Fiscal and Farm Level Consequences of "Shallow Loss" Commodity Support

May 30, 2012

Joseph Cooper, Benoît Delbecq, and Christopher Davis *

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2012 AAEA Annual Meeting, Seattle, WA, August 12-14, 2012.

This paper has not been previously presented in any other meetings.

*Cooper, Delbecq, and Davis are economists with the Economic Research Service, USDA. The views expressed are the authors' and do not necessarily represent those of the Economic Research Service or the US Department of Agriculture.
#jcooper@ers.usda.gov, bdelbecq@ers.usda.gov , chrisdavis@ers.usda.gov

Fiscal and Farm Level Consequences of "Shallow Loss" Commodity Support

Abstract

As with the 2008 Farm Act, the 2012 Farm Act is likely to have some sort of revenue-based support for producers of qualifying crops. Much debate over the negotiations on the 2012 Farm Act focuses on new programs for providing producers with support payments covering "shallow losses" in revenue. The main goal of this paper is to develop an approach to examine the sensitivity of the farmer's downside risk protection and federal budgetary costs of marginal changes in the deductible in shallow loss program scenarios based on the Average Risk Coverage (ARC) program in the Senate's April 26th draft of the 2012 Farm Bill. We find that average payments are elastic with respect to the revenue program's coverage rate. In addition, using this approach, the paper compares payments and their impacts on farm revenue for county and farm level implementations of the revenue program. We find that based on expected payments and impacts on downside revenue risk, producers are likely to prefer the county level implementation of the revenue support program to the farm level version.

Fiscal and Farm Level Consequences of "Shallow Loss" Commodity Support

Introduction

U.S. Federal Crop Insurance covers deep losses in crop revenue but the deductible leaves producers exposed to potential for out-of-pocket loss (i.e., shallow loss). What percentage loss is the dividing point between deep and shallow losses is somewhat arbitrary. Deep revenue losses can be considered as those exceeding 30 percent of expected revenue, based on the World Trade Organization's Agreement on Agriculture (in Annex 2, section 7(b)). We will consider "deep" losses to be revenue losses exceeding 20 percent of expected revenue, and shallow losses being those somewhere between 0 and 20 percent of expected revenue. Federal crop revenue insurance provides protection for losses exceeding 25% to 50% of expected revenue (in some areas, as low as 15% of expected revenue).

Many policy recommendations for Title I of the 2012 "Farm Act" – usually the main section dealing with commodity support – that is currently under negotiation have focused considerable debate over whether federal farm support programs should focus mainly on protecting farmers against "deep losses" in revenues (or yields) or also include protection against shallow losses (Shields and Schnepf, 2011). One possibility is for Federal crop insurance to cover deep losses, as it now does, and for Farm Act legislation to cover shallow losses.[1] In fact, the Average Crop Revenue Election Program (ACRE) in Title I of the 2008 Farm Act requires that state level crop revenue falls by at least 10%

[1] Much federal farm policy is included in "Farm Acts" – the most recent being the 2008 Farm Act – for which certain key support legislation expires at the end of the 2012 crop year. The "2012 Farm Bill" is the negotiations over the 2012 Farm Act legislation that will presumably cover the next 5 years. Note that Federal Crop Insurance, and major biofuel support for that matter, is covered in other legislation.

relative to the benchmark revenue in order to trigger a revenue payment (in addition, a farm level trigger with no deductable must be met). The 2012 Farm Act's Supplemental Revenue (SURE) program is a whole farm standing disaster assistance program that provides additional support on top of federal crop insurance, covering some of the deductible in the Federal crop insurance program for disasters occurring through the end of September, 2011. While the SURE program covered only shallow losses, the ACRE program cannot be truly be considered a shallow loss program. While the ACRE program has a 10% state level deductible, payments cannot exceed 25% of benchmark revenue, therefore fully covering State revenue losses when State revenue is between 67.5% and 90% of expected revenue, but with the payment at the cap when revenue is 67.5% or less of expected revenue. Even with the cap on payments, a portion of the deep losses are covered.

However, Title I of the April 26 Manager's Amendment of the 2012 Senate Farm Bill (U.S. Senate, 2012), has a new revenue, Agricultural Risk Coverage (ARC), with an 11% deductible (i.e., the coverage rate is 89%), but payments cannot exceed 10% of benchmark revenue. Effectively then, the ARC is purely a shallow loss payment, with a per acre payment rate fully covering farm or county revenue losses when revenue is between 80% and 89% of expected revenue. Presumably, the seemingly arbitrary 89% coverage rate was not chosen based on any general principles for farm risk management, but simply 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 farm revenues and government costs.

