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Full Research Article

A multi-region approach to assessing fiscal and farm level consequences of government support for farm risk management

Joseph Cooper[1,*], Benoît Delbecq[2]

[1] Economic Research Service, USDA, Washington DC, USA
[2] Brechbill Farms, Auburn, Indiana, USA

Abstract. The 2014 U.S. Farm Act has new programs for providing producers with commodity support payments covering "shallow losses" in revenue. We develop an approach to examine the sensitivity of the farmer's downside risk protection to marginal changes in the deductible in shallow loss program scenarios. The copula approach we use simultaneously considers price and yield correlation across all U.S. counties producing several major field crops. We find that average payments under the shallow loss program scenarios are elastic with respect to the program's payment coverage rate. To empirically assess where shallow loss is likely to most benefit producers, we map at the county level the ratios of expected shallow loss payments to crop insurance premiums for corn, soybeans, cotton, and winter wheat. As tail dependencies among individual crop yield densities may vary spatially, we propose a method for grouping counties in a t-copula that allows for heterogeneity in tail dependencies.

Keywords. 2014 U.S. Farm Act, copula, nonparametric yield density, shallow revenue loss

JEL Codes. Q10, Q18, C14

1. Introduction

The 2014 U.S. Farm Act (more precisely, the Agricultural Act of 2014) was signed into law in early February, 2014, after approximately three years of hearings. Many policy recommendations for Title I of the 2014 Farm Act – historically the main section dealing with commodity support – revolved around the 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). In its current form, U.S. Federal Crop Insurance offers revenue coverage levels ranging from 50% to as high as 85%, i.e., deductibles from 50% to 15%. Therefore, it covers deep losses in crop revenue but the deductibles leave producers exposed to potential for out-of-pocket

* Corresponding author: jcooper@ers.usda.gov.

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loss (i.e., shallow loss). One possible legislative response is for Federal crop insurance to be complemented by shallow loss coverage in the Farm Act legislation.

In fact, several characteristics of the Average Crop Revenue Election Program (ACRE) in Title I of the 2008 Farm Act fitted the general definition of a shallow loss coverage program. In particular, ACRE could trigger a revenue payment with state level crop revenue falls as low as 10% relative to the benchmark revenue (in addition, a farm level trigger with no deductible needed to be met). However, the ACRE program cannot be truly considered a pure shallow loss program. In addition to the 10% state level deductible, the ACRE program limited payments to 25% of benchmark revenue, hereby fully covering State revenue losses when State revenue was between 67.5% and 90% of expected revenue, but with the payment at the ceiling when revenue was below 67.5% of expected revenue. Hence, even with the cap on payments, a portion of the deep losses are covered. In addition to ACRE, the 2008 Farm Act's Supplemental Revenue (SURE) program was a whole farm standing disaster assistance program that covered some of the deductible in the Federal crop insurance program in case of disasters. A true (albeit conditional) shallow loss program, SURE, expired in September 2011.

Title I of the 2014 Farm Act allows the farmer to choose to enroll in Agricultural Risk Coverage (ARC), a shallow loss program. In the analysis in this paper, we examine the earlier but similar ARC that was included in legislation that U.S. Senate passed in 2012. That ARC, with an 11% deductible (i.e., the coverage rate is 89%), 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 revenue is between 79% 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 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.[1] In fact, the ARC that was actually passed by Congress has a coverage rate of 86 percent of expected (or benchmark) revenue, demonstrating the tweaking of program parameters during the development of program proposals.

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 to 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%). Given that the program that we examine has a payment ceiling of 10% of benchmark revenue, our analysis covers a program that would provide support for actual revenues in the range of (75 to 85)% to (85 to 95)% of benchmark revenue, i.e., losses between (5 to 15)% and (15 to 25)% of benchmark revenue are examined.

To analyze how the payment distribution changes with the coverage rate requires an estimation approach that can differentiate over small increments in the coverage rate, such as the kernel-based approaches in Goodwin and Ker (1998) and Cooper (2010). However, these approaches have never been simultaneously applied to more than one region. Since the federal government needs to concern itself with national level impacts as well

[1] In addition to ARC, the 2014 Farm Act has shallow loss support in the form of the Supplemental Coverage Option (SCO) for program crops besides cotton and the Stacked Income Protection (STAX) program specifically for upland cotton. A farmer's participation in individual-ARC precludes participation in SCO. For the sake of brevity in our discussion of shallow loss support, we focus on ARC.

as regional implications, minimizing aggregation bias requires using county level data (the lowest aggregation level available nationally). And as county yields are spatially correlated, to produce unbiased national level figures we require a simulation approach that can simultaneously account for correlation across all counties yet allow for examination of marginal changes in the coverage rate with the kernel-based densities (or parametric densities, for that matter).

We conduct our analysis for all counties that grow corn, soybeans, winter wheat, and upland cotton (the latter not an ARC crop but included here nonetheless for academic interest) for which the National Agricultural Statistics Service (NASS) of the U.S. Department of Agriculture (USDA) reports data. To date, the only published approaches to estimating Farm Act support that address the spatial correlation across multiple 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 historical data. Since each random draw is a cross-section of all regions included in the analysis, historical correlations between the regions are maintained. However, by imposing no other assumptions on the data, the empirical distribution for each region is 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, we had 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 copula approaches with nonparametric price and yield distributions that can simultaneously estimate revenue distributions across all counties reporting yields for each of the four crops using empirical distributions that are defined over arbitrarily small probability increments. In considering spatial relationships in yields, imposing only the historic correlations on the simulated marginal densities may be overly restrictive by not considering possibilities for tail dependencies in yields (i.e., extreme yield events may occur simultaneously across groups of counties). As tail dependencies among individual crop yield densities may vary spatially, we propose a method for grouping counties in a t-copula that allows for heterogeneity in tail dependencies. Using this approach, we compare payments and their impacts on farm revenue for county and farm level implementations of ARC. Next, we compare ARC support payments and their revenue impacts to those under the existing ACRE program. Finally, we generate maps to assess how the relative size of ARC payments to federal crop insurance varies regionally.

