nonirrigated acres, we do not separately identify them for this simulation exercise.

<sup>d</sup> Winter wheat (Spring wheat) \$/bu.

<sup>e</sup> Spring wheat.

Sources: USDA's Farm Services Administration, National Agricultural Statistics Service, and Risk Management Agency.

**Table 3. Simulated ACRE payments per acre, gross revenue per acre, and total gross revenue with ACRE payments, 2009 crop year**

Farm location	Crop	A. ACRE revenue payment per acre				B. Gross revenue per acre				C. Revenue per acre with ACRE payment			Reduction in coef. of variation (%) <sup>c</sup>
		Mean (\$/acre)	Upper bound, 90% CI (\$) <sup>a</sup>	Coefficient of variation	Percent of time payment is made	Mean (\$/acre)	Lower bound, 90% CI	Upper bound, 90% CI	Coefficient of variation	Mean (\$/acre)	Lower bound, 90% CI <sup>b</sup>	Coefficient of variation	
Logan, IL	corn	29.0	108	1.24	61	667	454	885	0.20	696	518	0.17	17.21
	soybeans	19.9	79	1.30	58	445	340	556	0.15	464	389	0.11	24.91
Butler, KS	corn	6.8	52	2.54	22	340	57	624	0.51	346	64	0.49	3.85
	soybeans	21.0	62	1.13	57	259	47	473	0.49	280	92	0.40	16.96
	wheat	10.0	42	1.48	43	198	99	300	0.31	208	121	0.26	15.66
Finney, KS	corn	12.8	103	2.41	24	651	461	870	0.19	664	508	0.17	11.40
	soybeans	24.3	91	1.36	47	451	275	649	0.25	475	307	0.22	14.69
	wheat	11.6	47	1.43	45	207	89	322	0.34	219	115	0.29	16.44
Barnes, ND	corn	19.8	88	1.62	36	448	33	853	0.55	468	92	0.49	11.32
	soybeans	10.9	57	1.75	34	289	150	429	0.29	300	178	0.25	14.00
	wheat	18.6	56	1.20	52	254	121	400	0.33	272	165	0.26	21.94

Notes:

a The 90% lower bound is \$0/acre in each case and hence, is not shown in the table.

b The 90% upper bound is the same as that for gross revenue without the ACRE payment (B), and hence, is not shown in the table.

c This is the percentage reduction in the coefficient in the of variation of revenue due to adding the ACRE payment.

**Table 4. Simulated hypothetical price-based payments per acre and total gross revenue with the payments for corn, 2009 crop year**

Farm location	Price-based payment per acre				Revenue per acre with the payment				Reduction in the coefficient of variation (%) <sup>a</sup>
	Mean (\$/acre)	Upper tail, 90% CI	Coefficient of variation	Percent of time payment is made	Mean (\$/acre)	Lower tail, 90% CI	Upper tail, 90% CI	Coefficient of variation	
I. Pseudo CCP									
Logan	28.8	103	1.27	58	695	487	899	0.19	6.92
Finney	12.7	61	2.27	34	663	495	870	0.17	9.90
II. Pseudo LDP									
Logan	29.6	136	1.66	44	696	482	906	0.19	3.38
Finney	12.8	80	2.31	27	664	491	870	0.17	9.03

*Notes*

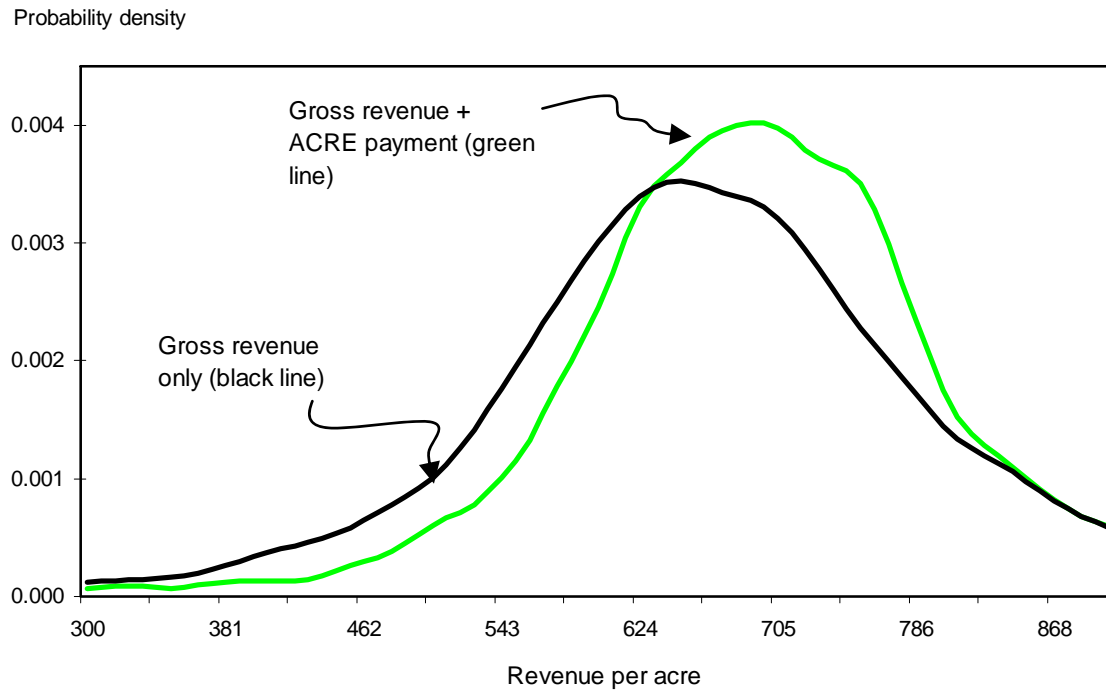
For each farm, the Pseudo-CCP (Pseudo-LDP), the target price (loan rate) of \$2.63/bu. (\$1.95/bu.) is increased by the amount necessary such that the mean payment per acre is approximately the same the mean ACRE payment. Gross revenue per acre is the same as in Table 3 and hence , not shown here. The target price was increased by a factor of 1.59 and 1.48 for the Logan and Finney farmers, respectively. The loan rate was increased by a factor of 1.83 and 1.74 for the Logan and Finney farmers, respectively.

