8-6-2011

Design and evaluation of customizable area whole farm insurance

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DESIGN AND EVALUATION OF CUSTOMIZABLE AREA WHOLE FARM INSURANCE

By

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A Thesis
Submitted to the Faculty of
Mississippi State University
In Partial Fulfillment of the Requirements
For the Degree of Master of Science
In Agriculture
In the Department of Agricultural Economics

Mississippi State, Mississippi

August 2011

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Title of Study: DESIGN AND EVALUATION OF CUSTOMIZABLE AREA WHOLE FARM INSURANCE

Pages in Study: 84

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The customizable area whole farm insurance (CAWFI) is proposed and evaluated as a possible whole-farm revenue protection design for crop farms. The evaluation included assessing appropriate weight, optimal scale, and optimal coverage level. The optimal CAWFI was tested against no insurance program, 90% farm level whole farm insurance (90% CFWFI), and CAWFI with scale and coverage level as provisioned in GRP product (restricted CAWFI) in representative farm in Kansas, North Dakota, Illinois, and Mississippi.

The study finds the optimal CAWFI outperforms no insurance program and restricted CAWFI asserting that CAWFI is a workable insurance model and relaxing restriction on scale and coverage level can increase expected utility of farmers. The optimal CAWFI results in a risk reduction roughly equal with 90% farm-level whole-farm insurance though the expected indemnities in it are at least three fold.

Key words: Certainty Equivalent, Indemnity Payouts, Crop Insurance

DEDICATION

I would like to dedicate this study to my family.

ACKNOWLEDGEMENTS

This work became possible only by the support of some key persons. First, I am very grateful to my major professor Dr. Keith Coble during the whole course of this dissertation for his concept, support, guidance and incredible assistance. Likewise, I would like to express my profound gratitude to my committee member Dr. Barry Barnett for his constructive suggestions in every endeavor of my work. Additionally, I'm very much thankful to my committee members, Dr. Jesse Tack and Dr. Ardian Harri for their contributions. My thanks go to substitute committee member Dr. John M. Riley for his valuable comments and suggestions that added quality to this work. I would like to also express my gratitude to Dr. David Ubilava for his assistance in this work.

Special thanks to all of my graduate colleagues and friends for their support. Last but not the least, I wish to express my love and gratitude to my beloved families for their emotional supports, understanding and endless love through out the duration of this studies.

Lekhnath Chalise

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CHAPTER I

INTRODUCTION

Background

Farmers are simultaneously confronted with multiple sources of risks. One source of risk is yield risk, which is affected by adverse weather and disease or a farmer's own management practices. Another major source of risk is market price variation, which is driven by the global market. To stabilize farm revenue even in harsh, risky environments, farmers adopt various strategies, including crop insurance, forward pricing, and participation in government price support programs.

Crop insurance is one form of risk transfer, exchanging a sure premium for an indemnity paid when negative outcomes occur. There are several reasons that make developing an agricultural insurance product challenging. Most agricultural producers in the same region are exposed to losses or gains at the same time because of correlated systemic risks. All farms of a particular region may suffer the same type of yield losses because of devastating weather, such as torrential rain, cyclones, droughts, excessively low or high temperatures, etc. The catastrophic loss in a large geographic region is known as systemic risk, which may lead to market failure (Miranda and Glauber, 1997). Thus, insurers need relatively large capital reserves and/or reinsurance to backstop their risk exposure. Adverse selection and moral hazard are two other major problems in developing a crop insurance product because of the hidden information and hidden behavior of the insured farmers. Therefore, a premium price of insurance consists of risk cost, which is the cost for the pure risk associated with the venture, administrative cost, which is a cost for informational control and service delivery, and the reserve-stock cost, i.e., an insurer would have sufficient reserves capable of paying off indemnity at all times (Skees et al. 2008). The US government offers yield insurance based on actual production history (APH) yield, area based insurance, revenue insurance, and more recently the whole farm insurance products.

In discussions of alternative risk protection programs, policy makers and farmers are sometimes attracted to the whole farm insurance concept because whole farm insurance can pool all price and yield risks of a farm into a single insurance policy and can provide insurance more cheaply as compared to commodity-specific revenue insurance or any individual price and/or farm-level yield insurance products. This is because of the diversification effect, i.e. different crop revenues being less than perfectly correlated with each other. However, one should note that Adjusted Gross Revenue (AGR) and AGR-lite are two whole farm insurance products already offered by Risk Management Agency (RMA). The AGR program has not been popular. It is based on the income tax schedule F form, which may not accurately represent the farm income. It is also complex in part because the need to make accrual adjustments to a schedule F based on cash accounting. The AGR program is inherently confronted with balancing the choice of very stringent underwriting rules to prevent fraud and abuse or an operationally simple program that will likely reward gamesmanship rather than good farming practices (i.e., more prone to adverse selection and moral hazard problems of farmers). Another issue with farm-level whole farm insurance is that the need to understand price variability, yield variability, and price-yield interactions for all the commodities grown on a farm makes developing insurance complex and opens up the potential for adverse selections due to inaccurate rating assumptions (Dismukes and Coble, 2006). However, another potential motivation for whole farm insurance designs is that whole farm insurance can potentially qualify as WTO-compliant up to a 70 percent coverage level (Coble and Miller, 2006).

Group Risk Protection (GRP) and Group Risk Income Protection (GRIP) are area-based insurance products that provide commodity-specific indemnity based on county yield/revenue shortfalls. The two major insurability problems of crop insurance, adverse selection and moral hazard, can be minimized through area-based insurance because individual farmers neither have better access to aggregated county data as compared to insurers nor may they influence county average through his/her individual behavior (Miranda, 1991). As the county yield is not perfectly correlated with the farm yield, area-based insurance products are subject to basis risk. As a result, there would be chances of getting indemnity if the farmer doesn't suffer from losses and also a chance of not receiving any indemnity if the farmer faces losses (Barnett et al. 2005, Deng, Barnett, and Vedenov, 2007).

In addition to crop insurance products, price/income risk protection was provided through the commodity title of farm bill through loan programs, deficiency payments, and more recently the counter cyclical program, which were introduced by legislation. The Supplemental Revenue (SURE) and Average Crop Revenue Election (ACRE) are two other programs provisioned through the 2008 Farm Bill. SURE is based on revenue losses and would provide compensation based on whole farm revenue shortfalls, including all crops produced on the farm to the farmers of disaster-declared counties. The total farm revenue under SURE payment is personal farm revenue plus any other payment received from any price/income support programs or indemnity received from any insurance program (FSA/USDA, 2011). The ACRE program pays indemnity based on state revenue shortfalls. Critics believe that the price support programs provide little support to crop yield losses due to bad weather. Then Chairman of House Agriculture Committee Collin Peterson mentioned that a more flexible whole farm revenue concept might be considered a better farm program relative to ACRE (Abbott, 2010). The ACRE program is also linked with crop insurance products (Cooper, 2010). Thus, some of these insurance products and Farm Bill programs appear redundant with each other they all protect against revenue risk (Anderson, Barnett, and Coble 2009). In practice, these price/income support and farm support programs are offered simultaneously with crop insurance products. The inclusion of these farm programs and insurance products together would mix up the effects of one program with other programs as a result it would be difficult to specify the individual program effect. This study focuses on whole-farm area insurance and attempts to design a program that best reduces farm revenue risk in an actuarially-fair context. While Customizable Area Whole Farm Insurance (CAWFI) would likely be provided in addition to other programs, these other price/income support and farm bill programs are omitted to focus on the actual risk reduction achieved by the newly proposed model.

Problem Statement

Area-based insurance products are exposed to basis risk that does not exist in farm-level products, but these farm-level products are more affected by moral hazard and adverse selection problems. Whole farm insurance can protect risks associated with multiple commodities at a lower premium than insuring each commodity separately, but whole farm insurance requires complex premium ratings and indemnity calculations. A trade off exists in farm-level and area-based products. Therefore, a hybrid between farm-based and area-based products that could customize area insurance to a specific farm might be considered a better crop insurance program if it could be developed.

This thesis posits a new approach to whole farm insurance. This approach would use area revenue as a trigger that could preclude many of the fraud and record keeping challenges of the current AGR program. However, whole farm insurance based on a county revenue trigger cannot cover some farm revenue shortfalls because of a lack of perfect correlation of aggregated revenue and the farm revenue. This is an issue that needs to be considered carefully, so that the appropriate weighting scheme is selected. One could simply use the sum of aggregated commodity revenue by county. However, this would implicitly weight all commodities by the crop mix of the county. A farm growing a different crop mix could potentially receive poor risk protection due to the lack of correlation between farm and county crop mix.

The linear response of county yield from its mean to the farm yield from its mean is considered as a scale, and used in an area yield GRP product imposing certain restriction on scale. The scale and coverage level in GRP has also been partially compensating each other when one of those is restricted (Deng, Barnett, and Vedenov, 2007). The existing literature examining the optimal scale and coverage level in yield index-based insurance does not consider either a single crop or multi-crop area revenue design. This study contributes to existing literature by taking into account a single-crop as well as multi-crop area revenue design and estimates optimal scale and coverage level along with appropriate weighting mechanism in the proposed model.

Hence, a customizable area revenue whole farm insurance model (CAWFI) was designed. The expectation in designing CAWFI is to incorporate the risk-reducing properties of whole farm insurance into the area-based insurance product that could minimize adverse selection and moral hazard problems as well as the complexities of premium ratings and indemnities calculations. Therefore, a weighting mechanism along with optimal scale and optimal coverage level seems necessary to customize the area crop mix to the farm crop mix.

Objectives

The general objective of this research is to develop and evaluate a customizable area whole farm insurance simulation model that can evaluate the cost and benefits of whole farm risk protection designs based on both farm and area revenue measures. Specific objectives are:

- Develop a simulation model capable of modeling correlated prices and yields with mixed marginal distributions of both farm and area revenue protection for representative farms in four diverse production regions.

- Develop the CAWFI design and evaluate optimal weights scale and coverage level to maximize producer risk reduction with CAWFI.
- Compare optimal CAWFI with the restricted CAWFI i.e. CAWFI model where scale and coverage level would be as provisioned in GRP.
- Compute and compare farmers' benefit of CAWFI versus whole farm insurance based on farm level yield (CFWFI).