The main goal of this paper is to develop an approach to examine the sensitivity of average payments as well as the farmer's downside risk protection of marginal changes in the deductible in shallow loss program scenarios, based on one percent increments over the 15% to 5% deductible range (i.e., revenue coverage rates in the range of 85 to 95 percent). Given that the program that we examine has a payment ceiling of 10% of benchmark revenue, our analysis covers a program that provides support for actual revenues in the range of 80 % to (85 to 95)% of expected revenue, i.e., losses between (5 to 15)% and 20% of benchmark result are examined. To analyze the change in the payment distribution over small changes in the coverage rate requires an estimation approach that can differentiate over small changes in the coverage rate, such as the kernel-based approaches in Cooper (2010) and Goodwin and Ker (1998). However, those approaches have never been simultaneously applied to more than one region.

We conduct this analysis for all counties that grow corn, soybeans, winter wheat, and upland cotton (albeit not an ARC crop) for which the National Agricultural Statistics Service of the USDA reports data. Since yields are spatially correlated across counties, national figures need to account for this correlation. To date, the only published approaches to estimating Farm Act support that address the spatial correlation across regions use block bootstrap approaches (e.g., Cooper, 2010; Dismukes et al., 2011). These approaches work by simply drawing with replacement vectors of a year's worth of detrended historical data. Since the random draw is a vector of a year's worth of data for however many regions are included in the analysis, the historical correlations between the regions are maintained. However, by imposing no other assumptions on the data, the empirical distribution for each region are only defined in $1/T$ probability increments, where T is the total number of data points for each region in the analysis. Since US county level data is relatively sparse before 1975, and full county level data beyond 2010 is not available at the time this paper was written, we have approximately 35 years of county level data for a broad coverage of the US. This is equivalent to estimating a density in 2.87% increments, which is not sufficiently defined for addressing incremental changes in the shallow loss coverage rate.

In response, this paper uses a copula approach with nonparametric price and yield distributions that can simultaneously estimate revenue distributions across all counties reporting yields for the four crops using empirical distributions that are defined over arbitrarily small probability increments. In addition, using this approach, we compare payments and their impacts on farm revenue for county and farm level implementations of ARC. Finally, we compare ARC support payments and their revenue impacts to those under the existing ACRE program.

Background

Like the ACRE program, the proposed ARC program is complex and we will only describe its principle properties here. Under the ARC Program, a qualifying producer would make a one-time choice for the life of the 2012 Farm Act to receive the revenue support based on farm or county level benefit calculations.

The ARC revenue payment (denoted as ARC_{ijt}) to producer i of crop j in period t is:

(1) $$ARC_{ijt} = \max\{\, 0, \min[(0.10 \cdot ARCG_{tj}), (\mathrm{ARCG}_{tj} - ACR_{tj})]\} \cdot EEij \cdot A_{ijt},$$

where:

$ARCG_{tj}$ is the *Agricultural Risk Coverage Guarantee Revenue* for crop j in crop year t, calculated as the 5-year Olympic moving average (an average that removes highest and lowest values) yield per planted acre for the individual or county times the national average marketing year price times 89%. In the case of the farm level payment, the national average marketing year price is the 10-year average, and in the case of the county level payment, it is the 5-year Olympic average price. If average yield for the individual is less than 60% (70 percent in 2013 cop years or later), then 60 (70)% of the applicable "transitional yield" is used in its place[2];

ACR_{tj} is *Actual Crop Revenue* for crop j in period t, calculated as yield (county or farm) for crop year t times the higher of the U.S. average midseason cash price for the marketing year t or the crop's marketing assistance loan rate;

EE_{ij} is the percentage of *eligible acres* planted to the commodity, and is 65% for the farm level payment and 75% for the county level payment. The prevented planting rate is 45% in either case.[3]

To the extent possible, the proposed legislation calls for making separate *ARCG* calculations for irrigated and nonirrigated acres. Note that unlike the 2008 Farm Act, this proposed 2012 legislation does not give the farmer the choice between enrollment in the revenue-support program or the "traditional" price-based supports, and the latter are eliminated. ARC payments are subject to total limits per recipient and spouse, as well as

[2] The "transitional yield' is defined as per the Risk Management Agency (USDA) and generally mirrors average county yield.

