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Developing Area-Triggered Whole-Farm Revenue Insurance

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Whole-farm revenue insurance is frequently suggested as a conceptually attractive alternative to commodity-specific insurance, but attempts to deliver farm-level whole-farm revenue insurance (FWFI) have been fraught with underwriting and actuarial challenges. This study develops customizable area-based whole-farm insurance (CAWFI) that overcomes some known impediments to existing designs. Certainty equivalents are generated for representative farms in Kansas, North Dakota, Illinois, and Mississippi. We find that a restricted CAWFI design generates significant risk reduction at much lower cost than FWFI.

Key words: crop insurance, farm policy, multivariate simulation, risk

Introduction

Farmers simultaneously face multiple sources of risk, including yield risk and price risk. Yield risk can result from adverse weather, disease, and pests, while events that affect global markets can drive variations in price. To stabilize farm revenue in risky environments, farmers adopt production strategies that mitigate their exposure to yield risk and use risk-transfer mechanisms such as crop insurance, forward pricing, and participation in government income support programs to reduce their exposure to yield and/or price risks. Crop insurance, widely available in the United States, is as a primary component of the farm safety net. Crop insurance policies allow an insured producer to pay a premium in exchange for the right to receive an indemnity in the event of a negative outcome.

U.S. producers may purchase a number of different types of crop insurance through programs established by the U.S. Department of Agriculture's Risk Management Agency (USDA-RMA). These programs include commodity-specific products such as farm-level yield insurance, farm-level revenue insurance, area-based (county-level) yield insurance, and area-based revenue insurance. To date, commodity-specific farm-level yield and revenue insurance are the crop insurance products most widely used by U.S. farmers. However, whole-farm (i.e., multiple commodity) farm-level revenue insurance products have recently become available in most of the country.

We consider an alternative revenue insurance product that allows a producer to customize multiple-crop area revenue insurance to a specific farm. Our approach uses area revenue as a trigger to preclude many of the moral hazard and recordkeeping challenges of the FWFI product known as Whole Farm Revenue Protection (WFRP) that is currently offered by the USDA-RMA.[1] Selecting an appropriate weight for each commodity becomes an important issue when designing whole-

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[1] In addition, for some locations farmers may choose a farm-level revenue insurance unit structure that insures the combined multiple crop revenues.

farm, area-based revenue insurance. A simple index based on the sum of crop revenue across all commodities produced in the county implicitly assigns commodity weights that reflect the crop mix of the county to every whole-farm, area-based revenue insurance policy sold in that county. As a result, a farm producing a different crop mix may receive poor risk protection.

Our proposed approach allows a policyholder to assign commodity weights to customize a multiple-crop, area-based revenue insurance product for the insured producer's crop mix. Farmers would benefit from the proposed customizable area-based whole-farm insurance (CAWFI) because they could purchase a whole-farm revenue insurance product customized to their commodity mix that does not require the complex record-keeping needed for the current WFRP. Insurance companies and the USDA-RMA would also benefit because CAWFI incorporates the risk-reducing properties of whole-farm insurance into an area-based product that minimizes adverse selection and moral hazard problems, thereby combining the primary advantages of both concepts. Additionally, insurance providers benefit from reducing the complexities of premium rating and indemnity calculations relative to farm-level whole-farm insurance designs.

Ultimately, we suggest that this paper makes a unique contribution to the crop insurance literature because it is the first manuscript to our knowledge to (i) describe the potential benefits to both farmers and insurers of a whole-farm, area-based revenue insurance product; (ii) describe how such a product could be operationalized; and (iii) empirically estimate the performance of the product relative to farm-level whole-farm revenue insurance.

Area-Based Insurance Designs

Farm-level insurance designs are susceptible to adverse selection and moral hazard (Quiggin, Karagiannis, and Stanton, 1993; Smith and Goodwin, 1996; Babcock and Hennessy, 1996; Coble et al., 1997; Smith and Glauber, 2012). The CAWFI design overcomes this limitation by utilizing county yields in a manner similar to current area-based insurance products such as Area Yield Protection (AYP) and Area Revenue Protection (ARP). These designs provide commodity-specific coverage based on shortfalls in county yields and county revenue, respectively. AYP and ARP minimize the potential for adverse selection and moral hazard because individual farmers possess no better information about expected county yields or revenues than do insurers, nor can the behavior of individual farmers significantly influence realized county-average yields or revenues (Miranda, 1991). However, AYP and ARP command a relatively small share of the U.S. crop insurance market, accounting for only 1.1% of all acres insured in 2015 (U.S. Department of Agriculture, Risk Management Agency, 2015).

Because farm yields and revenues are not perfectly correlated with county yields and revenues, area-based insurance products are subject to basis risk—the risk that farm-level variables will not fluctuate in the same manner as county-level variables (Skees, Black, and Barnett, 1997). Basis risk could create a situation in which a purchaser of an area-based insurance product receives an indemnity that either exceeds or fails to sufficiently cover the loss incurred. In extreme cases, a producer could receive an indemnity without incurring any loss or could incur a loss without receiving any indemnity (Barnett et al., 2005; Deng, Barnett, and Vedenov, 2007). In their study of area-based insurance in China, Shen and Odening (2013) find that basis risk significantly affects demand and that minimizing basis risk requires relatively small and homogeneous areas. Similarly, in their study of cotton farmers in Mali, Elabed et al. (2013) find that basis risk "significantly discourages" demand for area-based insurance. Despite this shortcoming, previous research suggests that area-based insurance can improve farmers' welfare even, in some cases, more than farm-level insurance (Barnett et al., 2005).

Whole-Farm Insurance Designs

The USDA-RMA first offered a whole-farm insurance product in 1999, when it introduced Adjusted Gross Revenue (AGR) and, later, AGR-Lite (Shields, 2012). Neither of these products was particularly popular with farmers; together AGR and AGR-Lite accounted for less than 0.5% of total U.S. crop insurance liability in 2014 (U.S. Department of Agriculture, Risk Management Agency, 2015). The lack of adoption principally stemmed from the overall complexity of the products as well as the perception among farmers that indemnities paid by the policies were smaller and more infrequent compared to other forms of crop insurance (Smith, 2011).

