Interactions of Shallow Loss Support and Traditional Federal Crop Insurance: Building a Framework for Assessing Commodity Support Issues for the Next Farm Act

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Abstract

The 2014 Farm Act ends some long-standing and some more recent commodity support programs and introduces new programs that offer producers an array of choices which will determine the support they will receive over the 5-year life of the Act. Programs covering soybeans that are included in these new programs are the so-called "shallow loss" programs, including Agriculture Risk Coverage (ARC) and the Supplemental Coverage Option (SCO). The traditional "deep loss" Federal crop insurance program (e.g., Revenue Protection, or RP) – the largest commodity outlay over the last few years – continues. While current program parameters are set for the life of the 2014 Farm Act, in future farm legislation, the USDA's expected budgetary allocations for shallow versus deep loss support could be adjusted by the "shallow loss" coverage rates in ARC and SCO, as well as by other policy parameters. Using regression analysis, we examine the ratio of expected net SCO and county-ARC payments to total net support benefits (shallow plus deep loss) as a function of variables that influence the size and distribution of these benefits, including key program policy parameters. For corn, winter wheat, and soybeans, we find the ratio to be approximately twice as sensitive to the deep loss coverage rate than to the shallow loss coverage rate.

Key words: supplemental coverage option, agricultural risk coverage, shallow loss, crop insurance, corn, winter wheat, soybeans

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Introduction

The 2014 Farm Act ends some long-standing and some more recent commodity support programs and introduces new programs that offer producers an array of choices which will determine the support they will receive over the 5-year life of the Act. Programs covering corn, soybeans, and winter wheat that are included in these new programs are the Price Loss Coverage (PLC) and the so-called "shallow loss" programs – Agriculture Risk Coverage (ARC), Supplemental Coverage Option (SCO). The traditional "deep loss" Federal crop insurance program (e.g., Revenue Protection, or RP) – the largest commodity outlay over the last few years – continues. In fact, outlays for SCO and STAX are explicitly linked to traditional crop insurance via program parameters, although STAX is also available as a stand-alone product. ARC is not explicitly linked to crop insurance and pays to historic base acres. Nonetheless, it too compensates farmers for shallow losses, i.e., losses smaller than those that would trigger traditional insurance payments because of deductible requirements. While current program parameters are set for the life of the 2014 Farm Act, in future farm legislation, the USDA's expected budgetary allocations for shallow versus deep loss support could be adjusted by the "shallow loss" coverage rates in ARC, SCO, and STAX, as well as by other policy parameters.

Take the example of ARC. ARC, with a 14% deductible (i.e., the coverage rate is 86%), and payments capped at 10% of benchmark revenue, is purely a shallow loss program, with a per acre payment rate fully covering revenue losses when county revenue is between 76% and 86% of expected revenue, and paying on 85% of base (historic) acreage. Presumably, the seemingly arbitrary 86% coverage rate was not chosen based on any general principles for farm risk management, but as a result of a budgetary scoring exercise. This choice of coverage rate begs the question of what the impacts of different coverage rates would be on program payments. In fact, at one stage of the 2014 Farm Bill negotiation process, some proposed legislation had ARC with a coverage rate of 89 percent of expected (or benchmark) revenue, demonstrating the tweaking of program parameters during the development of program proposals.

Using regression analysis, we examine the ratio of expected net SCO and county-ARC payments to traditional federal crop insurance net benefits as a function of variables that influence the size and distribution of these benefits, focusing on the key program policy parameters of the shallow and deep loss coverage rates. We set the stage for this analysis by first examining the comparative impacts of shallow loss supports SCO and county-ARC and deep loss insurance coverage on the revenue of corn, soybean, and wheat producers. To do this, we use nonparametric distributions of yields for a representative farmer in each U.S. county for which the USDA's National Statistics Service (NASS) has reported consecutive year production histories, along with a nonparametric distribution of prices. As estimation of the national summaries of second and higher moments of revenue require that the historical spatial and temporal relationships between county yields and between county yields and prices be maintained to the extent technically feasible, we use a copula approach to impose correlation on the price and yield distributions.

Analytical framework, Methods and Data

For the simulation of payments, we need to generate the distributions of market year price and county or farm yields. However, the procedure for doing so is considerably complicated by the fact that price and yields are temporally correlated with each other, and yields across regions are spatially correlated. Hence the estimated distributions must take these correlations into account or measures of the variability of payments and their impacts on revenue variability will be incorrect. We estimate the density function for payments based on: 1) estimates of price and yield densities for a particular base year; and 2) an empirical method for imposing the historical correlations on this simulated data. The appendix provides a schematic of the general steps in the methodological approach.

Modeling the Price-Yield Relationship Using Price and Yield Deviates

Our focus is on estimating the distribution of payments for a reference crop year *t*, given that at pre-planting time in *t*, season average prices and realized yields are unknown and treated as stochastic variables. As such, sector level modeling that separately identifies supply, demand, and storage is unnecessarily complex and would divert the focus of this article. A convenient way to address our questions is to model prices and yields 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.

The benefit of our reduced form approach is that it is computationally tractable and transparent. In principle, program payments may affect the farmer's production decisions. One potential limitation of our reduced form approach for generating the price–yield distribution is that it assumes that the price distribution does not shift in response to possible non-random switches in planted crop acreages (both within and across crops) due to the availability of a new program. Future research can focus on adapting the model to allow for potential price shifts due to the support. One could develop a model with supply functions for the principal crops, where supply is a function of the first and second moments of revenue per acre, and with downward-sloping farm-level demand curves. A recursive application of this model could find the market clearing prices at planting time associated with potential supply shifts induced by the support payments. A structural model with carryover stocks could permit payment analysis across years.

While the academic literature is rich with papers on price estimation for commodities (see Goodwin and Ker 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 was measured between years, yield change was not included in their analysis. Paulson and Babcock (2008) provide a rare example of analysis of within-season price-yield relationship in an examination of crop insurance. Like them and Cooper (2010), we re-express the historical price and yield data as proportional changes between expected and realized price and expected and realized yield within each period, respectively.

For the model, the realized county, state, and national average yields, Y_{it} , are detrended to 2013 terms to reflect the proportional change in the state of technology between that in time t and that in

2013[1]. We detrend yield based on the standard practice of using a linear trend regression of $Y_{it} = f(t)$.[2] The expected value of Y_{it}, or $E(Y_{it})$, is calculated from the fitted trend equation. Based on historical yield shocks, $\Delta Y_{it} = {(Y_{it} - E(Y_{it}))}/{E(Y_{it})}$, we generate the detrended yield distribution, Y_{it}^d, as

(1) $Y_{it}^d = E\left(Y_{i2011}\right)\left(\Delta Y_{it} + 1\right), \forall\, t \neq 2013,$

where index *i* corresponds to all geographical units for which NASS has provided data over the study period for the corresponding crop. Price is transformed into deviation form, ΔP_t, as the difference between the expected and realized (harvest time) price, or $\Delta P_t = {(P_t - E(P_t))}/{E(P_t)}$.

Using the short time series of available yield and price data, 39 years to be precise, to calculate Y_i^d and ΔP results in discontinuous distributions that are inadequate to investigate subtle incremental changes in the shallow loss coverage rate. Therefore, we start by simulating continuous distributions of Y_i^d and ΔP.

