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Revenue Risk, Crop Insurance and Forward Contracting

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Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2013 Crop Insurance and the Farm Bill Symposium, Louisville, KY, October 8-9, 2013

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Introduction

Over the past twenty years, the US government has dramatically enhanced the Federal Crop Insurance program. Subsidies and the number insurance contracts were expanded through both the 1996 Agricultural Reform Act and the 2000 Agricultural Risk Protection Act. As a result, insured acres increased from 100 million to 279 million between 1994 and 2012 ("USDA-RMA National," 2012). The Risk Management Agency (RMA), who oversees the Federal Crop Insurance program, provides enrolled producers with risk management benefits through a myriad of insurance contracts. With some insurance contracts providing more risk management benefits than others. What is unclear is how much different insurance contracts reduce risk and more importantly, risk reduction when private risk management tools, such as futures markets, are used in conjunction with crop insurance. The result could possibly be increased risk to the producer if they do not understand the impact of private hedging tools (i.e., futures markets) on revenue when a public tool (i.e., crop insurance) is present.

Of all available insurance contract choices, the introduction of revenue insurance, which adds price protection, creates a direct linkage with futures markets. This contract, called revenue protection, is the most popular representing 175 million of the 279 million insured acres in 2012 ("USDA-RMA National," 2012). Enrolled acreage evidence suggests producer prefers including futures prices into their crop insurance revenue guarantee.[1] Producers with a revenue protection may respond by reducing (or even quitting) participation in commodity futures markets-either directly or indirectly through cash forward contracts-because insurance has covered this risk source for them. This study is intended to help farmers understand how revenue insurance and futures trading complement each other to improve their risk management plan. We use a portfolio approach in making risk management decisions – distributing income sources through a variety of tools to understand the risk management linkages between these public and private tools.

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[1] Additionally, participating in futures markets via a subsidized insurance product makes price protection cost cheaper than direct futures market participation.

In this paper we examine risk from the producer's point of view. At the beginning of the year producers are faced with uncertain prices and yields. Producers have tools available to help tame this uncertainty. Different farmers have different objectives and different resources and are faced with a wide range of insurance choices and forward pricing opportunities. Consequences of different decisions are examined to help individual producers craft risk management plans that best support their individual resources, values, and objectives. We focus on the long term objective of farm survival and the short term objective of producing a positive net income each year. These are goals common to many family farmers across the US.

We investigate the risk of not meeting these objectives by modeling price expectation through the use of commodity futures prices estimated by the market's view of risk demonstrated by using prices of actual options traded viewed within the framework of the Black-Scoles-Merten model of futures market behavior and modeling yield expectation by analyzing historical farm yields aided and constrained by experience and common sense. Futures markets exist to provide the best information on what fall prices will be in the spring. Producers are attracted to futures markets because they provide a guaranteed price in the spring for fall delivery. Producers are attracted to crop insurance for risk management benefits from yield and price protection (under a revenue protection policy) and the presence of the subsidy. We use producer level historical yield risk adjusted for consensus longer term risk to capture farm specific risks, risks that could deviate substantially from aggregation to those based on county, state, or national level aggregate data (Miller and Kahl, 1987).

Futures price hedging introduces another risk. Sold crop must be produced; therefore, crop yield risk increases. Selling more crop than produced results in buying back presold futures positions.

Buying back presold positions can be financially and emotionally painful. Having the right crop insurance policy in place can reduce this pain substantially because it reduces yield risk. Consequently, forward contracting and crop insurance complement each other. But from the producer's point of view the question is how much do crop insurance and complement each other? Crop insurance with harvest price protection provides a partial hedge for short futures positions. However, the impact on the amount of available working capital when an adverse outcome arises is not fully understood. We develop a portfolio approach that can directly estimate (within the limits of the model and its data input) the level of working capital on hand for farm survival.

Investigating the relationship between crop insurance and futures markets on farm income risk provides challenges. A reasonable yield distribution, an approximate price distribution, and the dependence between yield and price must be determined. The primary issue facing the modeler is how to represent the producer's underlying joint distribution between yields and prices which comprehensively combines all this information. Often, this negative relationship between yields and prices is referred to as the 'natural hedge' and is relevant in decision making under uncertainty (Finger, 2012). Farm location influences the size of the price/yield joint distribution, making it difficult to identify the optimal crop insurance contract and hedging amount. Additionally, wide ranging statements about what producers should do becomes irrelevant if the price/yield joint distribution isn't taken into account or misunderstood. We describe the price/yield dependence structure through a copula. We then incorporate the copula into a Monte Carlo simulation model to analyze revenue risk faced by a Kentucky farm.

A number of valuable results come out of this study. All of the results help shed light on the producers' complex decision environment. First, we analyze tail risk (i.e., adverse unexpected outcomes) in probability space. Second, we incorporate a copula into the model to account for the inverse dependence between price and yields. This is an important feature because the strength of the dependence is the foundation for making risk management decisions. Third, the financial benefits of combining crop insurance and forward contracting can be easily calculated. Fourth, amount of working capital needed to ensure farm survival can be measured, in $, through different combinations of crop insurance and forward contracts. This allows us to calculate the benefits of crop insurance during adverse outcomes alone as well as when forward contracts are used.

Prior Literature

Analyzing price risk impacts producer revenue is not a new endeavor (e.g. Hanson and Ladd, 1991 and Coyle 1992). McKinnon, 1967 found that hedging depends upon the producers price/yield correlation. What is relatively new is analyzing impacts of crop insurance and hedging on farm revenue. Dhuyvetter and Kastens (1997) found that average income was similar across insurance types but revenue insurance resulted in the least income variability. Coble et. al., (2000) demonstrated that revenue insurance tends to result in slightly lower hedging demand when compared to yield insurance using the same coverage level. A follow up study by Coble et. al., (2004), that introduced Loan Deficiency Payments into the model, found that government programme levels profoundly alter producers' optional hedging strategy. Mahul (2003) found that revenue insurance tends to result in lower demand for futures contracts. Wang et. al., (2004) found that futures hedging is negatively affected by revenue protection.

The importance of accounting for yield and price dependence in measuring risk is important. For example, Tejada and Goodwin, (2008) found that for rating revenue insurance by incorporating the price/yield joint distribution (via a copula) resulted in a smaller probability of payout than present methods being used.

Our extension of previous work lies in the way we incorporate producer available information on yields and prices in the face of uncertainty. Producers use historical, trend adjusted, yields as the expectation for next year's yield. They understand yield variability exists from their on-farm yield data and from results of their neighbors' yields. Many producers also remember the widespread crop failures in the early 1980's, and their parent's recollection of the 50's. Some even remember the stories of the 30's handed down by their grandparents. This accumulated local knowledge has pushed farmers to embrace risk management tools such as crop insurance and limited forward contracting to protect revenue against adverse impacts. For prices, producers look forward in time, via futures markets, specifically new crop contracts for the most relevant price information. Consequently we incorporate historical yield realizations and forward looking new crop futures market prices in assessing revenue risk.

Modeling Producer Risk

Traditionally risk evaluation has been through the expected-utility framework where producers are presumed to be risk-averse, expected-utility maximizers (Chavas, 2004). We write the expected utility function as

$$(1) \qquad \mathrm{U} = \mathrm{E}(\pi) - \mathrm{f}[\mathrm{V}(\pi)],$$

where U is utility, $\mathrm{E}(\pi)$, and $\mathrm{V}(\pi)$ is the variance of profit. The variance term represents uncertainty stemming from unknown yields and unknown prices. Using this profit structure the insurance selection and hedging selection affect both $\mathrm{E}(\pi)$, and $\mathrm{V}(\pi)$. Futures hedging reduces price risk but increases yield risk. Yield protection, a specific crop insurance policy type, impacts only yield risk. Revenue protection, another specific crop insurance policy type, impacts both price risk and yield risk, but not in a simple linear additive fashion. Risk may be reduced when incorporating both crop insurance and hedging. The amount of risk protection depends upon the relationship between actual yield and price.