Despite the low levels of AGR and AGR-Lite purchasing, interest in whole-farm insurance continues, as evidenced by the Agricultural Act of 2014, which directed the USDA to conduct research on the feasibility of offering whole-farm insurance at higher coverage levels (Shields, 2015). As a result of changes created by the Agricultural Act of 2014, WFRP replaced AGR and AGR-Lite beginning with the 2015 crop year. Similar to AGR and AGR-Lite, WFRP renders payments based on shortfalls in revenue, where the measures of expected and realized revenue are derived from the Schedule F federal income tax form.[2] U.S. tax law allows farms to use cash (rather than accrual) accounting, whereas WFRP requires an accrual accounting measure of whole-farm revenue. Thus, the revenue listed on Schedule F must be adjusted to an accrual basis. Significant changes in the agricultural commodities produced on the farm from one year to the next require additional modifications.

While comparable to AGR and AGR-Lite, some of the WFRP policy provisions are notably different. Under the AGR products, premium subsidies were capped at 59%; premium subsidies under WFRP can reach as high as 80%, which is more in line with policies for individual crops (Shields, 2015). Coverage levels under WFRP can reach as high as 85% when insuring three or more crops, an increase from the levels offered under the AGR products. WFRP also provides premium discounts for farms producing up to seven crops and is offered in more states than AGR and AGR-Lite were. In 2015, WFRP accounted for 1.1% of total U.S. crop insurance liability which, though still a very small portion of total liability, was more than double the level of AGR and AGR-Lite liability in 2014.

Assuming that its goal is to protect against shortfalls in whole-farm revenue, an insurance product that subsumes all farm enterprises can specifically protect against the risk of interest. Whole-farm insurance can pool all of the price and yield risks of one farm into a single insurance policy at a lower cost compared to commodity-specific revenue insurance or combinations of forward pricing and farm-level yield insurance products (Stokes, Nayda, and English, 1997; Zhu, Ghosh, and Goodwin, 2008; Bielza Díaz-Caneja, Maria and Garrido, Alberto). Because revenues for different commodities are less than perfectly correlated, whole-farm insurance can account for diversification effects that result in lower premium costs than insuring each commodity separately. For example, Hennessy, Saak, and Babcock (2003) establish that whole-farm contracts are—due to the extent of idiosyncratic risk—considerably more efficient as risk management tools than portfolios of well-designed crop-specific contracts. Similarly, Bielza Díaz-Caneja, Maria and Garrido, Alberto find that whole-farm insurance can achieve reductions in actuarially fair premiums of 15–20% compared to crop-specific policies and significantly reduce premium subsidies without diminishing risk-reduction effects. In another example, Hart, Hayes, and Babcock (2006) find the premiums in their design for a whole-farm insurance product that includes a livestock enterprise are well below the combined premiums of the separate policies for each crop. Moreover, they note that the government could provide the whole-farm insurance product they developed free of charge for less than the value of the transfers of the federal crop insurance program.

Makki and Somwaru (2001, p. 665) note that a whole-farm contract "is less likely to distort markets because it is less likely to influence farmers' planting and other management decisions"

[2] The Schedule F, Profit or Loss from Farming, is filed along with Form 1040 and its equivalents with the Internal Revenue Service to report farm income and expenses.

compared to other types of insurance. Turvey (2012) examines producer behavior in the presence of whole-farm insurance modeled after the Canadian Agricultural Income Stabilization (CAIS) and AgriInvest programs. In particular, he focuses on whether non-crop-specific insurance might distort particular commodity markets. He concludes:

> On the one hand, because there is no specificity in the programs (i.e., one crop is not specifically targeted over another) whole farm programs are seemingly decoupled. The fact that farmers with different degrees of risk aversion, as indicated by the election of low versus high target incomes, would optimize differently, bolsters this argument. On the other hand, if farmers are generally homogenous [sic] in their attitudes toward risk, then optimizing according to the same rules may give the appearance of coupling. . . (p. 537)

Importantly, producer behavior cannot lead to moral hazard or adverse selection in Turvey's study because his models explicitly assume "full informational symmetry." Conversely, the CAWFI design avoids the moral hazard and adverse selection issues associated with farm-level insurance products by employing county yields in an approach similar to AYP and ARP.[3]

While conceptually simple, farm-level whole-farm products like those discussed above are operationally quite complex and prone to moral hazard problems. For example, crop seasons for different commodities vary, and evidence of losses on an early crop may be difficult to measure months after the loss occurs. A review of the AGR and AGR-Lite programs concludes:

> Insuring the tax-year revenue outcome of a number of commodities, with different growing seasons, under a single policy clearly opens the program to greater potential for moral hazard than is encountered in single-commodity insurance policies. This increased moral hazard problem arises because a producer who has crops with differing production seasons is more likely to encounter circumstances in which low revenue on crops harvested early in the accounting and tax year greatly increases the likelihood of an overall loss and therefore reduces the economic incentive to protect against losses on commodities produced and harvested later in the year. (Knight et al., 2006, p. 8)

Another issue with farm-level whole-farm insurance involves the need to understand price variability, yield variability, and price-yield interactions for all of the commodities grown on a farm. These factors complicate the development of insurance products and create the potential for adverse selection due to inaccurate rating assumptions (Dismukes and Coble, 2006). For example, whole-farm revenue insurance for a farm with three crops involves six random variables (yield and price for three crops). An appropriate rating model needs to somehow reflect a six-by-six correlation matrix. Typically, the absence of sufficient data prevents the accurate estimation of such correlations at the farm level.

The proposed CAWFI maintains the desirable characteristic of insuring a portfolio of commodities with one insurance policy but does so without many of the undesirable characteristics of FWFI products (such as the current WFRP). CAWFI requires no accrual accounting adjustments to federal Schedule F forms; in fact, it requires no farm-level yield or price data whatsoever. Unlike WFRP, CAWFI requires no complex adjustments to expected revenue if the commodity mix changes from year to year. Since indemnities are triggered at the area level rather than the farm level, CAWFI is much less exposed than WFRP to moral hazard and adverse selection problems. Finally, accurate whole-farm premium rates require accurate estimates of the variances and covariances of relevant stochastic yield and price variables. Long time series of publicly available county yield and futures

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[3] The consensus of the literature is area-level insurance leaves little opportunity for hidden information (adverse selection) because expected county yields and expected prices are equally observable to the insurer and the insured. Likewise, hidden action (moral hazard) is largely mitigated as long as the insured does not control a significant share of the acreage for the insured crop within the county (see, for example, Miranda, 1991; Skees, Black, and Barnett, 1997; Barnett et al., 2005; Deng, Barnett, and Vedenov, 2007).

price data can be used to rate CAWFI, whereas typically only relatively short time series of data are available at the farm level.

The Proposed Customizable Area-Based Whole-Farm Insurance Model

We begin developing the framework for the proposed CAWFI design by establishing revenue at the farm level from crop production. To this function we add a basic insurance design, and we complete the model by incorporating the CAWFI design.

