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Revenue Risk Reduction Impacts of Crop Insurance in a Multi-Crop Framework

This study develops a multi-crop insurance model which is employed to evaluate crop insurance decisions when several crops are produced jointly. The results suggest that the diversification effects derived from producing multiple crops can substantially alter the risk reduction impacts of crop insurance versus if the decision is viewed from the perspective of a single crop. Further, the relatedness of crop production and price responses among crops differs considerably across insurance products and strategies. As a result, insurance strategies that might provide the maximum risk reduction for an individual crop do not necessarily carry over to the multi-crop case.

Keywords: Multi-Peril Crop Insurance, revenue risk, crop yield distributions, multi-crop, insurance strategies, hedging effectiveness

Introduction

A producer's revenue distribution results from price and yield variability for the crops produced, correlations between prices and yields, as well as interactions among the crops produced. Producers employ several tools to manage revenue risk including Multi-Peril Crop Insurance (MPCI)—one of the cornerstones of risk management for the nation's farmers. MPCI is administered by the Federal government and is available in a wide variety of forms, including products to hedge revenue risk, yield risk, as well as group-based products.

Several previous studies have investigated the performance of crop insurance products in hedging yield and revenue risk in the context of alternative marketing behaviors and government programs (see e.g., Coble et al, 2004; Coble, Heifner, and Zuniga, 2000; Barnett, Black, and Skees, 2000; Schnitkey, Sherrick, and Irwin, 2003; Deng, Barnett, and Vedenov, 2007), but primarily in single-crop contexts.[1] Yet, when the producer grows more than one crop, diversification of farm revenue may occur due to the fact that crop yields and prices are not perfectly correlated, and thus the relevant revenue variability relates to the sum of revenues from the various crops jointly, not individually. Ignoring multi-crop relationships can potentially lead to misstatements of the impacts of crop insurance on overall revenue risk reduction and even lead to distortions in comparisons across different types of crop insurance products (e.g. individual revenue versus group revenue products).

This study expands upon earlier work by investigating the effects of the use of multiple single-crop insurance policies on the revenue risk of a producer growing multiple crops. Focus on this dimension stems from the fact that virtually all of the volume in the crop insurance program lies in the single-crop contracts. Yet, most producers produce at least two different types of crops. The study uses a rich farm-level data set from the Illinois Farm Business Farm Management recordkeeping association for farms with matched corn and soybean production data over a relatively long sample period from 1972-2007 to calibrate a simulation model of multi-crop revenues. The model is used to identify the sources and impacts of total farm crop revenue risk as well as the degree of correlation among crop insurance payments, single crop revenue, and multiple crop revenue in the context of popular crop insurance products and strategies.

The study finds that the diversification effects derived from multiple crop production substantially alter the risk reduction effects of crop insurance when considered in a multi-crop context. Further, the relatedness of crop production and price responses among crops differs considerably across alternative insurance products and strategies. As a result, insurance strategies that might provide the maximum risk reduction for an individual crop do not necessarily carry over to the multi-crop case. For Illinois corn and soybeans, the results suggest that group based products will perform relatively better than individual products when viewed in a multi-crop versus single-crop context. Consistent with Deng, Barnett, and Vedenov (2008), we also find that popular group based products tend to contain large positive “wedges”—or positive differences between expected indemnity payouts and producer paid premiums—relative to individual products.

This research may shed light on some of the factors affecting producer participation in the crop insurance program, and may help identify meaningful risk reduction strategies in a multi-crop context. It also highlights the potentially misleading analytical distortions which can arise when crop insurance and hedging decisions are viewed in a single crop context when the true crop revenue risk exposure is in fact composed of multiple underlying correlated exposures.

A Multi-Crop Revenue Simulation Model

Several methods of simulating farm yield and revenue distributions exist including a variety of parametric (e.g., Sherrick et al, 2004; Schnitkey, Sherrick, and Irwin, 2003) and non-parametric frameworks (e.g., Atwood, Bequet, and Watts, 1997; Coble et al, 1999). While non-parametric frameworks are attractive in that they necessarily allow for a wider set of distributional representations, a major shortcoming is that they tend to be prone to over-fitting and can produce highly inefficient estimates. For example, non-parametric bootstrapping approaches—while innovative and popular—have difficulties incorporating supplementary farm-level information (such as number of years of data available, acreage, soil quality, etc.) that may be relevant to the underlying "true" risk profile of the exposure under examination. These approaches also implicitly assume that the farm-to-county relationship observed in during some small sample for which farm data are available is the actual relationship between the farm and the county. The result is a farm-level yield distribution representation that—while technically unbiased—tends to be highly erratic and inefficient in practice.

In this study a parametric representation of price and yield distributions is adopted. Use of distributional approaches allows us to more easily and accurately incorporate external information and potentially reduce sampling variability in measuring farm risk. The focus in this study is on a case farm representation where the case farm exhibits characteristics similar to an average or typical farm in the county, a task particularly well suited for this approach. Ultimately, the primary decision point as it regards the choice between non-parametric and parametric representations is the analyst's preferences for efficiency versus bias; non-parametric methods will typically be unbiased but are potentially less efficient than comparable parametric frameworks. In the case of the Illinois FBFM data, the parametric assumptions have been validated in a wide variety contexts (Sherrick, 2004; Woodard, Sherrick, and Schnitkey, 2008; Pichon, 2002; Zanini, 2001) and thus concerns about potential biases in the yield distribution representations are substantially mitigated. The same may not be true in other contexts and so should be addressed on a case-by-case basis.