Instead of defining risk in a general framework, we rank decisions by how well and how likely they help the producer meet his/her specific objectives (Clemen, 1996). We define specific risks as the risk of not meeting specific objectives. For example, if the objective is to maximize income then decisions are measured by simply calculating the expected value of income. If the producer's objective is to maximize income while minimizing uncertainty both the mean and the variance of the distributions could be examined to find the decision that best supports that objective using the maximum expected utility approach given in equation (1). Here we concentrate on the specific risk of farm survival by examining the shape of the income probability distributions. This is similar to developing a safety first set of preferences where decision-makers try to minimize the chance of falling below a given subsistence level (Chavas, 2004). Farm survival is downside risk. Downside risk lies in the tail of the income distribution. Producer's decisions which support the objective of farm survival make decisions to minimize their exposure to downside risk while maintaining a positive expected income.

We model variance as farm survival or having a 1% chance of an income shortfall. With a 1% chance of failure, the producer then sets aside X dollars of working capital to cover the 1% income-at-risk level. By setting back the minimum to cover the 1% probability shortfall there exists a 99% chance of succeeding each year.[2] We chose 1% because it is a extremely rare (1 in 100 year) event and because working capital needed to cover a 1% chance will cover other low probability events, such as those coming from 5% and 10% income shortfalls.

Constructing Farm Income Distributions

Conceptually, we model farm income risk by looking at the farm yield and price combination in the eyes of uncertainty. We construct a Monte Carlo simulation model to analyze risks faced by a KY grain farm by calculating a distribution of income outcomes given reasonable input distributions for prices and yields combined with an estimate of the price/yield coupling. Risk can be measured by studying the shape of the resulting income distributions.

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[2] Assuming independent weather the chance of success to survive each year becomes .99^n. For n=20 years the producer who worries about protecting 1% income shortfall has an 82% chance of success.

Per acre profit, without insurance or hedging, is given by

(2) $\pi = p * y - c - z(y)$

Where p represents output price, y is actual yield, c is the fixed cost of production, and the function $z(y)$ represents the per bushel harvest cost. Purchasing insurance adds the term $I(r, r^{*}, z) - u(z)$ to equation (2), where $I(.)$ represents the insurance indemnity or payment from the insurance company to the producer, r represents actual revenue ($y * p_{harvest}$), where $p_{harvest}$ represents the insurance 'harvest price'; $r^{*}$is guaranteed revenue, calculated as ($y_{aph} * p_{base} * CL$), where y_{aph} represents the yield guarantee, p_{base} represents the insurance 'base price' and CL represents the percent insured.[3] Hedging, through the use of futures markets, adds the term $p_h * y_h$, where $p_h$represents the hedged production price and $y_h$represents the number of bushels hedged. Including hedging reduces the number of bushels to be sold at harvest, therefore, we replace yield in equation (2) with $y_r$which is the remainder of $y - y_h$. With unknown yields, it is possible for y_h to be greater than y. When given the option of purchasing insurance and hedging the producers profit per acre is

(3) $\pi = p * (y - y_h) - c - z(y) + I(r, r^{*}, z) - u(z) + p_h * y_h$

After the final yield and price are realized, it would be easy to plug the values into equation (3) and determine which decision choice maximizes income. Of course, insurance contract selection and forward contracting decisions must be made before p and y are known. In the spring, both p and y are uncertain. It is useful to think of p and y as random variables with only their joint probability, , $\mathscr{P}(p, y)$, known in March. The joint probability, $\mathscr{P}(p, y)$, measures the chance that a particular (p_i,y_i)

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[3] Under a revenue protection policy p_{base} in the revenue guarantee calculation could be replaced with $p_{harvest}$ if $p_{harvest} > p_{base}$. For a yield protection policy $p_{harvest}$is replaced with p_{base}in the actual revenue calculation.

combination will occur in December. Associated with each (p_i, y_i) pair and j^th^ decision is an $\text{income}_{i,j}$ generated by equation(2).

We can use a Monte Carlo approach to obtain an estimate of the income probability distribution. Monte Carlo methods are rooted in the similarity between probability and volume (Glasserman, 2004).[4] Once we know the joint probability we conduct a Monte Carlo simulation by randomly choosing p and y many times in a fashion that reproduces the shape of $\mathcal{P}(p, y)$ by insuring each $dpdyd\mathcal{P}$ segment has an equal chance of being visited (Vose, 2008). Equation (3) maps each pair of p, y into an income. The distribution (volume) of incomes produced reflects the probability of that income occurring. Risk to different objectives can be studied by examining the shape of the outcome volume. Each choice is going to produce a different shape for the income distribution. The income results are collected in a vector of outcomes with each decision labeling a different component.

Modeling the Distributions

The first step is to construct the joint probability distribution, $\mathcal{P}(p, y)$. We divide the problem into building a marginal distribution for yield, y, constructing an estimate for the marginal distribution for price, p, and developing an algorithm to model the dependence between y and p.

Yield Distributions

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[4] Think of a simple one variable histogram. The probability of a particular event occurring is related to the area, which represents volume in 2-D, occupied by the corresponding histogram divided by the total area of all possible events. This can be extended to higher dimensions. A three dimensional histogram representation of $\mathcal{P}(p, y)$ could be constructed by tossing all events that fall between p_i and p_{i+1} and y_i and y_{i+1} into a bin labeled $P(p, y)_l$ with the height of $P(p, y)_l$ given by the number of events which are collected in $P(p, y)_l$. Normalizing the volume of $P(p, y)_l$ by dividing the number of events landing in each bin by the total number of events turns the volume into a joint probability, $\mathcal{P}(p, y)$.

It is difficult to get a long enough time series of farm level yield data that adequately describes farm yield risk. As a result researchers often use county level data to describe farm yield variation. Aggregation to the county level could average out poor or excellent outcomes. In this study, to describe farm level yield variability we use yearly farm average yield for a single producer. This producer has been in business since 1979.

Since the farm started producing in 1979 through 2011 yields increased steadily. To determine the amount of yield risk we first remove the yield trend. Failure to remove the trend will result in an over estimate of farm yield risk. To calculate the trend, we regress current yield on the previous yield using Linear Least Squares using historical farm data from 1979 to 2011. The residual ratio distribution, $\mathcal{R}_f$, which we use as the sampling distribution, is calculated as

(4) $$\mathcal{R}_f = \frac{Y_t - YT_t}{YT_t}$$

where Y_t represents yield at time t, YT_t represents the estimated yield trend at time t , and $\mathcal{R}_f$ represents the residual ratio. We can express the unknown, next year's yield as

(5) $$Y_{t+1} = YT_t + YT_t * \mathcal{R}_f$$

We assume $\mathcal{R}_f$ can be used as a stationary sampling distribution ,i.e., that the distribution of ratios of difference from the trend divided by the trend do not change over time.

The 33 years of yield data are a sample drawn from a population distribution which is assumed to exist. Figure (1) shows the $\mathcal{R}_c$ distributions, for Hardin county KY, $\mathcal{R}_f$ shows the histograms for the farm under study, $\mathcal{R}_s$ and $\mathcal{R}_n$ show the histograms for the state and national levels, respectively. The normal distribution has shown does a poor job of representing yield data as has been reported by several authors (Hennessy, 2009; Sherrick et al., 2004; Atwood, Shaik, and Watts, 2002). Both the farm and county distributions are skewed to the left suggesting that a normal distribution would under estimate the probability of low yield events. Efforts to fit the farm data to several common functional forms proposed in the literature including the Beta function and Weibull function failed to adequately represent the low yield tail (Sherrick et al., 2004). We want our $\mathcal{R}_f$ distribution to adequately describe the chance of any major yield impacting event; therefore, we develop an empirical distribution by plotting the cumulative distribution and drawing a smooth line through the points with the additional constraint that the line must pass through a point with 1/30 probability that the yield will be at least as bad as it was in 1983. This constraint was added to model the extreme low yield events which have occurred in the 30's, 50's, and 80's which is about once every 30 years. This constraint leads to a fat low yield tail. This fat tail behavior was predicted before the major Kentucky drought event of 2012. The major yield shortfall which occurred in 2012 is easily explained within the model for $\mathcal{R}_f$ proposed for this farm.