For any given year t the gross revenue received from producing crop i on farm f is

$$R_{ift} = A_{ift} \times Y_{ift} \times P_{it}, \tag{1}$$

where A is acres, Y is the realized yield, and P is the price received for the commodity.[4] Yield and price are both stochastic, so realized gross revenue is also stochastic. The expected revenue from crop i is

$$E(R_{ift}) = A_{ift} \times \left((E(Y_{ift}) \times E(P_{it})) + Cov(Y_{ift}, P_{it})\right), \tag{2}$$

where $E(\cdot)$ designates the expectations operator.

If one or more of the crops is insured, the realized revenue net of insurance premium is

$$R^S_{ift} = (A_{ift} \times Y_{ift} \times P_{it}) - \pi^S_{ift} + n^S_{ift}, \tag{3}$$

where π is the insurance premium, n is any indemnity received, and the superscript S indicates a particular insurance scenario. If "no insurance" is included as one of the possible insurance scenarios (in which case both π and n will equal zero), equation (3) is generalized to incorporate equation (1). Realized "whole-farm" gross revenue net of insurance premium for farm f in year t is then calculated as

$$R^S_{ft} = \sum_i R^S_{ift}. \tag{4}$$

The proposed CAWFI indemnity function extends the function currently used for the ARP product. As with ARP, indemnities under CAWFI are based on realized revenue calculated using county-level rather than farm-level yield. Unlike ARP, CAWFI insures against shortfalls in whole-farm (multi-crop) revenue. Thus, for each crop i produced on the farm,

$$CAWFI\_R_{ift} = A_{ift} \times Y_{ict} \times P_{it}, \tag{5}$$

where *CAWFI_R* designates the CAWFI calculation of realized revenue and subscript c indicates the county in which farm f is located. Importantly, the farm acreage is multiplied by the county-level yield to estimate realized production in year t.

For each crop i the true expected value of *CAWFI_R* is

$$E(CAWFI\_R_{ift}) = A_{ift} \times ((E(Y_{ict}) \times E(P_{it})) + Cov(Y_{ict}, P_{it})); \tag{6}$$

however, consistent with procedures currently used for ARP, the covariance term in equation (6) is not considered when calculating the revenue guarantee for CAWFI.[5]

[4] For simplicity, price is assumed to be fully systemic (rather than farm-specific).

[5] Since yields and prices are often negatively correlated, this implies that the expected revenue used to calculate the revenue guarantee for ARP (and here for CAWFI) may be slightly higher than the true expected revenue. We ignore the covariance between yield and price only for the purposes of calculating the revenue guarantee (consistent with current ARP procedures). The simulated realized revenues described later account for the covariance between yield and price.

The whole-farm estimate of expected revenue used for CAWFI indemnity calculations is

$$E(CAWFI\_R_{ft}) = \sum_i (A_{ift} \times E(Y_{ict}) \times E(P_{it})), \tag{7}$$

while the whole-farm estimate of realized revenue is

$$CAWFI\_R_{ft} = \sum_i CAWFI\_R_{ift}. \tag{8}$$

When superscripts NI and $CAWFI$ are used to designate the "no insurance" and CAWFI insurance scenarios, respectively, CAWFI indemnities are calculated as

$$n_t^{CAWFI} = \max\left(\left(\frac{Trigger^{CAWFI} - CAWFI\_R_{ft}}{Trigger^{CAWFI}}, 0\right) \times (E(R_{ft}^{NI})) \times (scale),\right. \tag{9}$$

where

$$Trigger^{CAWFI} = E(CAWFI\_R_{ft}) \times coverage \tag{10}$$

and *scale* is a multiplicative factor variable that adjusts indemnities to allow for differences in how shortfalls in county-level whole-farm revenues translate into shortfalls in farm-level whole-farm revenues. The insured selects the choice variables *coverage* and *scale* at the time of purchase. Identical variables exist for ARP and AYP (see Skees, Black, and Barnett, 1997; Deng, Barnett, and Vedenov, 2007). For most insurance products, total coverage is less than 100% and the percentage deductible equals 100% minus the coverage level. For example, the maximum coverage for ARP and AYP is currently 90% (10% deductible); however, since area-based products are not subject to moral hazard, no compelling conceptual reason exists for restricting coverage to less than 100%.

Note also that the indemnity function in equation (9) contains a disappearing deductible. To see this, consider a complete loss with $CAWFI\_R_{ft}$ equal to zero. The percentage loss cost (the maximand in equation 9) becomes 100% and the insured receives an indemnity equal to the total value of the crop liability (i.e., the deductible disappears). Thus, the deeper the loss, the more the deductible disappears.

Assessing Risk Reduction

To evaluate the welfare effects of insurance, we consider a basic two-period model of wealth dynamics for farm f with non-stochastic beginning wealth W_f^0. Ignoring production costs,[6] ending wealth W_f^1 is

$$W_f^1 = W_f^0 + R_{ft}^S. \tag{11}$$

Insurance scenarios are evaluated using the constant relative risk aversion (CRRA) utility function (Pennings and Garcia, 2001):

$$U = \begin{cases} \frac{(W_f^1)^{1-\o}}{1-\o} & \text{if } \o \neq 1 \\ \ln W_f^1 & \text{if } \o = 1 \end{cases}, \tag{12}$$

where ø is the relative risk aversion coefficient. If W_f^1 has j possible outcomes, then

$$E(U) = \begin{cases} \sum_j \tau_j \frac{(W_{fj}^1)^{1-\o}}{1-\o} & \text{if } \o \neq 1 \\ \sum_j \tau_j \ln W_{fj}^1 & \text{if } \o = 1 \end{cases}, \tag{13}$$

[6] If production costs are assumed to be non-stochastic, their exclusion from equation (11) is effectively the same as reducing the level of W_f^0, which will not affect the ordinal ranking of W_f^1 values across different insurance scenarios.

where τ_j is the probability weight associated with outcome W^1_{fj}. Certainty equivalents are calculated as

$$(14) \qquad CE = \begin{cases} (E(U)(1-\text{ø}))^{(\frac{1}{1-\text{ø}})} & \text{if ø} \neq 1 \\ e^{E(U)} & \text{if ø} = 1 \end{cases}.$$

Ultimately, three parameters may be varied to optimize risk reduction in the CAWFI design: (i) commodity weights, (ii) coverage, and (iii) scale. All of these parameters could serve as choice variables for the producer in a completely flexible program or potentially be restricted to a reasonable range to simplify the program. For this study, we focus on optimizing risk reduction; therefore, we assume an unsubsidized, actuarially fair premium for each insurance product. The addition of premium subsidies or loads would needlessly complicate the analysis by altering the mean of ending wealth.[7]

A straightforward but critical component of CAWFI is the choice of commodity weights. Crop mixes on a particular farm will likely deviate greatly within a county. Thus, a farm may produce a mix of 25% corn and 75% soybeans but be located in a county where production consists of an aggregate mix of 50% corn, 25% soybeans, and 25% other crops. Given the available county price and yield data, one can construct an infinite set of revenue indices in the county by varying the commodity weights. Furthermore, given risk reduction as a goal, the same set of readily observable aggregate data can be used to tailor a whole-farm design to widely differing farms by optimizing the weights used for each farm. One rather intuitive approach would be to use the actual percentage crop mix of the farm (i.e., the percentage of acres devoted to each crop) to weight the commodity revenues used to construct the CAWFI index for that farm.