Model Overview

The model uses representations of farm-level yield distributions, county-level yield distributions, a forward price distribution for harvest price determination, government program parameters, production costs, as well as a correlation structure between county and farm yields, and between prices and yields. Initial steps in parameterization of the simulation procedure involve estimating the county and farm yield distributions, county-to-farm relationships, yield-to-price correlations, and forward price distributions. Having obtained estimates of the underlying distributions (i.e., price, farm and county yields) and their correlations, correlated random pseudo-data are then generated to represent price and yield outcomes and the related indemnity payments. Actual insurance conditions (base prices, RMA rates and premiums, and futures market conditions) are generated to mimic the information set the producer would have available at the time of the insurance purchase decision.

Yield Trend Estimation and Assumptions

Corn and soybean yields have trended upward through time due to technology gains, and thus failure to detrend yields will result in biased estimates of expected yield in the period being evaluated for insurance decisions (e.g., Skees and Reed, 1986). Thus, yields are detrended using a deterministic linear trend at the county level using OLS, and restated on a current-year basis (Zanini, 2001; Pichon, 2002; Sherrick et al, 2004; and Tannura, 2007). While numerous detrending procedures exist, we adopt a linear procedure for several reasons. First, previous research suggests that individual farm detrending may result in excessively high sampling variance when estimating trend (Atwood, Shaik, and Watts, 2003), thus detrending at the county- or regional-level seems appropriate. Second, the econometric properties of an uninterrupted series independent variable and the level of skewness typical in corn yields allows OLS to generate better yield trend coefficients than alternative robust estimators (Swinton and King, 1991). Third, while more complex deterministic or stochastic functional forms could be imposed on trend, previous research demonstrates that the high degree of sampling variance in measuring trend over small samples likely renders a simple linear trend more efficient than more complex detending procedures which allow for jumps, structural change, stochastic trends, or other non-linearities (Zanini, 2001; Tannura, 2007). Simply put, more complex detrending procedures tend to overfit the data and can result in highly inefficient and sometimes negative trend estimates. Furthermore, to the extent that trend is measured with error or is uncertain, it more appropriate and reasonable to relegate those errors to yield distribution itself as opposed to over-parameterizing the trend model.[2]

Estimating County-to-Farm Relationships

After county yields have been detrended, the next step is to estimate the county-to-farm relationship for a "typical" case farm. A moments-based approach to modeling the county-to-farm relationship using the first two moments through the mean and standard deviation is employed. Farm-level yield data from the Illinois Farm Business Farm Management (FBFM) dataset and county yield data from the National Agricultural Statistics Services (NASS) are used to estimate the county-to-farm mean and standard deviation relationships. The FBFM dataset contains individual farm yield records for about 14,000 different farm units from 1972 to the present. A subset of approximately 4,000 farms is obtained from the dataset by selecting farms which have at least 15 years of data. Estimates of the county-to-farm mean and standard deviation are obtained for each farm using the detrended yield observations. The county-to-farm mean and standard deviation ratios are then averaged for all farms in a county to obtain a "typical" case farm. Empirical validations of this approach indicate that this method recreates the underlying structure accurately.

Yield and Price parameterization, and Correlation Assumptions and Estimation

It is relatively well-accepted that yields tend to have negative skewness and can be viewed as having a reasonably stable distribution over time after accounting for trend – notwithstanding the current debate about trend acceleration (Tannura, 2007). Candidate parameterizations for farm and county yields identified in past work include forms of the Weibull, Burr, and various forms of the Beta distributions, among others. We adopt the Weibull two-parameter distribution as it has been shown to reasonably accurately characterize soybean and corn yields (Zanini, 2001; Pichon 2002; Sherrick et al, 2004), although early work also investigated a conditional Beta and found little practical difference in insurance valuation implications. The distributions are fit using a modified method-of-moments approach by minimizing the summed squared differences between the empirical mean and standard deviation and those resulting from the Weibull distribution with the chosen parameters.

County yield distribution estimation is straightforward. The NASS county yields are first detrended, and then the mean and standard deviation are estimated. Next, Weibull parameters are fit using the modified method-of-moments approach above. Obtaining farm-level yield distributions requires one extra step. As indicated earlier, the generally higher farm-level riskiness relative to county can be represented in terms of the ratios of the standard deviations of a farm's series to that of its county. Thus, to create a representative or typical case farm for each county, the county standard deviation is multiplied by the average farm-to-county standard deviation from its region. The case farm mean yield is set equal to the county level mean. Simulation and sensitivity tests confirm that this procedure is an adequate means by which to augment limited farm-level yield data with more extensive county datasets and results in unbiased and efficient estimates of farm mean yields and risk under the Weibull distribution.[3] With an augmented estimate of the farm mean and standard deviation, the modified method-of-moments technique above is applied to estimate farm-level Weibull distribution parameters. The result is a parametric representation of the county yield distribution for the given time period that serves as the base for both group product yields and for "scaling-up" to the case farm presented in each county.