Generating the Distribution of Yields and Prices

Like Deng, Barnett, and Vedenov (2007) and Goodwin and Ker (1998), we utilize the nonparametric kernel-based probability density function (Härdle, 1990; Silverman, 1986) for generating a smoother yield density than that which would be supplied by a block bootstrap. While a parametric density function such as the beta could be used as an alternative, the nonparametric density function allows more flexibility in modeling the density functions. The downside is the lower level of fit of nonparametric densities relative to the parametric densities, but then, given our relatively low sample

[1] The crop subscript is omitted.
[2] We examined the results across multiple counties using various forms of trend regressions (e.g. Loess and fully flexible Fourier), and found the simulation results to not be highly sensitive to the model specification.

size of years, we do not attempt to test best parametric versus nonparametrics fits. The kernel function, as applied to our notation and omitting the geographical subscript *i*, is

$$(2)\quad \hat{f}\left(y_l^d\right) = \frac{1}{Th}\sum_{t=1}^{T} K\left(\frac{y_l^d - Y_t^d}{h}\right),\ l = 1,\ldots,L.$$

where y_l^d are the yield points for which the density function is estimated. It allows us to generate values of Y^d distributions that approach a continuous function as L approaches infinity. Equation (2) gives support to generating yield values over the observed range of detrended yields, i.e., the (L x 1) vector $\boldsymbol{y}^d$ is drawn over the $\left(\min\left(Y^d\right), \max\left(Y^d\right)\right)$ interval. The function $K(.)$ is a Gaussian kernel (*ibid*.).[3] 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.[4]

We simulate a yield distribution for each {crop, geographical unit} combination by taking N = 10,000 draws of yield values, denoted as Y^{d*}, from each estimated kernel density. The draws are generated using a table-based inverse CDF approach combined with interpolation (e.g., Derflinger *et al.*, 2009). That is, we first construct tables of the yield values and their associated probabilities from the estimated kernel densities. Then, for each randomly chosen probability, the closest pair of probability values spanning the random probability draw are looked up in the table along with their associated pair of yield values. More precise approximations of the continuous distributions are constructed by linear interpolation between these two {probability, yield} points from the tables. The simulated price deviations are generated using the same kernel approach, again with 10,000 draws from the inverse CDF.

[3] We found the estimated density of program payments to be insensitive to the choice between Gaussian and biweight kernels.

[4] The bandwidth $h = 0.9/N^{0.2} \times \min[s(\vec{y}), z(\vec{y})/1.34]$, where $\vec{y}$ is the (Nx1) variable for which the density is to be estimated, $s(\vec{y})$ is the standard deviation, and $z(\vec{y}) = y_i - y_j$, is the inter-quartile range, where y_i and y_j are the 75th and 25th percentile values of the values of $\vec{y}$ sorted in ascending order.

Yields and prices 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 (but greater than with a parametric functional form). 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^{d*}. This approach and its application to generating farm level yields (Y^{Fd*}) is discussed in more detail below.

Imposing the historical correlations on the simulated densities

Of course, as drawn, the simulated national, state, and county detrended yields, and the simulated price deviation for each crop, being *i.i.d.*, do not have the same Pearson correlation matrix as the historical (actual) data, even if these have the correct means and variances. The historical correlations between these *m*+1 data vectors need to be imposed on their simulated counterparts, but without changing their respective means and variances, where *m* is the number of yield vectors in the model. To do so we rely on a copula-based approach (Nelsen, 2006). A block bootstrap would automatically maintain the historic relationship between the marginals. The downside of the copula relative to the block bootstrap is that by imposing the copula we may not well capture the true relationships between the marginal densities. On the other hand, as noted earlier, the block bootstrap produces insufficiently smooth densities given low degrees of freedom for yield data in many counties, particularly to analyze marginal changes in support payments (plus, there is the question of whether pre-1970s yield data is relevant to contemporary yield analysis). The results other than the mean values presented in Table 1 require that historic correlations be imposed on the estimated distributions. However, our regression does not as the dependent variable is the ratio of mean payment for a representative producer, which is invariant to correlation among yield correlations across counties.

Given $\mathbf{R}$, the *N*-by-(*m*+1) matrix of simulated data vector, the basic outline of the copula process is to: (1) generate a *N*-by-(*m*+1) matrix of quantiles, $\mathbf{U} = \{U_{ni}\}_{0 \le U_{ni} \le 1}$, that follow a desired multivariate distribution (in our case the meta-t distribution), which is defined over a target correlation matrix, $\boldsymbol{C}$, and a vector of potentially different degrees of freedom parameters, $\mathbf{v}$; and (2) use an inverse probability density function (PDF) approach to find $\mathbf{R}^* = U^{-1}(\mathbf{R})$, where U^{-1} is a loose mathematical notation. $\mathbf{R}^*$ will have (approximately) the same target inter-variable dependence relationship parameters as the historical data. The matrix $\mathbf{U}$ can be thought of as the structure of the association between the marginal distribution functions.

Formalized first by Sklar (1959, 1973), copulas are multidimensional functions that couple multivariate distribution functions with their univariate marginal distribution functions. Therefore, a copula can be used to convert a set of uncorrelated variables (e.g., our simulated yield and price distributions) to a multivariate distribution with a dependence structure defined by the target inter-variable relationship parameters of the chosen functional form.

For each crop *j* included in the analysis, we impose historical correlations on the *m i.i.d.* simulated detrended yield distributions and the price deviate distribution following steps outlined in Demarta and McNeil (2005). First we estimate nonparametrically the (unknown) marginal distributions of the actual data $\mathbf{D} = \{Y_1^d, \ldots, Y_m^d, \Delta P\}$ by so-called pseudo-likelihood (Genest *et al*., 1995). This method consists in extracting the "probabilities" associated with each value of the actual data to derive the empirical marginal distribution functions, $\hat{F}_{D_i}$, as follows:

(3) $$\hat{F}_{D_i}(d) = \frac{1}{1+T}\sum_{t=1}^{T} 1_{\{D_{i,t} \le d\}},$$

where 1 is the indicator function, which takes value one when the condition between brackets is met and zero otherwise. Note that if the matrix of actual data, $\mathbf{D}$, is not full rank, i.e., rank($\mathbf{D}$) < number of columns of $\mathbf{D}$, then it is bootstrapped to ensure full rank. This entails that, at this stage, *T* may be greater than the number of years of the historical data (T=10,000 in the present analysis).Using equation

(3), we can form the matrix of marginal distributions of the historical data, $\hat{\mathbf{V}} = \{V_t'\}_{t\in(1,T)}$, with

$$V_t = \left(V_{t,1},\ldots,V_{t,m+1}\right) = \left(\hat{F}_{D_1}\left(Y_{t,1}^d\right),\ldots,\hat{F}_{D_m}\left(Y_{t,m}^d\right),\hat{F}\left(\Delta P\right)\right).$$

We use the spectral decomposition-based approach proposed by Higham (2002) to force the obtained correlation matrix to be positive semi-definite and contain all ones on the diagonal in the event that it does not meet these requirements. With the estimated correlation matrix in hand, we can now build matrix $\mathbf{U}$.

We then generate discrete correlated simulated county, state and national yield, and national price distributions, $\mathbf{R}^*$, by using the same table-based inverse CDF functions for the kernel marginal densities discussed earlier. Spearman rank correlations are maintained throughout the successive steps.

The copula approach above imposed the historical correlations on the simulated densities for 1,001 corn counties, 889 soybean counties, and 510 winter wheat counties.