Coverage level is a common crop insurance choice variable that can reflect non-participation if assumed to equal zero. Typically, individual crop insurance coverage levels are limited to less than 100% to reduce incentives for moral hazard; this limit is also imposed on area-based products such as AYP and ARP. However, removing the yield used for indemnification from the farmer's control essentially negates the moral hazard concern. Deng, Barnett, and Vedenov (2007) confirm that optimal coverage levels for an area-yield product can often exceed 100% of expected area yield.

Since the model above proposes scale as a choice variable, a question arises regarding the appropriate scale value preferred by a risk-averse producer. Previous research addresses this issue in the context of AYP insurance. Miranda (1991) adapts a framework commonly used by optimal hedge ratio and capital asset pricing models to decompose farm yield deviations from expectations into systemic and idiosyncratic components. Specifically,

$$(15) \qquad Y_{ift} - E(Y_{ift}) = \beta_f(Y_{ict} - E(Y_{ict})) + \varepsilon_{ift},$$

where β_f is the responsiveness of farm yield deviations from expectations to county yield deviations from expectations. In this construction $\beta_f(Y_{ict} - E(Y_{ict}))$ represents the systemic component of farm yield deviations from expectations, while ε_{ift} represents the idiosyncratic component.

Miranda (1991) further demonstrates that if the indemnity function for an area-yield insurance product is constructed as

$$(16) \qquad n_{it} = max((Trigger_{ict} - ActualYield_{ict}, 0) \times (E(Y^{NI}_{ift}))(scale),$$

then the optimal value for *scale* is equal to β_f. The scale parameter that provides the greatest risk protection to the producer exactly matches the parameter that reflects the marginal change in farm yield deviations when a systemic deviation in yield occurs. While β_f can assume values greater

[7] The current high levels of premium subsidy in the U.S. crop insurance program would likely reduce demand for an area-level whole-farm revenue insurance product such as CAWFI relative to a farm-level whole-farm revenue insurance product such as WFRP in the same manner that the current high levels of premium subsidy are believed to reduce demand for the area-level ARP product relative to the generally more expensive farm-level RP product.

than or less than 1.0 for any given farm, Miranda demonstrates that the acre-weighted average of all farms in a county must equal 1.0 due to the composition of county yield, which is an aggregate of the individual yields. However, this aggregation does not imply that, on average, the total variability of farm yields in a county equals the county yield variability, because the latter excludes the additional idiosyncratic risk of the individual farms. Secondly, contrary to the common perception that a scale parameter is needed to adjust for differences in mean yield, the scale parameter is actually optimal when it scales deviations from the mean. Thus, it may be thought of as an adjustment to the county yield deviation to best match the area insurance product to the systemic portion of farm risk. The actual indemnity function used for AYP is

$$n_{it} = max\left(\left(\frac{Trigger_{ict} - ActualYield_{ict}}{Trigger_{ict}}\right), 0\right) \times (E(Y_{ift}^{NI}))(scale). \tag{17}$$

In this case, optimal *scale* is equal to β_f only if Miranda's decomposition is converted to percentage terms such that

$$\frac{Y_{ift} - E(Y_{ift})}{E(Y_{ift})} = \beta_f\left(\frac{Y_{ict} - E(Y_{ict})}{E(Y_{ict})}\right) + \acute{\varepsilon}_{ift}. \tag{18}$$

Similarly, for ARP the optimal *scale* is equal to β_f if

$$\frac{R_{ift} - E(R_{ift})}{E(R_{ift})} = \beta_f\left(\frac{R_{ict} - E(R_{ict})}{E(R_{ict})}\right) + \tilde{\varepsilon}_{ift}. \tag{19}$$

For the proposed whole-farm CAWFI indemnity function, the optimal *scale* is equal to β_f when

$$\frac{R_{ft} - E(R_{ft})}{E(R_{ft})} = \beta_f\left(\frac{CAWFI\_R_{ft} - E(CAWFI\_R_{ft})}{E(CAWFI\_R_{ft})}\right) + \varepsilon_{ft}. \tag{20}$$

Data and Empirical Application

This study focuses on four representative farms from four different states to reflect varied crop and geographical regions. These farms include a Yazoo County, Mississippi, corn-soybean farm; a McLean County, Illinois, corn-soybean farm; a Sheridan County, Kansas, corn-wheat farm; and a Barnes County, North Dakota, corn-wheat farm.

County yield data were obtained from USDA-NASS for the period 1975 to 2009 (National Agricultural Statistics Service, 2013). All yields were adjusted to 2011 technology using a linear trend specification. Representative farm-level yields are simulated from the detrended county-level yields according to Miranda's formulation, as shown in equation (15). Idiosyncratic risk is assumed to be distributed $\varepsilon_{ift} \sim N(0, \sigma_f^2)$. For each county and crop, we find the standard deviation of ε_{ift} by conducting a grid search for the value of σ_f that generates farm-level yield variability consistent with current USDA-RMA premium rates for farm-level yield insurance at the 65% coverage level (see Coble and Dismukes, 2008; Coble and Barnett, 2008). Individual farm correlations were estimated using APH yield data from USDA/RMA. These data are the ten-year yield histories from 1999 to 2008 that were used to establish expected yields for 2009 insurance policies. Only insured units that reported actual yields for the entire ten years for both crops were considered in the analysis. Farms were selected based on their representativeness of farms in the county.