Forward price distributions intended to reflect the information set at the date of signup are also estimated. Price distributions are fit using live options market data on the harvest price contracts (December Corn, and November Soybeans) to extract estimates of the price distribution assuming a lognormal price distribution (Sherrick, Garcia, and Tirupattur, 1995). As of the first full trading day after the first signup date of March 1st, all settlement prices for the options on December Corn futures (November Soybean Futures) are collected. Strikes with no volume or more than five strike intervals from the current futures price are discarded, and both puts and calls are used simultaneously to recover the implied forward price distribution using the following:

$$\min_{\varphi}\left[\sum_{i=1}^{k}\left(\left(V_{c,i}-b(T)\int_{x_i}^{\infty}g(Y_T\mid\varphi)(Y_T-x_i)dY_T\right)^2\right)+\sum_{j=1}^{l}\left(\left(V_{p,j}-b(T)\int_{0}^{x_j}g(Y_T\mid\varphi)(x_j-Y_T)dY_T\right)^2\right)\right] \quad (1)$$

where $V_{c,j}$ is the price of the call option at strike x_j, $V_{p,j}$ is the price of put option with strike x_j, $b(T)$ is the discount rate that applies between now and the expiration date, Y_T is the price of the underlying commodity and $g(Y_t|\varphi)$ is the density function given parameters φ, and l and k are the number of puts and calls. The model assumes time-additivity in variance to scale the variance to the appropriate interval for products that use October versus November settlement averages.

To implement the simulation procedure, the correlations between county and farm yields must also be estimated and imposed between farm and county yields and prices. As is standard in this context, the correlation is estimated using the Spearman Rank Correlation. The county-level price-yield correlation is employed for each county; the state average of this statistic across counties was -0.437 for corn and -0.510 for soybeans.

Crop Insurance Indemnities

The next step is to define the crop insurance indemnity functions. The simulated price and yield values will be passed to these functions to calculate simulated indemnities. Three popular products are assessed in this study: Traditional Yield Insurance (*APH Yield*); Revenue Assurance with a Harvest Price Option (*RA-HP*); and Grip Risk Income

Protection with a Harvest Option (*GRIP-HR*). The *GRIP-HR* indemnity can be expressed as:

$$GRIP-HR\ Indem = 1.5 \times Prot \times Max\left[0, E(Y_C) \times Max(HP, BP) - \frac{HP \times Y_C}{Cover}\right] \quad (2)$$

where $Prot$ a price protection level election between 60% and 100%, $E(Y_C)$ is the expected county yield set by the Risk Management Agency (RMA), *BP* is the base price at planting, *HP* is the realized price at harvest, Y_C is the realized county yield, and *Cover* is the coverage level election. The *RA-HP* indemnity is expressed as:

$$RA-HP\ Indem = Protection \times Max[0, E(Y_F) \times Max(BP, HP) \times Cover - HP \times Y_F] \quad (3)$$

where $E(Y_F)$ is the expected farm yield (or APH) and Y_F is the realized farm yield. In addition, the relevant price limit controls for RA-HP and GRIP-HR are stated in terms of the 2009 price limit of 200% of the base price. The *APH Yield* indemnity is modeled as:

$$APH\ Yield\ Indem = Protection \times BP \times Max[0, E(Y_F) \times Cover - Y_F]. \quad (4)$$

For this study we restrict attention to *GRIP-HR* at the 90% coverage level, and *RA-HP* and *APH* at the 85% coverage level. These are very popular products in the area and crops under investigation and thus the most relevant for this study. While some earlier studies have employed methods to optimize the coverage and protection level choice (see e.g. Deng et al, 2008), this study is more concerned with evaluating those insurance strategies which have been most represented in the market, and not necessarily those predicted from normative models which are typically sensitive to the parameterization of the assumed objective function.

Expected Payment Simulation

The next step in the procedure is to generate farm revenues and associated insurance indemnities. Correlated pseudo-random data are generated from the price, farm and county yield distributions using the inverse distribution method. The Cholesky decomposition of the covariance matrix is used to induce correlation in the individual marginal distributions (Iman and Conover, 1982).[4] Next, the simulated prices and yields are passed through the necessary indemnity functions (i.e., *APH*, *RA-HP*, *GRIP-HR*) at the necessary coverage level to obtain a simulated indemnity. 5,000 iterations of the simulator are conducted using a stratified sampling method. The revenue measure reported is net of total non-land costs plus government payments, and is thus a proxy of economic rent.[5] Therefore, the uninsured simulated net revenue is calculated as the simulated price times the simulated yield, plus government payments, minus total non-land costs. Total non-land costs and government payments were obtained from 2009 estimates compiled by the *farmdoc* project office at the University of Illinois (Schnitkey, 2009). The simulated net insured revenue is calculated as uninsured net revenue plus indemnities, minus premiums. Risk measures and other summary statistics are then tabulated from the simulated insured and uninsured net revenues (hereafter, revenues).

Risk Measures

As noted, the focus of this study is on the distributional impacts of crop insurance on revenue risk in the context of multi-crop decisions. Thus, while several authors have adopted explicit utility representations—such as certainty equivalents—in similar risk management contexts (e.g., Woodard and Garcia, 2008; Deng, Barnett, and Vedenov, 2007), here attention is restricted to the revenue distribution itself. In addition to the cumulative distribution, three different summary statistics of the revenue distribution are reported to evaluate the effectiveness of alternative crop insurance strategies and products. The first is the average revenue, which is calculated as the simple average of the revenues produced from the simulation. It is common in the crop insurance program to observe significant positive "wedges", or relative mispricings, across product types (see e.g., Deng, Vedenov, and Barnett, 2007). Thus, the choice of product could have large impacts on the mean of the revenue distribution.