CHAPTER II

LITERATURE REVIEW

The US Congress first authorized Federal Crop Insurance in 1930, and the Federal Crop Insurance Corporation (FCIC) was formed to carry out delivery of the crop insurance programs in 1938 (RMA/USDA, 2008). Prior to 1980, the crop insurance program was limited to major crops and specific regions of the country. The Crop Insurance Act of 1980 expanded the program to many more crops and regions of the country and began premium subsidy provision up to 30%. Due to these actions, the participation in the crop insurance program increased, but still it did not achieve the participation that Congress had expected. Government subsidy on crop insurance program influences production decisions of farmers and prices of the commodity (Young et al, 2001). Congress continued funding the Federal Crop Insurance program while also simultaneously passing frequent ad hoc disaster bills though both programs compensated for yield losses. Per the 1994 Crop Insurance Act, Catastrophic (CAT) coverage was made mandatory to the farmers to be eligible for ad hoc disaster payments. In 1996, the Risk Management Agency (RMA) was created to administer FCIC programs, and it repealed the mandatory CAT coverage participation but catastrophic coverage remained highly subsidized. The acreage insured reached 180 million in 1998. That was three fold the acreage insured in 1988 and more than double the acreage insured in 1993. In 2000, crop insurance was available on 88 crops. In the same year, Congress authorized the private sector's participation in crop insurance research and development. Premium subsidies on higher coverage levels were increased to encourage purchasing higher insurance coverage levels (RMA/USDA, 2008).

Figure 1 shows various US farm support and crop insurance programs introduced since 1930 and still in place today. Ad hoc programs are also continuing side by side since then to date.

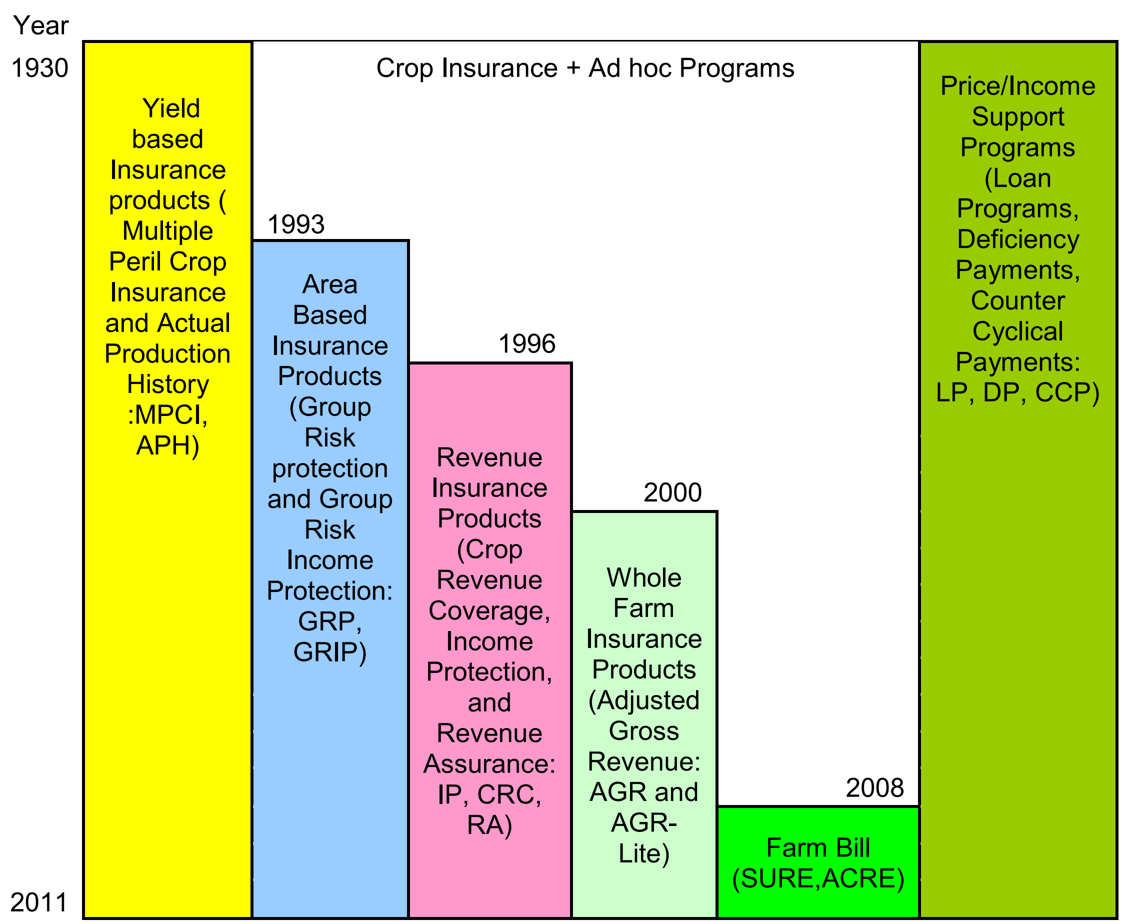

Figure 1

History of Crop Insurance and Farm Support Programs in the United States

Prior to 1996, the yield-based crop insurance program and ad hoc disaster payment protected yield risk. Since 1930, price risk protection was provided through loan programs (LP), deficiency payments (DP), and more recently the counter-cyclical program (CCP) and ACRE program. The crop yield insurance gradually moved towards area yield, area revenue and farm level commodity specific revenue insurance, and most recently towards the farm level whole farm insurance.

Different crop insurance products and simulation technique used in agricultural economics research are reviewed in detail under the following two subheadings of the literature review.

a. Crop Insurance Programs
b. Simulation Methods

Crop Insurance Programs

Crop insurance in the US began with the yield insurance program. The Actual Production History (APH) insurance and Multiple Peril Crop Insurance (MPCI) programs are based on APH yield, which is a simple average of four to ten years of historic yield of a farm. The APH yield also suffers from sampling errors, and being yield insurance, it cannot cover price risk. The commodity specific revenue insurance products protect price as well as yield risk of crops in the farm. The premium cost for the whole farm insurance is much cheaper compared to summing up the individual crop revenue insurance in a farm, but the whole farm insurance products have complexities in designing premium ratings and indemnity claims due to inaccurate assumptions that open up the chance of asymmetric information. Whole farm insurance incurs huge costs to maintain farm-level data, which raises the transaction costs. The area-based products like GRP and GRIP are less prone to problems of asymmetric information and also can reduce the transaction costs, but because of the imperfect correlation of farm yield to area yield, these area-based products are exposed to higher basis risk. The following sections contain detailed discussions about each of these insurance products.

Yield Insurance

Until 1995, all agriculture insurance products were yield based and crop-specific, and would provide compensation based on individual crop yield losses. Actual production history (APH) is the modern version of yield insurance in the United States. Expected yields are based on the farmer's crop-yield records over multiple years, and FCIP uses those records in its crop insurance program to determine normal production levels for a farmer. MPCI uses the APH yield to estimate the indemnity that is driven by yield shortfalls. MPCI is one of the dominant yield insurance products that protect insured farmers' yield loss caused by multiple perils, such as rainfall, disease, and droughts. The major drawback of this product is that the exact cause of loss is not always identified, which is problematic to the insurers. Those multiple perils are also spatially correlated. As a result, the cost of MPCI may challenge the financial reserves of a private insurer in a year where many insured simultaneously make a claim (Skees et al. 2008). MPCI benefits may vary sharply among farms, crops, and regions (Knight and Coble, 1997). Because the APH yield is based on four to ten years of historical average yield, it suffers from sampling error. This sampling error in APH yield could potentially reduce farmers' welfare at varying magnitudes across crops and geographical regions (Adhikari et. al. 2010).

Area-Based Insurance

In 1993, the USDA first offered an area yield insurance product, the Group Risk Protection (GRP), where the indemnity is paid to all the insured farmers of the county based on county average yield shortfalls. Later in 2000, the area revenue based product group risk income protection (GRIP) was introduced. GRIP pays indemnity based on county revenue rather than county yield. The two major insurability problems of crop insurance, adverse selection and moral hazard, can be minimized through area yield insurance as it is advantageous over crop insurance products, which are based on individual farm yield (Miranda, 1991). The basis risk that occurs here is from the measure of correlation between farm and county yield. The higher the positive correlation between the farm and county yield will lower the basis risks. As the county average yield is not perfectly correlated with the area average yield, GRP is subject to basis risk (Barnett et al.2005, Deng, Barnett, and Vedenov, 2007); as a result, farmers are unable to protect their farm losses all the time.

GRP has less moral hazard problems and lower transaction costs as it avoids establishing APH yields and on-farm loss adjustment. For some crops and in some regions, GRP can perform better in homogenous as well as heterogeneous production regions relative to MPCI (Barnett et. al. 2005). In 2005, approximately 76% of total Federal Crop Insurance Program (FCIP) acres were for farm-level yield and revenue insurance products. The area-based insurance products have grown by 6% and have reached to 9% of FCIP in 2005, compared to 3% of FCIP in 2002. Area insurance could become an available alternative insurance product instead of farm-level insurance even in heterogeneous geographical production regions when premium rates for farm-level insurance contain large positive wedges, where the wedge is defined as the gap between insurance premium cost and expected indemnity of the insurance product (Deng, Barnett, and Vedenov, 2007). In FCIP, premium rates are designed to have negative wedges because government pays administrative and operating costs and also subsidizes the premium.

The Group Risk Income Protection (GRIP) is an area-revenue product, introduced in 2000. National price, county-level yields, and farm-level acreage are used to calculate GRIP where the indemnity is paid to all the farmers of the county based on county average revenue shortfalls. The GRIP policies are based on futures prices and county average yields rather than individual farm yields (Edwards, 2009). Paulson and Babcock (2008) illustrate that although the ad hoc disaster-assistance program may not be perfectly substituted by GRIP, as GRIP covers price as well as yield risk, it could be financed from the Farm Bill program or Crop Insurance program savings. GRIP did not become popular, and the acres insured under it consisted of 3.5% of revenue insured acres in 2005 (Coble and Miller, 2006). Dismukes and Glauber (2004) speculated that if GRIP is strengthened to substitute for the ad hoc disaster program, the premium subsidy to buy up level coverage would be more costly.

Commodity-Specific Revenue Insurance

In 1996, two crop revenue insurance programs, Income Protection (IP) and Crop Revenue Coverage (CRC), were introduced in limited areas for specific crops. In the next year, Revenue Assurance (RA) was added as a third crop revenue product. These revenue insurance programs guarantee a certain level of farm revenue for a given crop rather than just production and pay an indemnity if revenues fall beneath the guarantee. As this indemnity payment scheme deals with both price and yield risk, it is supposed to be highly correlated with a farm's need (Zhu et al., 2008). Crop revenue products rapidly became popular among farmers as they protect from price as well as yield shortfalls. In crop year 2001, FCIC acreage under revenue insurance reached 58% of total crop insurance premium. Revenue insurance represented 60% of total crop insurance premium in 2003, which was 55% of that year's total crop insured acres (RMA/USDA, 2004). For the crop years 1999 and 2000, Congress increased the premium subsidy and passed the Agricultural Risk Protection Act 2000. As a result, the overall participation in crop insurance programs increased by 20% from 1998 to 2003 (Glauber, 2004). Coble et al. (2000) discussed revenue insurance products substitute for other risk-reducing strategies such as futures hedging and option. This effect increases rapidly beyond 70% coverage level, i.e., higher insurance coverage level would lead to lower optimal hedge.