Futures contract price changes over the production season for 1975–2009 were obtained from the Commodity Research Bureau (CRB) database (2014). For each crop and year an expected price was calculated as the mean of February daily closing prices for the futures contract that expires immediately after harvest (e.g., the December contract for corn). Similarly, a harvest price was calculated as the mean of daily closing prices for the same futures contract during the month prior to expiration (e.g., the mean of November daily closing prices for the December corn contract). In this

Table 1. Descriptive Statistics of Simulated Data ($n = 100,000$)

Variable	Mean	C.V.	Mean	C.V.
Ending Futures Price of Corn	6.19	0.09		
	(0.53)			
Ending Futures Price of Soybeans	13.11	0.12		
	(1.54)			
Ending Futures Price of Wheat	9.08	0.10		
	(0.94)			
Ending Cash Price of Corn	6.02	0.08		
	(0.49)			
Ending Cash Price of Soybeans	13.39	0.10		
	(1.28)			
Ending Cash Price of Wheat	9.02	0.08		
	(0.74)			
	Mississippi		Illinois	
Corn farm yield	145.45	0.34	182.72	0.24
	(49.53)		(43.20)	
Corn county yield	148.70	0.08	180.48	0.12
	(12.62)		(22.24)	
Soybean farm yield	37.53	0.60	53.29	0.21
	(22.69)		(11.19)	
Soybean county yield	32.76	0.19	52.56	0.10
	(6.38)		(5.12)	
	North Dakota		Kansas	
Corn farm yield	129.98	0.59	143.58	0.54
	(76.27)		(77.76)	
Corn county yield	119.75	0.18	137.95	0.14
	(21.93)		(19.27)	
Wheat farm yield	46.76	0.39	32.74	0.66
	(18.25)		(21.60)	
Wheat county yield	45.29	0.18	35.67	0.31
	(8.14)		(11.09)	

way, a time series of within-growing-season price changes was created. Additionally, a time series of harvest time basis between cash and futures prices was computed using the CRB harvest month data and USDA-NASS reports of harvest cash prices.

Ultimately, a time series of detrended county yields, historical futures price changes, and basis risk values were obtained, along with an estimate of σ_f for each crop and location. These data were then used to parameterize a multivariate parametric simulation. The detrended county yield data were fit to a beta distribution with a lower bound of zero and an upper bound of 120% of the maximum yield (Nelson and Preckel, 1989; Sherrick et al., 2004). The shape parameters of the beta distribution were obtained through a method-of-moments calculation. Futures prices and price basis were assumed to be log normally distributed. Thus, the mean and standard deviation of log prices were used to parameterize the price distribution. As previously described, idiosyncratic farm risk was assumed to be distributed $\varepsilon_{ift} \sim N(0, \sigma_f^2)$. These assumptions do not preclude non-normal yield distributions if the county yield is non-normal. The correlation matrix was obtained from the empirical data.

Table 2. Correlation Matrices

Sheridan County, Kansas	Corn Farm Yield	Corn County Yield	Wheat Farm Yield	Wheat County Yield	Corn Futures Price	Corn Cash Prices	Wheat Futures Price	Wheat Cash Price
Corn farm yield	1.00	0.89	0.25	0.25	0.19	−0.40	0.01	−0.36
Corn county yield	0.89	1.00	0.30	0.29	0.25	−0.42	0.11	−0.27
Wheat farm yield	0.25	0.30	1.00	0.83	0.08	−0.02	0.20	−0.28
Wheat county yield	0.25	0.29	0.83	1.00	0.00	0.03	0.18	−0.29
Corn futures price	0.19	0.25	0.08	0.00	1.00	−0.49	0.08	−0.26
Corn cash prices	−0.40	−0.42	−0.02	0.03	−0.49	1.00	−0.43	0.74
Wheat futures price	0.01	0.11	0.20	0.18	0.08	−0.43	1.00	−0.42
Wheat cash price	−0.36	−0.27	−0.28	−0.29	−0.26	0.74	−0.42	1.00

McLean County, Illinois	Corn Farm Yield	Corn County Yield	Wheat Farm Yield	Wheat County Yield	Corn Futures Price	Corn Cash Prices	Wheat Futures Price	Wheat Cash Price
Corn farm yield	1.00	0.78	0.35	0.50	0.50	−0.39	−0.31	−0.37
Corn county yield	0.78	1.00	0.33	0.44	0.43	−0.36	−0.23	−0.21
Soybean farm yield	0.35	0.33	1.00	0.76	0.10	−0.02	−0.09	−0.03
Soybean county yield	0.50	0.44	0.76	1.00	0.23	−0.09	−0.27	−0.33
Corn futures price	0.50	0.43	0.10	0.23	1.00	−0.49	−0.71	−0.46
Corn cash prices	−0.39	−0.36	−0.02	−0.09	−0.49	1.00	0.50	0.69
Soybean futures price	−0.31	−0.23	−0.09	−0.27	−0.71	0.50	1.00	0.76
Soybean cash price	−0.37	−0.21	−0.03	−0.33	−0.46	0.69	0.76	1.00

Yazoo County, Mississippi	Corn Farm Yield	Corn County Yield	Wheat Farm Yield	Wheat County Yield	Corn Futures Price	Corn Cash Prices	Wheat Futures Price	Wheat Cash Price
Corn farm yield	1.00	0.83	0.21	0.22	−0.02	0.06	0.14	0.09
Corn county yield	0.83	1.00	0.14	0.14	0.07	0.10	0.13	0.08
Soybean farm yield	0.21	0.14	1.00	0.78	0.38	−0.29	−0.29	−0.21
Soybean county yield	0.22	0.14	0.78	1.00	0.27	−0.08	−0.22	−0.12
Corn futures price	−0.02	0.07	0.38	0.27	1.00	−0.49	−0.71	−0.46
Corn cash prices	0.06	0.10	−0.29	−0.08	−0.49	1.00	0.50	0.69
Soybean futures price	0.14	0.13	−0.29	−0.22	−0.71	0.50	1.00	0.76
Soybean cash price	0.09	0.08	−0.21	−0.12	−0.46	0.69	0.76	1.00

Barnes County, North Dakota	Corn Farm Yield	Corn County Yield	Wheat Farm Yield	Wheat County Yield	Corn Futures Price	Corn Cash Prices	Wheat Futures Price	Wheat Cash Price
Corn farm yield	1.00	0.87	−0.04	0.15	0.17	0.10	−0.08	0.07
Corn county yield	0.87	1.00	−0.09	0.05	0.18	0.11	−0.13	0.05
Wheat farm yield	−0.04	−0.09	1.00	0.81	0.27	−0.39	0.10	−0.28
Wheat county yield	0.15	0.05	0.81	1.00	0.39	−0.33	0.04	−0.19
Corn futures price	0.17	0.18	0.27	0.39	1.00	−0.49	0.08	−0.26
Corn cash prices	0.10	0.11	−0.39	−0.33	−0.49	1.00	−0.43	0.74
Wheat futures price	−0.08	−0.13	0.10	0.04	0.08	−0.43	1.00	−0.42
Wheat cash price	0.07	0.05	−0.28	−0.19	−0.26	0.74	−0.42	1.00