Generating the Farm Level Yield Distribution

In general, farm level yields with adequate time series and relevance to specific regions are not available from the USDA. One approach to developing farm level yield is to infer it from Federal crop insurance premiums in conjunction with information from NASS on county yields, using the assumption that the premiums are actuarially correct, that the NASS county yields have the same distribution as the county yields for the crop insurance participants, and that the difference between county and farm level yield is distributed normally with mean zero (Coble and Dismukes, 2008). These first two assumptions are strong and are hard to test in general, but Cooper *et al.* (2012) suggest some empirical evidence for the third.

We select the inflation factor, α_{ki}, where *i* is the index for counties\representative farmers, and such that the Actual Production History (APH) indemnity calculated from our yield distribution is equal to the APH premium:

$$(4) \qquad \min_{\alpha_{ki}} \left[\omega_i^k - N^{-1} \sum_n \max\left\{ \; p_i^{APH} \left(\theta E(Y_{i,2008}^k) - y_{ni}^k \right), 0 \; \right\} \right]^2 \quad ,$$

where $y_{ni}^k = \hat{Y}_{in}^k + h_{in} \left(\left(\alpha_{ki} \cdot \sigma(\hat{Y}_i^k) \right)^2 - \left(\sigma(\hat{Y}_i^k) \right)^2 \right)^{0.5}$, $\hat{Y}_{in}^k = E(Y_{i,2010})(1 + \Delta \hat{Y}_{in}^k)$, h_{in} is a $N(0,1)$ random variable, $\sigma(\hat{Y}_i^k)$ is the standard deviation for $\hat{Y}_i^k$, ω_i^k is the RMA base premium rate for the crop and county, p_i^{APH} is the APH price, and the coverage rate, θ, is .65.[5] Note that $n=1,\ldots,N$ is the index of the simulation. For each county-crop combination, we generate the simulated farm-level yields by adding a normally distributed random shock with mean zero and standard deviation α_{ki} to our simulated county-level yield data to generate simulated farm-level yields.

Another approach to generating the county to farm noise could be to use to use a "rule of thumb" potentially based on analysis of actual farm level yield data. The Risk Management Agency maintains farm level data on farmers enrolled in the programs, but the length of the time series on this data has been relatively low, but is growing and may be sufficient within a few years to make this approach a feasible alternative to inferring the standard error of yields from crop insurance premiums. See Cooper et al. (2012) for additional discussion of this topic.

Data

Data on county, state, and national planted yields 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 benchmark yield for the purpose of ARC calculations is simply the county average yield.

[5] According to a personal communication in 2012 with the chief actuary of the USDA's Risk Management Agency, the base premium rate is the appropriate crop insurance rate from which to infer the farm level standard deviation of yield. Here we assume that the producer does not choose enterprise units, but if one wanted to account for these, ω_i^k could be scaled by a ratio of the premium under some average choice of enterprise units versus that under the basic option. This ratio would be less than one, thus lowering α_{ki} .

For each crop, we follow the Risk Management Agency's (RMA) definitions of the expected and realized prices as used in their revenue-based insurance policies. For example, for realized price P_t for corn, we use the average of the daily November prices (October prices starting in 2011) of the December Chicago Board of Trade (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 CBOT corn future in period t, t = 1975,…,2013.

Shallow loss programs under the 2014 Farm Act

Three shallow programs were introduced in the 2014 Farm Act: Agricultural Risk Coverage (ARC), Supplemental Coverage Option (SCO) and Stacked Income Protection Plan (STAX) programs. The latter is open only to producers of upland cotton and is outside the scope of this paper.

SCO provides partial support for losses not exceeding the traditional crop insurance policy's deductible (RMA, 2014b). For example, in 2013, the highest number of acres was covered using Revenue Protection crop insurance (RMA, 2014c; RMA, 2014d) with a 75 percent coverage level for corn and soybeans and a 70 percent coverage level for wheat. If a producer has a revenue-based crop insurance policy with a coverage level of 75 percent, this means that any revenue loss of 25 percent or less is fully borne by the farmer. SCO is designed to help producers bear a portion of this remaining cost to the producer, and does so as an area-based (generally county) program. ARC operates similarly although it can cover either county or farm level losses (again, aimed at helping to pay the producer's deductible). However, ARC payments are not tied to current production, although individual level ARC requires sufficient production to determine the appropriate yields for each crop produced on the farm. Because SCO and ARC cover a portion of losses generally not covered by traditional federal crop insurance, they have come to be colloquially known as "shallow loss" programs in the agricultural media.

Eligibility constraints prevent producers from being able to enroll a particular acre in both the SCO and the ARC programs. However, if the producer enrolls an acre in the Price Loss Coverage (PLC) program, which provides a target price support similar to the old counter-cyclical payment program, that acre remains eligible for enrollment in the SCO program. Finally, to minimize overlap between these programs, growers cannot simultaneously enroll in either ARC or PLC for the same crop on the same farm, nor can a producer enroll a crop in both ARC and SCO on the same crop and farm. However, enrolling in PLC and SCO is allowed. Furthermore, once the election to enroll in either ARC or PLC is made, the producer is committed to this choice for the duration of the Farm Act.

Agricultural Risk Coverage (ARC)

The ARC program is a revenue-based program that works through the Commodity Title (Title I of the Farm Act) and is managed by the U.S. Department of Agriculture's Farm Service Agency (FSA, 2014; Effland, Cooper, and O'Donoghue, 2014). Producers interested in enrolling do not need to pay any premium for participating, and support is limited to 10 percent of the benchmark (expected) revenue and is furthermore subject to payment limitations. Because past national prices and county yields are used to generate the benchmark revenue, the revenue guarantee changes from year to year. To construct the benchmark revenue, a benchmark price and yield are required. The benchmark price is the greater of either the National Olympic average market price or the reference price established by Congress. The benchmark yield is the Olympic average yield.

Producers also have the choice to enroll in either individual or county level coverage. If they select county level coverage, they can enroll in ARC on a crop-by-crop basis and the payments they receive are paid to 85 percent of their base (historic) acres. If the producer enrolls in individual level coverage, the entire farm must be enrolled in individual level coverage, meaning that support is provided when the revenue for the entire farm (the sum of revenues from all commodities produced on the farm) falls below the benchmark for the entire farm. Selection of individual level coverage also means that payments are paid to 65 percent of the farm's base acres in proportion to current plantings of covered commodities.

The ARC guarantee is 86 percent of the benchmark revenue. The realized revenue is the realized yield multiplied by the greater of the realized price or the commodity loan rate. The highest level of support provided by the ARC program is 10 percent of the benchmark – and is only paid out on 85 percent of historic (base) acres. If less than 10 percent, the actual payout rate is the (positive) difference between 86 percent of the benchmark (since ARC only helps to cover those losses below 86 percent of expected revenues) and the realized yield multiplied by the higher of the realized price or the loan rate price (loan rate price for soybeans is $5, for example). If this difference turns out to be negative (i.e., realized revenues exceed 86 percent of expected revenues) then no payouts accrue. In other words, the per-acre county-ARC payment can be expressed in concise equation form as:

(5) County-ARC/acre =

$$0.85 * min[max\{ARC\ Guarantee - Realized\ Revenue, 0\}, 0.1 * Benchmark\ Revenue].$$

Given the 86 percent coverage rate and the maximum payment being 10 percent of benchmark revenue, ARC effectively covers realized revenue losses between 76 and 86 percent of the benchmark revenue.