Assuming farm family utility is the function of initial wealth and variability of wealth across all risky enterprises, single revenue insurance products provide risk protection at a lower cost than separate price and yield risk protection programs in perfectly competitive markets. Single revenue insurance products protect farmers against revenue variability. The commodity-level crop revenue protects against individual crop revenue, and the premium is subsidized through FCIC (Monke and Durst, 2000). The revenue variability occurs due to variation in price, yield, or interaction of both. The price is determined mostly by world markets, and the yield is based on micro climatic factors, so farm revenue tends to be highly responsive to fluctuations in farm yield. In some crops and regions, the relation between price and yield is negative, which makes revenue less variable, maintaining a natural hedge. All else equal, a more negative correlation between price and yield reduces revenue risk. Thus, the revenue insurance meets the farmer's needs, and it is relatively cheap as compared to yield insurance. Therefore, in the areas of more negative price-yield correlation with low yield variability (also known as low risk area) where revenue insurance premium is lower, farmers have rapidly adopted revenue insurance. This is especially true in the Midwestern corn and soybeans farms (Dismukes and Coble, 2006).

According to Dismukes and Coble (2006), acres insured in revenue insurance were 57% of total FCIC insured acres in 2006 consisting of three quarters of all insured acres of the top three crops: corn, soybean, and wheat. FCIC encouraged farmers to buy up level coverage increasing premium subsidies for higher coverage levels especially in revenue insurance. Dismukes and Coble further discuss that because of the increment of the 30% premium subsidy to 56%, half of the insured acres of 70% or higher coverage level in 1999 reached to two thirds in 2002 where most producers had purchased insurance coverage between 70 and 75%.

Mishra and Goodwin (2006) point out that the revenue insurance can shift taxpayer's burdens to subsidize farmers' insurance premiums more efficiently. While the experienced and resourceful farmers are less likely to purchase revenue insurance compared to new and resource-poor farmers. The total sum of commodity specific revenue insurance premiums for a farm is a good deal higher than the estimated proposed single whole farm insurance product of a farm, and insurance premium is sensitive to price volatility and commodity mix (Hart et al., 2006). In other words, at the same coverage level, summation of crop-specific insurance premium is more expensive than a single whole farm insurance premium (Zhu et al., 2008.; Stokes et al., 1997).

Whole Farm Insurance

In 2000, whole farm insurance based on farm-level yield referred to as, Adjusted Gross Revenue (AGR) was also introduced. AGR covers risks of all the commodities grown in a farm in single insurance policy. Whole farm revenue insurance is more efficient than the summation of commodity-specific revenue insurance (Stokes et al., 1997). Whole-farm insurance pools all of a farm's insurance risks into a single insurance policy that provides cheaper premium rate at the same coverage level against the gross farm revenue. Whole farm insurance is superior to crop-specific insurance as it takes care of whole farm revenue risk at a low premium cost. For instance, Zhu et al. (2008) mentions a 36% less insurance premium in whole farm insurance as compared with commodity-specific revenue insurance products.

The price, yield, and price-yield interaction of all the commodities grown in a farm are covered in a single insurance policy, which makes complex to design insurance premium. It is also very difficult to verify revenue losses and indemnity payments. Both AGR and AGR-lite use the income tax schedule, which may not reflect underlying revenue risk, making whole farm insurance products unpopular. In the case of multiple-year income declines, neither commodity revenue nor whole farm revenue covers the risk (Dismukes and Coble, 2006). Coble and Miller (2006) also mention that the use of income tax forms as a starting point for farm revenue calculation is a major cause of AGR being unpopular among farmers because income tax forms vary from the farmer's actual annual income, as farmers typically use cash accounting rather than accrual accounting. They further mention that the AGR and AGR-lite combined had 3.53% market share in 2005.The whole farm insurance up to 70% coverage level falls under WTO Amber box, and hence, it is WTO-compliant, too (Coble and Miller, 2006).

Simulation Method

The practice of using simulation tools to deal with agricultural risk management is increasing (Richardson et al., 2000). Typically, historical multivariate simulation has most often been performed by assuming multivariate normality. However, imposing normality on the marginal distribution of crop yields and prices is often not supported by empirical data (Harri, Erdem, Coble, and Knight, 2009). The different marginal price distributions are correlated with each other, and marginal yield distributions are also potentially correlated. The interaction between price and yield has also been noted. Only by using a procedure capable of modeling and simulating multivariate distributions can one analyze such complex combinations (Ramirez, 2000). Ramirez further mentions that, in general, both the mean and the variance of the marginal distributions of crop productions and prices are found to be shifting over time. As all the crops grown in a region are affected simultaneously through disease, pest, and/or weather, the non-normally distributed yield has been found to often appear skewed to the left. On the other hand, price data tends to be auto-correlated over time, and non-normally distributed left-skewed yield may cause price to be right-skewed through market equilibrium. Marginal price distributions are typically correlated with each other because crop production is typically correlated and many crops also substitute for each other in output markets.

IC (1982) and PQH (2004) Methods

In practice, the Iman and Conover (IC) (1982) procedure is commonly used in agricultural risk simulation in agricultural economics research (Mildenhall, 2005). The Phoon, Quek, and Huang (PQH) (2004) procedure has also been used in agricultural economics. The PQH is a multivariate simulation procedure for correlated stochastic variables from mixed marginal distribution based on Eigen decomposition of a rank correlation matrix.

Anderson, Harri, and Coble (2009) compared these two simulation procedures. Compared with the popular IC simulation procedure, the PQH procedure is straightforward and distribution free. Their study revealed that the IC simulation procedure produces significantly different crop insurance premium rates relative to PQH simulation procedures. The PQH procedure also produces a more accurate relationship between interdependent random variables, as the t-test for rank correlation matrix from simulated data does not differ significantly to that of the original correlation. Though the mean squared error (MSE) of the correlation coefficient for small samples is relatively higher in PQH simulation, it can be corrected by increasing sample size. The PQH simulated data has relatively small bias. As the IC procedure produces biased estimates of correlation between simulated variables, the PQH was found more accurate compared to the IC procedure. However, PQH is likely to produce more outliers than IC. PQH is well suited for multi-crop insurance modeling because researchers can easily obtain more accurate rates. Further, they suggest that multivariate simulation from mixed marginal distribution is essential to analyze the revenue counter cyclical program provisioned in the 2008 Farm Bill and a whole-farm disaster compensation program.

CHAPTER III

CONCEPTUAL FRAMEWORK

Risk Aversion Behavior

People's response varies towards risk environments. Some people are willing to take risks, i.e., they love to play with risk thus displaying risk-loving behavior. For these individuals, the utility function of wealth is convex to the origin. The more convex the curvatures, the more risk-loving the individuals are. People who do not care about risk while making decisions are called risk neutral. These people face the straight line utility function of wealth. The behavior of an individual response towards risk is described in Figure 2.

A person who always refuses a fair bet is risk averse. Likewise, people who prefer certainty and dislike gambles are described as risk averse. These risk-averse individuals face the concave utility function of wealth and are willing to pay some amount of premium to get rid of a risky venture, as shown in Figure 2. A more concave curvature indicates a more risk averse behavior, and a curvature close to a straight line indicates less risk averse decision maker.

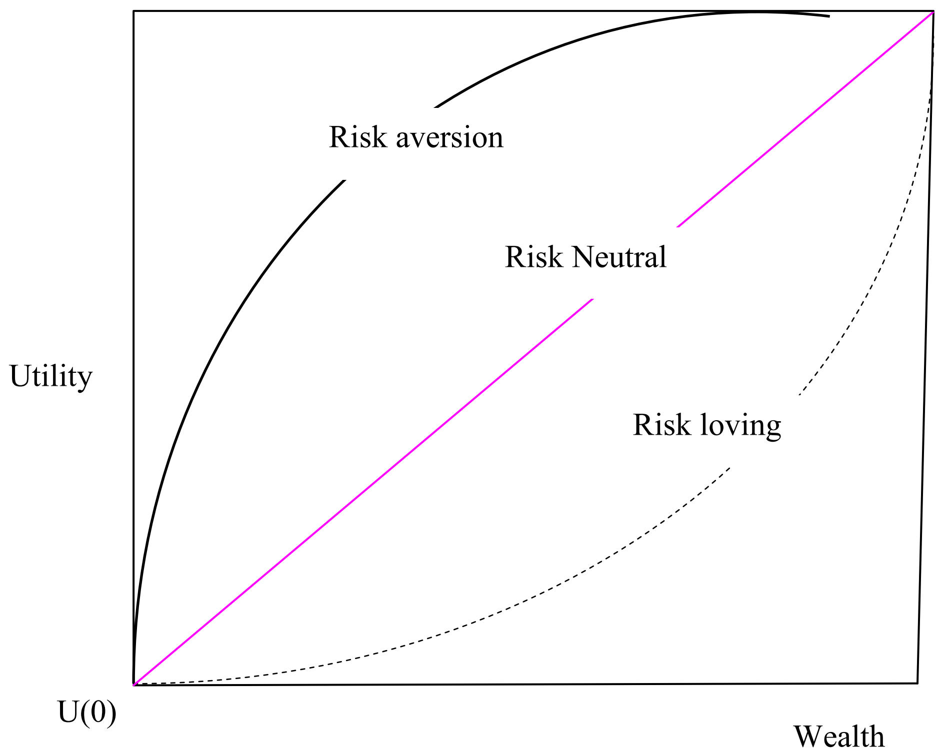

Figure 2

Risk Behavior of an Individual

Expected Utility Model

The expected utility hypothesis says that risk-averse decision makers make decisions based on the expected utility from the gamble (Chavas, 2004: 21-30). Let a decision maker have utility function *U(z)*, with two possible outcomes z_1 and z_2 with some probability, then this risk-averse decision maker's objective function is to maximize the expected utility. The expected utility, certainty equivalents, and insurance premiums are key concepts in this model, which is shown in Figure 3.

Figure 3 also demonstrates the concept of how the expected utility model works.