[3] A functionally equivalent statement to Equation (1) is $ARC_{ijt} = \min\{ (0.10 \cdot ARCG_{tj}), \max[0, (\mathrm{ARCG}_{tj} - ACR_{tj})]\} \cdot EEij \cdot A_{ijt}$.

limits based on adjusted gross income (as defined in Federal tax code). The ARC does not cover cotton, which has its own support option under Title XI of the proposed bill. Nonetheless, the benefit of the research process is that we can still model cotton support under ARC. Title XI also has a various supplemental support options, but those are beyond the scope of this study.

There are a number of differences between the ARC program and the ACRE program that are too numerous to cover here. Besides differences in the coverage rate and the maximum payment rate, these include the omission of the farm to aggregate yield ratio and the double trigger. Unlike under ACRE, the farmer enrolling in ARC does not receive a percentage of Direct Payments; the April 26th version of 2012 Farm Bill does not include Direct Payments. Like ACRE, ARC payments are made to planted acres, but while total acres receiving payments under ACRE are limited to base acres on the farm, total planted acres receiving payments are limited to acres planted on the farm over the 2009 to 2012 crop years (plus some allowed acreage adjustments). Unlike the ACRE revenue guarantee, the ARC's revenue guarantee has no floor and ceiling on how much it is allowed to move from year to year, but on the other hand, the ARC's revenue guarantee uses a longer time frame than ACRE for calculating average prices. For the sake of brevity, we do not include a detailed description of the ACRE program here. Such a description is available in Cooper (2010).

Methodology for Estimating the Density Function for ARC Payments

For the simulation of ARC 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 prices and yields are temporally correlated with each other, and yields across regions are spatially correlated. Hence the estimated distributions must take this correlation 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.

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 and would divert the focus of this article. 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.

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 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 and Cooper (2010), 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.

For the model, the realized county average yield, Y_t , is transformed to the yield deviation ΔY_t according to $\Delta Y_t = {(Y_t - E(Y_t))}/{E(Y_t)}$, where the county and crop subscripts are omitted. To generate a distribution for Y_{2011} based on historic yield shocks, the historic yields must be detrended to reflect the proportional change in the state of technology between that in 2011 and that in time *t*, i.e., Y_{it} is detrended to 2011 terms as

(1) $Y_{it}^d = E(Y_{i2011})(\Delta Y_{it} + 1), \forall\, i$ counties, *t* periods, $t \neq 2011$.

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 ΔY_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 change in the realized price at harvest, ΔP_t, is the difference between the expected and realized (harvest time) price, or $\Delta P_t = {(P_t - E(P_t))}/{E(P_t)}$. Given the estimated trend yields as the predictions of $E(Y_t)$, we can construct ΔY_t^d . Then, we simulate the distributions of ΔP_t and ΔY_t^d and next, impose the historical correlations among the ΔP_t and ΔY_t^d , where the ΔY_t^d include the county yields for all counties for which NASS has provided data over the study period. We simulate farm level yields from county level yields when necessary based on assumptions of county-to-farm noise.

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 (Hardle, 1990; Silverman, 1986) for generating a smoother yield density than that which would be supplied by a block bootstrap. This function, as applied to our notation, is

(2) $$\hat{f}\left(y_j^d\right) = \frac{1}{Th}\sum_{t=1}^{T} K\left(\frac{y_j^d - Y_t^d}{h}\right), j = 1,\ldots,J.$$

This function allows us to generate values of ΔY^d for each county for distributions 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* x 1) vector $\boldsymbol{y}^d$ is drawn over the range {min(Y_t^d)…max(Y_t^d)}, $t = 1\ldots T$, where y_i^d are the yield points for which the density function is estimated. The function *K*(.) is a Gaussian kernel (*ibid*.).[4] 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.[5] We simulate the yield distribution by taking *N* = 10,000 draws of yield values, denoted as Y_n^{d*}, from the estimated kernel density. The draws are generated using an inverse CDF approach that is table-based combined with interpolation (e.g., Derflinger *et al.*, 2009). That is, tables of the yield

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

[5] 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.

values and their associated probabilities are saved in the computer's memory. Then, for randomly chosen probabilities in the tables, the associated yield value is looked up in the table. Continuous distributions are constructed by linear interpolation between the yield points in the tables. Given the expected (trend) yield for a reference year, the yield deviate ΔY_n^{d*} is calculated for each Y_n^{d*}. The simulated price deviations are generated using the same kernel approach, again with 10,000 draws from the inverse CDF.