The measure used to evaluate risk exposure is the square root of the lower partial moment (*SqrLPM*), which can be expressed as:

$$SqrLPM = LPM(\mathbf{R}, \delta, \alpha)^{1/2} = \left[\sum_{i=1}^{N} Max(0, \delta - R_i)^{\alpha} / N \right]^{1/2} \tag{5}$$

where $\mathbf{R}$ is a vector of simulated revenues, δ is a baseline return, N=5000 is the sample size (or number of simulated observations), and α is the order of the order of the partial moment and can be viewed as reflective of the level of risk aversion (Mattos, Garcia, and Nelson, 2008). In this study we evaluate *SqrLPM* with $\alpha = 2$ and δ equal to the average revenue for the *uninsured* baseline case. Notice, this measure is identical to the common semi-standard deviation measure with the exception that the uninsured average revenue is used in the comparison across products rather each revenue distributions own average. This allows us to more accurately capture the impact of downside risk reduction when the revenue distribution is impacted by the relative rating of the underlying insurance products (i.e., when the products have different implied "wedges"). To provide a measure of tail-risk we also report the expected shortfall (ES) measure (Dowd and Blake, 2006). ES is essentially the conditional expected value of the revenue distribution in tail for the worst α outcomes. It can be expressed in the simulation case as:

$$ES_{\alpha} = \frac{1}{\alpha} \sum_{i=1}^{I=N\alpha} (R_{(i)}) / N \tag{6}$$

where $R_{(i)}$ is the ith order statistic of the revenue distribution, and is reported for α = 1%, 5%, and 10%. For example, the ES 1% equals the average of all simulated observations below the 1st percentile. The ES measure is typically preferred to the Value-at-Risk (VaR) because it is subadditive and thus less likely to produce puzzling results in risk management applications (Dowd and Blake, 2006).

Results and Discussion: Multi-Crop versus Single-Crop Framework

Results are presented below for the comparisons of single- versus the multi-crop framework. A single county is employed in the presentation for tractability. McLean County, IL is selected as it is a high production, high acreage county and thus is very relevant for this analysis. Summary statistics as well as correlations are provided in Table 1. Corn and soybean farm-level yields are both highly correlated with the county yield, 0.79 and 0.63. Corn and soybean farm yields are less correlated, about 0.40. Corn and soybean prices were calibrated using mean and volatility estimates extracted from the options complex in the beginning of March 2009; corn (soybeans) was estimated to have a mean of $4.04 ($8.80) and standard deviation of $1.54 ($2.69). The corn and soybean price correlation was estimated using their historical correlation, 0.73.

Single-Crop Comparisons

First we focus attention on the single-crop cases. Figure 1 presents cumulative distribution plots for net corn revenues with and without insurance for the typical case farm in McLean County, IL. Revenues are presented net of non-land costs and crop insurance premiums, plus government payments. The x-axis measures the dollar amount of return in $/acre, and the y-axis indicates the probability that the net revenue experienced is less than or equal to $\$x$. Four series are depicted, one for each insurance choice: *No insurance*, *APH 85%*, *RA-HP 85%*, and *GRIP-HR 90%*. For example, there is approximately a 10% probability that net corn revenues are less than $70.00/acre in McLean County, IL, given 2009 premium, volatility, and rate levels.

Several observations stand out. First, *APH* insurance alone does not appear to be very effective at hedging revenue risk. Of course, this is not surprising since *APH* covers yield risk, but provides no price protection. *GRIP-HR 90%* appears to be clearly preferred relative to no insurance. *GRIP-HR* has a higher expected return at virtually every probability outcome depicted relative to *No Insurance*. *RA-HP* is effective at reducing risk at low revenue outcomes, but is less preferred at any revenue outcome greater than the minimum revenue guarantee, whereat the revenue distribution function is vertical. This vertical break is present because of the fact that at any revenue outcome greater than the revenue guarantee, the indemnity on *RA-HP* is zero; at revenues below the revenue guarantee, the indemnity payment on *RA-HP* is equal to the revenue loss below the guarantee.

Of most interest in Figure 1 is the relationship between *RA-HP* and *GRIP-HR*. Notice, for all but the lowest probability levels *GRIP-HR* has higher revenue at any give probability relative to *RA-HP*. This ordering occurs because *GRIP-HR* will indemnify in many cases in which the producer's individual revenue is greater than the guarantee under *RA-HP*. For outcomes below about the 2% worst outcomes, *RA-HP* outperforms *GRIP-HR* since the *RA-HP* series has a higher payoff. This difference represents the basis risk of area-based insurance products such as *GRIP-HR*. Figure 2 presents similar findings for Soybeans.

Panel 1 in Table 2 presents summary statistics for corn net revenues (viewed as a single-crop) depicted in Figure 1.[6] The average uninsured revenue is $190.11/acre, while the *SqrLPM* measure of downside risk is $153.06. Revenues insured with *GRIP-HR* had a higher expected return, $243.50, than *RA-HP,* $181.89. This reflects that *RA-HP* is rated, or priced, higher than *GRIP-HR* relative to its expected loss. These "wedges" in group-based products relative to individual products are not uncommon and have been observed in other crops and regions (Deng, Barnett, and Vedenov, 2007). *GRIP-HR* was also more effective at reducing downside risk than *RA-HP* as reflected in the *SqrLPM* measure. Note that a lower value of *SqrLPM* indicates lower risk, or more effective risk reduction. The interpretation on the *ES* statistics is that a higher value indicates less risk, since the ES is the expected value in the worse α% event. *GRIP-HR* outperformed *RA-HP* at the 10% level, while RA-HP performed better at the 5% and 1% levels. Panel 2, Table 2—which presents soybean single-crop results—reveals similar results for soybeans.