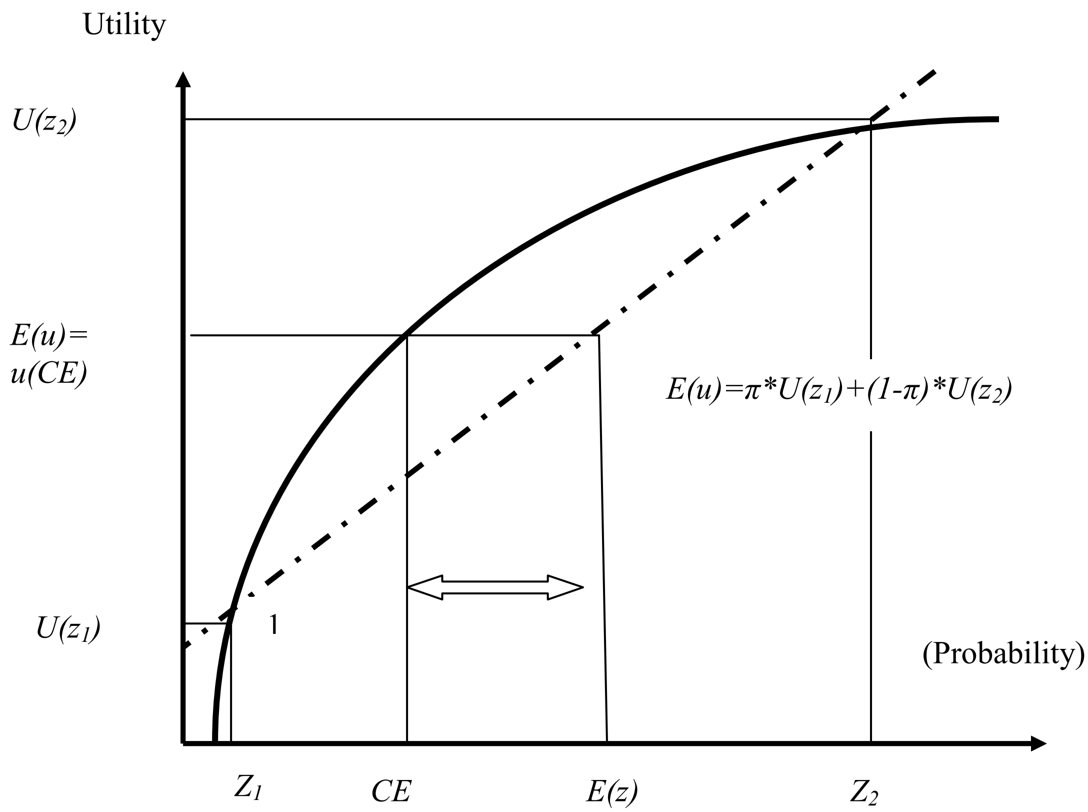

Figure 3

Expected Utility Model

Expected Utility

The utility of an uncertain prospect is its expected utility. In Figure 3, in a hypothetical example, the expected utility is *E(u)*. The player who is taking part in a gamble asks if a sum of money is equivalent to a risky venture if it derives the same expected utility as the non-risky venture. The expected utility from this gamble is the probability weighted average of the utility of the two possible outcomes. If the gamble has equal chance of winning and losing, then the average is halfway between the individual’s utility from wining and losing. This simple example illustrates the expected utility derived from a bivariate discrete outcome event. However, in the case of a continuous distribution, to estimate the expected utility, the PDF is multiplied by the assumed utility function.

Certainty Equivalent

The certainty equivalent of a risky venture is the sure amount of money that if received would have a utility equal to expected utility. Certainty equivalent (CE) is a definite amount of return from a risky venture. Once, expected utility is estimated, then it can be converted to the income i.e. certainty income for that venture. The *CE* in Figure 3 is certainty equivalent from the risky venture. An individual wants to take the amount equivalent to *CE* rather than taking part of gamble, but he/she becomes ready to play gamble below the income of *CE*.

Risk Premium

A risk premium is the minimum amount of money by which the expected return of the risky venture must exceed the known or the risk-free venture in order to induce an individual to hold the risky venture rather than the risk-free venture. If there is an opportunity to avoid risk, a risk-averse individual is willing to pay some sort of amount. The amount is the difference between expected value of possible outcomes and certainty equivalent for the outcome. In the above example, this individual is willing to pay not to take part in this gamble, i.e., insurance premium is positive and decision maker is risk averse. For a risk-neutral individual, premium would be zero, and for a risk-loving individual, premium would be negative.

In this figure, an event has π probability of obtaining z_1 outcome that provides utility $U(z_1)$ while there is another event with a $(1-\pi)$ probability to obtain z_2 outcomes that will provides utility $U(z_2)$.

The expected value of outcome is

(1) $E(z) = \pi * z_1 + (1-\pi) * z_2$

This expected outcome provides utility is $U[E(z)]$

While the expected utility for the outcome is

(2) $E(u) = U(z_1) * \pi + U(z_2) * (1-\pi)$

In Figure 3, the difference between expected wealth and the certainty equivalent is indicated by the horizontal arrow. A risk-averse decision maker's expected utility is always lower than the utility of the expected outcome. Or in other words, we can express as:

(3) $U[E(z)] > E(u)$

While making decisions under uncertain circumstances, decision makers make decisions based on their expected utility rather than the utility of the expected outcome.

Constant Relative Risk Aversion (CRRA) Utility Function

CRRA is a risk preference theory where downside risks are given higher weight than upside risks. CRRA gives greater weight to downside risk as compared to upside risk (Chavas, 2004: 31-51).

The CRRA function explains that proportionate increase in initial wealth would permit to increase in the same proportionate increment in risk. The risk aversion coefficient of 0.5 in CRRA indicates hardly risk averse at all; 1 indicates somewhat risk averse (normal); 2.0 indicates rather risk averse (moderately risk averse); 3.0 indicates very risk averse; and 4.0 indicates extremely risk averse. The CRRA function has a problem with a 4 or higher level risk aversion coefficient, implying very high marginal utility for low values of wealth with a sharp fall to give essentially zero marginal utility for higher values. A risk-aversion level above 5 is perceived to be unrealistically risk averse (Hardakar et al., 2004: 92-120).

Risk averse farmers will have a decreasing marginal utility over the amount of pay off. This study makes assumption that decision makers maximize a constant relative risk aversion (CRRA) utility function of wealth. Consider a farm where there are two crops 1 and 2, risk aversion coefficient *r*, weighted probability to possible outcome *t* is ϖ_t then, expression for net return, utility, and expected utility can be written as

(4) $NR_t = \varpi_1 NR_{1t} + \varpi_2 NR_{2t}$

where

$W_t = W_o + NR_t$

W_o=initial wealth

W_t=terminal wealth

And NR_t= net return from different scenarios which are stochastic.

(5) $U = \dfrac{W_t^{1-r}}{1-r}$ if $r \neq 1$ and $U = \ln(W_t)$ if $r = 1$.

The farmer's expected utility is

$$(6)\ E(U) = \sum_{t=1}^{n} \eta_t \frac{W_t^{1-r}}{1-r} \quad \text{if } r \neq 1$$

and $$E(U) = \sum_{t=1}^{n} \eta_t \ln(W_t) \quad \text{if } r = 1.$$

where η is the weight assigned based on probability to possible outcome *t*.

CAWFI Model

The actual farm revenue based on planted acres under CAWFI is the same as it appears under whole farm insurance computation except that the CAWFI replaces farm yield with county level yield. The expression to estimate CAWFI actual farm revenue is

$$(7)\ CAWFI_{\mathrm{Re}v} = \sum_{i} A_{i,f} \times P_i \times Y_{i,c}$$

Where $CAWFI_{\mathrm{Re}v}$ is actual farm revenue under CAWFI.

$A_{i,f}$ is planted acres of crop *i*, on farm *f*;

P_i is output price of crop *i,*

$Y_{i,c}$ is output quantity per acre of crop *i,* in county *c*.

Guaranteed revenue under CAWFI is estimated as;

$$(8)\ CAWFI_{Guar} = E(CAWFI_{\mathrm{Re}v}) * CL$$

Expectation of price and expectation of county yield are used to determine expected revenue under CAWFI, which are also customized by appropriate weight. Therefore, this equation can be extended as

$$(9)\ CAWFI_{Guar} = \sum_{i} \mu_{i,f} \times E(P_i) \times E(Y_{i,c}) \times CL$$

Where

$CAWFI_{Guar}$ = guaranteed revenue under CAWFI.

$\mu_{i,f}$ = appropriate weight for the planted acres of crops *i*, in the farm *f*,

CL = coverage level,

$E(P_i)$= expected output price for crop *i*,

$E(Y_{i,c})$= expected output of crop *i* in county *c*.

The equation used by Skees, Black, and Barnett (1997) to estimate indemnity payout for area yield product GRP is

$$(10)\, GRP_{INDEM} = Max\left[\left(\frac{GRP_{Guar} - GRP_{Yield}}{GRP_{Guar}}\right)\left(E(GRP_{Yield})\right)\left(scale\right), 0\right]$$

Where GRP_{Guar} is critical area yield in GRP

GRP_{Yield} is area yield in GRP

$E(GRP_{Yield})$ is insurer's forecast of the area yield in GRP.

In the GRP model, farmers are restricted to a scale ranging from 0.9 to 1.5 and allowed to select a different scale at that range and are also allowed to select different coverage levels ranging from 0.70 to 0.90. Scale is a multiplier that adjusts the magnitude of the indemnity. The optimal scale in this equation is derived as β_1 from the following equation,

$$(11)\, y_i = \beta_0 + \beta_1(y_c - E(y_c)) + \varepsilon_i$$

Where y_i is the county yield for crop *i*,

$E(y_c)$ is expected county yield for the same crop *i*,

ε_i is the error term.

The indemnity is paid only when, $y < y_c$.

The above equations are used here with some extensions. Basically, CAWFI replaces the area yield by area revenue. The indemnity under CAWFI is paid only when CAWFI revenue falls below the guaranteed CAWFI revenue, otherwise indemnity paid would be zero. The equation to estimate indemnity is

$$(12)\, CAWFI_{INDEM} = Max[\{\frac{CAWFI_{Guar} - CAWFI_{\mathrm{Re}v}}{CAWFI_{Guar}}\}(ECAWFI_{\mathrm{Re}v})(Scale),0]$$

Where, $\mathrm{CAWFI}_{\mathrm{INDEM}}$ is indemnity under CAWFI model.

The optimal scale is obtained as a beta coefficient, which is a response of county revenue deviation from its mean to farm revenue deviation from its mean. This beta coefficient measures the linear relationship between the county revenue and farm revenue. The error term reflects the idiosyncratic (basis) risk associated with this farm's revenue variability. The scale in the form of β_1 is estimated from the following equation

$$(13)\, CFWFI_{\mathrm{Re}v} - E(CFWFI_{\mathrm{Re}v}) \ = \beta_1(CAWFI_{\mathrm{Re}v} - E(CAWFI_{\mathrm{Re}v})) + \varepsilon_i$$

where

$CFWFI_{\mathrm{Re}v}$ is the revenue under whole farm insurance based on farm level yield

$E(CAWFI_{\mathrm{Re}v})$ is the expected revenue in CAWFI from multiple crops.