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_n^{d*}. This approach is discussed in more detail below in its application to generating farm level yields.

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 (Y^{Sd*}) off of the county level Y^{Cd*}.

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 assumptions and are hard to test in general, but Cooper et al., (2012) suggest some empirical evidence for the third. Here we use the relatively simple approach of Goodwin (2009) of simply adding a normally distributed random shock with mean zero to the simulated county yield data. While Goodwin assumed that the standard deviation of the shocks are equal to 75% of the standard deviations of the detrended state yield distribution, we use 50%, which appears more appropriate for inflating county level distributions, based on our analysis of the Kansas and Illinois farm management association data used in Cooper et al. (2012).

Imposing the historic correlations on the simulated densities

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 means and variances. The historic correlations between the national, state, and county level yields need to be imposed on their simulated counterparts, but without changing the means and variance of each yield vector. To do so we rely on a copula-based approach (Nelsen, 1996). We start by generating 10,000 draws of multivariate random normals with means and variance-covariance matrix from the historic yield vectors. By applying the inverse cumulative distribution function (CDF) of the standard normal distribution, we obtain the probabilities (or quantiles) P associated with each generated correlated normal value. We then generate discrete correlated simulated county, state and national yield distributions by using the same table-based inverse CDF functions for the kernel marginal densities discussed earlier, in which the *P*'s from the multivariate normal are used to find the corresponding prices and yields from the nonparametric distributions (that is, the *P*-values from the multivariate normal are matched with same *P*-values in the linearly interpolated tables for the kernel density, and the associated price and yield values for the latter *P*-values are looked up in these tables). Spearman rank correlations are maintained throughout the successive steps.

The copula approach imposed the historic correlations on the simulated densities for 1,171 corn counties, 1,017 soybean counties, 734 winter wheat counties, and 117 upland cotton counties.

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 insurance and ARC calculations is simply the county average yield.

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 in period t, $t = 1975,\ldots,2011$. For corn and soybeans, the values of $E(P_{2011})$ are the same as the official RMA base prices for the RA insurance products for the 2011 crop year.

ARC actual revenue is calculated using the midseason average national cash price, but as this value tends to follow the season average cash price quite closely over time, we assume a 0 basis value between the two.[6] We convert P_{2011} to the cash price using the basis defined as the median difference between P_t and the NASS price in t over the ten years prior to 2011.

Discussion of the payment simulation results

Tables 1 and 2 present the simulation results for ARC Payments per acre, gross revenue per acre, and total gross revenue with ARC payments for the 2011 crop year for corn, soybeans, winter wheat, and upland cotton (noting that upland cotton is not included as an ARC eligible crop in the proposed legislation). The results are weighted by planted acres for all counties for which NASS reported county level data over 1975 to 2010.

Table 1 has the results assuming producers have chosen the farm level option, and Table 2 the results assuming farmers have chosen the county level option. To conserve space, the lower bound of the 95% confidence intervals for payments per acres (section A in the tables) is not shown, but the values are close to zero. Similarly, the upper bound of the confidence intervals are not shown for gross revenue plus the payments (section C), but these are the same as in the gross revenue only case (section B). To preserve the impacts of spatial correlation in the reported national-level statistics, the data in the (number of counties) x10,000 matrix of simulation results is summed vertically through each of the 10,000 columns to derive the 1x10000 draws of the national level impacts.

[6] Based on an examination of monthly cash prices and sales volumes over the last 30 years for corn, soybeans, and winter wheat, we find that the mid-season price is on average 97% to 98% of the season average price.

As can be seen in the first output column of Tables 1 and 2, average payments per acre tend to be relatively low, and not exceeding \$2.77/acre in any scenario. The county-based average payments are larger than the farm-level ones except in the case of cotton. Note that the difference between the farm and county payments is not only attributable to differences in yield risk between the two tables (and we expect payments to be increasing in yield variability), but also to the farm level program paying to a lower share of planted acres than the county level program. Hence, without an empirical analysis, one cannot say which program would provide greater benefits.