2. Background

2.1 General background

Before moving to the discussion of the mechanics of specific shallow loss programs, we provide a more general background on government policy for farm risk management in the US, and contrast it with that in the EU, focusing on policies covering field crops. In this paper, we use the term "farm risk management" as a convenience. That is, the term is not intended to imply the purpose of the government support we examine, e.g., whether it is to augment mean and/or higher moments of income. Historically, the Risk Manage-

ment Agency (RMA) of the USDA oversees multiple peril crop insurance programs that address within season yield and/or revenue risk, where the base price is calculated from futures price falling in the crop year the policies cover. The Farm Services Administration (FSA) of the USDA traditionally oversees policies in Title I of the Farm Act, with price targets that are fixed for the life of a Farm Act (typically 4-5 years), and starting with the 2008 Farm Act, policies with revenue garantees based on interseasonal calculations. These general policy differences between federal crop insurance programs and Title I commodity support programs suggest that, at least to some extent, these two sets of programs have different policy goals.

While farm risk management policy in the EU is very differentiated between countries, all significant farm risk management policy in the US is managed by the federal government. The latter means that program rules do not differ across the US, but which is not to suggest that all qualifying crops are insurable under the federal crop insurance in all regions and up to the same coverage levels (RMA, 2014a). While EU support has largely moved to lump sum supports, such as single area payments, with the 2014 Farm Act, such support (i.e., Direct Payments) is eliminated in the US, save for some transitionary cotton support while new rules are implemented. See the chapters on Titles I and XI in ERS (2014) for an overview of commodity support in the 2014 Farm Act, Cafiero et al (2007) for a detailed discussion of risk management policy in the EU, and Capitano (2010) for a detailed comparison of EU-US differences.

In the not too distant past, Title I of the Farm Act addressed price risk (e.g., the marketing loan program and the counter-cyclical payment program), and the multiple peril federal crop insurance programs addressed yield risk, although FSA does administer ad hoc disaster assistance that historically has been yield-based (an exception was the Marketing Loss Assistance of the late 1990s). Today however, RMA's revenue-based crop insurance policies cover more acres than do yield-based insurance policies. With the 2008 Farm Act, FSA began administering revenue-based programs – ACRE and SURE, and while these programs have expired, the 2014 Farm Act has new revenue support programs administered by FSA – the ARC program – and Supplemental Coverage Option (SCO) and Stacked Income Protection Plan (STAX), which are administered by RMA (Effland, Cooper, and O'Donoghue, 2014). STAX, which only applies to cotton, is essentially a substitute for price-based and lump sum support that was adminstered by FSA under Title I of the 2008 Farm Act, suggesting some bluring of the traditional risk management niches of RMA and FSA.

With lump sum support eliminated in the U.S., all support is now counter-cyclical to low yields, prices, or revenues (while noting that ARC and Price Loss Coverage [PLC] in Title I of the 2014 Farm Act are paid to base [historic] acres), which is a marked distinction to the EU, with its continued use of lump sum support. Another distinction between the two regions is the higher emphasis on crop insurance in the US. Federal crop insurance is administered by the government, including rate setting, but is delivered to farmers by private companies. Federal crop insurance is supported by the government via premium subsidies, support for administrative and operating expenses, and sharing of underwriting risks. In recent years, it has become a larger budgetary item than Title I support. In fact, crop insurance in the U.S. has become widespread enough, with 119 million insured hectares in 2014 (RMA, 2014b), that even in the aftermath of the 2012 drought that resulted in massive yield shortfalls in major field crops in much of the country, ad

hoc disaster payments were not made for these crops. At least in some EU countries, crop insurance covers only "exceptional events" (Capitano et al, 2010), while in the US, traditional federal crop insurance can cover up to 85% of expected yields or revenue depending on the crop and region, and the new shallow loss programs providing protection for losses between the chosen coverage rate under the traditional insurance program and a higher "shallow" rate, albeit at different levels of yield aggregation. At what coverage rate level systemic risk in yields taper off and idiosycratic risk begins to predominate is difficult to say, but it seems safe to say that federal support in the US can cover multiple sources of idiosycratic (e.g. hail) and systemic (e.g., drought) risk.