$E(CFWFI_{\mathrm{Re}v})$ is the expectation of revenue in the farm level.

Whole Farm Insurance Based on Farm Level Yield (CFWFI) Model

To evaluate the performance of CAWFI, a hypothetical farm-level whole farm policy is also modeled. Farmers are assumed to have the option to buy whole farm insurance based on farm-level yield. The actual farm revenue, guaranteed revenue, and indemnity in whole farm insurance were estimated using the following equation:

$$(14)\ CFWFI_{\mathrm{Re}v} = \sum_i A_{i,f} \times P_i \times Y_{i,f}$$

where, $CFWFI_{\mathrm{Re}v}$ is actual whole farm revenue,

$A_{i,f}$ is planted acres of crop *i*,in the farm *f*,

P_i is output price of crop *i*,

$Y_{i,f}$ is the output of crop *i* in farm *f*.

The guaranteed revenue in whole farm insurance was estimated as

$$(15)\,CFWFI_{Guar} = A_{i.f} \times E(P_i) \times E(Y_{i,f}) \times CL$$

where, $CFWFI_{Guar}$ is guaranteed revenue in whole farm insurance,

$E(P_i)$ is the expected output price of crop *i,*

$E(Y_{i,f})$ is the expected farm yield for crop *i* in the farm *f*,

CL is the insurance coverage level.

The indemnity pay out in the whole farm insurance was estimated using the equation

$$(16)\,CFWFI_{INDEM} = Max\{CFWFI_{Guar} - CFWFI_{\mathrm{Re}v}), 0\}$$

Where, $CFWFI_{INDEM}$ is the indemnity payout in the whole farm insurance.

The indemnity is paid only when the actual farm revenue falls below the guaranteed farm revenue, otherwise indemnity would be zero.

Certainty Equivalent Calculations

For purposes of comparison, similar calculations are performed for a hypothetical CAWFI model under restricted and optimal level and whole farm insurance based on farm-level yield (CFWFI). The estimated expected utility under different scenarios based on net return on each scenario was converted into certainty equivalents of dollar value to make comparison easier by using the following equations:

$$(17)\ CE_j = e^{E\,Uj} - W_o \text{ if } r=1,$$

$$CE_j = EU_j(1-r)^{\frac{1}{1-r}} - W_o \text{ if } r\neq 1.$$

where EU_j is expected utility for scenario j,

W_o is initial wealth,

And CE_j is certainty equivalent of scenario j.

CHAPTER IV

DATA AND METHODS

Study Site

Four representative farms from four different states reflecting varied crop/geographical regions were selected for this study. A representative Mississippi soybean-corn farm, a representative Illinois soybean-corn farm, a representative Kansas wheat-corn farm, and a representative North Dakota wheat-corn farm were selected. Yazoo County from Mississippi, Mclean County from Illinois, Sheridan County from Kansas, and Barnes County from North Dakota were considered for county-level yield data.

The following crops were considered under this study in four diversified geographical states:

a. Mississippi-Corn and soybean
b. Illinois-Corn and soybean
c. North-Dakota-Corn and wheat
d. Kansas-Corn and wheat

Crop Mix/Farm types

In this study, single crop as well multi-crops farm were considered. The farm types are discussed below.

Single Crop Farm

A farm where only one crop is grown is defined as a single crop farm. In this study, the following single crop farms have been considered:

1. Corn Farm, Mississippi
2. Soybean Farm, Mississippi
3. Corn Farm Illinois
4. Soybean Farm, Illinois
5. Corn Farm, Kansas
6. Wheat farm, Kansas
7. Corn Farm, North Dakota
8. Wheat Farm, North Dakota

Multiple Crops Farm

In this study, farm types have been defined based on the acreage shares of crops on the farm. The term crop mixes is also used synonymously with farm types in the case of multiple crops grown on the farm. The following crop mix/farm types were considered in this study in multi-crop farm scenario.

(a) Equal Acres Farm

A multiple crop farm where all the crops are grown in the farm share on equal (50:50) acres is called equal acres farm. For example, on 1000 acres of corn-soybean farm, each crop is planted on 500 acres of land.

(b) Corn Major Farm

A multiple cropping farm where corn occupies 70% of acres and the other crop only 30% of acres is called a corn major farm. The representative corn-soybean farm in Mississippi where corn occupies 70% of the farm acreage is an example of a corn major farm.

(c) Wheat Major Farm

A multiple cropping farm where wheat is grown on 70% of the total farm acres and any other crop on 30% of the land is referred to as a “wheat major” farm. For example, in Kansas where wheat is grown in 70% of the farm acres and corn on 30%, it is called a wheat major farm.

(d) Soybean Major Farm

A multiple cropping farm where soybean is grown on 70% of the farm acres is a soybean major farm. For example, an Illinois farm where soybean is grown on 70% of total farm acres and corn on 30% is called a soybean major farm.

Based on the above criteria, this study would have the following 12 multiple crop farm types or crop mixes:

1. Equal Acres Farm, Mississippi
2. Corn Major Farm, Mississippi
3. Soybean Major Farm, Mississippi
4. Equal Acres Farm, Illinois

5. Corn major Farm, Illinois
6. Soybean Major Farm, Illinois
7. Equal Acres Farm, Kansas
8. Corn Major Farm, Kansas
9. Wheat Major Farm, Kansas
10. Equal Acres Farm, North Dakota
11. Corn Major Farm, North Dakota
12. Wheat Major Farm, North Dakota

Yield Data

The county yield data from the selected county of four states were obtained from the National Agricultural Statistics Service (NASS) of the United States Department of Agriculture (NASS/USDA, 2010). Corn, soybean and wheat yield data were used for this study. The yield data for Illinois, Mississippi, Kansas, and North Dakota are from 1975 to 2009.

Detrending County Yield

Technology changes overtime tend to affect crop yield (Anderson and Hazel, 1987). As such, in order to make the yield data comparable across years, the trend of the yields were taken out and adjusted to the current year 2010 yield. A linear trend specification of yields is used for each county and crop (Hafner 2003, Tweeten 1998, Hazell 1984). These were estimated separately using the 35 years of data from 1975 to 2009. The regression model is:

$$(18)\ Y_{it} = \alpha_{0i} + \alpha_{1i}t + \varepsilon_{it}$$

where, Y_{it} is yield for crop i=1, 2 in year t=1 for 1975, 2 for 1976,….35 for 2009.

α_{0i} is intercept,

α_{1i} is the trend coefficient for the trend component,

ε_{it} is the error term for crop i in year t.

Adding this trend coefficient times the difference between 2010 and observed year, the detrended yield for each year from 1975 to 2009 on each geographical region were obtained and adjusted by the current year, 2010 using the following equation,

$$(19)\ Y_{it}^{\det} = \hat{\alpha}_{0i} + (36 - t)\hat{\alpha}_{1i} + \hat{\varepsilon}_{1t}$$

Where, the $\hat{\alpha}_{0i}, \hat{\alpha}_{1i}, and\, \hat{\varepsilon}_{it}$ are estimated from the equation (18) above,

$Y_{it}^{\det}$ is detrended yield for crop i in year t,

the trend component t=36 for the current year 2010.

Simulation of Farm Yield

The farm-level yields were simulated from the detrended county-level yields according to Miranda's formulations as described in Coble and Dismukes (2008). Miranda's specification is given as:

$$(20)\ Y_{f,t} = \mu_f + \beta_f(y_{c,t} - \mu_c) + \varepsilon_{f,t}$$

Where, $Y_{f,t}$ and $y_{c,t}$ are random farm yield and county yield respectively at period t,

μ_f and μ_c are the expected farm and county yields,

β_f is the responsiveness of a farm yield to county yield deviations from the expected county yield

$\varepsilon_{f,t}$ is the idiosyncratic risk. The idiosyncratic risk here is the variance in yield resulting from randomness observed uniquely in each farm.

Coble and Dismukes (2008) describe that, the beta coefficient from the equation (20) is the response of county yield deviation from its mean on farm yield. The idiosyncratic risk shown by Miranda is indicated by the error term. In this process, the error term is assumed to be normally distributed with mean 0 and variance σ^2, i.e. $\varepsilon_f \sim N(0,\sigma^2)$ where standard deviation of idiosyncratic farm risk is denoted by σ. Assuming that county yields are true aggregations of all farms in the county, then for a representative farm, the beta coefficient would be equal to 1, which is the average of all beta's in the county weighted by acreage.

By comparing the ratio of indemnity payoffs conditioned on the guaranteed price, P_{Guar} and coverage level *CL*, the expected loss cost was derived. Locking down the coverage level at 65%, a grid searched was performed from 0.1σ to 10σ by intervals of 0.01σ, where σ is the standard deviation of a county-level yield for a given crop and location. The standard deviation of idiosyncratic farm yield was thus obtained.

A grid search was performed to estimate the idiosyncratic risk of each crop in each farm by inserting equation (20) into the following equation to simulate RMA crop insurance premium rates.

$$(21)\ Min\left|PR_{65} - ELC_{\sigma}\right|, \text{where } ELC_{\sigma} = E\left[\frac{P_{Guar}(CL*\mu_f - \tilde{y}_{ft_{\sigma}})}{P_{Guar}*CL*\mu_f}\right]$$

Where, PR_{65} is premium rate for crop yield insurance in each county at 65% coverage level which comes from the RMA premium rate, and ELC_{σ} is expected loss cost under a given standard deviation of σ.

The only unknown parameter in the right hand side of equation (20) is the standard deviation of idiosyncratic yield risk (σ) of ε_{ft}. The investigation of σ value is the major interest here to obtain farm-level yield. The expected farm yield (μ_f) is assumed to be equal to expected county yield (μ_c), where yield μ_c is obtained from the county-level yield, which have mentioned in table 3. The y_{ct} is observed county-level yield for year *t.* In equation (21), P_{Guar} cancel out each other, and *CL* is chosen as 65%, $\mu_f = \mu_c$, and y_{ft} is obtained for different values of σ. The stepwise procedure to obtain farm-level yield from county-level yield is summarized into following three steps.

Step I:

Assuming a value for σ equal to some constant c_1, 1,000 values of ε_{ft} were generated. Plugging those ε_{ft} values into equation (20), 1,000 random Y_{ft} were obtained. These Y_{ft} values with σ=c_1 were inserted into second part of equation (21) and the average across observations for each σ i.e., expected loss cost (ELC_{σ} for σ =c_1) is estimated and used in first part of equation (21) to obtain an absolute difference of the objective function. Obtained absolute difference of objective function for the given σ value is recorded. This process is replicated assuming different values of σ, like σ =c_2, c_3…c_n.