The programs in Tables 1 and 2 also produce relatively low decreases in the coefficient of variation of revenue (last column), with the maximum change being a 3 percent decrease in the case of wheat. However, the coefficient of variation is limited in informational value in the case of the asymmetric distributions assessed here. As an alternative, the tables also provide the change in the lower bound of the empirical 95% confidence interval of revenue in moving from the case of gross revenue (section B of the table) to gross revenue plus the payment (section C). The lower bound of the 95% confidence interval of revenue increases from 4.5% to 24.5% depending on the scenario, with the latter being for winter wheat in with the county option in Table 2. Hence, while the average benefits provided by the ARC appears small for 2011, its impact on reducing downside revenue risk does not appear trivial, particularly for the winter wheat farmers. In general for 2011, except for cotton, the county program tends to provide higher mean benefits and greater reductions in downside revenue risk than the farm program, suggesting that most farmers would likely tend to prefer the county level program.

Table 3 has the same output format as Tables 1 and 2, but for the ACRE revenue payment. The difference in program design between the ACRE and ARC revenue payments are big enough that *a priori* assessments of the empirical differences between these two programs are difficult to make. In general, the magnitude of the ACRE results are in line with those of ARC. Average payments under the ACRE were slightly lower than for ARC in table 2 except for cotton. Based on the change in the lower bound of the empirical 95% confidence interval of revenue moving from the case of gross revenue to gross revenue plus the payment, the ACRE provided lower downside revenue risk protection than the individual level ARC for all crops, and lower downside revenue risk protection than the county level ARC for all crops except cotton. Nonetheless, the results are similar enough that the farmer – assuming he had a choice – would prefer ACRE over ARC. In particular, under the ACRE program, the farmer receives 80% of the (fixed) Direct Payments, as well marketing loan benefits, albeit at a 30 percent reduction in marketing assistance loan rates, in addition to the revenue payment.[7]

Finally, Figure 3 provides the change in the average ARC payment ($/acre) as a function of the ARC coverage rate, for both the farm and county level implementations of the program. Moving from the 85% coverage rate to the 95% coverage rate, the largest change in the average payment was an 87% increase for the county level soybean program and the smallest a 28% increase for the farm level cotton program. The functions tend to be relatively linear in the coverage rate although a couple of them exhibit a small positive second derivative. In each case, the functions are elastic with respect to the coverage rate.

[7] Note that the 2012 Farm Act could have some additional form of support under Title XI, as a replacement for the SURE program in the 2008 Farm Act.

Conclusions

As with the 2008 Farm Act, the 2012 Farm Act is likely to have some sort of revenue-based support for producers of qualifying crops. Much debate over the negotiations on the 2012 Farm Bill focuses on new programs for providing producers with support payments covering “shallow losses” in revenue. The main goal of this paper is to develop an approach for examining the sensitivity of the farmer’s downside risk protection and federal budgetary costs of marginal changes in the deductible in shallow loss program scenarios based on the April 26th Senate Farm Bill. In particular, this paper develops an approach with nonparametric price and yield distributions that can simultaneously estimate revenue distributions across all counties reporting yields for four major crops using empirical distributions that are defined over arbitrarily small probability increments. We find that average payments are elastic with respect to the revenue program’s coverage rate. In addition, using this approach, the paper compares payments and their impacts on farm revenue for county and farm level implementations of ARC. We find that based on our estimates of expected payments and their impacts on downside revenue risk, producers are likely to prefer the county level implementation of the revenue support program to the farm level versions.

For this analysis, no attempt was made to adjust the price deviates for exogenous variables (e.g., changes in interest rates) that may have caused a shift in the distribution of price deviates over time. An econometric approach for accounting for the effects on these variables on price deviates is addressed in Cooper (2010). Future analysis can seek to apply information from that approach to re-centering the price distributions as modeled here.

References

Anton, J., and C. Le Mouel. 2004. "Do Counter-cyclical Payments in the 2002 US Farm Act Create Incentives to Produce?" *Agricultural Economics* 31(2-3):277-284.

Charmpis, D. and P. Panteli. 2004. "A Heuristic Approach for the Generation of Multivariate Random Samples with Specified Marginal Distributions and Correlation Matrix." *Computational Statistics* 19(2):283-300.

Coble, K., and R. Dismukes. 2008. "Distributional and Risk Reduction Effects of Commodity Revenue Program Design." *Review of Agricultural Economics* 30: 543-553.