2.2 Agricultural Risk Coverage

The ARC program is complex and we will only describe its principle properties here. Under the Senate's ARC Program, a qualifying producer would make a one-time choice for the life of the next Farm Act to receive the revenue support based on farm or county level benefit calculations.[2]

The ARC revenue payment (denoted as ARC_{ijt}) to producer i of crop j in period t as defined in the 2012 proposed legislation is:

$$ARC_{ijt} = \max\{ 0, \min[(0.10 \cdot BR_{ijt}), (ARCGR_{ijt} - ACR_{ijt})]\} \cdot PE \cdot A_{ijt} \quad (1)$$

where:
BR_{ijt} is the *Benchmark Revenue*, calculated as the 5-year Olympic moving average (an average that removes highest and lowest values) yield per eligible acre of crop j for farm or county i times the 5-year Olympic moving average of the national marketing year average price. If average yield for the individual is less than 60% (70% in 2013 crop years or later), then 60 (70)% of the applicable "transitional yield" is used in its place;[3]
$ARCGR_{ijt}$ is the *Agricultural Risk Coverage Guarantee Revenue*, calculated as 89% of the Benchmark Revenue (BR).
ACR_{ijt} is the *Actual Crop Revenue*, calculated as county or farm yield for crop year t times the higher of the U.S. average midseason cash price for marketing year t or the crop's marketing assistance loan rate;
PE is the percentage of eligible acres planted and is 65% for the farm level payment and 80% for the county level payment. The prevented planting rate is 45% in either case;[4]
A_{ijt} is the total of eligible acres for farm or county i. In the case of ARC, eligible acres are all acres planted to crop j.

To the extent possible, the proposed legislation calls for making separate *ARCGR* calculations for irrigated and nonirrigated acres. Note that unlike the 2008 Farm Act, the

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[2] This paper examines the Senate version of ARC. The version actually passed into law with the 2014 Farm Act differs in some parameters and provisions, but not in the manner that is germane to the focus of this paper.
[3] The "transitional yield' is defined as per the Risk Management Agency (USDA) and generally mirrors average county yield.
[4] A functionally equivalent statement to Equation (1) is $ARC_{ijt} = \min\{ (0.10 \cdot BR_{jt}), \max[0, (\mathrm{ARCGR}_{jt} - ACR_{jt})]\} \cdot EE_{ij} \cdot A_{ijt}$.

proposed 2012 Senate bill 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 limits based on adjusted gross income (as defined in Federal tax code). The ARC program 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 of the 2014 Farm Act also has two shallow loss options, which are designed to complement federal crop insurance, and while we cannot address these here for the sake of brevity, our analysis approaches can be extended to those as well as to other federal crop insurance policies.

There are a number of differences between the ARC and ACRE programs 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, which are eliminated in the proposed legislation as well in the 2014 Farm Act. Like ACRE, ARC payments in the 2012 Senate bill are made to planted acres, but total acres receiving payments are limited to acres planted on the farm over the 2009 to 2012 crop years (plus some allowed acreage adjustments) under ARC instead of base acres on the farm under ACRE. Unlike the ACRE revenue guarantee, the ARC revenue guarantee has no floor or ceiling on how much it is allowed to move from year to year, but on the other hand, calculation of average prices uses a longer time frame under ARC than under ACRE. A more detailed description of the ACRE program is available in Cooper (2010).

3. 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 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.

3.1. 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 yields 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 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 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 (for an overview see Goodwin and Ker, 2002), 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 2011 terms to reflect the proportional change in the state of technology between that in time t and that in 2011[5]. We detrend yield based on the standard practice of using a linear trend regression of $Y_{it} = f(t)$.[6] The expected value of Y_{it}, or $E(Y_{it})$, is calculated from the fitted trend equation. Based on historical yield shocks,

$$\Delta Y_{it} = \left(Y_{it} - E\left(Y_{it}\right)\right) \Big/ E\left(Y_{it}\right)$$

we generate the detrended yield distribution, Y_{it}^{d} as

$$Y_{it}^{d} = E\left(Y_{i2011}\right)\left(\quad Y_{it} + 1\right) \neq 2011, \tag{2}$$

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

$$\Delta P_t = \left(P_t - E\left(P_t\right)\right) \Big/ E\left(P_t\right)$$

Using the short time series of available yield and price data to calculate Y_i^d and ΔP results in discontinuous distributions that are inadequate to investigate subtle incremen-

[5] The crop subscript is omitted.

[6] 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.

tal changes in the shallow loss coverage rate. Therefore, we start by simulating continuous distributions of Y_i^d and ΔP.

3.2. 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 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

$$\hat{f}\left(y_l^d\right)=\frac{1}{Th}\sum_{t=1}^{T} K\ \frac{y_l^d-Y_t^d}{h} \quad l=1,\ldots,L. \tag{3}$$

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 $\mathbf{y}^d$ 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.*).[7] 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.[8]

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.

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,

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

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

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.

3.3. 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).

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 $\mathbf{U}=\{U_{ni}\}_{0\le U_{ni}\le 1}$ 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. The t-copula is of particular interest when modeling crop yield distributions because it has the ability to capture lower and upper tail dependence. This is a desirable feature if extremely low (crop failure) or high yields are likely to occur contemporaneously at neighboring locations. A downside of the t-copula is that it has symmetric tail dependencies.[9]

The t-copula is the unique copula of a random vector $\mathbf{X}$ that has a multivariate t distribution with ν degrees of freedom and univariate t-distributed marginal distributions, each with the same degrees of freedom parameter, ν (e.g., Demarta and McNeil, 2005). There is an inverse relationship between ν and extreme value (or tail) dependence (Embrechts *et al.*, 2002). Because all marginal distributions share a common degrees of

[9] Archimedean copulas (e.g. Clayton and Gumbel) have asymmetric tail dependencies but do not appear practical for application to the large number of marginal distributions that we consider.

freedom parameter, the tail dependence imparted by the t-copula is highly symmetrical. Given the geographical extent of our analysis, this constitutes a non-negligible limitation to generating multivariate yield densities. We address this issue by relying on the so-called grouped t-copula described in Daul *et al.* (2003) and Demarta and McNeil (2005). The grouped t-copula is similar to the t-copula except that subgroups of the univariate t-distributed marginal distributions of random vector $\mathbf{X}$ are now allowed to have different degrees of freedom parameters, resulting in varying levels of asymptotic tail dependence. In this paper, we estimate different degrees of freedom parameters for groups of counties classified by Farm Resource Region. These regions were constructed by the Economic Research Service to represent "geographic specialization in production of U.S. farm commodities" based on physical (climate, soils, topography, water), and socioeconomic farm characteristics (Heimlich, 2000). We form two other groups, one with all state-level yield marginal distributions and the other one with the national yield and price marginal distributions. In total, we estimate 11 degrees of freedom parameters for corn and winter wheat, 10 for soybeans, and 8 for cotton.