Supplemental Coverage Option (SCO)

Assuming a revenue-based underlying individual insurance policy with upward price protection, i.e. Revenue Protection (the most common policy purchased by producers), SCO support works in a similar fashion to ARC, but with some key differences. When the underlying policy is Revenue Protection, the SCO expected area revenue consists of the higher of base insurance and harvest time price multiplied by the expected yield (for the sake of argument, we use 50 bushels per acre again – although it is possible that the expected area yields for SCO and ARC may differ since they use different methodologies to calculate them). As with the ARC program, losses between 100 and 86 percent of expected revenue are not covered. As the SCO expected area and farm revenue uses an expected price set within the crop year while the ARC revenue guarantee uses an Olympic average of prior years' prices, the SCO payment rate adjusts more quickly to current market conditions than the ARC payment rate.

Another notable distinction between SCO and ARC is that the amount of coverage offered by SCO is based on the deductible amount of the underlying insurance policy – the difference between the level of coverage of the underlying insurance policy and 86 percent. Formally, the SCO payment per acre can be expressed as:

(6.1) SCO/acre =

$$min\left[max\left\{\frac{\left(0.86-\frac{Final\ Area\ Rev}{E(Area\ Rev)}\right)}{(0.86-Cov.level)},0\right\},1\right]*E\ (Farm\ Rev\ per\ acre)*(0.86-Cov.level)$$

$$-Premium\ per\ acre,$$

where *Rev* denotes "revenue" and *E*(.) denotes the expected value of the variable inside the parentheses. The formula in the inner curly brackets is the "revenue payment factor", and to the right of the square brackets, *E*(*Farm Rev per acre*) * (0.86- Cov. Level) is the "supplemental protection", to use the RMA terminology. A functionally equivalent way to express the SCO payment per acre is

(6.2) SCO/acre =

$$min\left[max\left\{\left(0.86-\frac{Final\ Area\ Rev}{E(Area\ Rev)}\right),0\right\},(0.86-Cov.level)\right]*E(Farm\ Revenue\ per\ acre)$$

$$-Premium\ per\ acre.$$

In words, the above equation says that the payment rate (the function in the outer square brackets) that is multiplied by *E(FarmRevenue per acre)* has a range between 0 and (0.86 – *Cov. Level*).

The above two SCO equations are expressed generically to cover various choices of the underlying insurance policy. When the underlying policy is Revenue Protection, price in *E*(*Area Rev*) and *E*(*Farm Rev*) is the maximum of the base price and the harvest price, and price in *Final Area Rev* is the harvest price. When the underlying policy is Revenue Protection with Harvest Price Exclusion, price in *E*(*Area Rev*) and *E*(*Farm Rev*) is the base price, and price in *Final Area Rev* is the harvest price. When the underlying policy is Yield Protection, price in *E*(*Area Rev*), *E*(*Farm Rev*) and *Final Area Rev* is the base price.

Similar to ARC payment rates, SCO payment rates vary by the realized price. However, unlike ARC payment rates, SCO payment rates for a given yield outcome depend on the level of coverage of the individual producer's underlying crop insurance policy. For example, if the underlying coverage guarantees 70 percent of the producer's expected revenue, SCO payments will begin when county revenues drop below 86 percent of expected county revenues and will end when county revenues drop below 70 percent of expected county revenues (when the individual coverage kicks in). If the underlying coverage guarantees 80 percent of the producer's expected revenue instead, SCO payments would end when county revenues drop below 80 percent of expected county revenues.

As the traditional deep loss coverage (RP) is better known than the new ARC and SCO, for RP we bring in the subscripts and equation style notation. In our notation and omitting the crop subscript, the RP indemnity payment per acre for producer *i* in county *j* in period *t* is

$$\text{(7)} \qquad RP_{ijt} = \max \left[0, \left(\theta \cdot \max\left[E\left(P_{jt}\right), P_{jt}\right] \cdot Y_{ijt}^{APH} - P_{jt} \cdot Y_{ijt}\right)\right],$$

where $E\left(P_{jt}\right)$ and P_{jt} are expected and harvest time futures prices, respectively, Y_{ijt}^{APH} is the actual production history yield for the farm, Θ is the coverage rate, and Y_{ijt} is the farmer's actual yield.

RMA's historic lost cost ratio (LCR) approach for determining premiums implies that actuarial correctness is achieved when the expected loss ratio is 1.0. Thus, in a simulation context (e.g., Turvey, 1992), the RP insurance premium, $PremRP_{ijt}$, for farmer *i* in county *j* is set equal to $E\left(RP_{ijt}\right)$. $E\left(RP_{ijt}\right)$ is the mean of all outcomes of equation 7 given our (G ×1) vector of prices and a (G ×1) vector $\mathbf{Y}_{ij}$, i.e., the mean of G price-yield combinations; and *alt* is the farm yield densities under each of the three scenarios. The total insurance premium per acre can be expressed mathematically as (omitting the time subscript)

$$\text{(8)} \qquad PremRP_{ij} = \sum_{g=1}^{G} \max\left\{0, \left(\theta \cdot \max\left[E\left(P\right), P_g\right] \cdot Y_{ij}^{APH} - P_g \cdot Y_{gj}\right)\right\}$$

$$\approx \int_0^{Y_{ij}^{APH}} \int_0^{\theta \cdot \max\left[E\left(P\right), P\right]} \left[\max\left\{0, \left(\theta \cdot \max\left[E\left(P\right), P\right] \cdot Y_{ij}^{APH} - P \cdot Y\right)\right\}\right] dP dY$$

The farmer pays a percentage of this premium, where the percentage is a function of the coverage rate and the unit level chosen (see the appendix), where the latter is outside the scope of this paper. It is mathematically trivial to show that the net benefit of RP to the farmer is equal to the government paid portion of the premium. The same principle holds for SCO. Since ARC comes at no cost to the farmer, the ARC net benefit is simply the expected value of the ARC payments.

While ARC is a commodity program modeled after crop revenue insurance policies, the SCO program works as a crop insurance policy, relying on the underlying individual-level policy to determine the characteristics of support (RMA, 2014b; FCIC/RMA, 2014). This program is provided through the Crop Insurance Title (Title XI of the Farm Act) and is administered by the U.S. Department of Agriculture's Risk Management Agency (RMA). Enrollment requires the farmer to pay a premium and support is not subject to any payment limitations. SCO takes the basic trait of the underlying policy selected by the producer – being either yield or revenue based – and extends it (generally) as a county-based program to 86 percent coverage regardless of the underlying level of coverage. For example, if a producer who enrolled in a yield protection plan with 75 percent coverage also enrolled in SCO, the producer would receive additional yield protection coverage, at the county level, from 75 up to 86 percent. If the producer had a revenue protection policy instead with a coverage level of 80 percent, the SCO would provide additional county-level revenue protection coverage from 80 to 86 percent.