Joseph Cooper. "Average Crop Revenue Election: A Revenue-Based Alternative to Price-Based Commodity Payment Programs," American Journal of Agricultural Economics, Vol. 92/4 (July 2010): 1214-1228.

Joseph Cooper, Carl Zulauf, Michael Langemeier, and Gary Schnitkey. "Implications of Within County Yield Heterogeneity for Modeling Crop Insurance Premiums", Agricultural Finance Review, Vol. 72/1 (2012):134-155.

Deng, X., B. Barnett, and D. Vedenov. 2007. "Is There a Viable Market for Area-Based Crop Insurance?" *American Journal of Agricultural Economics* 89:508-19.

Derflinger, G.,W. Hormann, J. Leydold, and H. L'Ecuyer, "Efficient Numerical Inversion for Financial Simulations", in A.B. Owen (eds.), *Monte Carlo and Quasi-Monte Carlo Methods* , Springer-Verlag, 2008.

Robert Dismukes, Keith H. Coble, David Ubilava, Joseph C. Cooper, and Christine Arriola. “Alternatives to a State-Based ACRE Program: Expected Payments Under a National, Crop District, or County Base”, Economic Research Report No. (ERR-126), 42 pp, Economic Research Service, USDA, September 2011.

Efron, B. 1979. “Bootstrap Methods: Another Look at the Jackknife.” *Annals of Statistics* 7:1–26.

Efron, B. 1987. “Better Bootstrap Confidence Intervals.” *Journal of the American Statistical Association* 82(1987):171-185.

Fenton, V., and A. Gallant. 1996. “Qualitative and Asymptotic Performance of SNP Density Estimators.” *Journal of Econometrics* 74(1996):77-118.

Gallant, A. 1987. “Identification and Consistency in Semi-Nonparametric Regression.” In T. F. Bewley, ed. *Advances in Econometrics*, New York: Cambridge University Press, pp. 145-169.

Goodwin, B. K. (2009). “Payment limitations and acreage decisions under risk aversion: a simulation approach.” *American Journal of Agricultural Economics* 91(1): 19-41.

Goodwin, B., and A. Ker. 1998. “Nonparametric Estimation of Crop-Yield Distributions: Implications for Rating Group-Risk Crop Insurance Contracts.” *American Journal of Agricultural Economics* 80: 139-153.

Goodwin, B. and A. Ker. 2002. “Modeling Price and Yield Risk.” In R. Just and R. Pope, eds. *A Comprehensive Assessment of the Role of Risk in Agriculture*, Norwell, MA: Kluwer Academic Publishers, pp. 289-324.

Goodwin, B., and A. Mishra. 2006. “Are ‘Decoupled’ Farm Program Payments Really Decoupled? An Empirical Evaluation.” *American Journal of Agricultural Economics* 88:73-89.

Greene, R. 2000. *Econometric Analysis*. 4th Edition, Upper Saddle River, NJ: Prentice-Hall.

Härdle,W. 1990. *Applied Nonparametric Regression*, Cambridge, UK: Cambridge University Press.

Heimlich, R. 2000. *Farm Resource Regions*, U.S. Department of Agriculture, Economic Research Service, August, AIB-760.

Hennessy, D. 1998. “The Production Effects of Agricultural Income Support Polices Under Uncertainty.” *American Journal of Agricultural Economics* 80:46-57.

Lapp, J. and V. Smith. 1992. “Aggregate Sources of Relative Price Variability among Agricultural Commodities.” *American Journal of Agricultural Economics* 74:1-9.

Nelsen, Roger B. (1999), *An Introduction to Copulas*, New York: Springer.

Paulson, N. and B. Babcock. 2008. “Get a GRIP: Should Area Revenue Coverage Be Offered through the Farm Bill or as a Crop Insurance Program?” *Journal of Agricultural and Resource Econ*omics 33(2):137-153.

Roberts, M., N. Key, and E. O'Donoghue. 2006. “Estimating the Extent of Moral Hazard in Crop Insurance Using Administrative Data.” *Review of Agricultural Economics* 28:381-390.

Sckokai, P., and D. Moro. 2006. “Modeling the Reforms of the Common Agricultural Policy for Arable Crops under Uncertainty.” *American Journal of Agricultural Economics* 88:43-56.

Serra, T., D. Zilberman, B. Goodwin, and A. Featherstone. 2006. "Effects of Decoupling on the Mean and Variability of Output." *European Review of Agricultural Economics* 33(3):269-288.