Single Versus Multi-Crop Results

Panel 3 in Table 2 presents summary statistics for net revenues for corn and soybeans where the rotation is 55/45. Figure 3 is a graphical representation of this case. In the multi-crop case, the performance of *GRIP-HR* is superior to *RA-HP* in terms of average revenues and *SqrLPM*; however, an interesting finding emerges with respect to the *ES* statistics. In contrast to the single crop cases, *GRIP-HR* is more effective at increasing *ES* relative to *RA-HP*. For example, Table 2 Panel 3 indicates that the *ES 5%* statistic for *GRIP-HR*, $26.76, is *greater* (with a higher *ES* indicating risk reduction) in the multi-crop case than the *ES 5%* for revenues insured with *RA-HP*, $5.01. Panels 4 and 5 also present multi-crop results for a 55/45 corn/soybean exposure, but instead only one crop (corn in Panel 4, and soybeans in Panel 5) is insured. The results are in fact even starker in these cases.

Turning attention to Table 4 (which presents changes in the revenue statistics for each crop/insurance product relative to the uninsured case) also reveals that *GRIP-HR* outperforms *RA-HP* in the multi-crop case by more than would be implied by assessing only a single-crop. For example, when viewing corn in a single-crop context the percentage reduction in *SqrLPM* from insuring with *RA-HP* is 18.97%, and 53.44% for *GRIP-HR*; in contrast, when moving to the multi-crop context *GRIP-HR* is more effective at reducing *SqrLPM* than in the single-crop context (a reduction of 56.32% versus 53.44%). The same is not true for *RA-HP,* which only reduces *SqrLPM* by 17.45% in the multi-crop case versus 18.79% in the single-crop case. Similar conclusions emerge when evaluating the cases in Panels 2 and 3 in Table 4 in which only one of the two crops is insured (as opposed to both). Furthermore, Figures 4 (corn portion insured only) and 5 (soybean portion insured only) present multi-crop results when insuring one crop only. In both cases *GRIP-HR* strongly outperforms *RA-HP* in virtually any outcome. Notice in both Figures 4 and 5 that *RA-HP* no longer has a revenue guarantee for the aggregate exposure since only one crop is insured. This is striking since the situation depicted in Figure 4—in which corn is insured but soybeans are not—is a somewhat common strategy employed by producers.

Product Performance Comparison under Actuarially Fair Farmer Premiums

Next we examine the difference in crop insurance performance for *GRIP-HR* and *RA-HP* when farmer paid premiums are adjusted to actuarially fair rates (i.e., so that the net return from insurance is zero). This treatment will have an impact on risk reduction if the "wedges" in the underlying product rating structures differ because *SqrLPM* is measured relative to a static uninsured baseline return and the *ES* measure is simply an expectation in the tail (and thus shifts up and down with the whole distribution). Thus, comparisons at the actuarially fair premium levels can provide insight into the relative sources of the risk reduction effectiveness of *GRIP-HR* versus *RA-HP.* Specifically, if *GRIP-HR* contains large positive "wedges" relative to *RA-HP*, then more of the overall reduction in risk as indicated by these measures can be attributed to return enhancement. Initially, it may seem counterintuitive to attribute risk reduction to the average return enhancement of a risk management product such as insurance. The meaning is made clear, however, if one considers the impact a shift in the insured distribution will have on the risk measures under consideration relative to those under the baseline revenue distribution.

Referring to Figure 6, the results suggest that the presence of these "wedge" differentials can have a large impact on hedging performance of *GRIP-HR* versus *RA-HP*. For example, at actuarially fair rates (Table 3), net revenues insured with *GRIP-HR* have a lower *ES* at all levels. Also, the *SqrLPM* measure indicates that net revenues insured with *GRIP-HR* have only slightly less downside risk than those for *RA-HP* ($73.07 versus $87.51), in stark contrast to the differences in *SqrLPM*s between products under actual rates ($48.37 versus $93.53). Thus, consistent with Deng, Barnett, and Vedenov (2008), the presence of large positive "wedges" in *GRIP-HR* relative to *RA-HP* rates renders *GRIP-HR* relatively much more effective than it otherwise would if both were rated actuarially fair from the producer's perspective.

Conclusions

This study develops a multi-crop insurance model to investigate the impacts of viewing insurance decisions in a single-crop framework when the true structure of the underlying exposure is multi-crop in nature. The results suggest that failure to account for the fact that most producers plant multiple crops can have significant impacts on the interpretations of the impacts of crop insurance. In the case of Illinois corn and soybeans, the impact of modeling crop insurance decisions in a single-crop versus multi-crop context can lead to dramatically different results when assessing the impact of different crop insurance choices. A key finding is that the risk reduction effectiveness of individual revenue products such as *RA-HP* decrease relative to group based products such as *GRIP-HR* when moving from single-crop to multi-crop modeling frameworks. This difference is partially due to the fact that *GRIP-HR* indemnities tend to be less correlated across crops than the indemnities of individual revenue products, but it is also due to the fact that *GRIP-HR* contains large positive "wedges" relative to individual-based products in the area under consideration. Thus, group based products appear even more attractive in this region when modeled in a multi-crop framework, a result that corroborates and expands upon the findings of Deng, Barnett, and Vedenov (2007) who find that the presence of large positive "wedges" that are typical in the group products increase the attractiveness of those products.