Price Distributions

We are interested in the change in December futures price from March 1 to December 1. We build an approximately stationary sampling distribution by taking the Ln of the December futures price on 1 divided by the December futures price on March 1 and we designate this distribution as $\mathcal{L}n\mathcal{P}_h$. Assuming the data resulted from sampling of a LogNormal price distribution, we can use this data set to estimate the parameters of $\mathcal{L}n\mathcal{P}_h$ which leads to an estimate of a LogNormal historical distribution of prices. In the next section we investigate the coupling between our price sampling distribution, $\mathcal{L}n\mathcal{P}_h$, and our yield sampling distribution, $\mathcal{R}_f$.

Instead of using $\mathcal{L}n\mathcal{P}_h$ directly as a sampling distribution, we chose to use the new crop futures contract market information on March 1 to produce a forward looking distribution to account for the possible increase or decrease in price volatility. Option market prices were used to estimate the price probability distribution.[5] Our goal is to focus on price change, but we construct $\mathcal{L}n\mathcal{P}_b$ by using a Black-Scholes-Merton stochastic model to relate a starting point on March 1 to a distribution on December 1.

In order to determine the price probability distribution we first calculate the implied volatility. We used the average of premiums paid for the at-the-money call and the at-the-money put for new crop futures contract option prices and the one year LIBOR rate to estimate implied volatility using DerivaGem software (Hull, 2012). This implied volatility was used in Black's model for valuing option contracts at expiration (Hull, 2012). Blacks' model assumes that European options can be used to model American style options.[6] Black's model provides a lognormal price probability distribution. We estimate the price probability distribution in the spring on March 1st, just after the crop insurance base was set.[7] December corn option prices expire approximately one week before futures contracts enter the delivery period.

Joint dependence and Copulas

We base our analysis of farm income risk on the joint distribution between yields and prices. Yields and prices are related through supply, lower yields reduce supply which holding everything else constant would result in higher prices. The strength of the inverse price-yield relationship depends upon producer location relative to the primary crop growing area.[8] For example, because Iowa is the primary corn growing state, a very large decline for an Iowa producers farm yield would likely be associated with less corn market supply, which, holding everything else constant, would push corn prices higher. As producer location increases away from the primary corn growing area the inverse price-yield relationship would weaken or possibly disappear. Corn yields in Washington State would have little to no impact on corn futures prices since Washington State is so far removed from the primary corn growing region.[9] Due to the presence of an inverse price yield relationship it is important to model this as a joint distribution through the use of copulas. Copulas allows two functions, who we think are related, to be tied together. Copulas are a relatively new method in answering risk management questions (Embrechs (2002), Embrechs (2003), Kole (2007), Goodwin (2012)). An important factor when using copulas is the copula selection. Kole et al. (2007) found that risks were over or under stated depending upon the type of copula used.

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[5] For a discussion of probability price distributions using this approach see https://www.msu.edu/~hilker/crnfut.htm

[6] European style options, once purchased, must be held until expiration vs. American style options that can be continuously traded any time before expiration.

[7] For corn in Kentucky the spring base price is the average of December corn futures market during the month of February.

[8] Irrigation would also play a role but is not included in this analysis.

Copulas are the combination of multiple joint densities into one joint distribution through Sklar's theorem (Sklar, 1973). The copula describes the dependence between the random variables through mapping from the individual distribution functions to the joint distribution function

$$(6) \qquad F(x_1, \dots, x_h) = C(F_1(x_1), \dots., F_h(x_h))$$

where $x_1, \dots, x_h$ represents an h continuous random variables with a cumulative distribution function $F(x_1, \dots, x_h)$, marginal distribution functions of $F_1(x_1), \dots., F_h(x_h)$ and copula function C.[10]

For our model we are concerned identifying a copula displaying tail dependence. The Clayton copula, from the Archimedean copula family, displays tail dependence. The Clayton copula takes the form

$$(7) \qquad C(x_1, x_2, \theta) = (x_1^{-\theta} + x_2^{-\theta} - 1)^{-1/\theta}$$

where θ, the dependence parameter, is restricted to be greater than zero. Archimedean copula's have the special property that allows them to be constructed from a generator, ⍰,(Nelson)

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[9] It would likely impact regional corn basis.

[10] For a thorough background on copula modeling see Trivedi and Zimmer (2005).

(8) $C(x_1, x_2) = \phi^{[-1]}(\phi(x_1) + \phi(x_2))$

with the Clayton generator(Nelson, 2006) given by

(9) $\phi_{\upsilon}(t) = (1/\upsilon)(t^{-\upsilon} - 1)$

As θ approaches zero the marginal distributions become independent. As θ increases in size the marginal distributions become more dependent. The Clayton copula with $\theta > 0$ accounts for positive dependence, not negative dependence and our historical data suggests very strong negative dependence; low yields imply a much strong chance for higher prices. For the Clayton copula to work with negative dependence we transform the data into positive dependence by changing the sampling distribution for prices from $\mathcal{LnP}_{b}$ price ratio to 1- $\mathcal{LnP}_{b}$ price ratio. The historical data for this farm does not suggest that high yields imply a strong chance of lower prices. We found that the Clayton copula exhibits this type of relationship; strong tail dependence on one side of the distribution and weak dependence on the other side.

An Archimedean copula can be related to Kendall tau ,τ, which is a global measure of dependence between two random variables (Mari and Kotz, 2001) by

(10) $\tau = 1 - 4\int_{0}^{1} (\phi_{\upsilon}/\phi'_{\upsilon})$

Using the generator for the Clayton copula (Nelson, 2006 and Vose,2008) relates the parameter ,υ, to τ as shown in equation (11)

(11) $\upsilon = 2\tau/(1 - \tau)$

We estimate θ using equation (11) and historical farm yields and prices to calculate Kendal tau between $\mathcal{R}_{f}$ and 1- $\mathcal{LnP}_{b}$.

To run the final Monte Carlo model several steps were taken to incorporate the Copula. The first issue is given any x_1 how to get the corresponding x_2. We use the Laplace transform method because it is straightforward with the Clayton copula since its generator is the inverse Laplace transform of the Gamma function with arguments $1/\upsilon$ and 1 (Nelson, 2006) and computationally efficient (Chrisman, 2013). With (x_1, x_2) pairs we then find yields and prices by taking the inverse of their respective CDF. Because 1- $\mathcal{L}n\mathcal{P}_{b}$ was assumed to have a normal distribution we take the inverse of the normal distribution using the library routine provided by ANALYTICA decision software (Lumina Decision Software, 2013). The sampling distribution, $\mathcal{R}_f$, connected to yield is empirical. A two dimensional array with dimensions (30000,2) is built containing x_1 in one column and CDF array for $\mathcal{R}_f$ in the other. Because x_1 and the CDF's domains are [0,1] and the CDF is a increasing function on [0,1] the inverse can be numerically estimated by using a table lookup method. We use a library routine in Analytica which uses cubic spines to interpolate between the elements of the array.