Exploring Producer Returns under Alternative Program Choices

Table 1 presents various moments of payments and returns using our statistical model to generate distributions of simulated prices and yields that are centered around their expected values at planting time in 2014. It shows the average of the revenue and payment simulations across representative producers in each county producing corn, soybeans, or wheat. The results show the national weighted average of what a typical U.S. producer would expect to generate in revenues from one acre planted to corn, soybeans, or wheat under the different support scenarios. For the payments coming from ARC or PLC, the averages reported in the table are generated by weighting the results for each producer by the total commodity base acres in the producer's county. Payments that do not involve ARC or PLC, the weights are total planted commodity acres in the county. If a producer did not enroll in any programs, but simply planted their acres to soybeans, they would expect to earn a per-acre revenue of $664 for corn, $498 for soybeans, or $276 for winter wheat. For simplicity, following corn only, based on 10,000 simulations, 95 percent of the time the revenue fell within the interval of ($232, $1,157) suggesting that with a 95 percent probability, the farmer could expect to receive no less than $232 per acre (in bad years) or no more than $1,157 per acre(in a good year) from simply the gross revenue and no program payments – based on price and yield realizations – of the crop. Of course, this does not rule out the possibility of complete disaster wiping out the crop entirely (for a revenue of $0) or a revenue that exceeds $1,156 per acre, but the model suggests that such extreme outcomes are likely to happen less than 5 percent of the time.[6]

When SCO and ARC are separately combined with an underlying Revenue Policy with 75 percent coverage, the resulting expected level of revenue and range of likely revenue outcomes are close for the 2014 planting time price scenario, suggesting that the two county-based programs work similarly under the current scenario of historic and expected yields and prices. Overall, under the 2014 scenario, ARC appears to be a better choice, but this can change over time as prices and yields change over time.

The relationship between shallow and deep loss support to farm revenue risk

Under SCO and RP, the average net benefit to the producer is equal to the government paid portion of the insurance premium. Under ARC, the average net benefit is the average payment[7]. While the previous discussion has focused on comparing the overall expected level and variance of revenues for the various program choices producers face, it remains difficult to obtain a good understanding of how these two new programs, SCO and ARC, reduce risk above and beyond that already covered by traditional crop insurance. Relative to the benefits of traditional crop insurance, how large are the added benefits these

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[6] Note that the 95% upper bounds with RP and RP plus SCO are lower than without program support (the "unenrolled" column) or with ARC only because the RP and SCO calculations include the farmer-paid premiums for these products.

[77] Of course, a pragmatic difference between the RP or SCO net benefit and the ARC net benefit is that the latter is literally paid to the farmer.

programs provide? And do these relative benefits differ for producers facing different levels of risk? In other words, are the SCO and ARC more valuable relative to the underlying crop insurance policy for some producers than others?

To explore this concept, we generate measures of the net benefits of the SCO and ARC programs relative to the total net benefit (defined as the sum of the net benefits of deep and shallow loss support). For SCO and RP, the net benefit is the implied government transfer, which is equal to the government-paid portion of the premium.[8] Note that in our simulation approach, the total premium equal to the expected value of the indemnity payment. For ARC, the net benefit is simply the expected payment, ignoring administrative costs. We then create a ratio of the shallow loss to the total benefits, using either SCO or ARC in the calculation. If the ratio is close to 0, this would suggest that the SCO (ARC) program provides little, if any, additional value to the producer in terms of net benefits above and beyond the benefits of the underlying RP crop insurance policy. If close to 1, SCO (ARC) provides the bulk of the total value. We then graph these ratios of relative benefits according to the riskiness of the producer (measured by the CV of revenues).

Figure 1 shows these ratios in graphical form. A clear relationship emerges showing that the ratio tends to be higher when the farmer's revenue risk is lower. Thes graph demonstrates that the shallow loss programs are relatively more important for low risk producers than they are for high risk producers. This makes sense since producers in low risk areas of the country have low probability of incurring large losses – the primary losses they face tend to be smaller in nature and the shallow loss programs help with exactly these types of losses. For these lower risk producers, the shallow loss programs are almost as important, if not more important, in terms of mitigating the risk they face when compared to the traditional, underlying RP policy. Producers in these riskier parts of the country are more worried about the large losses they have to face and the benefits of the shallow loss programs—SCO and ARC—are relatively small when compared to the benefits received from the traditional underlying RP policy. Under 2014 conditions, the CV explains more of the variation for ARC than for SCO.

[8] The government share of the underwriting risk is not included here.

Regression analysis on the share of shallow loss support to total support

What helps explain the ratio of shallow loss to total support? Variables such as planting time prices and coverage levels may play a role. To explore this issue, we randomly select values of these variables and re-calculate the benefits. For these controlled experiments, the variables will be assigned to representative farmers/counties through random uniform and independent draws. Given this data, we can use regression analysis to explain the relationship between the share of the shallow loss payments to the total commodity support (shallow loss payments + deep loss payments) and other key variables. In principle, regression analysis is not necessary to establish the average national elasticity of deep and shallow loss coverage rates given that the impacts of these programs on a representative farmer in each county could be calculated using official RMA formulas under the assumption that the RMA payment calculators are actuarially correct (before the premium subsidy). However, doing so for independently drawn coverage rates and across all eligible counties is not practical. Also such an approach would not help for a similar examination for ARC. Hence, we generate our own payments from the simulated data, and use the regression analysis.

This process provides us with the data necessary to econometrically estimate for each crop and shallow to total support combination the following equation:

E[*shallow loss support*]/E[*total support*] =

f(*Planting time futures price*, *coefficient of variation of farm revenue*, *coverage rate for RP insurance*, *shallow loss coverage rate* [SCO, ARC], *interaction between the two coverage rates*) .

For the purpose of this analysis, we define total support simply as the sum of the shallow loss support and the deep loss (RP) support. The coverage for RP is chosen by the farmer from a set of coverage rates ranging from 50% to as high as 85%, in 5% increments. The current shallow loss coverage rate in SCO and ARC is set by the legislation at 86%. The planting time futures price is explicitly a parameter of SCO and RP, and is implicit in ARC as the randomly draws of the season average and harvest time futures prices are centered around this value. Note that as a theoretical model of farmer behavior, this equation is endogenous.   However, this equation is not intended to provide understanding the choices producers make but instead, represents the “hard-wired” connection between the coverage rates and the ratio of shallow loss to total benefits. In fact, as a model based on real world observed data, it is endogenous in the coverage rates. However, our empirical model is not endogenous in the coverage rates as our simulation approach allows us to randomly and independently draw these values, and generate the payments based on them.

Key parameters for policy simulation are the estimated elasticity on the ARC and SCO coverage rates.   Raising or lowering these coverage rate levels changes the share of support going to the shallow loss programs, which has implications for downside revenue risk reduction and mean benefits, as well as for geographic implications related to those factors, ceteris paribus.   We include the expected price at planting time as this can change significantly from year to year, making it useful to capture its effect.

The RP coverage rate is randomly drawn from {0.50, 0.55, 0.60, 0.65, 0.70, 0.75, 0.80}, with 0.85 left out to avoid overlap with potential randomly chosen shallow loss coverage rates that are lower. The shallow loss coverage rates are randomly drawn from {0.84, 0.85, 0.86, 0.87, 0.88, 0.89, 0.90, 0.91, 0.92, 0.93, 0.94, 0.95}. Expected price is randomly chosen from a uniform distribution ranging from 75 to 125% of the 2014 planting time price.