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 $\mathbf{D}=\left\{Y_1^d,\ldots,Y_m^d,\ P\right\}$ 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:

$$\hat{F}_{D_i}(d)=\frac{1}{1+T}\sum_{t=1}^{T}1_{\{D_{i,t}\le d\}} \tag{4}$$

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., $\mathbf{D}$ < 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 (4), we can form the matrix of marginal distributions of the historical data, $\hat{\mathbf{V}}=\{V_t\}_{t\in(1,T)}$, with $V_t=\left(V_{t,1},\ldots,V_{t,m+1}\right)=\left(\hat{F}_{D_1}\left(Y_{t,1}^d\right),\ldots,\hat{F}_{D_m}\left(Y_{t,m}^d\right),\hat{F}(\ P)\right)$. The unknown parameters that uniquely define the grouped t-copula are the correlation matrix and, in our particular case, the degrees of freedom associated with each of the *m*+1 marginal distribution functions. In the context of the t-copula, Lindskog *et al.* (2003) suggests a method-of-moments estimator for the correlation matrix. Following this procedure, we first construct the empirical Kendall's tau rank correlation matrix of the actual data, $\hat{\mathbf{C}}_\tau$ which is an unbiased and consistent estimator of the true Kendall's tau matrix. Second, we transform this matrix into the corresponding Pearson correlation matrix, $\hat{\mathbf{C}}$ using the result of Lindskog *et al.* (2003) who prove that there is a direct correspondence between Kendall's tau and Pearson correlation's coefficient for the family of elliptical distributions, to which the multivariate-t belongs:

$$\hat{\mathbf{C}}=\sin\ \frac{\pi}{2}\hat{\mathbf{C}}_\tau. \tag{5}$$

Daul *et al.* (2003) show that the equality cannot be maintained in the case of meta-t distributions in which degrees of freedom parameters differ across groups of univariate marginal distributions, but the approximation error is small.

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. Next, we estimate a separate degrees of freedom parameter for each of the m+1 univariate marginal distributions in $\hat{\mathbf{V}}$ by maximizing the likelihood function of the t copula (e.g., Bouyé *et al.*, 2002).

With the estimated degrees of freedom parameters and correlation matrix in hand, we can now build matrix $\mathbf{U}$. The multivariate t distribution is a mixture of a multivariate random normal distribution (MVN) and the root of a univariate inverse gamma distribution (Ig). Generalizing this mixture construction, we simulate the grouped t-copula following Demarta and McNeil (2005). We start by generating N=10,000 draws of a (m+1)-dimensional MVN distribution, $\mathbf{Z}$ with mean vector from the historical yield and price data and correlation matrix $\hat{\mathbf{C}}$ We then construct m+1 perfectly dependent[10] W_i variates by applying the inverse cumulative distribution function (CDF) of each univariate $Ig(\nu_i/2,\nu_i/2)$ to the same N=10,000 random draws of a uniform distribution U(0,1). The next step is to calculate the so-called multivariate meta t random vector (Embrechts *et al.*, 2002), $\mathbf{X}$ as:

$$\mathbf{X} = \left\{ \sqrt{W_i} Z_i \right\}_{1 \le i \le (m+1)} \tag{6}$$

where each vector of $\boldsymbol{X}_i$ is a univariate t distribution with ν_i degrees of freedom, the correlation amongst which is $\hat{\mathbf{C}}$ Finally, the matrix of marginal distributions of the grouped t-copula, $\mathbf{U}$ is formed by applying the CDF of the univariate t distribution with ν_i degrees of freedom to the corresponding vector $\mathbf{X}_i$.

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, in which the "probabilities" from the grouped t copula are used to find the corresponding price and yields from the nonparametric distributions in $\mathbf{R}$ (that is, the *P*-values from the grouped t copula 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 above imposed the historical correlations on the simulated densities for 1,171 corn counties, 1,017 soybean counties, 734 winter wheat counties, and 117 upland cotton counties.

3.4. 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

[10] Perfect dependence in this case means that Kendall's tau is equal to one (Demarta and McNeil, 2005).

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} such that the Actual Production History (APH) indemnity calculated from our yield distribution is equal to the APH premium:

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

where $y_{ni}^k = \hat{Y}_{in}^k + h_{in}\left(\left(\alpha_{ki}\cdot\sigma(\hat{Y}_i^k)\right)^2 - \left(\sigma(\hat{Y}_i^k)\right)^2\right)^{0.5}$, $\hat{Y}_{in}^k = E(Y_{i,2010})(1+\ \hat{Y}_{in}^k)$, h_{in} a $N(0,1)$ random variable, $\sigma(\hat{Y}_i^k)$ 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} the APH price, and the coverage θ is .65.[11] 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} 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.

4. 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.

For each crop, we follow ther 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,…,2011.

[11] 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 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}.