This study adds insight about the factors influencing producer participation in the crop insurance program and thus may be of interest to insurers, regulators, and policymakers. The modeling frameworks can also be easily employed to aid in identifying meaningful risk reduction strategies when production exposures are composed of multiple crops. Future research could focus on other crops, regions and insurance products, and on assessment of the impact of alternative dependency structures (e.g., copulas) in modeling multi-crop exposures.

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Endnotes

[1] An exception is Miller, Coble, and Barnett (2000), who present limited simulation results for comparisons between multi-crop (or whole-farm) insurance contracts and individual contracts with Mississippi producers. The focus here differs substantially from that work in that we choose to focus on the implications of considering one crop versus multiple crops when assessing popular crop insurance strategies and products. Whole-farm products essentially have no market in the areas under consideration so do not present a relevant avenue of investigation in the context of the current study.

[2] In addition to the linear OLS trend, other trend estimation procedures were investigated to evaluate robustness. While modest differences arose, the particular choice did not appear to have any substantial impact on this analysis or the nature of the results.

[3] Note, in small samples direct application of this method to *individual farms* will result in an upward biased estimate of the farm standard deviation since the county and farm are not perfectly correlated. However, the impact and relative size of the bias decreases very quickly and is virtually negligible after the sample size reaches about ten observations. For example, with ten observations, the size of the bias in this the farm standard deviation estimator is about $1/11^{th}$ of a standard error of the estimator, which is negligible. Comparisons of this method with regression estimators indicated that the size of the bias is again negligible and that little is to be gained by employing regression estimators in lieu of the farm-to-county estimators. Simulations are available from the author upon request.

[4] Explicit copula structures could also be employed in inducing correlation between yields and prices. While analysis of sensitivities to alternative copula structures is an interesting empirical question, it is beyond the scope of this study and is thus left as an interesting area of future research.

[5] Total non-land costs equal fixed and variable operating and financing costs, but exclude land costs and operator return; thus it represents the residual claimant stream to the land and operator. Government payments include Direct Payments and crop insurance subsidies only. We do not explicitly model Loan Deficiency and Counter-Cyclical Payments. Based on current price levels and option market volatilities, there is an exceedingly small probability that those programs will pay out in the target regions/crops, and thus their inclusion is not likely to impact the analysis here.

[6] As depicted in Figure 1, the *APH* insurance product did not appear to be very effective at reducing risk. Thus, we do not include *APH* in Table 1 or thereafter as it lacks relevance. Results are available for *APH* from the author upon request.

Table 1. Correlation Matrix, Corn and Soybean Yields and Prices, McLean County

	Corn County Yield	*Corn Farm Yield*	*Soy County Yield*	*Soy Farm Yield*	*Soy Price*	*Corn Price*
Average	177.57	177.57	51.97	51.97	8.80	4.04
Standard Deviation	22.57	27.55	5.18	7.00	2.69	1.54
Correlation Matrix						
Corn County Yield	1.00					
Corn Farm Yield	0.79	1.00				
Soy County Yield	0.43	0.38	1.00			
Soy Farm Yield	0.34	0.40	0.63	1.00		
Soy Price	-0.27	-0.21	-0.29	-0.28	1.00	
Corn Price	-0.44	-0.33	-0.20	-0.21	0.73	1.00

Table 2. Revenues Minus Total Non-Land Costs with and without Insurance, McLean County, Illinois

	No Insurance	*RA-HP 85%*	*GRIP-HR 90%*
Panel 1: Corn Net Revenues			
Average	$190.11	$181.89	$243.50
SqrLPM	$153.06	$124.02	$71.27
ES 10%	-$154.14	-$3.30	$18.38
ES 5%	-$192.52	-$3.30	-$9.86
ES 1%	-$259.74	-$3.30	-$70.56
Panel 2: Soybean Net Revenues			
Average	$127.88	$119.19	$148.53
SqrLPM	$83.50	$70.56	$46.11
ES 10%	-$63.40	$15.15	$15.04
ES 5%	-$85.43	$15.15	-$3.94
ES 1%	-$122.49	$15.15	-$45.02
Panel 3: Combined Corn/Soybean Net Revenues, 55/45 Rotation, Both Crops Insured			
Average	$162.11	$153.68	$200.76
SqrLPM	$113.30	$93.53	$48.37
ES 10%	-$95.02	$5.01	$45.27
ES 5%	-$126.88	$5.01	$26.76
ES 1%	-$182.58	$5.01	-$8.95
Panel 4: Combined Corn/Soybean Net Revenues, 55/45 Rotation, Corn Insured Only			
Average	$162.11	$157.59	$191.47
SqrLPM	$113.30	$96.97	$59.74
ES 10%	-$95.02	-$27.25	$25.74
ES 5%	-$126.88	-$38.69	$8.15
ES 1%	-$182.58	-$56.81	-$26.82
Panel 5: Combined Corn/Soybean Net Revenues, 55/45 Rotation, Soybeans Insured Only			
Average	$162.11	$158.19	$171.40
SqrLPM	$113.30	$108.56	$88.98
ES 10%	-$95.02	-$74.09	-$32.22
ES 5%	-$126.88	-$96.67	-$52.10
ES 1%	-$182.58	-$135.71	-$86.71

Notes: Assumes Total Non-Land Costs + Government Payments of $513/acre for Corn, and $324/acre for Soybeans at 2009 Rates, Prices, and Volatility. Insurance is for 100% of Maximum Protection. Results expressed in $/Acre.