Shields, D. and R. Schnepf."Farm Safety Net Proposals for the 2012 Farm Bill", Report 7-5700, Congressional Research Service, November 10, 20011.

Silverman, B.W. 1986. *Density Estimation*, London: Chapman and Hall.

Sunding, D. and D. Zilberman. 2001. "The Agricultural Innovation Process: Research and Technology Adoption in a Changing Agricultural Sector Collection." In *Handbook of agricultural economics. Volume 1A. Agricultural production*, ed. B. Gardner and G. Rausser, 207-261. London and New York: Elsevier Science, North-Holland.

Tomek, W., and R. Gray. 1970. "Temporal Relationships Among Prices on Commodity Futures Markets: Their Allocative and Stabilizing Roles." *American Journal of Agricultural Economics* 52:372-80.

U.S. Department of Agriculture. 2008. "2008 Farm Bill Side-By-Side," Economic Research Service, Washington, DC, http://www.ers.usda.gov/farmbill/2008/

U.S. Department of Agriculture. 2009. "RMA Premium Calculation." Risk Management Agency, Washington, D.C., April. http://www3.rma.usda.gov/apps/premcalc/

U.S. Senate. "Manager's Amendment to the Committee Print: The Agriculture Reform, Food and Jobs Act of 2012", Agriculture Committee, U.S. Senate, May 2012. http://www.ag.senate.gov/download/?id=546fabdc-aa13-453d-8639-881a5871d0ff

Yatchew, A. 1998. “Nonparametric Regression Techniques in Economics.” *Journal of Economic Literature* XXXVI(June):669-721.

Table 1. Simulated ARC Payments Per Acre, Gross Revenue Per Acre, and Total Gross Revenue with ARC Payments, 2011 Crop Year, Farm-level trigger

	A. ARC revenue payment per acre				B. Gross revenue per acre				C. Revenue per acre w/ARC			D. % Change C-B	
Crop	Mean ($/acre)	Upper bound, 95% CI ($)	Coefficient of variation	% of time payment is made	Mean ($/acre)	Lower bound, 95% CI ($)	Upper bound, 95% CI ($)	Coefficient of variation	Mean ($/acre)	Lower bound, 95% CI ($)	Coefficient of variation	Lower bound, 95% CI ($)	Coefficient of variation
Corn	1.12	4.42	1.030	5.40	842	633	1142	0.154	843	637	0.153	+0.60	-0.57
Soybean	0.82	2.54	0.802	5.49	576	435	762	0.154	577	437	0.154	+0.50	-0.57
Winter wheat	1.31	2.86	0.503	18.34	248	167	371	0.215	250	170	0.212	+1.71	-1.41
Cotton[a]	2.77	7.60	0.709	16.15	770	404	1210	0.277	773	411	0.274	+1.73	-1.07

[a]Note that upland cotton is not included as an ARC eligible crop in the proposed legislation.

Table 2. Simulated ARC Payments Per Acre, Gross Revenue Per Acre, and Total Gross Revenue with ARC Payments, 2011 Crop Year, County-level trigger

	A. ARC revenue payment per acre				B. Gross revenue per acre				C. Revenue per acre w/ARC			D. % Change C-B	
Crop	Mean ($/acre)	Upper bound, 95% CI ($)	Coefficient of variation	% of time payment is made	Mean ($/acre)	Lower bound, 95% CI ($)	Upper bound, 95% CI ($)	Coefficient of variation	Mean ($/acre)	Lower bound, 95% CI ($)	Coefficient of variation	Lower bound, 95% CI ($)	Coefficient of variation
Corn	1.90	9.96	1.438	5.88	842	633	1142	0.154	844	641	0.152	+1.29	-1.26
Soybean	1.75	7.74	1.175	7.72	576	435	762	0.154	578	441	0.152	+1.42	-1.76
Winter wheat	2.27	6.16	0.710	20.95	248	167	371	0.215	251	173	0.208	+3.66	-3.09
Cotton[a]	2.45	11.04	1.269	11.74	770	404	1210	0.278	773	414	0.274	+2.43	-1.31