Of course, more variables than shown in the equation above explain the ratio of shallow loss to total support. To focus on just the impacts of the key variables on relationship of shallow loss support to total support , an alternative would be to run the regression in first difference form. Using a first difference, variables that do not change between the base and alternative state are dropped (e.g. coefficient of variation of revenue).[9]

[9] The difference form likely reduces spatial correlation in the residual. Nonetheless, future analysis could test for such spatial correction, and if present, correct for it by including a spatial weights matrix in the

Regression results for the first difference are shown in tables 2 and 3 for the cases of SCO and ARC, respectively (the appendix provides the results in non-difference form). To account for the influence of county size, the variables are weighted for the regressions by the number of base acres or planted acres for the crop in the county, depending on the support program. For table 2 and table 3, the coefficient estimates for the variables of interest are statistically different from zero at the 1% level. In table 2 and table 3, a couple patterns emerge for the regression analysis for the ratio of shallow loss to total support. Increasing the coverage rate of Revenue Protection, i.e. deep loss coverage, will decrease the ratio of the shallow loss to total support holding all else constant, and increasing the coverage rates of SCO or ARC will increase the ratio of shallow loss to total support. These results are intuitive since an increase in the coverage level of Revenue Protection will increase the expected payout thus increasing total support and decreasing the ratio of shallow loss to total support. Likewise, increasing the coverage rates of SCO and ARC will increase the shallow loss payment, increasing the ratio of shallow loss to total support.

The regression results for table 2 and 3 do have several notable differences. First the change in the expected price has a positive impact on the ratio of shallow loss to total support for SCO but a negative impact on the ratio of shallow loss to total support for ARC. Since SCO and RP payments will likely increase from a positive change in price due to the harvest price replacement, it is not surprising that there is a small increase in the shallow loss to total support ratio for SCO. Since the ARC guarantee of 86% of benchmark revenue is not affected by a positive price change but RP is affected, the ratio of shallow loss to total support decreases. Note the changes in the ratio of shallow loss to total support is small with regards to price changes, for corn, soybeans, and winter wheat; increasing the expected price by $1.00 will increase the ratio of shallow loss to total support by 0.0581, 0.0321, and 0.0221 for SCO, respectively, and decrease the ratio of shallow loss to total support by 0.0888, 0.0403, and 0.0312 for ARC, respectively. Regarding the coefficient estimates for the deep loss and shallow loss, the estimates

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analysis. However, given the high level of regression fit, we do not concern ourselves here with this issue of efficiency of the coefficients.

are of a larger magnitude for SCO compared to ARC. For example for corn the coefficient estimate for deep loss is -1.6802 for SCO, while the same coefficient estimate under ARC is -0.9622. This indicates that one can expect if the coverage level increases by 1 point for Revenue Protection, the ratio of shallow loss to total support will decrease by 0.0068 under SCO and decrease by 0.0096 under ARC. For the coefficient estimate of shallow loss, a 1 point change in the coverage rate will increase the ratio of shallow loss to total support by 0.0189 under SCO and 0.0099 under ARC.

Table 4 shows the elasticity estimates for SCO and ARC as shares of total support. All elasticites are significant different from zero at the 1% level. The elasticities show that changes in deep loss coverage have a much greater impact on the ratio of shallow loss to total support compared to changes in shallow loss coverage. For example, for soybeans, the elasticities for deep loss are 0.5128 and 0.5924 for SCO and ARC, respectively, while the elasticities for shallow loss are 0.3464 and 0.3283 for SCO and ARC, respectively. Also, as seen in table 2 and table 3, the effect of change in expected price are small to the effects of changing coverage levels of deep loss or shallow loss programs. For soybeans, the price elasticities are -0.0056 for SCO and 0.0114 for ARC.

Policy Implications and Conclusion

Based on historical precedent, negotiations over the next Farm Bill debate will include discussion of the overall strategy for handling farm risk and the government's role in this strategy. Does the addition of revenue-based supports, which started with the 2008 Farm Act and continues under the 2014 Farm Act, complicate the message of which risks should be borne, at least partially, by the government and which program designs best deliver this support? Under recent farm programs, the risk support niches filled by FSA and RMA have shifted. Before 2008, RMA-managed programs covered yield and revenue risk and FSA programs addressed price risk. With the ACRE program in 2008 Act and under the ARC program in the 2014 Act, FSA also now has programs that manage revenue risk. Expansion of the Non-insured Crop Assistance Program (NAP) to include buy-up yield coverage further moves FSA into an area previously managed by RMA. These changing roles for administrative agencies reflect evolving policy views on appropriate ways for government to provide risk reduction. In considering policy approaches and program design for the next Farm Bill, a key political economy question will be what combination of government support best balances available resources for risk reduction across yield risk, price risk, and revenue risk. While we are not in the position to addressnormative questions such as the extent to which government should reduce the risk of shallow versus deep losses, the empirical model developed here provides a basis for answering both the positive and normative program design questions that will be debated for the next Farm Bill. For example, can the desired ends be achieved while avoiding program overlap and in ways that increase transfer efficiency and reduce the costs of adapting to climatic variability?

Producers will also likely consider the trade-offs between traditional crop insurance and SCO, since the cost and benefits of SCO coverage are linked to the level of coverage chosen under traditional crop insurance. While producers' price expectations will be critical in the annual decisions they make regarding the purchase of crop insurance coverage, premium subsidy rates may also help guide producers' choices.

The subsidy for SCO premiums is fixed at 65 percent. For traditional crop insurance policies, however, subsidy rates vary depending on the level and type of coverage purchased. Producers can choose coverage rates from 50 to 85 percent of expected yield or revenue. The subsidy on premiums decreases from 80 to 38 percent depending on the coverage level and type of insured unit (i.e. basic, optional, enterprise, or whole farm) chosen by the producer. The units chosen define the way coverage on the farm can be divided, allowing the producer to customize insurance coverage for the various parts of their operation. The more aggregated the unit, the higher the subsidy rate —the goal is to encourage combined coverage across a more diverse operation, which can be expected to reduce insurance risks.

SCO covers the difference between the producer's traditional insurance revenue or yield loss coverage and 86 percent of the producer's expected revenue or yields. For producers who choose traditional crop insurance using basic and optional units, the SCO subsidy rate of 65 percent is higher than that for any traditional insurance coverage level above 50 percent. Based simply on this subsidy difference, these producers may choose to reduce their coverage level under traditional crop insurance and purchase an SCO policy to cover the remaining range of losses up to 86 percent.

A further consideration for producers, however, will be that SCO payments are based on county average yield or revenue, while most traditional crop insurance coverage is based on farm level yield or revenue. Shifting insurance coverage to SCO thus may come at the cost of less efficient risk protection if the farm's yields differ markedly from county averages.

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Table 1. Summary of per-acre shallow loss program payments, deep loss (RP) insurance, and total revenues for representative producers in all U.S. counties, given 2014 expected prices and yields

	Avg (net) Payment/Acre	Avg Total Revenue/Acre	95% Confidence Interval of Revenue/Acre	Coefficient of Variation of Total Revenue/Acre[c]
		Corn		
Not enrolled-pltd[b]	--	664	[232, 1157]	0.36
Not enrolled-base[b]	--	671	[239, 1164]	0.36
SCO only[a]	13	677	[281, 1154]	0.34
ARC only[b]	28	699	[296, 1167]	0.32
RP (75%)	23	687	[494, 1138]	0.27
RP + SCO[bd]	35	700	[494, 1136]	0.26
RP + ARC[b]	50	721	[517, 1148]	0.24
		Soybeans		
Not enrolled-pltd[b]	--	498	[151,910]	0.40
Not enrolled-base[b]	--	507	[166, 911]	0.38
SCO only[a]	9	507	[177, 909]	0.38
ARC only[b]	13	520	[194, 911]	0.36
RP (75%)	19	517	[359, 894]	0.30
RP + SCO[bd]	27	526	[354, 893]	0.29
RP + ARC[b]	31	537[a]	[367, 897]	0.27
		Winter Wheat		
Not enrolled-pltd[b]	--	261	[32, 556]	0.55
Not enrolled-base[b]	--	276	[31, 589]	0.54
SCO only[a]	7	268	[50, 555]	0.52
ARC only[b]	4	280	[43, 590]	0.52
RP (75%)	16	278	[180, 543]	0.40
RP + SCO [bd]	23	284	[177, 542]	0.38
RP + ARC[b]	21	297	[190, 575]	0.38

[a]"SCO only" presumes a 75% coverage rate on the RP policy.