Simulation Approach

The Phoon, Quek, and Huang (2004) procedure is a multivariate simulation procedure for correlated stochastic variables from mixed marginal distributions based on an eigen decomposition of a rank correlation matrix. Anderson, Harri, and Coble (2009) demonstrate that the primary advantage of the Phoon, Quek, and Huang procedure compared to other techniques such as the Iman-Conover procedure is that it is straightforward and distribution free (Iman and Conover, 1982). We use the Phoon, Quek, and Huang simulation technique to generate 100,000 sample observations for futures prices, basis risk, county yields, and idiosyncratic yield risk for each crop in each county using eigenvalues and the decomposition of the correlation matrix . We initially assume moderately risk-averse farmers with a risk-aversion coefficient of 2.0, while certainty equivalents are calculated

Table 3. Share of Revenue by Crop Mix across Representative Farms

		Revenue Share of Crops		
State	**Crop Mix (Acres)**	**Corn**	**Soybeans**	**Wheat**
Kansas	50/50	0.750	-	0.250
	Majority corn	0.875	-	0.125
	Majority wheat	0.562	-	0.438
Illinois	50/50	0.618	0.382	-
	Majority corn	0.791	0.209	-
	Majority soybeans	0.410	0.590	-
Mississippi	50/50	0.647	0.353	-
	Majority corn	0.810	0.190	-
	Majority soybeans	0.440	0.560	-
North Dakota	50/50	0.655	-	0.345
	Majority corn	0.816	-	0.184
	Majority wheat	0.448	-	0.552

Notes: By assumption majority crop totals 70% of planted acres.

as shown in equation (14). Optimal choice levels were selected through a grid search for choice variables: scale and coverage level. Coverage levels were evaluated in 5% increments (consistent with allowed program coverage intervals), while scale was evaluated in 1% increments. The certainty equivalent was computed for all combinations and optimal levels determined by the maximum value.

Results

Descriptive Statistics

Table 1 presents descriptive statistics for the 100,000 simulated observations used in this study. The Illinois representative corn farm has a higher mean yield and lower standard deviation than the other corn farms. Relative farm-level yield risk (as measured by the coefficient of variation) is highest for the Kansas and North Dakota representative corn farms. The Mississippi and Kansas representative farms have similar mean farm-level corn yields, but the Kansas farm has a higher standard deviation and thus higher relative risk. The relative county-level yield risk for corn is lowest for the county in Mississippi and highest for the county in North Dakota. At both the farm and county levels the Mississippi farm has a higher relative yield risk for soybeans than the Illinois farm. Likewise, at both the farm and county levels the North Dakota farm has a lower relative yield risk for wheat than the Kansas farm. The relative risk of ending futures prices and ending marketing year average prices is similar across all crops. We note that these simulations are for a relatively high-price scenario, but sensitivity analysis suggests that relative price variability matters most.

Table 2 provides the eight-by-eight empirically-estimated correlation matrices associated with each of the four locations. Notably, differences occur in the price yield correlations across locations and in the positive yield-yield correlations.

Table 3 presents the expected percentage of revenue attributable to each crop for different crop mixes on each representative farm. A “50/50” crop mix indicates that the available acres are divided equally between the two crops. When the scenario refers to a majority crop, we assume the majority crop is planted on 70% of the available acres and the other crop is planted on the remaining 30%. Corn production is responsible for at least 80% of the total revenue in each of the four states under the majority corn mix. Under the 50/50 crop mix, corn production is responsible for over 60%

Table 4. Optimal Unrestricted CAWFI and Optimal Restricted CAWFI by State and Crop Mix

State	Crop	Optimal Scale for Unrestricted CAWFI	Optimal Coverage for Unrestricted CAWFI	Optimal Scale for Restricted CAWFI	Reduction in Certainty Equivalent due to Scale and Coverage Restrictions
Kansas	Corn only	2.74	1.35	1.50	12.98%
	Wheat only	1.63	1.40	1.50	10.77%
	50/50	2.02	1.25	1.50	9.15%
	Majority corn	2.28	1.35	1.50	10.36%
	Majority wheat	1.87	1.35	1.50	8.49%
Illinois	Corn only	1.45	1.30	1.45	4.78%
	Soybeans only	1.46	1.40	1.46	3.12%
	50/50	1.29	1.20	1.29	3.64%
	Majority corn	1.32	1.30	1.32	3.92%
	Majority soybeans	1.41	1.20	1.41	3.56%
Mississippi	Corn only	2.01	1.25	1.50	9.61%
	Soybeans only	2.32	1.50	1.50	11.94%
	50/50	2.40	1.20	1.50	11.27%
	Majority corn	2.12	1.25	1.50	9.95%
	Majority soybeans	2.85	1.20	1.50	13.85%
North Dakota	Corn only	2.59	1.30	1.50	13.57%
	Wheat only	1.79	1.35	1.50	5.44%
	50/50	1.98	1.35	1.50	6.28%
	Majority corn	2.21	1.45	1.50	8.38%
	Majority wheat	1.81	1.30	1.50	4.48%

Notes: All optimal scale coefficients are significant at the 1% level.

of the total revenue in each location, and in Kansas the revenue share from corn reaches 75%. In Illinois and Mississippi, the two states that produce soybeans, under the majority soybeans crop mix the share of total revenue from soybeans remains under 60%. Similarly, for the two states with wheat production—Kansas and North Dakota—under the majority wheat crop mix the share of total revenue from wheat is no higher than approximately 55%.

Insurance Products Compared

With CAWFI commodity weights based on the acreage share of crops on the farm, the optimal unrestricted CAWFI scale was determined for each farm and crop mix combination as the beta coefficient from equation (20). Conditioned on the optimal unrestricted scale, a grid search was then conducted to find the optimal unrestricted coverage, or the coverage that generates the highest certainty equivalent. CAWFI was evaluated with optimal unrestricted scale and coverage levels for both single- and multiple-crop revenue scenarios for the four geographical regions.