Table 3. Revenues Minus Total Non-Land Costs with and without Insurance, McLean County, Illinois, Adjusted to Actuarially Fair Farmer Premiums

	No Insurance	*RA-HP 85%*	*GRIP-HR 90%*
Combined Corn/Soybean Net Revenues, 55/45 Rotation, Both Crops Insured			
Average	$162.11	$162.11	$162.11
SqrLPM	$113.30	$87.51	$73.07
ES 10%	-$95.02	$13.44	$6.62
ES 5%	-$126.88	$13.44	-$11.90
ES 1%	-$182.58	$13.44	-$47.60

Notes: Assumes Total Non-Land Costs + Government Payments of $513/acre for Corn, and $324/acre for Soybeans at 2009 Rates, Prices, and Volatility. Insurance is for 100% of Maximum Protection. Results expressed in $/Acre. Premiums adjusted to actuarially fair levels.

Table 4. Changes in Risk Exposure, Revenues Minus Total Non-Land Costs, McLean County, Illinois

	RA-HP 85% Versus Uninsured			*GRIP-HR 90% Versus Uninsured*		
	Corn	***Soy***	***Combined***	***Corn***	***Soy***	***Combined***
Panel 1: Combined Corn/Soybean Net Revenues, 55/45 Rotation, Both Crops Insured						
% Δ Average	-4.32%	-6.80%	-5.20%	28.08%	14.62%	23.30%
% Δ SqrLPM	-18.97%	-15.50%	-17.45%	-53.44%	-42.29%	-56.32%
Δ ES 10%	$150.84	$78.55	$100.03	$172.52	$75.86	$137.91
Δ ES 5%	$189.22	$100.58	$131.88	$182.65	$79.68	$151.24
Δ ES 1%	$256.45	$137.64	$187.59	$189.18	$78.18	$171.81
Panel 2: Combined Corn/Soybean Net Revenues, 55/45 Rotation, Corn Insured Only						
% Δ Average	-4.32%	0.00%	-2.79%	28.08%	0.00%	18.11%
% Δ SqrLPM	-18.97%	0.00%	-14.42%	-53.44%	0.00%	-47.27%
Δ ES 10%	$150.84	$0.00	$67.78	$172.52	$0.00	$120.76
Δ ES 5%	$189.22	$0.00	$88.18	$182.65	$0.00	$135.02
Δ ES 1%	$256.45	$0.00	$125.77	$189.18	$0.00	$155.76
Panel 3: Combined Corn/Soybean Net Revenues, 55/45 Rotation, Soybeans Insured Only						
% Δ Average	0.00%	-6.80%	-2.41%	0.00%	16.15%	5.73%
% Δ SqrLPM	0.00%	-15.50%	-4.19%	0.00%	-44.78%	-21.47%
Δ ES 10%	$0.00	$78.55	$20.94	$0.00	$78.44	$62.81
Δ ES 5%	$0.00	$100.58	$30.20	$0.00	$81.49	$74.78
Δ ES 1%	$0.00	$137.64	$46.88	$0.00	$77.48	$95.87

Notes: Assumes Total Non-Land Costs + Government Payments of $513/acre for Corn, and $324/acre for Soybeans at 2009 Rates, Prices, and Volatility. Insurance is for 100% of Maximum Protection. Results expressed in $/Acre.

Figure 1. Corn Net Revenues with and without Insurance, McLean County, IL, Both Crops Insured

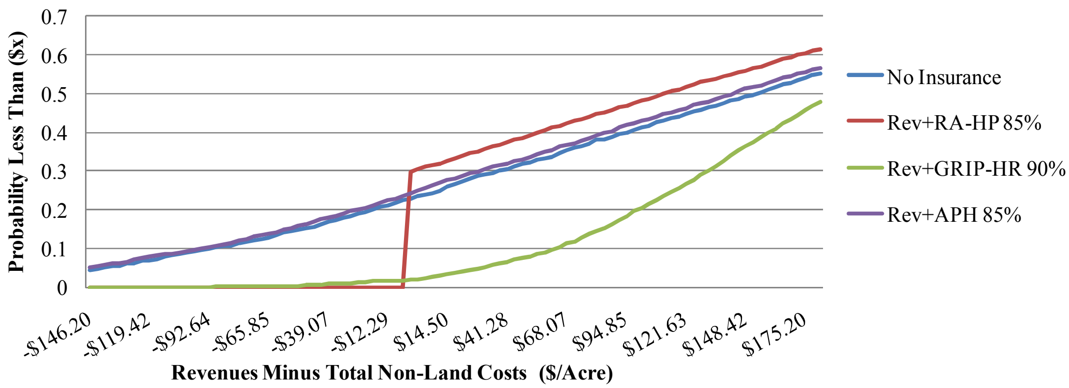

Figure 2. Soybean Net Revenues with and without Insurance, McLean County, IL, Both Crops Insured