Model

To analyze revenue risk model we run a Monte Carlo probability simulation with 30,000 iterations. Monte Carlo probability simulation allows the probability calculation of, farm revenue. From this we can assess the level of income risk and impact from risk management tools (crop insurance and futures hedging). Risk management variables included were Crop insurance (no insurance and revenue protection ,RP, and revenue protection with harvest price exclusion, RP-HPE, at different coverage levels), hedging (futures market, no hedging to 110% of expected production hedged in 10% increments). For crop insurance unit choice we limit our analysis to only enterprise units because the producer is trying to manage farm income and fields entering and exiting production over time makes it difficult to obtain field level yield probability distributions. We limit hedging to the futures market via a hedging account at a brokerage firm. The producer is completely responsible for margin payments.[11] Grain is to be valued on December 1 at harvest using the historical basis on December 1. Historical basis is estimated as the average over the 20 years at the elevator the producer traditionally delivers to. We use ANALYTICA, decision support software specializing in risk analysis using Monte Carlo methods, to analyze our income risk model.

Farm production costs are calculated in two components, costs that are independent of yield and costs dependent upon yield. This calculation method accurately reflects farmer costs. Given the same crop insurance yield guarantee on two fields the producer would be financially better off with a zero yield vs. a yield one bushel below the guarantee.[12] Items used to calculate costs are the same as those found in a Land Grant University extension budget. For costs dependent upon yield, those were estimated using historical per acre harvest costs. Costs included would be: combine costs, trucking costs (both from the field to bin and bin to elevator), and drying costs. The cost per acre including land costs was assigned $606 for this farm while the estimated per bushel yield is %0.58. The average yield is 143 bu/acre leading to a total cost of $689 per acre. This average total cost per acre is similar to the average costs found in the University of Kentucky no-till corn budgets (Halich, 2012).

We analyze farm revenue portfolio at two distinct points in time. The first point is in the spring, right after the crop insurance base price is determined. This also corresponds to the time when the producer is making investment decisions on which crop or how much crop to plant. The second point is in the fall, just before December futures go into delivery. Harvest is completed so crop size has been determined as well as crop insurance harvest price. For simplicity the crop insurance harvest price is set equal to futures price on December 1.[13] These points in time are important because of the relationship to spring planting investments and how crop insurance functions to protect prices. For hedging in this first order model, crop can only be pre sold at the first point (March 1) in the spring. Any remaining unsold bushels must be sold at the second point (December 1) and oversold bushels are bought back at the second point. We do not consider storage past December 1 because it is outside the crop insurance price protection window. Any income or loss incurred by storing un-priced crop past December 1 can be credited to a separate storage enterprise and estimated using a different model; therefore, post-harvest price decision are separated from pre-harvest decisions.

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[11] Here we do not include the risk produced by day to day margin fluctuations. Instead in the spirit of zero drift (the perfect market assumption) we charge the commission plus the interest on the initial margin requirement incurred from March 1 to December 1. Margin risk is very real. The model has been expanded to include the option of using over-the-counter derivatives such as hedge-to-arrive or cash contracts. We usually present results to farmers using these more specific derivatives in order not to be seen as encouraging risky behavior.

[12] This only applies to the current year. The following year's yield guarantee would be lower for the zero yield producer than the one bushel below yield guarantee producer.

Our data is limited to one producer with 33 years of experience. With only one producer over a relatively short time frame our results could lead to an inaccurate assessment of linkages between crop insurance and hedging. Specifically, our producer could have yield risk that is not representative of either the county or state yield risk. As a result we calculate yield risk at the farm (our producer), county, state and national level over the same data period as our producer. Figure 1 presents these histograms.[14] It is the distance below zero on the x-axis that is important. Aggregation from the farm to the county does not change the level of yield risk. However, aggregation from the farm to the state or even national level reduces the amount of yield risk. Consequently, one would expect similar results from farm or county analysis but not from the state or national level.

Results

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[13] The fall price guarantee for KY is the December futures averaged over the month of Oct. Under the Black-Scholes-Merton assumptions of a stochastic process following geometric Brownian motion this is a path dependent quantity (Glassman, 2004). We have modeled this quantity and its distribution has a slightly smaller spread and the same average(zero drift) as the December 1 futures price distribution. Harvest price protection is not a perfect hedge for a futures position lifted on December 1; however, we feel this approximation will not significantly alter our results.

[14] FfCn represents the farm yield histogram, CtCn represents the county yield histogram, StCn represents the state yield histogram, and NtCn represents the national yield histogram.

December 2013 corn futures prices Cumulative Distribution Function (CDF), which was analyzed on March 1, 2012 because that is the first day after the crop insurance base price was set, is presented in figure 2. According to option prices and Black's options pricing model there exists a ten percent chance of futures prices of less than $4.00 per bushel at expiration. There also exists a ten percent chance of futures price being greater than $7.55 per bushel at expiration. The median price is $5.60 per bushel.

The historical, de-trended corn farm yield CDF is presented in figure 3. According to historical yields, there exists a ten percent chance that yields could be below 100 bushels per acre and a ten percent chance of yields being above 170 bushels per acre. The median yield is 155 bushels per acre. Farm corn yield risk displays strong 'tail risk' in that there exists a much better chance of low yields than high yields.

Income risk, in probability space, faced by the producer with and without crop insurance policy (Revenue protection, enterprise units, 80% coverage level policy) are presented in figure 4. Large differences in income risk exist when crop insurance is present. For example, at the ten percent cumulative probability level (or a 1 in 10 event) there exists a approximately a $100 per acre revenue increase when crop insurance contract is purchased. The difference in revenue between no crop insurance and crop insurance increases (decreases) as the cumulative probability level decreaes (increaes). Both paths cross zero income at approximately the same point. A result indicating, for this producer, crop insurance does not enhance income it makes losses smaller. The chance of losing money is approximately 25%. As income becomes more positive the no insurance path results in more income, with the difference being the premium.

Including hedging (50% expected production hedged) into the income risk model indicates a further reduction in tail risk (see Figure 5). At the 10 percent risk cumulative probability level there exists approximately a $130 per acre revenue increase when crop insurance is purchased with hedging vs. hedging alone. More importantly, at the 10 percent cumulative probability area, including hedging with crop insurance provides positive income of about $30 per acre. Hedging lowers risk of losing money. Without hedging there was about a 25% of losing money (see figure 3). With hedging the chance of losing money drops to 17 percent for the no insurance path and drops an astonishing amount to 4% when crop insurance is used. No insurance path crosses the insurance path at approximately 31% cumulative probability level; above this there exists small differences in both paths.

Figure 6 presents reductions in income risk from different coverage levels with 50% hedging. 60% coverage level provides the most income risk while 85% coverage level provides the least. At 70% cumulative probability level results are opposite; 60% coverage level provides the most revenue and 85% provides the least. Differences are equal to premium amounts.

Figure 7 provides the efficient frontier of different portfolios. From table 7 we can identify the set of optimal portfolios or portfolios that maximize return relative to an acceptable risk level. Portfolios with the highest expected return and lowest tail risk represent the efficient frontier. What stands out in table 7 is that no points from the ‘no insurance’ path exist on the efficient frontier and at all hedging levels risk increases over no hedging. Hedging, when no insurance is present, increases the risk of not meeting the farm survival objective (1% tail risk). Hedging reduces variability, but it increases tail risk because each contracted bushel not raised must be bought back if the fall price is higher than the contract price (Hedging starches the tails even as it reduces the variance). Negative correlation between farm yield and fall price makes this worse. Shapes of yield and price distributions determine this outcome.

Both RP and RP-HPE insurance policy types exist on the efficient frontier. However, only one RP-HPE point exists and that is with no hedging. RP and RP-HPE with no hedging provide the highest expected return with an improvement in risk at the 1% level of just over $292 per acre over no insurance. As hedging increases past zero percent the efficient frontier exits only on the RP path.[15] At the 1% probability level revenue risk is minimized with RP between 30-40% of expected yield hedged. Hedging at 30 to 40% of expected yield, under a RP insurance policy (other contract elements are 80% coverage level and enterprise units), reduced 1% revenue risk by an additional $39 per acre. After 55% hedged revenue risk increased steadily. The highest revenue risk with insurance and hedging, at 120%, was considerably lower than no insurance and no hedging.