Step II:

The absolute difference across different values of σ noted in step I from the first part of equation (18) were compared and the minimum absolute difference was selected. The value of σ at the minimum absolute difference would be the optimized standard deviation (σ) value for the idiosyncratic yield risk.

Step III:

Once standard deviation for error term σ is obtained, then it is plugged into the equation (20) to obtain the farm yield for 35 consecutive years using observed county-level yield for respective years from 1975 to 2009.

Price Data

For this study, price data of the 1975 to 2009 were obtained from the Economic Research Services of United States Department of Agriculture (ERS/USDA, 2010). The price at planting and harvesting futures prices at planting time of corn, soybean, and wheat were used. The change in price from planting to harvesting time for each crop was obtained for each year. These price changes were used in the study.

Developing a Simulation Model

A simulation model was developed to simulate correlated random prices and yields using multivariate simulation technique.

<u>Monte Carlo Simulation</u>

In stochastic simulation, by identifying the probability distribution of the known stochastic variables, the prediction to the actual scenario would be made. Monte Carlo simulation is one of the most popular sampling methods that can generate thousands of observations having the same properties as the original set of data. Monte Carlo sampling uses Cumulative Distribution Function (CDF) where distribution would range 0-1 (Hardakar et al., 2004: 157-166). A value from the Y-axis is taken randomly, and CDF is computed. By inverting the CDF function, the value on the X-axis is obtained. This is shown in Figure 4.

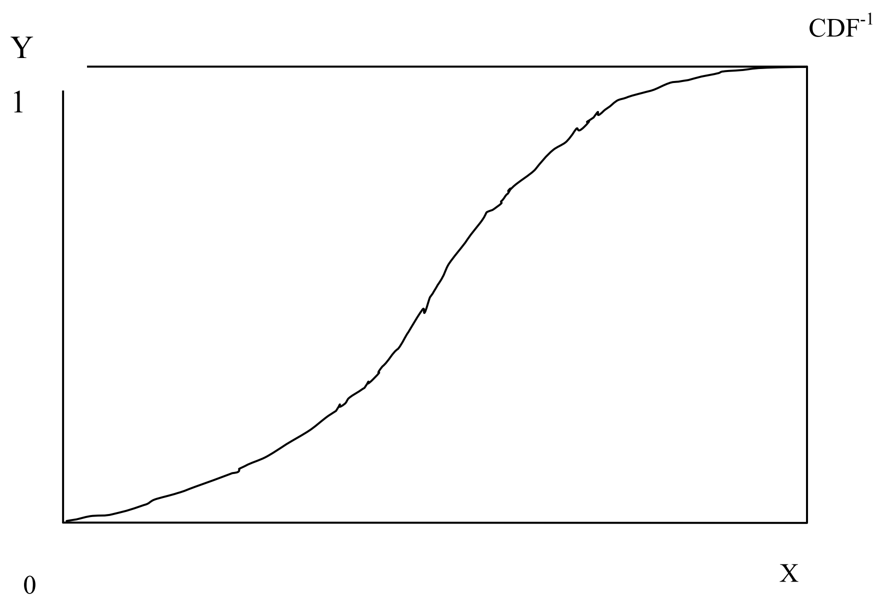

Figure 4

Inverse Function of Cumulative Distribution Function (CDF)

Multivariate Simulation

A multivariate stochastic simulation technique has been developed to generate analogous samples and used to evaluate alternative insurance products (Anderson, Barnett, and Coble, 2009).

Parametric distribution fitting imposes a family of probability density to a data series while non-parametric does not impose a specific density structure and allows the empirical data to drive probability. The parametric distribution smoothes the data and a distribution will generate observations outside the range of empirical data. Parametric distribution procedures add information to the estimation and make the estimation more efficient if the data is drawn from the distribution imposed. However, imposing the wrong distribution introduces error. Estimating CDFs precisely, reliable simulation techniques are important for conducting a rigorous agricultural risk analysis. To use the PQH simulation technique, the yield trend will be estimated and removed from the data before fitting parametric distributions.

Several studies in agricultural economics support the use of beta distribution for yield data and log normal distribution for price data (Roberts, Goodwin and Coble, 1998). Crop yields are non-negative, and the beta distribution ranges from 0 to 1, but can be scaled to any interval. However, one must impose or estimate the upper and lower bound to assume for scaling. Price is non-negative having lower bound value zero to upper bound positive infinitive. These parametric assumptions were tested for historical data. The marginal probability distribution and correlation matrix for the original data set were obtained. Using Eigen values and decomposition of correlation matrix, 100,000 sample data for price and yield were generated through PQH simulation technique.

Price and yield are random variables but may not be independent. The correlation of price-price, yield-yield, and price-yield has been noticed. Crop yield has often been found negatively correlated with price. The stochastic price, stochastic yield, and interaction of both price and yield were allowed in the simulation procedure (Hardakar et. al., 2004:157-181).

While moving from farm-level data to county-level data, basis risk would occur as those yields tend to be positively but not perfectly correlated with each other. Therefore, the basis risk was analyzed for each available insurance model and was used in indentifying the certainty equivalent of each model. Assuming the farmers are moderately risk-averse and considering the risk-aversion coefficient of 2, returns from all available insurance products were converted to utility values using the constant relative risk aversion (CRRA) function as mentioned above. Likewise, the certainty equivalent for differing expected utility risk-aversion values was compared to measure the benefit of CAWFI to producers of varying regions and crop mixes.

Construction of CAWFI Model

Customizable area whole farm insurance (CAWFI model was constructed assigning appropriate weighting mechanism, searching for optimal scale, and investigating optimal coverage level.

<u>Assign of Appropriate Weight in CAWFI Model</u>

Crop revenue weights were required to construct the CAWFI model. The percentage of expected crops revenue in the multiple crop farming was chosen as an appropriate weighting mechanism to customize county revenue to farm level. In the case of a single crop farm, the weight is obviously one. The reason behind choosing revenue share as an appropriate weight for CAWFI is that farmers would plan to grow crops based on the revenue percentage of the particular crop in the farm. For instance, there are two crops corn and soybean in a farm where corn shares 75% of expected revenue and soybean shares 25% of expected revenue. A crop that is generating a higher percentage of expected revenue would be more likely to have higher weight and vice versa.

Optimal Scale and Optimal Coverage Level Assign on CAWFI Model

One of the fundamental issues addressed in this study was also to find an optimal scale to the CAWFI model so that it could customize area yield into farm-level more accurately. Based on crop mix, different optimal CAWFI scales were expected across the farm types. The optimal weights obtained as a revenue share of crops in the farm were fixed, and a search was conducted to find optimal scale for the CAWFI model.

In search for the optimal scale, initially it was allowed that both scale and coverage levels vary simultaneously to arrive at an optimal point. Scale and coverage level were unrestricted, and the optimal scale was obtained for different crop mixes in Kansas and North Dakota. Using equation (13), beta coefficients were estimated for each crop and crop mix independently. It was found that those beta coefficients were very close to optimal scales obtained for Kansas and North Dakota. In the same way, beta coefficients for all single crops as well as multiple crop revenue cases were obtained and used as optimal scales, which later were used in estimating indemnity in the CAWFI model. Based on these beta coefficients (optimal scale), a grid search was performed for optimal coverage level for the model in the interval of 0.05 starting from 0.80 to 1.80. This grid search was performed on each farm type across all regions. Thus, the CAWFI model with optimal scale and optimal coverage level was developed and will be called 'optimal CAWFI' hereafter.

Evaluation of Optimal CAWFI with Restricted CAWFI

Optimal CAWFI was evaluated for the single crop as well as multiple crop revenue scenarios with its baseline in four geographical regions. The optimal scale and coverage level were assigned to estimate optimal CAWFI-certainty equivalents revenue. GRP uses a scale ranging from 0.90 to 1.50 and a maximum coverage level 0.90. For the restricted CAWFI model, the maximum GRP coverage level of 0.90 was used. For the optimal scale 1.50 or optimal CAWFI scale, whichever would be lower was used. The baseline model is referred to as "restricted CAWFI model" as its coverage level and scale are restricted per the GRP model. The certainty equivalents revenue were estimated, and the relative difference in certainty equivalent revenue between optimal and restricted CAWFI were estimated for each crop on the single crop farm and for each crop mix in the multiple cropping farm.

Optimal CAWFI's Performance over No-Insurance and CFWFI

The optimal CAWFI model was compared with the No-insurance program as well with the CFWFI program. We followed basically two criteria to compare CAWFI's with CFWFI:

(i) Certainty equivalents revenue

(ii) Indemnity payoff

The certainty equivalent criterion was used to observe which model would generate higher certainty equivalents to insurers. Both the CAWFI and CFWFI were the hypothetical insurance products, so the actuarially fair premium rate was used to compare with. In actuarially fair premium rate, the indemnity generated is equaled to expected indemnity. The indemnity pay out criteria was used to observe the magnitude of payments for the farmer. The expected indemnity is the actuarially fair premium for the insurance product that explains the risk reduction ability of the model. The market premium rate includes transaction cost, government subsidy, and administrative cost, from which risk reduction of the model cannot be accessed.

The logic behind the comparison of CAWFI against no-insurance program is that risk-averse farmers will buy insurance when they can protect their revenue at least better than no-insurance program. Because the program is actuarially fair, participation would not change mean ending wealth, but an effective risk management tool will reduce risk, which increases the certainty equivalent for a risk-averse farmer. The CFWFI was taken as an instrument to compare with this as a whole farm insurance product based on farm-level yield. The optimal CAWFI was evaluated across geographical regions for all farm types in the multiple crop case and for all crops in the single crop case.

For the all types of evaluation in this study, initially, the net return under different crop and crop mixes across all regions was estimated and converted into expected utility assuming CRRA utility function of wealth for the moderately risk-averse farmers, assuming the risk aversion coefficient 2. Finally, those expected utility values were converted into the certainty equivalents revenue, and comparisons were made based on these certainty equivalents revenues.

Sensitivity Test on the Optimal CAWFI Model

In this study, mainly two assumptions have been made. The revenue share of crop in the farm was considered as an appropriate weight in the optimal CAWFI, and all calculations were made assuming the moderately risk-averse behavior of farmers. Sensitivity tests for these two assumptions were made to confirm what else would result if the assumptions were not held.

CHAPTER V

RESULTS AND DISCUSSIONS

Data Description

The county-level yields and planting and harvesting prices at planting for corn, soybean, and wheat were used in this study. The brief description of the data is discussed below.