By definition, the Senate's ARC's actual crop revenue (ACR) is calculated using the midseason average national cash price. Based on an examination of monthly cash prices and sales volumes over the last 37 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. Therefore, we assume a 0.02 basis value between the two. We convert P_{2011} to the cash price using the basis defined as the median difference between P_t and the NASS season average price in t over the ten years prior to 2011.

5. 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, assuming that producers have chosen the county-level option or the farm-level option, respectively (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. 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), because 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) ×10,000 matrix of simulation results is summed vertically through each of the 10,000 columns to derive the 1×10,000 draws of the national level impacts.

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 $5.08 per acre in any scenario given 2011 price and yield assumptions. The farm-based average payments are larger than the county-level ones despite the farm-level program paying to a lower share of planted acres than its county-level counterpart. The difference between the farm and county payments can be attributed, at least in part, to differences in risk between farm- and county-level yields (and we expect payments to be increasing in yield variability). Hence, without an empirical analysis like this paper, one would not be able to say which program would provide greater benefits.

Section D of Tables 1 and 2 presents two measures of downside risk reduction. We show that ARC would produce relatively low decreases in the coefficient of variation (CV) of revenue (last column), with the maximum change being a 4.18-percent decrease in the case of wheat with the farm-level trigger. However, CV is limited in informational value in the case of the asymmetric distributions assessed here. Alternatively then, 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 tables) to gross revenue plus the payment (section C). This measure of downside risk reduction ranges from 1.35% to 3.89% depending on the scenario, with the latter being for winter wheat with the county option (see Table 2). Hence, while the average benefits that would be provided by the ARC program would appear small for 2011, its impact on reducing downside revenue risk would not appear trivial, particularly for winter wheat producers. In general for 2011,

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

Crop	A. ARC revenue payment per acre				B. Gross revenue per acre				Skew	C. Revenue per acre w/ARC			D. % Change C-B		Skew
	Mean ($/acre)	Upper bound, 95% CI ($)	Coeff. of variation	% of time payment is made	Mean ($/acre)	Lower bound, 95% CI ($)	Upper bound, 95% CI ($)	Coeff. of variation		Mean ($/acre)	Lower bound, 95% CI ($)	Coeff. of variation	Lower bound, 95% CI	Coeff. of variation	
Corn	4.64	12.04	2.70	15.24	844	636	1155	0.38	0.23	848	646	0.37	1.70	-2.90	41.08
Soybean	5.08	10.41	2.10	17.62	580	429	771	0.43	0.33	585	439	0.42	2.36	-3.67	28.27
Winter wheat	3.28	5.96	1.61	22.12	249	171	367	0.57	0.55	253	177	0.55	3.42	-4.18	14.89
Cotton[a]	4.77	10.63	2.09	28.43	783	422	1232	0.66	0.66	787	432	0.65	2.46	-1.90	6.60

[a]Note that upland cotton is not included as an ARC eligible crop in the Senate's 2012 farm bill legislation nor in the 2014 Farm Act.

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

Crop	A. ARC revenue payment per acre				B. Gross revenue per acre				Skew	C. Revenue per acre w/ARC			D. % Change C-B		Skew
	Mean ($/acre)	Upper bound, 95% CI ($)	Coeff. of variation	% of time payment is made	Mean ($/acre)	Lower bound, 95% CI ($)	Upper bound, 95% CI ($)	Coeff. of variation		Mean ($/acre)	Lower bound, 95% CI ($)	Coeff. of variation	Lower bound, 95% CI	Coeff. of variation	
Corn	2.30	11.57	5.22	6.56	844	636	1155	0.38	0.23	846	644	0.37	1.35	-1.45	19.67
Soybean	2.25	9.85	4.73	12.00	580	429	771	0.43	0.33	582	437	0.43	1.97	-1.40	8.16
Winter wheat	2.63	6.89	2.23	9.33	249	171	366	0.57	0.52	252	178	0.55	3.89	-2.92	7.31
Cotton[a]	2.75	12.62	5.42	7.41	783	422	1232	0.66	0.66	785	432	0.66	2.26	-0.94	1.83

[a] Note that upland cotton is not included as an ARC eligible crop in the Senate's 2012 farm bill legislation nor in the 2014 Farm Act.

if implemented, the farm-level program would tend to provide higher mean benefits than the county program across all crops. It would also yield marginally greater reductions in downside revenue risk than the county-level program for corn, soybeans, and cotton, while this conclusion is reversed for winter wheat.

Table 3 has the same output format as Tables 1 and 2, but for the ACRE program from the 2008 Farm Act. The difference in design between ACRE and ARC are big enough that *a priori* assessments of the empirical differences between these two programs are difficult to make. Average payments under ACRE were lower than for both farm-level and county-level ARC across all crops. Based on the percent change in the lower bound of the empirical 95% confidence interval between gross revenue and gross revenue plus the payment, ARC's downside revenue risk protection was superior to ACRE's for all crops but cotton for which ACRE is dramatically better. When considering the coefficient of variation as a measure of risk, while we reach the same conclusion, it is worth noting that the superiority of ACRE over ARC for cotton is not as pronounced. Assuming she or he had a choice, a farmer would prefer ARC over ACRE given yield and price conditions similar to 2011. However, under the ACRE program, farmers still received 80% of the (fixed) Direct Payments, as well as marketing loan benefits, albeit at a 30 percent reduction in marketing assistance loan rates, in addition to the revenue payment.