ARP and AYP use a scale ranging from 0.90 to 1.50 and levels of coverage ranging from 70% to 90% in 5% increments. Thus, the restricted CAWFI model imposes these constraints on the determination of both optimal scale and coverage. The percentage difference in certainty equivalents between the optimal unrestricted and optimal restricted CAWFI is estimated for each farm and crop mix combination.

We also compare both the unrestricted and restricted CAWFI certainty equivalents to certainty equivalents from a "no insurance" scenario and those from a hypothetical, customizable farm-level whole-farm insurance (FWFI) product with 90% coverage. The premium used in all scenarios is actuarially fair (i.e., premium equals expected indemnity). While the assumption of an actuarially fair premium is inconsistent with current federal crop insurance products, this assumption allows for results that reflect only the certainty equivalent value of any risk reduction provided by the insurance product.

Optimal Unrestricted CAWFI Scale and Coverage

Table 4 presents optimal unrestricted CAWFI scale and coverage values for each of the representative farms and different crop mixes. Optimal scale values, while varying across regions and crop mixes, always exceed 1.00, consistent with the findings of Deng, Barnett, and Vedenov (2007). In general, the Illinois representative farm has lower optimal scale values than the Kansas, North Dakota, or Mississippi farms. The optimal scale values for Illinois also vary much less than those of the other locations, ranging from 1.29 to 1.46. Optimal unrestricted coverage also varies across regions and crop mixes but is always at least 1.20. The lowest values occur for the 50/50 and majority soybean crop mixes in Illinois and Mississippi. The highest optimal coverage is 1.50 and occurs solely for the soybeans-only crop mix in Mississippi. Thus, the Mississippi farm also has the greatest range of optimal unrestricted coverage levels among the four locations.

Comparing Optimal Unrestricted and Optimal Restricted CAWFI

Table 4 also presents optimal restricted CAWFI scale and coverage values for each farm and commodity mix. The upper bound restricts scale to 1.50; therefore, if the optimal unrestricted scale is less than 1.50, the optimal *restricted* scale is equal to the optimal unrestricted scale. This situation occurs only for the Illinois farm. For the other farms, the optimal unrestricted scale is greater than 1.50, so the optimal restricted scale is equal to the upper bound of 1.50. With scale values restricted to less than or equal to 1.50, the optimal restricted coverage is always equal to the upper bound of 0.90.

As expected, restricting scale and coverage reduces the welfare of the insured farmer. Table 4 lists the percentage reduction in certainty equivalents that occurs due to restricting scale and coverage. The magnitude of the reduction ranges from 3.12% (for soybeans only in Illinois) to 13.85% (for majority soybeans in Mississippi). In general, the restrictions reduce producer welfare the most in riskier production scenarios. For example, the range of reduction in certainty equivalents across crop mixes is approximately 10–14% in Mississippi and approximately 3–5% in Illinois.

Table 5 presents the change in revenue coefficient of variation (C.V.) and the certainty equivalent estimates expressed as ratios comparing different insurance scenarios. The change in C.V. does not require a behavioral assumption to specify. In this case it reflects the restricted CAWFI model without subsidy. In every location and crop mix scenario, CAWFI reduced the revenue risk. In many instances the C.V. is reduced by 40% or more. However, the risk reduction is generally lower in North Dakota than in other locations.

As a baseline, the fourth column expresses the certainty equivalent of 90% FWFI to the certainty equivalent of no insurance. We use a 90% coverage level because, given the susceptibility of farm-level insurance products to moral hazard, the USDA-RMA likely will not offer a coverage level higher than 90% (the maximum coverage level for current USDA-RMA farm-level insurance products is 85%). As expected, all of the ratios exceed a value of 1.00, indicating a producer with the assumed degree of risk aversion prefers 90% FWFI to no insurance. A more specific interpretation can be made by focusing on the example of the corn-only Kansas farm. In this case, the certainty equivalent for 90% FWFI is 23% higher than the certainty equivalent for no insurance. In general, the 90% FWFI policy increases certainty equivalents for the Kansas, North Dakota, and Mississippi representative farms by much more than for the Illinois representative farm. The insurance proves

Table 5. Comparing Certainty Equivalents (CE) across Different Insurance Scenarios by State and Crop Mix

State	Crop	% Reduction in CV Given Restricted CAWFI	90% FWFI CE / No Insurance CE	Optimal Unrestricted CAWFI CE / No Insurance CE	Optimal Restricted CAWFI CE / No Insurance CE	Optimal Unrestricted CAWFI E(Indemnity) / 90% FWFI E(Indemnity)	Optimal Restricted CAWFI E(Indemnity) / 90% FWFI E(Indemnity)
Kansas	Corn only	63%	1.23	1.23	1.08	3.84	0.28
	Wheat only	56%	1.31	1.32	1.18	2.36	0.75
	50/50	61%	1.15	1.17	1.07	3.41	0.39
	Majority corn	63%	1.18	1.19	1.08	4.09	0.34
	Majority wheat	58%	1.15	1.17	1.08	4.41	0.44
Illinois	Corn only	50%	1.10	1.10	1.04	4.94	0.63
	Soybean only	41%	1.03	1.05	1.02	7.49	0.56
	50/50	48%	1.03	1.06	1.02	5.67	0.52
	Majority corn	49%	1.04	1.07	1.03	6.48	0.59
	Majority soybeans	44%	1.01	1.04	1.01	7.07	0.44
Mississippi	Corn only	40%	1.10	1.13	1.03	4.14	0.16
	Soybeans only	10%	1.81	1.70	1.55	3.36	0.32
	50/50	28%	1.09	1.15	1.03	4.20	0.14
	Majority corn	34%	1.09	1.13	1.03	4.76	0.15
	Majority soybeans	21%	1.11	1.18	1.04	4.06	0.13
North Dakota	Corn only	20%	1.28	1.27	1.12	2.86	0.35
	Wheat only	15%	1.11	1.12	1.06	3.76	0.57
	50/50	18%	1.1	1.11	1.05	4.40	0.45
	Majority corn	19%	1.15	1.16	1.07	4.43	0.40
	Majority wheat	17%	1.07	1.09	1.04	4.66	0.48

less beneficial for the Illinois farm because of its exposure to relatively less revenue risk. Revenue risk is lower for the Illinois farm because it experiences lower yield risk and has a larger negative correlation between price and yield.