For RP only there is evidence of nearly identical risk levels using different hedging levels, Figure 7. For example, 10 and 70 percent hedging provides -41 to -44 dollars per acre of revenue risk, respectively. While both hedging levels provide the same risk, expected income at the 70 percent hedging level is nearly $14.00 per acre less than that found at the 10 percent hedging level. Recall that the producer selected 80% coverage level. Evidence suggests that having a high coverage level does not imply hedging to that coverage level for optimal risk/reward. In our case, hedging to levels similar to the selected coverage is not on the efficient frontier, expected income can be improved while holding risk constant.

Reported in figure 8, the average income from crop insurance was higher than without insurance across all hedging levels. A result indicating that over time, 30,000 years in our case, crop insurance indemnities will be larger than producer paid premiums. The difference is the amount of the subsidy. Crop insurance is set up to be actuarially fair, meaning that over time indemnities equal premiums. However, producers do not pay the entire premium, just a portion of it. As a result, over time, producers will get more money in indemnities than paid in premiums.

Our findings suggest that a revenue protection crop insurance plan in combination with forward contracting minimizes revenue risk. They are counter to findings previously noted by Coble (2000) and

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[15] RP-HPE increases in revenue risk past the 10 percent hedging level because yield risk is greater than the reduction in price risk.

Wang (2004) that crop insurance negatively impacts the need for forward contracting. However, our results are sensitive to both futures price risk and also producer yield risk. Two variables that when changed could lead to different conclusions.

Conclusions

In this paper, we investigated revenue risk impacts from crop insurance and forward contracting for a producer growing corn. Our findings contribute to the value of insurance to the producer and demonstrate the importance of crop insurance when hedging is present. This article can aid in the debate of the importance of crop insurance.

Revenue risk impacts from crop insurance and forward contracting were analyzed using a portfolio approach on two days, one in the spring just after the crop insurance base price was set and the other in the fall right before December futures go into the delivery period. We analyze how different crop insurance coverage levels and hedging levels impact revenue risk. Understanding the revenue risk linkages between crop insurance and hedging would result in producers making better informed decisions and policy makers' better understanding of the value of crop insurance. While crop insurance improves risk management over doing nothing the combination of crop insurance and hedging provides further risk reduction. The magnitude of risk protection benefits was quite large. The costs of risk management for financially beneficial outcomes are quite small.

Just purchasing crop insurance, without hedging, provides a exceptionally large decrease in 1% tail risk. For our producer, there is a $292.2 per acre reduction in tail risk. As a result, the producer can release these dollars from working capital and apply them to other investments, making the farm more efficient. This change in working capital on hand for adverse events has a positive impact on the farm economy because these dollars would be invested. While 1% risk was reduced from just purchasing insurance without hedging expected income rose. For our producer, purchasing insurance increased expected income by $23.7 per acre. With purchasing an insurance product one would expect a reduction in expected income; however, we find an increase in expected income. The answer to why is clear – the presence of the premium subsidy. Producers pay a portion of the actuarially fair insurance, thereby over time, allowing them to gain back more in indemnity than their out-of-pocket costs.

Results indicate exceptionally large revenue risk reduction at the 1% risk level when crop insurance is present and futures hedging with a revenue protection policy. Our results are specific and require caution when interpreting results. First, results are specific to 2013 crop insurance base price or spring futures prices. Changes in these prices would directly impact level of revenue risk protection so it is impossible to infer long term results. Second, results are specific to futures price volatility. Changes in volatility would directly impact the level of hedging. Third, we analyze only one crop, corn, different crops would undoubtedly lead to different revenue risk impacts. Fourth, we do not identify statistically significant differences in different portfolios. Especially crucial when there are small changes in risk at different hedging levels. Fifth, our model does not allow grain storage or any other type of hedging tools (i.e., hedge-to-arrive contracts or options). Slight improvement in the results is expected using these tools. Likely the largest gain would be in saving interest expense on margin payments by using hedge-to-arrive contracts vs. futures contracts directly.

One particularly interesting result is that of hedging without insurance. Results indicate that risk increases at all levels of hedging. Hedging under our objective of farm survival, the 1% revenue risk level in our case, increases tail risk because each contracted bushel must be bought back if the fall price is higher than the contract price. Negative correlation between farm yield and fall price makes this worse. The combination of experiencing low yields, higher prices and hedging commitments is the worst scenario for the un-insured producer. Because our model analyzes two points in time, once in the spring and the other in the fall, it cannot allow for buying back hedged bushels, at the lowest possible price, once there is a strong chance that contracted bushels will not be met. Additionally, the producer could ‘roll’ un-deliverable contracted bushels into the next crop year, a feature our model does not allow for. It is possible that our model contains the worst case financial scenario of not meeting hedged bushels. Less financial outcomes exist and would likely be exercised.

Results lead to additional research questions. For instance, revenue risk impacts from different crops and regions. Further investigation into the impact of the natural hedge on revenue risk reduction and optimal levels of hedging would be useful for both producers and policy makers.

Acknowledgments

The authors are grateful to Jerry Skees for helpful modeling suggestions.

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Figure 1 Farm, County (Hardin County), State (Kentucky), and National yield distributions