County-Level Yield

The descriptive statistics of raw data (before detrending yield) is presented in table 1. It describes mean, standard deviation, minimum, and maximum values of data set across crops for all locations.

Among the three crops (corn, soybean, and wheat), Illinois corn has a higher mean value with respect to the other locations. Both the mean and standard deviation for wheat are similar in Kansas and North Dakota. Mean soybean yields are higher in Illinois as compared to Mississippi, but the two locations have similar standard deviations.

Table 1

Descriptive Statistics of County-Level Yield Prior to Detrending

Location	Crop	Mean	Standard Deviation	Minimum	Maximum
Mclean County, Illinois	Corn	143.28	31.36	62.00	196.00
	Soybean	45.40	6.64	25.50	54.00
Yazoo County, Mississippi	Corn	95.10	31.61	29.50	150.80
	Soybean	26.45	7.60	16.00	40.00
Sheridan County, Kansas	Corn	137.75	18.80	97.00	177.00
	Wheat	37.65	9.66	17.00	58.00
Barnes County, North Dakota	Corn	78.79	32.31	20.90	146.00
	Wheat	35.41	10.24	15.40	59.00

Yield Detrending and Current Adjustment

The county-level yields from 1975 to 2009 were detrended. The estimation of trend coefficient using equation (18) along with the standard errors and p values is presented in table 2.

Table 2

Estimation of Trend Coefficient for County Yield

Location	Crop	Coefficient	Std. Error	p value
Mclean County, Illinois	Corn	2.15 ***	0.378	<.0001
	Soybean	0.40***	0.087	<.0001
Yazoo County, Mississippi	Corn	2.81***	0.22	<.0001
	Soybean	0.42***	0.106	0.0003
Sheridan County, Kansas	Corn	0.36	0.313	0.2557
	Wheat	0.41	0.163	0.682
Barnes County, North Dakota	Corn	2.49***	0.335	<.0001
	Wheat	0.61***	0.136	<.0001

*** indicates significance at 1% level.

The trend coefficients are significant in all crops across states except in Kansas. The trend coefficient for corn in Kansas is very low as compared with the trend coefficient of corn in other locations. The Kansas corn yield seems increasing in decreasing order until 2000, but after 2000, it has dropped down continuously, which might be the possible reason the trend coefficient was low. Based on these trend coefficients, detrended county yield were obtained in the counties for all crops across states using equation (19). The detrended county yield data were subsequently used to simulate farm level yield.

The descriptive statistics of county yield after detrending and adjusting to current year 2010 yield have been presented in table 3 which describe mean and standard deviation.

Table 3

Descriptive Statistics of Detrended Yield after Current Adjustment

Location	Crop	Mean	Std. Deviation
Mclean County, Illinois	Corn	180.33	22.25
	Soybean	52.56	5.11
Yazoo County, Mississippi	Corn	148.69	12.6
	Soybean	32.77	6.36
Sheridan County, Kansas	Corn	137.97	19.35
	Wheat	35.67	11.05
Barnes County, North Dakota	Corn	119.71	21.9
	Wheat	45.28	8.14

From table 3, Illinois corn yield is shown to have a higher mean as compared with corn yields in other locations. The mean soybean yield is higher in Illinois as compared to Mississippi. The mean wheat yield of North Dakota is higher than Kansas while the standard deviation in North Dakota is lower Kansas.

Farm-Level Yield Simulation from County-Level Yield

To simulate farm yield from county level yield, the standard deviation of idiosyncratic farm yield was obtained through a grid search. The results of grid search conducted to obtain the standard deviation value for all crops across all locations has presented in figure 5

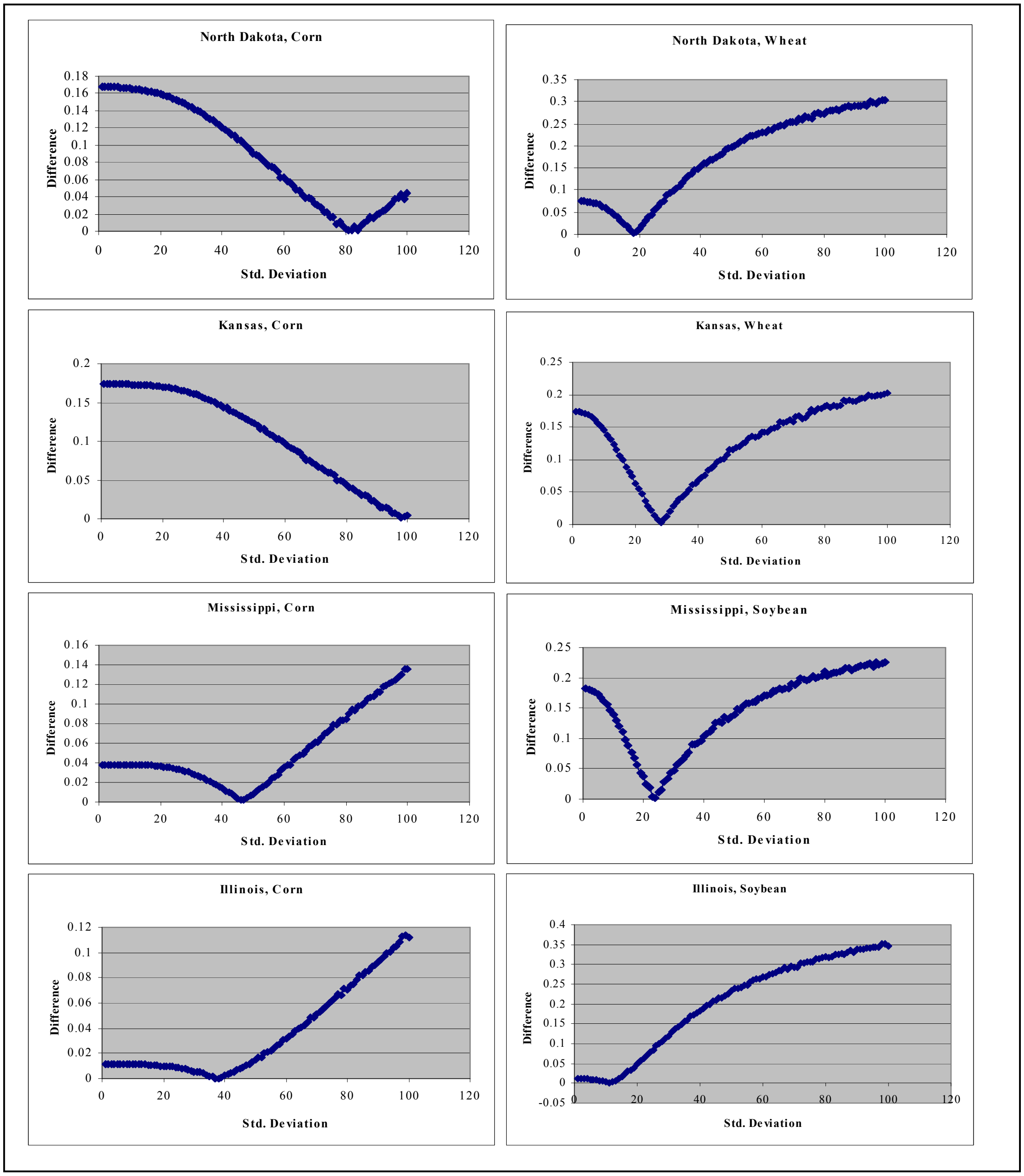

Figure 5

The Grid Search Results to Obtain Standard Deviation of Idiosyncratic Yield Risk in All Locations across Crops

The graphical result in figure 5 suggests that in the representative corn farm in Kansas, the optimization solution is at the end of the range. In the representative soybean farm in Illinois, the optimal solution is relatively flat. For the rest of the representative farms, the optimal solution can clearly be observed at the bottom of U-shaped curve.

The estimated standard deviations of the idiosyncratic yield risk, based on grid search results presented in figure 5 using the equations (20) and (21) are presented in table 4.

Table 4

Standard Deviation of Idiosyncratic Yield Risk across Crops and States

Location	Crop	Standard Deviation of the Idiosyncratic Yield risk
Mclean County, Illinois	Corn	37
	Soybean	11
Yazoo County, Mississippi	Corn	48
	Soybean	23
Sheridan County, Kansas	Corn	96
	Wheat	27
Barnes County, North Dakota	Corn	79
	Wheat	18

Comparing across the crops and the states, the idiosyncratic yield risk was the highest in Kansas corn ($\sigma = 94$), and the lowest in Illinois soybean ($\sigma = 11$). Farm yields were simulated for each crop in each state by incorporating the estimated idiosyncratic yield risk values in the equation (20) into equation (21).

The standard deviation of county yield was compared with the standard deviation of representative farm-level yield for all crops across states using table 3 and table 4. The standard deviation of county level yield is relatively lower as compared to the standard deviation of representative farm yield for all crops across states. The representative farm yield has a standard deviation almost double that of the standard deviation of county-level yield in soybean farm in Illinois. In the same way, the standard deviation of representative farm yield of corn in Mississippi is almost four folds as compared to standard deviation of county yield of corn in Mississippi.

Descriptive Statistics of Simulated Observations (N=100,000)

The farm-level yields, county-level yields, and prices were simulated to generate 100,000 observations. The descriptive statistics of 100,000 simulated observations used during this study are presented in Table 5. This table shows the mean and standard deviation of the study data. The ending futures price of soybean has the highest standard deviation from its mean as compared to other crops, 1.53 and 1.28, respectively. The ending futures price deviation for wheat, corn, and cotton are less than one. The corn farm yield is less variable in Mississippi and Illinois and more variable in Kansas and North Dakota. The Illinois corn yield has a higher mean and lower variance as compared to Mississippi corn. Mississippi and Kansas corn has similar mean yields but standard deviation is very high in Kansas corn as compared to Mississippi corn. For corn county yield, variation is lowest in Mississippi and seems very close in the other three States. The Mississippi soybean farm yield is more variable than Illinois (i.e., the standard deviation of soybean farm yield is double in Mississippi as compared to Illinois). Illinois soybean has higher mean and lower variance as compared to Mississippi soybean. The county-level soybean yield variation is similar in Illinois and Mississippi. In the case of wheat, the farm- as well as county-level yield in North Dakota has higher mean with lower variance as compared to Kansas.