Note that the 95% confidence intervals in Tables 1 to 3 are nonparametric and account for asymmetry, but of course, the mean and coefficient of variation do not. To provide further information on the (a)symmetry of the revenue distributions, we include the skewness measure (third moment) for gross revenue and the percentage change in skewness of gross revenue plus the payments relative to the base gross revenue distribution to Tables 1 to 3. A value of zero for this measure means that a distribution is symmetric. For our revenue distributions, the average skewness is positive, showing that the right tail of gross revenue is long relative to the left tail, a not surprising result based simply on the fact that the distribution of revenue is truncated at $0. The average percentage change in skewness is positive, demonstrating that with the addition of the payments, the distributions have become increasingly skewed to the right, which is as one would expect adding the payments to do if they work as planned.

The ARC program proposed by the Senate is only one option among many commodity support programs that could be designed to protect farmers against shallow losses in crop revenue. While ARC in its 2012 Senate version covers losses between 11% and 21% of benchmark revenue, one could envision lowering or increasing the coverage rate. We investigate what happens to average ARC payments per acre when letting the coverage rate vary from 85% to 95%, which corresponds to losses ranging between (15% to 25%) and (5% to 15%) of benchmark revenue, respectively. Resulting farm- and county-level payments are represented on Figure 1. Average payments as a function of the coverage rate tends to be relatively linear although a couple of cases exhibit small positive second derivatives. All functions are elastic with respect to the coverage rate. Moving from a coverage rate of 85% to 95% (or reducing the deductible from 15% to 5%), average payments increase by a minimum of $0.60 for the farm-level cotton program to $1.44 for the farm-level soybean program. In percentage terms, the most dramatic increased is observed for the county-level soybean program with 69%. Not only does the level of coverage matter to the farmer but it also impacts the total cost of the program to the government. American

Table 3. Simulated ACRE Payments Per Acre, Gross Revenue Per Acre, and Total Gross Revenue with ACRE Payments, 2011 Crop Year.a

Crop	A. ACRE revenue payment per acre				B. Gross revenue per acre				Skew	C. Revenue per acre w/ACRE			D. % Change C-B		Skew
	Mean ($/acre)	Upper bound, 95% CI ($)	Coeff. of variation	% of time payment is made	Mean ($/acre)	Lower bound, 95% CI ($)	Upper bound, 95% CI ($)	Coeff. of variation		Mean ($/acre)	Lower bound, 95% CI ($)	Coeff. of variation	Lower bound, 95% CI	Coeff. of variation	
Corn	1.20	11.96	9.83	2.79	844	636	1155	0.38	0.23	845	642	0.38	1.07	-0.70	7.26
Soybean	1.04	9.27	10.16	4.22	580	429	771	0.43	0.32	581	436	0.43	1.74	-0.68	3.77
Winter wheat	0.76	4.67	7.39	2.73	249	171	366	0.57	0.52	250	174	0.56	1.94	-1.06	3.11
Cotton	2.23	26.41	6.17	4.52	783	422	1232	0.66	0.66	785	446	0.66	5.68	-0.79	1.98

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

Table 4. Simulated Average Payments and Downside Risk Reduction For Farm-level (F-ARC) and County-level (C-ARC) ARC and ACRE Given Three Cash Price Scenarios.

% cash price		Corn		Soybeans		Winter wheat		Cotton	
		Avg. Payment ($/acre)	% change CI lower bound	Avg. Payment ($/acre)	% change CI lower bound	Avg. Payment ($/acre)	% change CI lower bound	Avg. Payment ($/acre)	% change CI lower bound
F-ARC	80%	8.49	3.52	8.69	4.66	4.84	5.98	6.17	3.59
	100%	4.64	1.70	5.12	2.39	3.28	3.46	4.77	2.46
	120%	3.01	1.02	3.42	1.32	2.43	2.14	3.97	1.66
C-ARC	80%	5.05	3.62	6.18	5.71	4.95	7.88	4.42	4.06
	100%	2.30	1.35	2.25	1.97	2.63	3.89	2.75	2.26
	120%	1.31	0.69	0.97	0.69	1.60	1.98	1.92	1.21
ACRE	80%	8.48	7.69	8.02	11.14	2.99	9.04	8.51	17.51
	100%	1.20	1.07	1.04	1.74	0.76	1.94	2.23	5.68
	120%	0.29	0.15	0.14	0.21	0.28	0.46	0.70	1.07