[b]With ARC, the results across counties are weighted by base acres, while SCO and RP are weighted by planted acres. Also, note that the confidence interval is nonparametric (i.e., does not assume any particular distribution), and as such, and may not be symmetric around the average.

[c]"Coefficient of variation of revenue" is the standard deviation of revenue divided by average revenue, and is a standardized measure to allow comparability of variability across programs.

Source: USDA, ERS calculations using model developed by ERS economists

dA producer enrolled in Price Loss Coverage (PLC) can also enroll in SCO on a crop-by-crop basis, and in deep loss insurance such as RP. However, we do not examine the combination of PLC, SCO, and RP to focus on deep versus shallow loss support issues.

Table 2. Regression results for SCO support as a share of total support (regression in difference form)

	Corn		soybeans		Winter Wheat	
variable	coef est	t-stat	coef est	t-stat	coef est	t-stat
Const	0.0169	5.74	0.0267	7.75	0.0047	1.88
ΔE(P)	0.0581	25.03	0.0321	28.54	0.0221	14.02
$\Delta\theta^{deep}$	-1.6802	-82.96	-1.4386	-60.89	-1.4299	-73.35
$\Delta\theta^{shallow}$	1.8982	37.31	2.0142	36.30	1.7654	37.38
N	1,001		889		510	
Rsq	0.94		0.92		0.96	
F-stat	3,939		2,561		3,045	

Note: ΔE(P) is the randomly chose planting time price minus the futures price at planting time in 2014 ($4.62/bu for corn, $11.36/bu for soybeans, $7.02/bu for wheat). $\Delta\theta^{deep}$ is the randomly chosen deep loss (ie. traditional federal crop insurance) coverage rate minus the base coverage rate of 0.75. $\Delta\theta^{deep}$ is the randomly chosen SCO coverage rate minus the base coverage rate of 0.86. The dependent variable is the difference between (*government-paid SCO premium*)/(*government-paid SCO + RP premiums*) in the base and alternative case.

The regression approach is weighted least squares. The weight is planted acres in the county multiplied by the ratio of total sample size N to the sum of acres across all observations.

Table 3. Regression results for ARC support as a share of total support (regression in first difference form)

	Corn		soybeans		Winter Wheat	
variable	coef est	t-stat	coef est	t-stat	coef est	t-stat
Const	-0.0135	-6.79	0.0073	2.49	0.0048	2.30
ΔE(P)	-0.0888	-56.80	-0.0403	-42.80	-0.0312	-24.05
$\Delta\theta^{deep}$	-0.9622	-70.50	-1.0238	-51.91	-0.4673	-28.68
$\Delta\theta^{shallow}$	0.9866	28.38	1.1760	25.67	0.7246	18.62
N	1,001		889		510	
Rsq	0.92		0.90		0.85	
F	2,961		2,032		737	

Note: ΔE(P) is the randomly chose planting time price minus the futures price at planting time in 2014 ($4.62/bu for corn, $11.36/bu for soybeans, $7.02/bu for wheat). $\Delta\theta^{deep}$ is the randomly chosen deep loss (ie., traditional federal crop insurance) coverage rate minus the base coverage rate of 0.75. $\Delta\theta^{deep}$ is the randomly chosen ARC coverage rate minus the base coverage rate of 0.86. The dependent variable is the difference between (*mean ARC benefit*) / (*mean ARC benefit + government paid premium)* in the base and alternative case.

The regression approach is weighted least squares. The weight is planted acres in the county multiplied by the ratio of total sample size N to the sum of acres across all observations.

Table 4. Elasticity point estimates SCO and ARC support as a share of total benefits (from regression in first difference form)

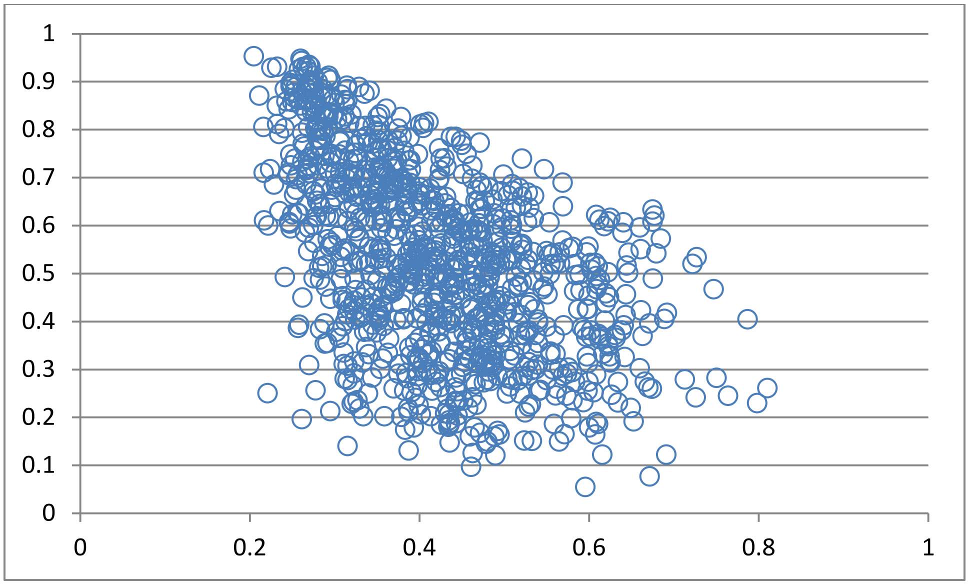
	Corn		soybeans		Winter Wheat	
variable	SCO	ARC	SCO	ARC	SCO	ARC
ΔE(P)	0.0077	-0.0257	-0.0056	0.0114	-0.0025	0.0090
$\Delta\theta^{deep}$	0.6094	0.7646	0.5128	0.5924	0.6278	0.5362
$\Delta\theta^{shallow}$	0.3256	0.3707	0.3464	0.3283	0.3819	0.4096

Note: All elasticities are significantly different from zero at the 1% level or better.