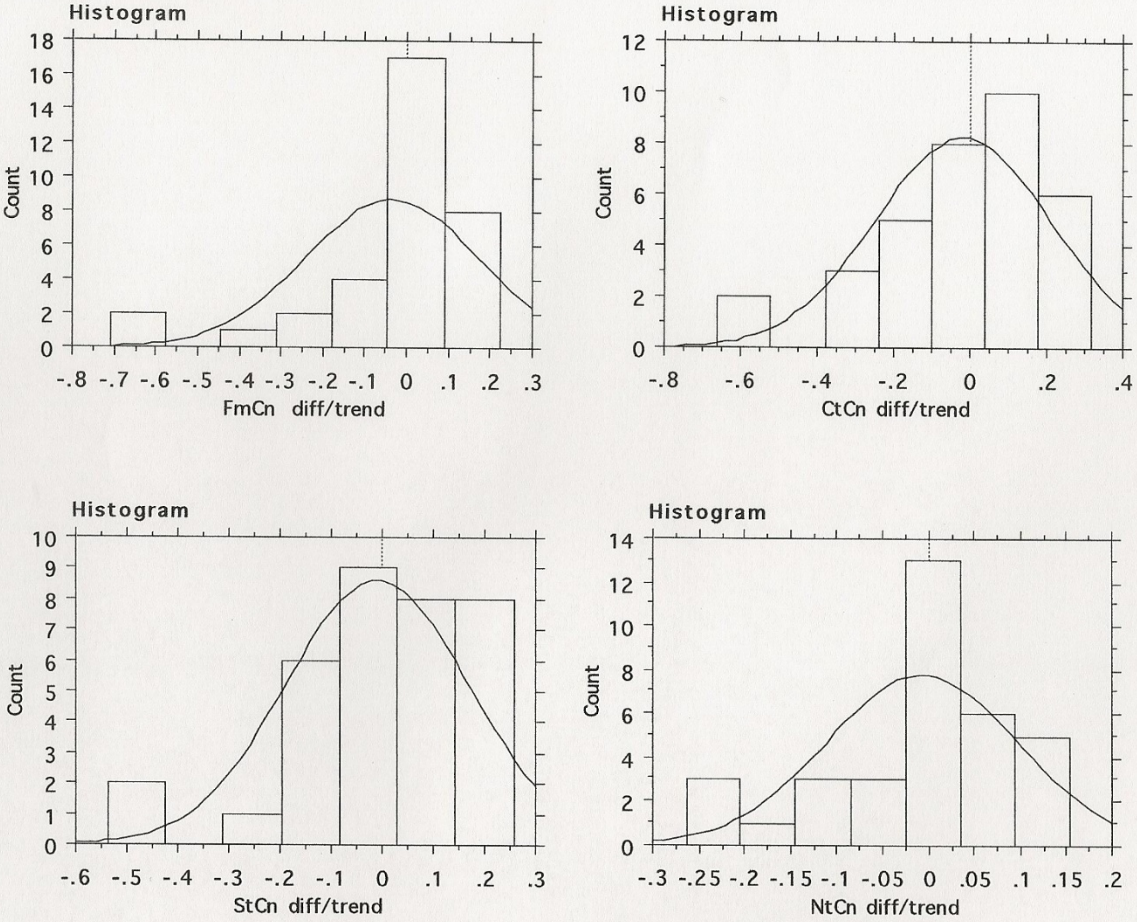


Figure 2. December Futures Price Cumulative Distribution Function

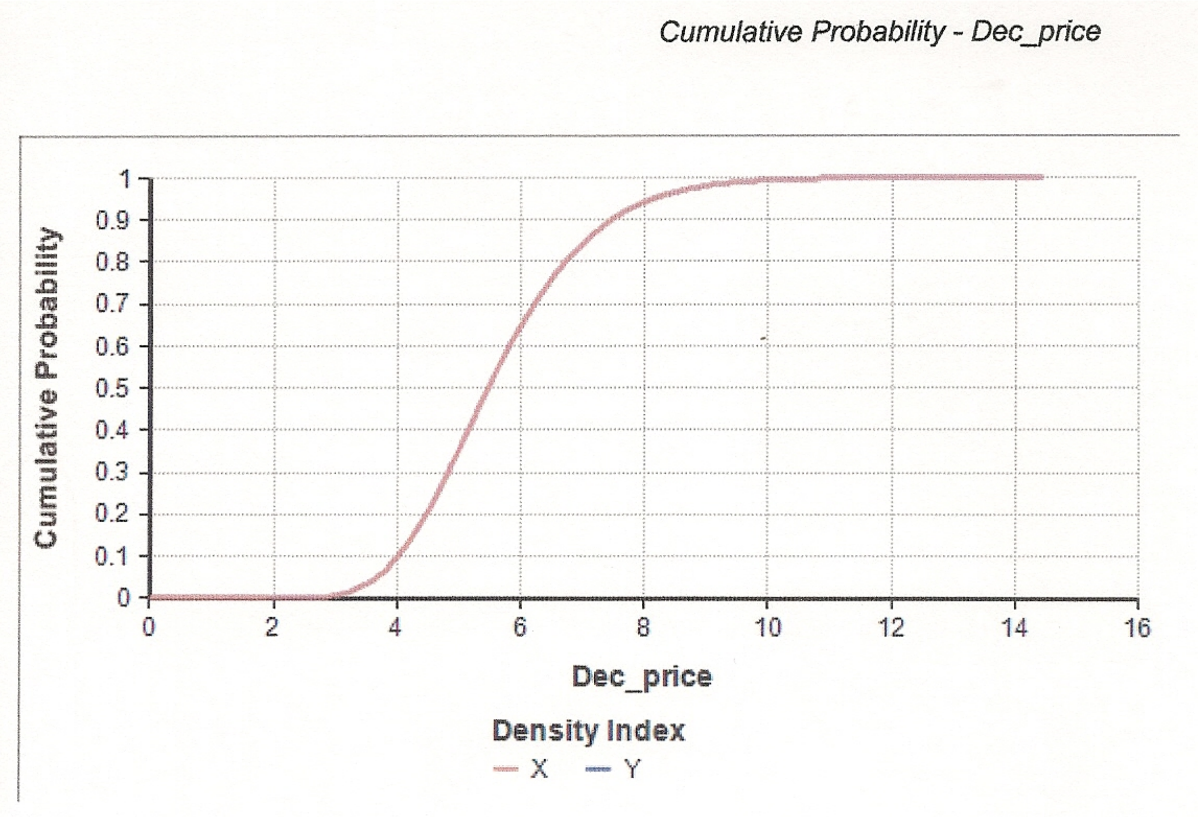


Figure 3. Farm Yield Cumulative Distribution Function

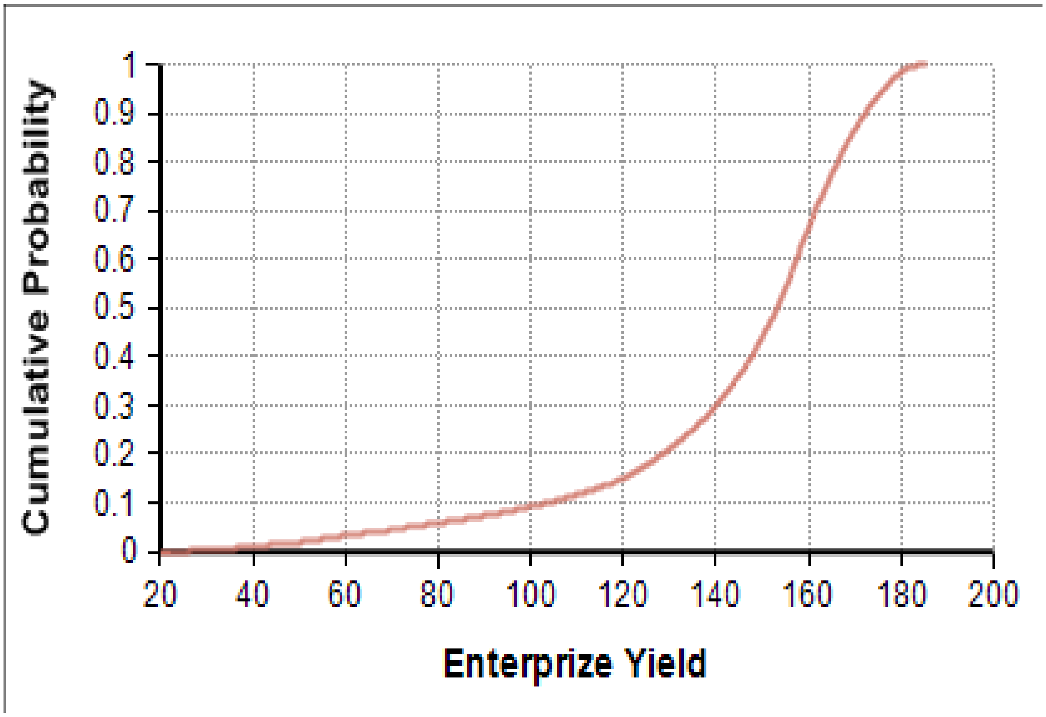


Figure 4. Farm Revenue Risk CDF with and without Insurance.