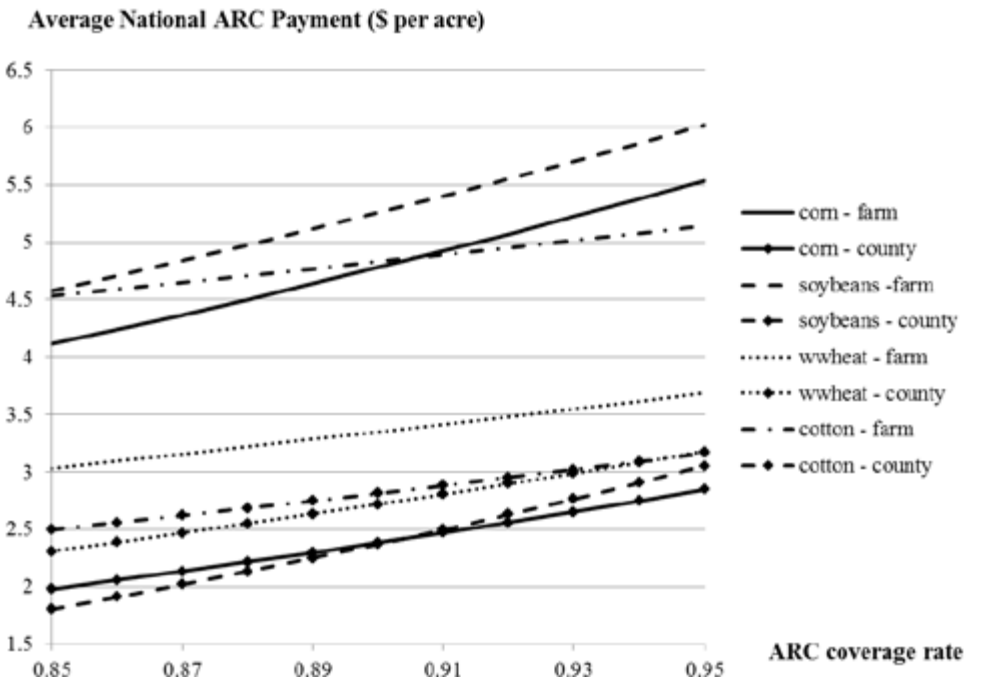

Figure 1. Average National ARC payments as a function of the coverage rate factor in the ACR's "Guarantee Revenue".

farmers planted 92.3 million, 75.2 million, and 41.1 million acres of corn, soybean, and winter wheat in 2011. Based on our estimates, increasing the coverage rate from 85% to 95% would raise the cost to the government by $267 million and $209 million under the farm- and county-level options, respectively.

The ARC payments presented up to this point were estimated under the assumption that cash prices, used to calculate actual revenues, were at the 2011 levels. In Table 4, we report what would happen to payments if market prices were 80% and 120% of their 2011 levels based on our simulations. We first observe that average program payments per acre and downside risk protection, measured by the percent change in the lower bound of the confidence interval of average revenue, both have a negative (as expected) and nonlinear relationship with cash prices. Furthermore, while downside risk protection is higher for ACRE than ARC at low price levels (relative to 2011), the drop off in this metric as cash prices increase is much more rapid for ACRE than ARC. At relatively higher cash prices, average payments per acre and downside risk protection remain comparatively higher for the farm-level ARC program (F-ARC). At lower prices, C-ARC has more impact on reducing downside risk than F-ARC, for all crops considered in this study.

More broadly speaking, it would seem that when benchmark revenue is determined at an aggregate level (e.g., county for C-ARC or state for ACRE), average payments and downside revenue protection tend to skyrocket as cash prices fall. With a farm-level trigger (as in F-ARC) the rate of change in these two metrics is noticeably slower. That is,

payments remain more "under control" with the more targeted F-ARC as prices drop. When taking all these observations into account, it would seem that C-ARC is an intermediate between ACRE and F-ARC, with more moderate increases in payments as pre-