The fifth column of table 5 presents the certainty equivalents of optimal unrestricted CAWFI relative to the certainty equivalents of no insurance. Again, as expected, all of the ratios exceed a value of 1.00, indicating a preference for optimal unrestricted CAWFI over no insurance. More interesting is a comparison of the fourth and fifth columns for each farm and crop mix. While the ratios of certainty equivalents are similar, optimal unrestricted CAWFI generally has a higher certainty equivalent relative to the no insurance scenario than does 90% FWFI. The only notable exception is the soybeans-only Mississippi farm. In other words, when the coverage level of the FWFI product is restricted to 90% to control for moral hazard, the optimal unrestricted CAWFI can generally provide risk protection at least as good as that provided by FWFI.

The sixth column of table 5 presents certainty equivalents for optimal restricted CAWFI relative to the certainty equivalents for no insurance. While the optimal restricted CAWFI is still preferred to no insurance, in many cases certainty equivalents are greatly reduced relative to those of optimal unrestricted CAWFI. Again, this result is consistent with the findings of Deng, Barnett, and Vedenov (2007) regarding crop-specific AYP policies. For every farm and crop mix scenario, the certainty equivalent for 90% FWFI is at least as high as that of optimal restricted CAWFI. In a few instances (e.g., Kansas corn-only and Mississippi soybeans-only) the 90% FWFI certainty equivalent is considerably higher than that of optimal restricted CAWFI but, more commonly, the differences in certainty equivalents are more modest.

Sensitivity analysis was also conducted with respect to the degree of risk aversion. CRRA risk aversion coefficients of one and three were also examined. The magnitude of certainty equivalents changed as expected in that higher risk aversion increased certainty equivalent values. Higher risk aversion led to slightly higher optimal scale and coverages. But the optimal coverage level for the restricted CAWFI remains robust to the risk aversion level.

Moving beyond Actuarial Fairness

The assumption of actuarially fair premiums allows the analysis to focus solely on the risk reduction provided by the various insurance designs; however, this assumption also leads to a serious limitation because it ignores transactions costs and administrative costs. This situation is revealed by observing the data in the sixth and seventh columns of table 5. The sixth column lists the expected indemnity for an optimal unrestricted CAWFI policy as a ratio of the expected indemnity for a 90% FWFI policy. This column can also be interpreted as the relative change in actuarially fair premium for the optimal unrestricted CAWFI versus the expected payouts for 90% FWFI. The actuarially fair premiums for optimal unrestricted CAWFI are between two and seven times higher than those for 90% FWFI. The very high actuarially fair premiums for optimal unrestricted CAWFI are not surprising given the levels of the optimal scale and coverage presented in table 4. This result reflects the common insurance finding that when premiums are actuarially fair, the optimal decision is to fully insure to protect against the maximum possible loss because there are no transactions or administrative costs associated with "swapping money" with the insurer.

A more realistic scenario would include a premium that exceeds the actuarially fair premium due to multiplicative loads that account for transactions and administrative costs, the cost of contingent capital, rating ambiguities, and return on equity. With a loaded (rather than actuarially fair) premium, one cannot afford to routinely swap money with the insurer; therefore, one cannot afford to insure at optimal unrestricted levels of scale and coverage. The seventh column of table 5 presents the ratio of the actuarially fair premium for optimal restricted CAWFI to the actuarially fair premium for 90% FWFI. The ratios vary from 0.13 to 0.75, but the ratio exceeds 0.60 in only two instances (Kansas wheat-only and Illinois corn-only). This finding indicates that in most cases the actuarially fair premium for optimal restricted CAWFI is far less than that of 90% FWFI. Since index insurance also has significantly lower transactions and administrative costs than farm-level insurance, the premium loads on the optimal restricted CAWFI policy also would likely be significantly lower than those for a 90% FWFI policy.

Therefore, in the absence of large premium subsidies a restricted CAWFI policy in most cases should cost much less than a 90% FWFI policy. While 90% FWFI generally offers more risk reduction than optimal restricted CAWFI (assuming moderate CRRA), the differences are often modest. For example, the optimal restricted CAWFI actuarially fair premium for the Illinois farm varies between 44% and 63% of the 90% FWFI actuarially fair premium (depending on the crop mix), but very little difference exists between the certainty equivalents for optimal restricted CAWFI and 90% FWFI. The differences in certainty equivalents are larger for the other farms, but the optimal restricted CAWFI actuarially fair premium is generally also much lower than the 90% FWFI actuarially fair premium.

Conclusions

This study develops and evaluates a customizable area-based whole-farm insurance (CAWFI) product for four representative farms producing corn, wheat, and soybeans in Illinois, Kansas, Mississippi, and North Dakota. Constructing the insurance product is relatively straightforward for areas where adequate area yield data are available. While basis risk exists with CAWFI, the product is not subject to the onerous record keeping and data adjustments necessary to implement other whole-farm insurance designs such as WFRP. Like the existing commodity-specific ARP policy, CAWFI mitigates moral hazard concerns by using county yields rather than farm yields to determine indemnities. Furthermore, potential adverse selection problems caused by the inability of the insurer to obtain information about the within-farm correlation matrix of random variables are precluded since the correlation matrix of interest is based entirely on publicly available data.

The optimal scale and coverage for CAWFI were determined both when these choice variables are unrestricted and when they are restricted as with AYP and ARP. When unrestricted, the optimal CAWFI scales for the Kansas, North Dakota, and Mississippi farms exceed the AYP and ARP maximum scale value of 1.50. For all farms, the unrestricted optimal coverage level exceeds the AYP and ARP maximum value of 0.90. Imposing the AYP and ARP restrictions on scale and coverage causes reductions in CAWFI certainty equivalents of between 3.1% and 13.9% (depending on the farm and crop mix).

Both optimal unrestricted and optimal restricted CAWFI were compared to a 90% FWFI product. The optimal unrestricted CAWFI provides risk protection at least as good as that provided by FWFI in all but one case (the Mississippi farm producing only soybeans). However, expected indemnity payouts (and thus, actuarially fair premium rates) for unrestricted CAWFI are more than three to seven times those of 90% FWFI. Thus, with typical multiplicative premium loads, most producers will likely find an optimal unrestricted CAWFI policy unattractive.

CAWFI with scale and coverage restricted, as in existing AYP and ARP policies, increases certainty equivalents (relative to a no insurance scenario) but less than 90% FWFI does. In some cases (e.g., Illinois), the certainty equivalent differences between optimal restricted CAWFI and 90% FWFI are small. In other cases (e.g., Mississippi), the differences are more significant. In all cases, the expected indemnity payouts for restricted CAWFI are much lower than those for 90% FWFI, implying that while restricted CAWFI may offer somewhat less risk reduction than 90% FWFI, it could be offered at much lower actuarially fair premium rates. Furthermore, as an index insurance product, CAWFI would have much lower premium loads for administrative and operating expenses.

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