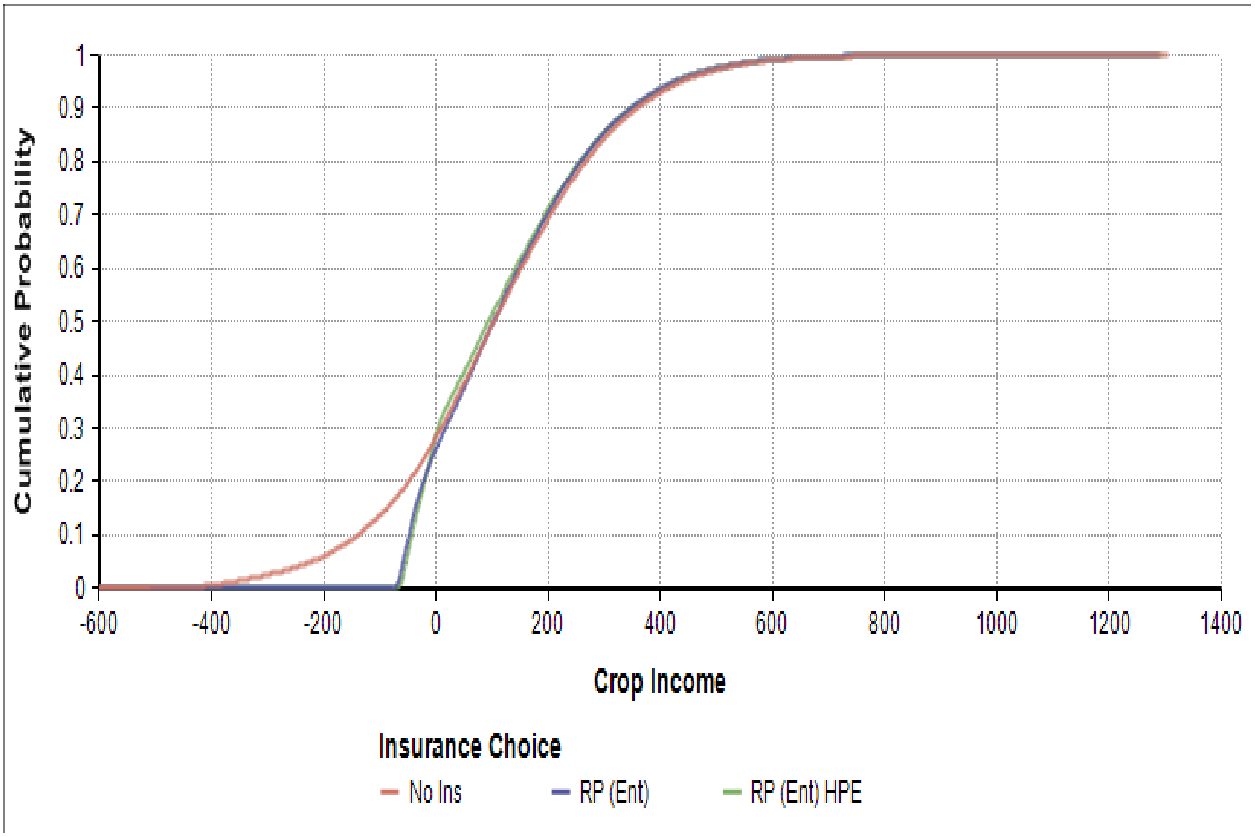


Figure 5. Farm Revenue Risk CDF Hedging with and without Crop Insurance.

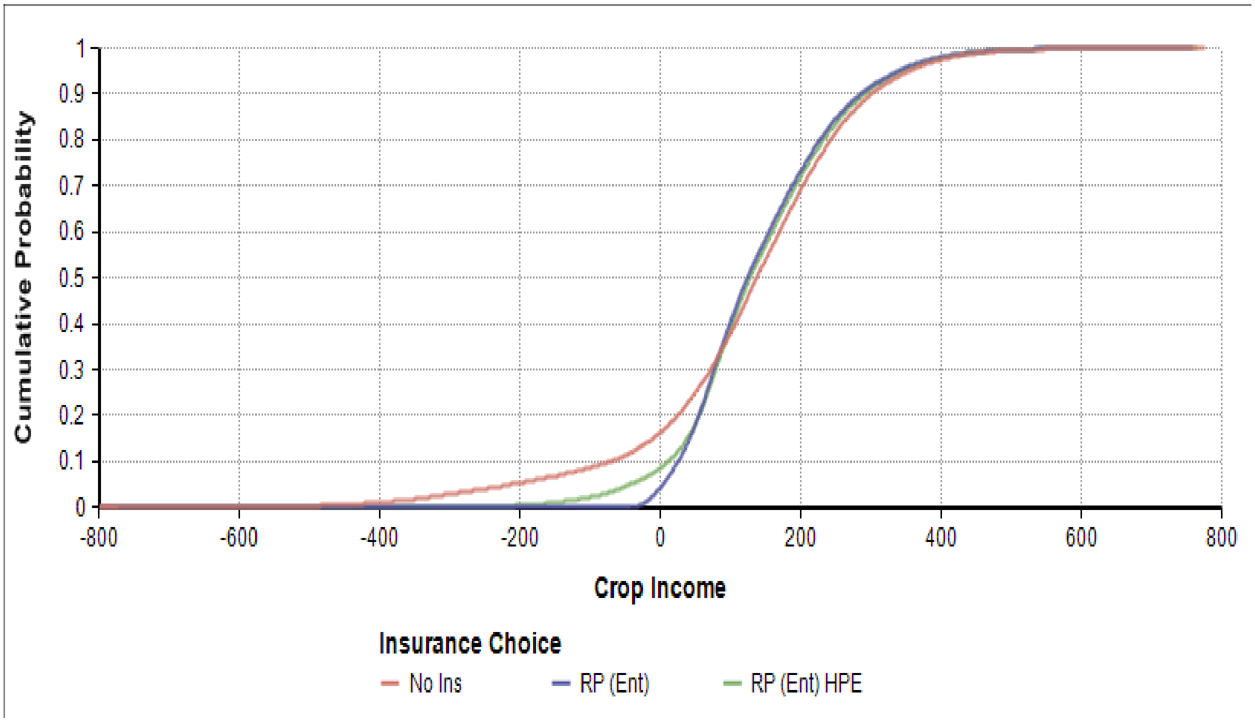


Figure 6. Revenue Risk CDF, Hedging (50%) and Insurance across Different Coverage Levels