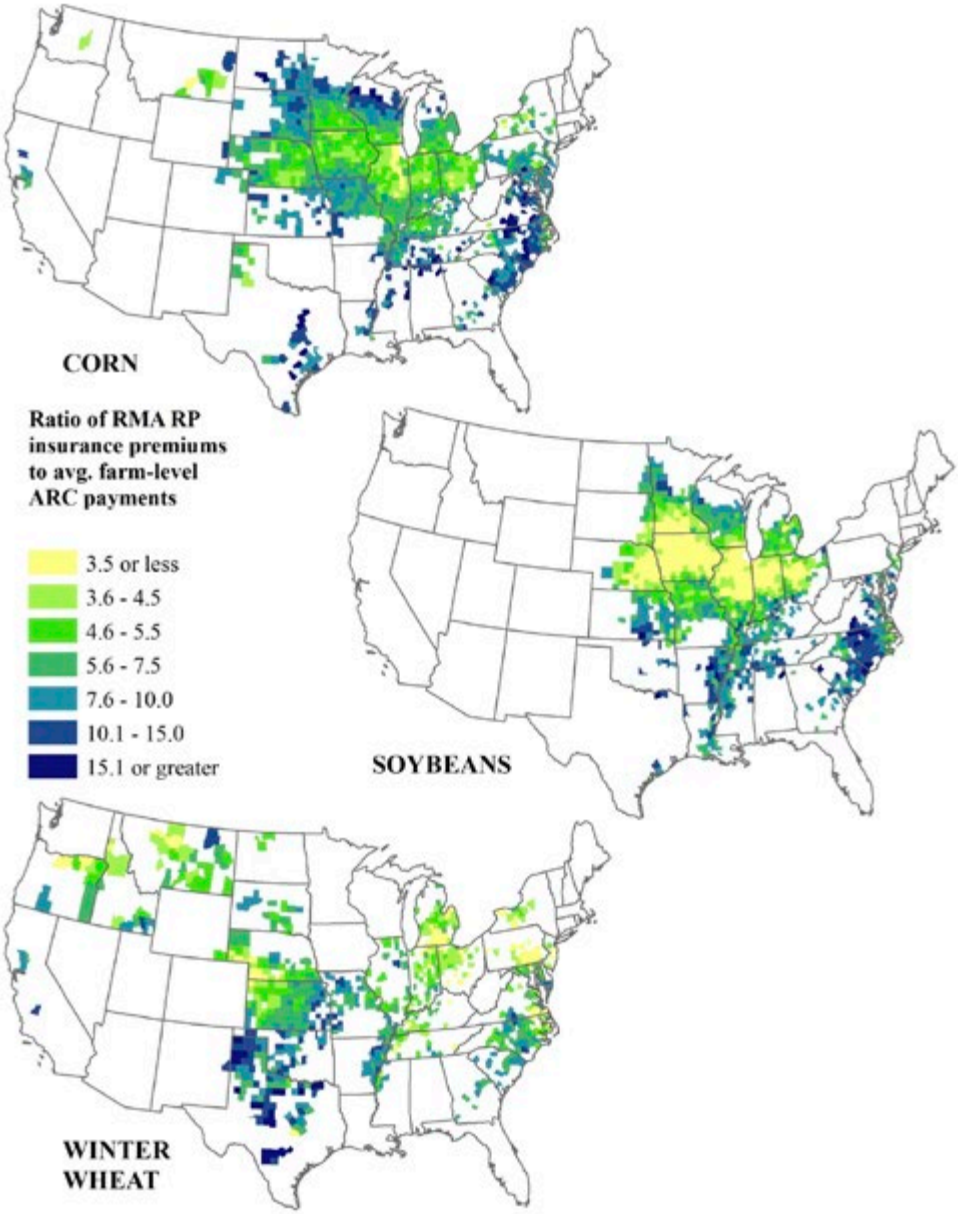

Figure 2. Ratio of Federal RP crop insurance premiums to farm level ARC payments for a representative farmer in each county.

vailing cash prices decrease compared to the former, and a higher likelihood of no payments being made than the latter.

We hypothesize that shallow loss support like ARC is likely to be of relatively greater interest to farmers in less risky production regions. Figure 2 shows maps of county level the ratio of the (pre-subsidy) federal RP insurance premium to average farm level ARC payments for a representative farmer for each county in the data set. RP is farm revenue-based crop insurance product, and we assume the producer chosen coverage rate is 70%. When actuarially correct, the RP premium is equal to the mean RP indemnity payment. Since the RP insurance covers deep (or at least deeper) losses and the ARC covers shallow losses, we presume *a priori* that RP insurance premiums will be larger relative to average ARC payments the riskier the production region.

This hypothesis is visually affirmed by the maps in Figure 2. For corn and soybeans, the ratio tends to be lower for counties in the Corn Belt, and higher in riskier areas such as the South East or far north. For winter wheat, the ratio is clearly higher in Texas than the generally less risky production areas in Kansas. As the premium subsidy on RP is expressed as a percentage of the total premium, the results in these maps show that in riskier production regions, federal commodity support in the form of ARC payments will tend to be lower relative to federal commodity support in the form of insurance premium subsidies

6. Conclusions

The 2014 Farm Act provides farmers with options for "shallow loss" revenue support, including a variant of the ARC program discussed in this paper. The choice of the deductible for determining the ARC payment was in flux over the negotiations period leading to the 2014 Farm Act, and may be so again in negotiations over the next Farm Act, given the significant impact this choice can have on support payments. The main goal of this paper is to develop an approach for examining the sensitivity of the farmer's downside risk protection to marginal changes in the deductible in shallow loss program scenarios. 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 farm-level implementation of the revenue support program to the county-level versions, as least for the 2012 Senate proposal ARC. Furthermore, our maps show a tendency for shallow loss support to be a greater proportion of total commodity support (defined here as ARC payments plus federal crop insurance support) in primary production regions.

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 of 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.

While the empirical analysis in this paper is for a U.S. policy subject, the methods discussed here are general and apply to a wide variety of subjects for which the analysis requires that systemic risk across large geographic regions be addressed. For example, in the EU, the second pillar of the Common Agricultural Policy reform for 2014-2020 offers a new risk-management toolkit including insurance schemes for crops, animals, and plants. The methods discussed in this paper could be directly applied to assessing the budgetary costs and impacts on farm revenues in the EU of possible insurance programs in a manner that accounts for systemic weather risks within and across EU member countries.

But the methods discussed here have applications beyond crop insurance. Many models that seek to empirically assess how producers respond to changes in risk require the simulation of prices and yields. Since weather impacts can be systemic, correct analysis of how producers may respond across a wide region to these impacts require that the simulated yields across the producers maintain the correlations of the actual historic data. The approach demonstrated here can impose these relationships across thousands of representative farmers, or sub-regions. Furthermore, the same approach can be used to simulate correlated weather data across a large number of regions, which is useful in modeling multi-region (e.g., counties, provinces) impacts of risk management strategies for climate change.

Based on historical precedent, negotiations over the next Farm Bill will include discussion of what is the overall strategy for handling farm risk, and what is the government's role in this strategy. Does the addition of revenue supports to the Farm Act, which started with the 2008 Farm Act and continues into the 2014 Farm Act, complicate the message of which risks – e.g., downside revenue risk in general, idiosyncratic risk, systemic risk, price risk, yield risk – are to covered, and if so, why? That is, what risks should be partially borne by the government, and in what forms does the support get delivered to producers? With the 2008 Farm Act, and continuing into the 2014 Farm Act, risk support niches provided by FSA and RMA have shifted. Before 2008, RMA-managed programs covered revenue risk and FSA programs addressed price risk. Now, FSA also has a program that manages revenue risk. With the 2014 Farm Act, risk/income support programs for cotton producers under FSA purview (in Title I) have been transferred to RMA albeit in another form (in Title XI). These evolving roles for administrative agencies beg the question of how the government might rebalance its resources on reducing yield risk, price risk or revenue risk, or some combination of these. Can these ends be achieved while avoiding program overlap and in ways that increase transfer efficiency and also in ways that reduce costs of adapting to climatic variability? Economics cannot easily answer the normative aspects of some of these questions, but the empirical approach presented here can help inform the debate over the government's role in risk management.

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Appendix. Schematic of the general steps in the methodological approach discussed in section 3.