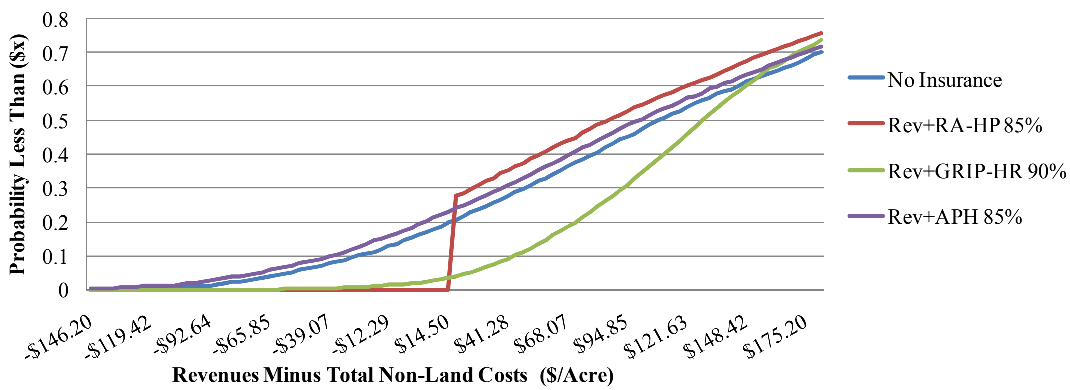

Figure 3. Combined Corn and Soybean (55/45 Rotation) Net Revenues with and without Insurance, McLean County, IL, Both Crops Insured

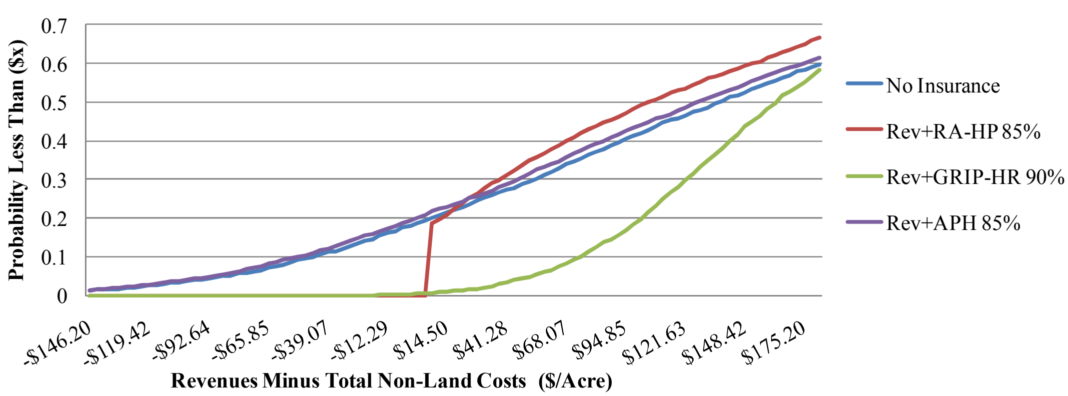

Figure 4. Combined Corn and Soybean (55/45 Rotation) Net Revenues with and without Insurance, McLean County, IL, Corn Insured Only

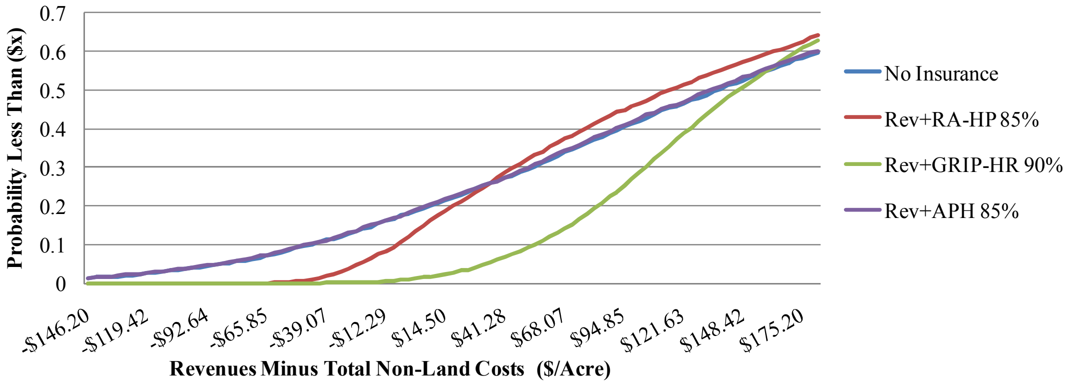

Figure 5. Combined Corn and Soybean (55/45 Rotation) Net Revenues with and without Insurance, McLean County, IL, Soybeans Insured Only

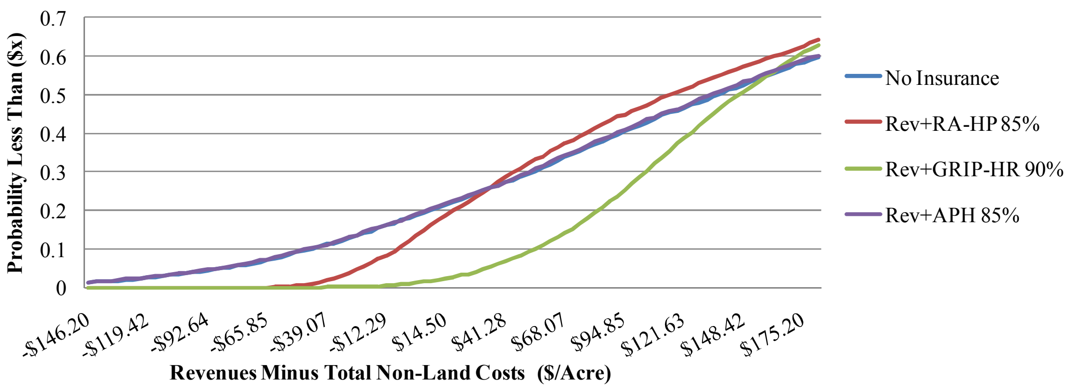

Figure 6. Combined Corn and Soybean (55/45 Rotation) Net Revenues with and without Insurance, McLean County, IL, Both Crops Insured, Adjusted to Actuarially Fair Farmer Premiums