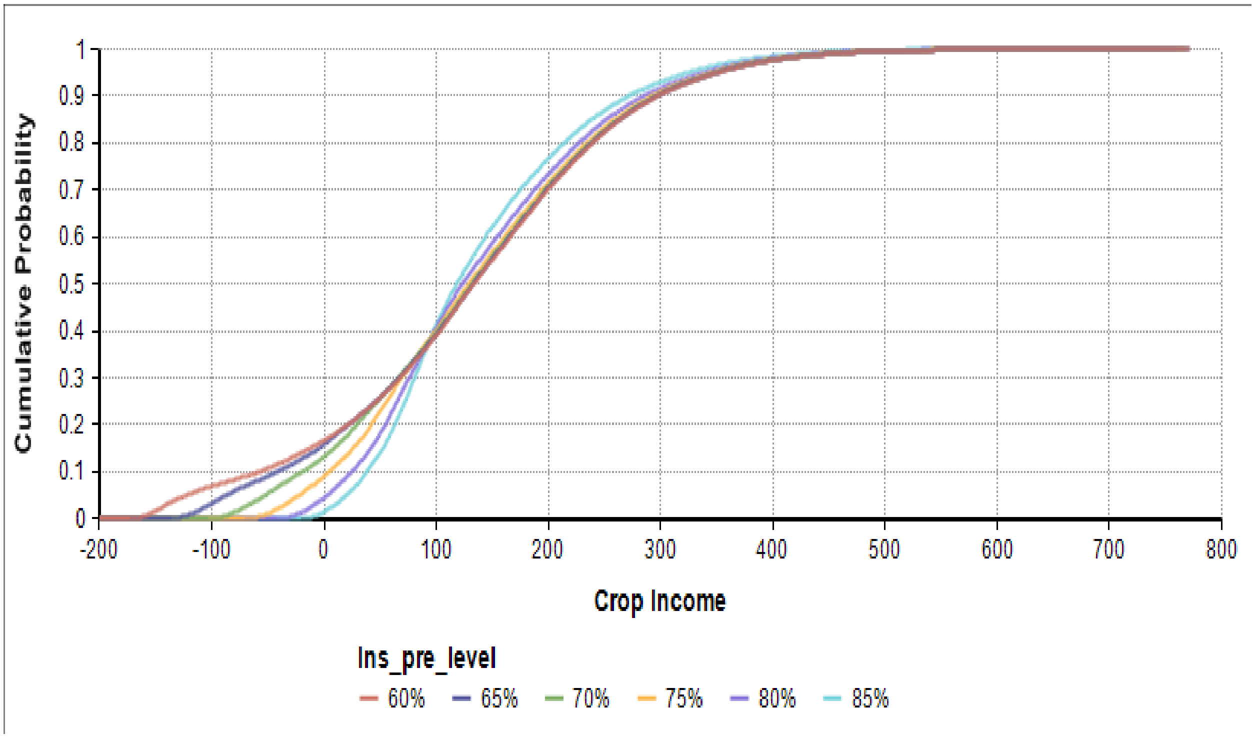
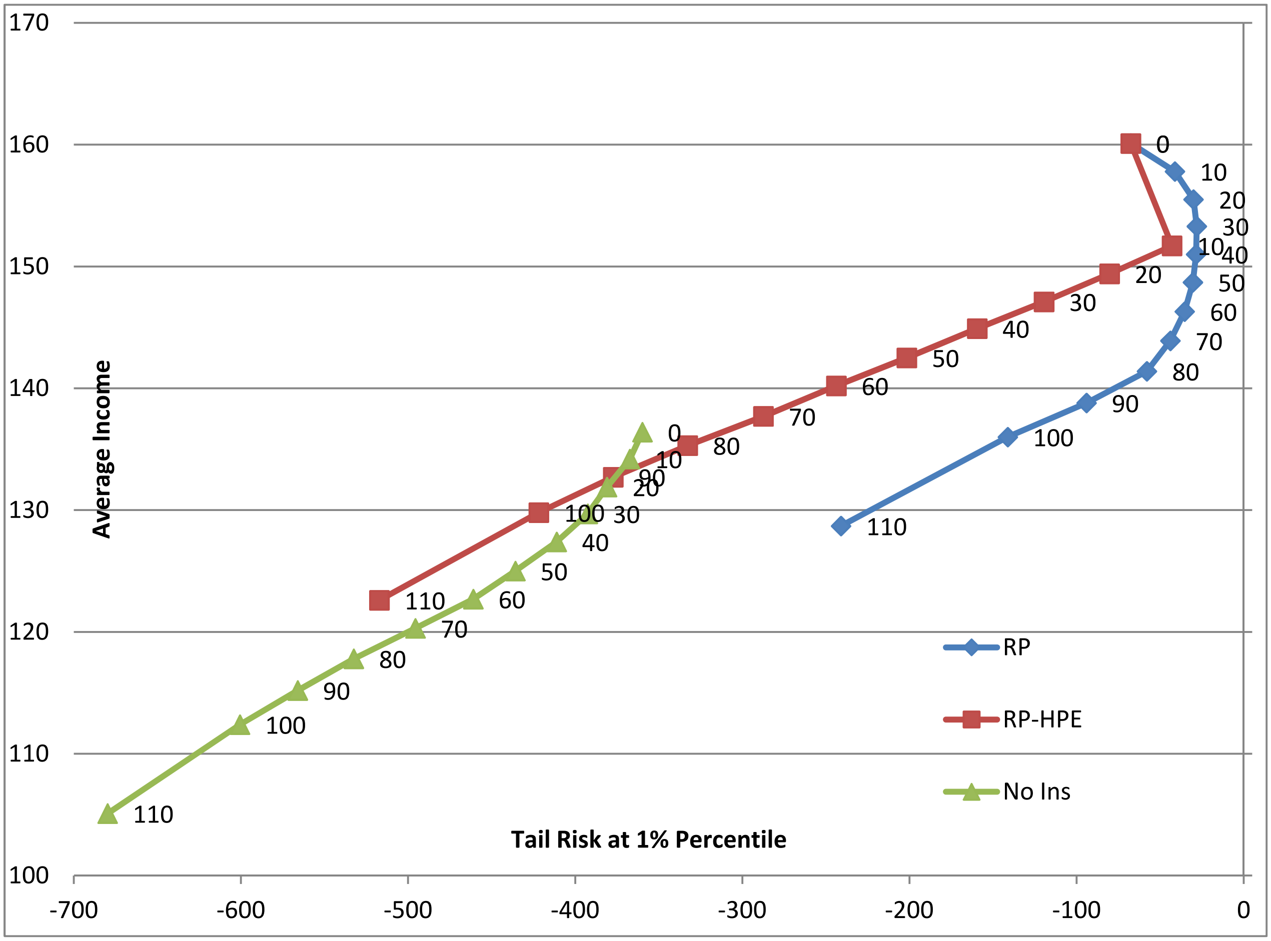
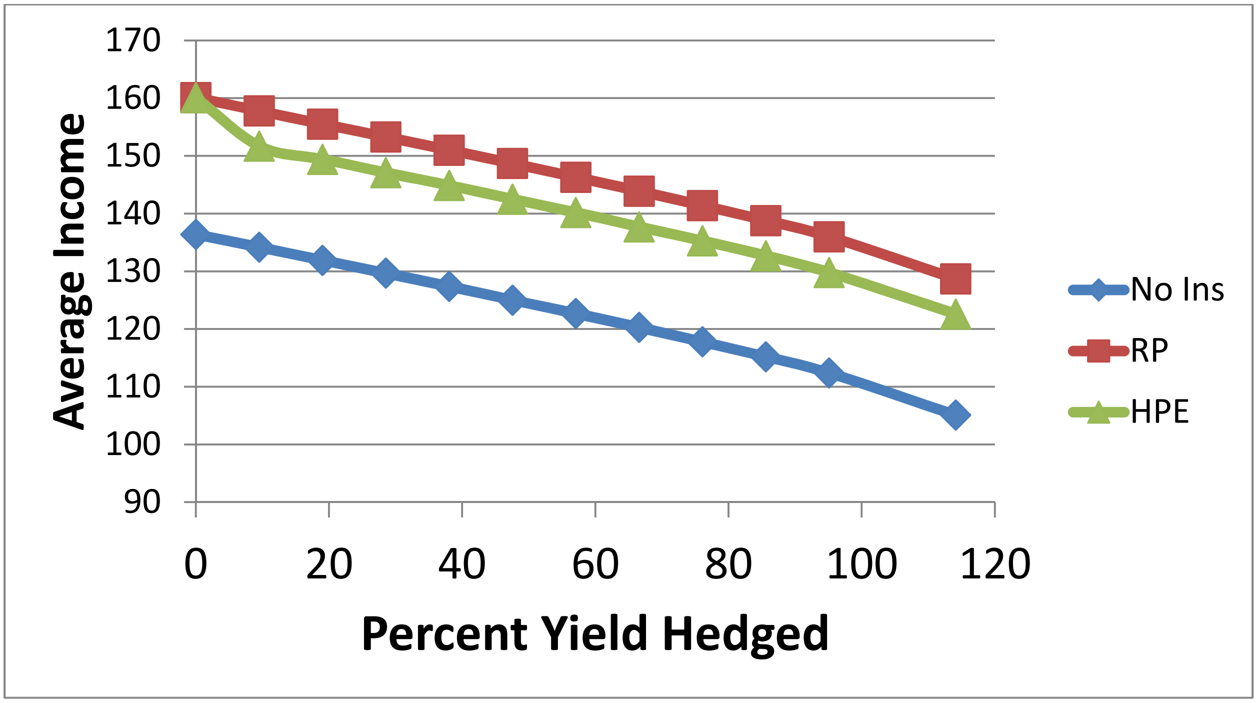


Figure 7. Income and Tail Risk Efficient Frontier under Different Portfolios.



Figure 8. Average Income with and without Insurance.