<sup>a</sup> This column is the percentage reduction in the coefficient of variation of revenue due to adding the payment.



Figure 1. Probability density of revenue per acre – corn producer, 2009 crop year

(a) Representative producer in Logan County, Illinois



(b) Representative producer in Barnes County, North Dakota

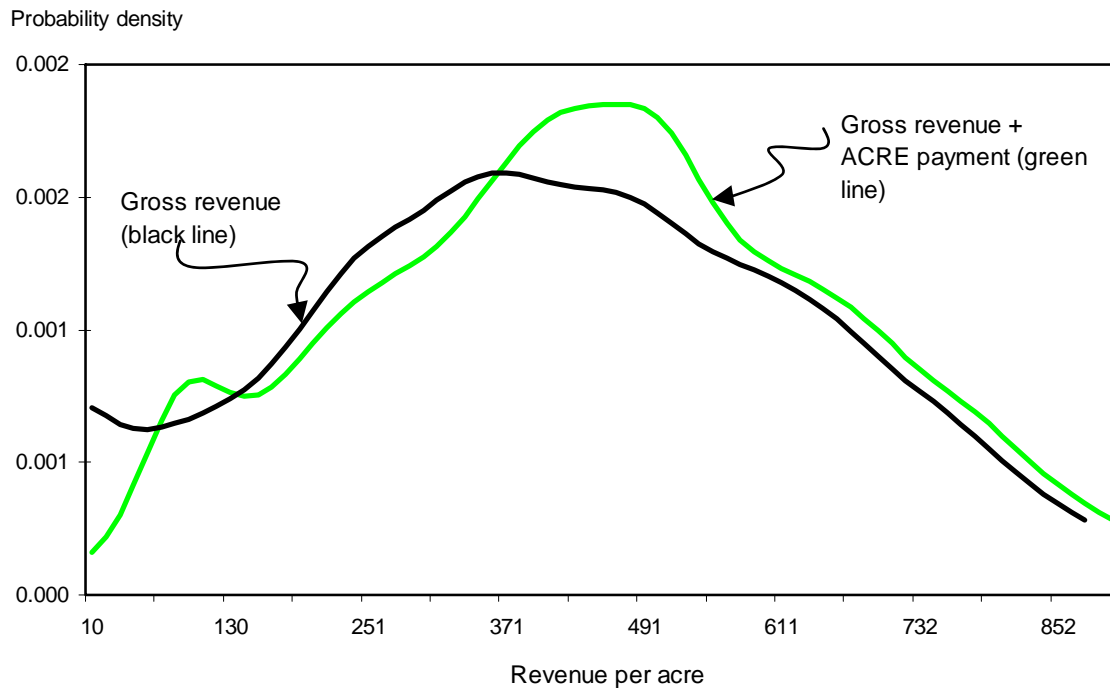


Table 5. Federal Insurance premium per acre without and with integration with the ACRE revenue payment (2009 crop year)

Farm location	Crop	RMA full premium <sup>a</sup>	RMAfull premium if integrated with ACRE	Percent decrease in premium
Logan, IL	corn	23.76	15.63	34
	soybeans	14.56	10.07	31
Butler, KS	corn	46.73	42.28	10
	soybeans	30.02	18.31	39
	wheat	32.98	25.52	23
Finney, KS	corn	53.20	47.13	11
	soybeans	39.12	27.44	30
	wheat	33.76	23.69	30
Barnes, ND	corn	60.59	43.44	28
	soybeans	24.32	18.73	23
	wheat	18.27	11.05	41

Notes

<sup>a</sup> Revenue assurance with base price option, 70% coverage (source, RMA/USDA). These are the full premiums unsubsidized by the Federal government, i.e.,  $(1-0.41) \times \text{farmer premium}$ .

Table 6. Percent change in planted acreage in associated with enrollment in ACRE relative to the traditional support programs for the expected utility maximizing farmer.

Farm location	Crop	Percent change in planted acreage
Logan, IL	corn	80
	soybeans	81
Butler, KS	corn	8
	soybeans	90
	wheat	25
Finney, KS	corn	64
	soybeans	39
	wheat	20
Barnes, ND	corn	143
	soybeans	71
	wheat	38

*Notes:*

Costs per acre are calibrated so the *EU*-maximizing acreage under the traditional program is 400 acres in each case. The farmer is assumed to have 400 base acres. The single-crop farmer is assumed to choose planted acres to maximize the expected value of a negative exponential utility model. No pass-through of government payments into land rents is assumed.