Figure 1. Shallow loss support for corn as a share of total support versus the coefficient of variation of gross revenue (all counties – based on 2014 expected price and yields and RP with 75% coverage rate)

(a) SCO government paid premium as a fraction of (RP + SCO gov. paid premium)

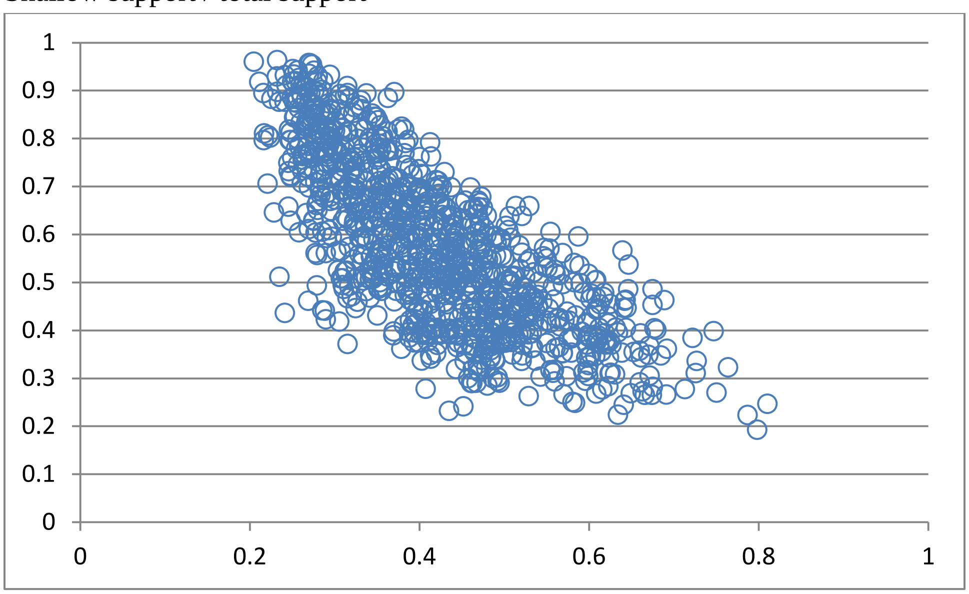
Shallow support / total support



Coefficient of variation of revenue

(b) ARC average payment as a fraction of (RP gov. paid premium plus ARC avg. pymt)

Shallow support / total support



Coefficient of variation of revenue

Appendix table A.1. **Premium subsidy rates for traditional crop insurance and the Supplemental Coverage Option (SCO)**

	Insurance coverage level (percentage of yield or revenue loss covered)							
	50	55	60	65	70	75	80	85
	Premium Subsidy Rate (percentage of premium paid by Federal government)							
Traditional insurance (by type of unit insured)								
Basic or optional unit	67	64	64	59	59	55	48	38
Enterprise unit	80	80	80	80	80	77	68	53
Whole Farm unit	80	80	80	80	80	80	71	56
Supplemental Coverage Option (SCO)								
All units	65	65	65	65	65	65	65	65

Source: USDA, Risk management Agency.
Note: Insured units are based on the location of the land, the crops grown, the production practices used, and the rental arrangements in place to help determine policy eligibility. A basic unit may include all land planted to a single crop within a county that (a) a producer owns and/or cash rents or (b) that is share-rented with a single landlord (share-rentals with separate landlords require separate basic units). Basic units can be divided into optional units based on location (if the basic unit covers more than one township) or production practices (if the basic unit incorporates, e.g., irrigated and non-irrigated land). Basic units can be combined into enterprise units which include all of an operator's acres of a single crop within a county regardless of ownership, rental arrangement, or production practice. Whole farm units combine all of an operator's eligible crops and farm units within a county regardless of ownership, rental arrangement, or production practice. Whole farm insurable units are generally only available for crops insured under revenue protection plans.

Table A.2. Descriptive Statistics (associated with the regressions in the appendix)

Variable	Corn		Soybeans		Winter Wheat	
	Mean	Stand. deviation	Mean	Stand. deviation	Mean	Stand. deviation
Dep. Var. (SCO)	0.526	0.194	0.486	0.185	0.436	0.171
Dep. Var. (ARC)	0.572	0.170	0.493	0.177	0.242	0.098
E(P)	4.647	0.732	11.325	1.777	7.003	1.114
θ^{deep}	0.675	0.085	0.678	0.085	0.682	0.086
$\theta^{shallow}$	0.895	0.034	0.895	0.035	0.894	0.034
Coefficient of var. of revenue	0.419	0.113	0.435	0.113	0.541	0.115

Note: E(P) is the randomly chose planting time price minus the futures price at planting time in 2014 ($4.62/bu for corn, $11.36/bu for soybeans, $7.02/bu for wheat). θ^{deep} is the randomly chosen deep loss (ie. Traditional federal crop insurance) coverage rate. θ^{deep} is the randomly chosen SCO coverage rate. Coefficient of var. of revenue is the coefficient of variation of revenue per acre for a representative farmer in the county. The dependent variable *Dep. Var. (SCO)* is (*government-paid SCO premium*)/(*government-paid SCO + RP premiums*). The dependent variable *Dep. Var. (ARC)* is (*government-paid SCO premium*)/(*government-paid SCO + RP premiums*).

Table A.2. Regression results for SCO support as a share of total support (dependent variable is logged)

variable	Corn coef est	coef./SE	Soybeans coef est	coef./SE	Winter Wheat coef est	coef./SE
Const	-1.8794	-12.00	-2.7702	-14.18	-1.3679	-5.09
E(P)	0.1314	17.55	0.0616	14.75	0.0620	7.00
θ^{deep}	-3.1901	-48.95	-3.1316	-35.74	-3.8358	-34.70
$\theta^{shallow}$	3.9962	24.43	4.8140	23.40	4.2543	15.94
Coefficient of var. of revenue	-2.1702	-35.43	-2.0996	-28.88	-2.1551	-27.25
N	1,001		889		510	
Rsq	0.89		0.85		0.95	
F-stat	1,643		1,021		2,090	

Note: E(P) is the randomly chose planting time price minus the futures price at planting time in 2014 ($4.62/bu for corn, $11.36/bu for soybeans, $7.02/bu for wheat). θ^{deep} is the randomly chosen deep loss (ie. Traditional federal crop insurance) coverage rate. θ^{deep} is the randomly chosen SCO coverage rate. Coefficient of var. of revenue is the coefficient of variation of revenue per acre for a representative farmer in the county. The dependent variable is (*government-paid SCO premium*)/(*government-paid SCO + RP premiums*).

The regression approach is weighted least squares. The weight is planted acres in the county multiplied by the ratio of total sample size N to the sum of acres across all observations. *N* is the number of counties, each of which is proxied by a representative farmer.

Table A.3. Regression results for ARC support as a share of total support (dependent variable is logged)

	Corn		soybeans		Winter Wheat	
variable	coef est	coef./SE	coef est	coef./SE	coef est	coef./SE
Const	0.3898	5.00	0.2764	3.04	-0.1273	-0.44
E(P)	-0.1379	-37.42	-0.0752	-37.13	-0.1118	-11.71
θ^{deep}	-1.4304	-44.49	-1.9628	-46.27	-1.6415	-13.57
$\theta^{shallow}$	1.6536	20.21	2.5519	25.84	2.0722	7.22
Coefficient of var. of revenue	-2.0364	-61.26	-2.6575	-67.85	-2.3576	-23.87
N	1,001		889		510	
Rsq	0.92		0.95		0.97	
F	2,412		3,370		2,920	

Note: E(P) is the randomly chose planting time price minus the futures price at planting time in 2014 ($4.62/bu for corn, $11.36/bu for soybeans, $7.02/bu for wheat). θ^{deep} is the randomly chosen deep loss (ie., traditional federal crop insurance) coverage rate. θ^{deep} is the randomly chosen ARC coverage rate less 0.86. The dependent variable is (*mean ARC benefit*) / (*mean ARC benefit + government paid premium)*. Coefficient of var. of revenue is the coefficient of variation of revenue per acre for a representative farmer in the county.

The regression approach is weighted least squares. The weight is planted acres in the county multiplied by the ratio of total sample size *N* to the sum of acres across all observations. *N* is the number of counties, each of which is proxied by a representative farmer.