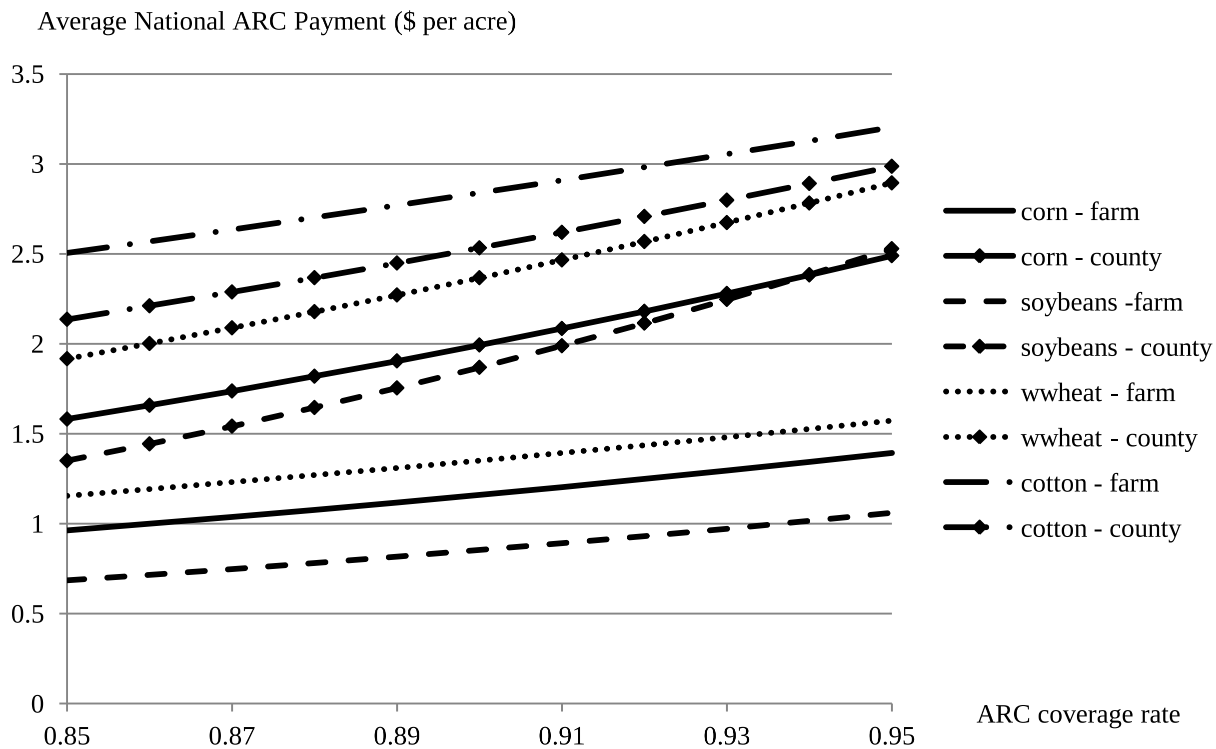
[a]Note that upland cotton is not included as an ARC eligible crop in the proposed legislation.

Table 3. Simulated ACRE Payments Per Acre, Gross Revenue Per Acre, and Total Gross Revenue with ARC Payments, 2011 Crop Year[8]

	A. ARC revenue payment per acre				B. Gross revenue per acre				C. Revenue per acre w/ARC			D. % Change C-B	
Crop	Mean ($/acre)	Upper bound, 95% CI ($)	Coefficient of variation	% of time payment is made	Mean ($/acre)	Lower bound, 95% CI ($)	Upper bound, 95% CI ($)	Coefficient of variation	Mean ($/acre)	Lower bound, 95% CI ($)	Coefficient of variation	Lower bound, 95% CI ($)	Coefficient of variation
Corn	1.38	13.01	2.968	2.64	842	633	1142	0.154	844	644	0.152	+1.73	-1.47
Soybean	0.98	7.80	2.568	3.18	576	435	762	0.154	577	442	0.152	+1.50	-1.54
Winter wheat	0.87	4.88	1.745	5.74	248	167	371	0.215	249	171	0.211	+2.67	-1.73
Cotton	2.73	35.64	3.269	5.62	770	404	1210	0.277	773	434	0.271	+7.50	-2.23

[8] ACRE calculates revenue losses at the county level but also includes a farm level trigger.

Figure 1.



Average National ARC Payment ($ per acre)
3.5
3
2.5
2
1.5
1
0.5
0
0.85
0.87
0.89
0.91
0.93
0.95
ARC coverage rate
corn - farm
corn - county
soybeans -farm
soybeans - county
wwheat - farm
wwheat - county
cotton - farm
cotton - county