Table 5

Descriptive Statistics of Simulated Data (N=100000)

Variable	Mean	Std Dev.	Mean	Std Dev.
Ending Futures Price of Corn	6.19	0.53		
Ending Futures Price of Soybean	13.11	1.54		
Ending Futures Price of Wheat	9.08	0.94		
	Mississippi		**Illinois**	
Corn Farm Yield	145.45	49.53	182.72	43.20
Corn County Yield	148.70	12.62	180.48	22.24
Soybean Farm Yield	37.53	22.69	53.29	11.19
Soybean County Yield	32.76	6.38	52.56	5.12
	North Dakota		**Kansas**	
Corn Farm Yield	129.98	76.27	143.58	77.76
Corn County Yield	119.75	21.93	137.95	19.27
Wheat Farm Yield	46.76	18.25	32.74	21.60
Wheat County Yield	45.29	8.14	35.67	11.09

Revenue Share of Crop as an Appropriate Weight

The revenue percentage of individual crops in the multi-crop farm is presented in Table 6 for the multiple crop case on Kansas, Mississippi, North Dakota, and Illinois farms.

Table 6

Revenue Share of Crops in Different Crop Mixes across States

		Revenue Share of Crops		
State	Crop Mix	Corn	Soybean	Wheat
Mississippi	Equal Acres	0.647	0.353	
(2 Crops)	Corn Major	0.810	0.190	
	Soybean Major	0.440	0.560	
Illinois	Equal Acres	0.618	0.382	
(2 crops)	Corn Major	0.791	0.209	
	Soybean Major	0.410	0.590	
Kansas	Equal Acres	0.750		0.250
(2 crops)	Corn Major	0.875		0.125
	Wheat Major	0.562		0.438
North Dakota	Equal Acres	0.655		0.345
(2 Crops)	Corn Major	0.816		0.184
	Wheat Major	0.448		0.552

Note: All crop mixes are as defined in method section

The ending futures prices for corn, soybean, and wheat were used to estimate revenue share of crops in the farm under different crop mixes. To estimate revenue share of crops, mean farm yield of each crop was multiplied by the respective ending futures prices. Then, those percentages were converted according to the crop mix. For example, in the Mississippi corn-soybean farm, revenue share of crops in equally distributed acres of crops in the farm is given as:

Corn farm yield * ending futures prices of corn* 0.50.

As mentioned in Table 6, the revenue share of crops is quite different across farm types in the same state. In Mississippi, Illinois, and North Dakota, when corn is not the major crop, its revenue share is below 50%. Either it is in equally distributed acres or on a corn major farm; corn revenue share is fairly greater than other crops. In Kansas, corn is sharing more than half the farm's revenue even in soybean major farms. Corn's dominance over soybean or wheat can be observed in contributing revenue in the farm.

These results suggest that revenue percentage of crops in the multi-crop farm vary according to states and farm types. This is the reason why different weights were assigned to crops according to crop mix across states.

Optimal CAWFI Estimation

In the four different geographical locations, the optimal scale and coverage level were identified for single crop farms as well as for multi-crop farms. The CAWFI model with these optimal scale and coverage level is known as optimal CAWFI.

Single-Crop Farm

For the single crop in four states, the optimal scales (beta coefficient), optimal coverage levels were estimated for all crops in all locations.

Optimal Scale

The response of deviation of county revenue from its mean on farm revenue for single crop scenarios in Kansas, North Dakota, Illinois, and Mississippi were estimated using OLS from the 100,000 samples. The coefficient estimation using equation (13) in single crop context is presented in table 7.

Table 7

Single-Crop: Estimation of Optimal Scale

State	Crop/Crop Mix	Coefficient	Standard Error	P Value
Kansas	Corn	2.74^{***}	0.005	<0.0001
	Wheat	1.63^{***}	0.002	<0.0001
North Dakota	Corn	2.59^{***}	0.005	<0.0001
	Wheat	1.79^{***}	0.003	<0.0001
Mississippi	Corn	2.01^{***}	0.005	<0.0001
	Soybean	2.32^{***}	0.007	<0.0001
Illinois	Corn	1.45^{***}	0.002	<0.0001
	Soybean	1.46^{***}	0.003	<0.0001

*** Significant at 1% level.

These beta coefficients are used as the optimal scale in the CAWFI model. The beta coefficients are significant in all crops for all locations. This beta coefficient is the measure of linear response of county revenue deviation to farm revenue deviation from mean. These optimal scale values vary across crops as well as regions. In Kansas, corn shows higher optimal scale than wheat -- 2.74 versus 1.63. A similar result is found in the North Dakota corn and wheat, which are 2.59 and 1.79, respectively. Both states are assumed to grow the same crops -- corn and wheat. The case of Illinois is different than previous states where optimal scale for corn and soybean are almost equal, i.e., 1.45 and

1.46, respectively In Mississippi; optimal scale for soybean is higher than corn, which is also seen in Illinois. Mississippi and Illinois are growing the same crops, corn and soybean.

Optimal scale also varies for the same crops across states. Corn is the only crop in this study assumed to grow in all four states. While comparing the scale for corn across states, Kansas has the highest value, and then North Dakota, Mississippi, and Illinois in descending order ranging from 2.74 to 1.45. Optimal scale for soybean in Mississippi is 2.32, which is higher than the optimal scale in Illinois, 1.46. In the same way, North Dakota wheat and Kansas wheat have different optimal scales, respectively 1.79 and 1.63.

The optimal scales for all crops across states are above 1.00. These results are consistent with Deng, Barnett, and Vedenov (2007) and Miranda (1991), but note that their works were on single crop area yield not in the area revenue.

Optimal Coverage Level

Optimal coverage levels are investigated based on the optimal scale, and are presented in Table 8 for single crop farms in four states.

Table 8

Single-Crop: Optimal Coverage Level for Optimal Scale

State	Crop	Optimal Scale	Optimal Coverage Level
Kansas	corn	2.74	1.35
	Wheat	1.63	1.40
North Dakota	Corn	2.59	1.30
	Wheat	1.79	1.35
Illinois	Corn	1.45	1.30
	Soybean	1.46	1.40
Mississippi	Corn	2.01	1.25
	Soybean	2.32	1.50

The optimal coverage level also varies across crops as well as regions. Mississippi soybean has the highest optimal coverage level, 1.50, while Mississippi corn has the lowest optimal coverage level (1.25) among all the crops. Illinois corn and soybean have different optimal coverage levels, 1.30 and 1.40, respectively. Corn has different optimal coverage levels across states: it is highest in Kansas, 1.40, and lowest in Mississippi, 1.25. Wheat in Kansas and North Dakota has 1.40 and 1.35 optimal coverage levels, respectively. Soybean optimal coverage levels range among the two states more than wheat (1.50 in Mississippi and 1.40 in Illinois). The optimal coverage levels for soybean are also higher than other crops, which reflect that farmers would have to go for higher coverage levels in soybean to fully protecting their farm revenue. Illinois corn and soybean have the lowest optimal scale, but their optimal coverage levels are not the highest among all.

For all crops across states, optimal coverage levels for optimal scales are greater than 1.00. In area product, GRP, Deng, Barnett, and Vedenov (2007) have found the similar result -- when the restriction is relaxed, optimal coverage level moves above 1.00. Deng, Barnett, and Vedenov's study proved this in the case of area yield insurance, which, based on this analysis, applies to CAWFI as well. Deng, Barnett, and Vedenov assert that optimal scale partially compensates for optimal coverage level when one of those is restricted. In this analysis, the scale and coverage levels were relaxed, so, that relationship could not be observed here.

Multiple Crops Farm

In the two crops revenue case, the beta coefficient (optimal scale) for each crop mix across all four states was also estimated. Based on those optimal scales, optimal coverage level was investigated using a grid search for all crop mixes in all locations.

Optimal Scale

The response of deviation of county revenue from its mean to farm revenue deviation from its mean in multiple crop case in Kansas, North Dakota, Illinois, and Mississippi for all crop mixes was estimated using equation (13) in multi-crop revenue is presented in table 9.

Table 9

Multiple Crops: Estimation of Optimal Scale

State	Crop/Crop Mix	Coefficient	Standard Error	P Value
Kansas	Equal Acres	2.02***	0.003	<0.0001
	Corn Major	2.28***	0.004	<0.0001
	Wheat major	1.87***	0.003	<0.0001
North Dakota	Equal Acres	1.98***	0.003	<0.0001
	Corn Major	2.21***	0.004	<0.0001
	Wheat major	1.81***	0.003	<0.0001
Mississippi	Equal Acres	2.4***	0.005	<0.0001
	Corn Major	2.12***	0.005	<0.0001
	Soybean Major	2.85***	0.005	<0.0001
Illinois	Equal Acres	1.29***	0.002	<0.0001
	Corn Major	1.32***	0.002	<0.0001
	Soybean Major	1.41***	0.002	<0.0001

*** Significant at 1% level.

These beta coefficients are the optimal scales that are used in optimal the CAWFI model for multiple crop revenues. As in single crop cases, these beta coefficients in multiple crop revenue cases are the linear response of farm revenue deviation from its mean on county revenue deviation from its mean. All the coefficients are significant.

In the multiple crop revenue cases, beta coefficients are varied across crop mixes and also across states in the same crop mix. The soybean major farm in Mississippi has the highest beta coefficient, and the equal acres farm in Illinois has the lowest beta coefficient among all.

The optimal scales found are the beta coefficient, varies for the same crop mix across states. The coefficients for all crop mixes are very low in Illinois as compared to others. Likewise, in single crop, and in this multiple crop revenue case, optimal scales are greater than 1.0 for all crop mixes across all geographical regions. This finding is similar with Deng, Barnett, and Vedenov (2007), Miranda (1991) asserts that in single-crop area yield context when the farmers are freed to choose scale, they would go beyond 1.00. The scales differ across states, even in the same crop mix.

Optimal Coverage Level

The optimal coverage levels for optimal scale in each crop mix across states in multiple crops are in the Table 10.

Table 10

Multiple Crops: Optimal Coverage Level for Optimal Scale

Region	Crop Mix	Optimal Scale	Optimal Coverage Level
Kansas	Equal Acres	2.02	1.25
	Corn Major	2.28	1.35
	Wheat Major	1.87	1.35
North Dakota	Equal Acres	1.98	1.35
	Corn Major	2.21	1.45
	Wheat Major	1.81	1.30
Illinois	Equal Acres	1.29	1.20
	Corn Major	1.32	1.30
	Soybean major	1.41	1.20
Mississippi	Equal Acres	2.40	1.20
	Corn Major	2.12	1.25
	Soybean major	2.85	1.20

These optimal coverage levels are varied across crop mixes. For example, in Kansas, optimal coverage levels are lower, 1.25 on equal acres farms, whereas corn major and soybean major farms have higher than optimal coverage levels as compared to equal acres farms, 1.35. In both Illinois and Mississippi, optimal coverage levels are lower than other states. In Mississippi, the range is 1.20 – 1.25 whereas in Kansas the range is 1.20-1.30.

The optimal coverage levels in CAWFI are varied across states for the same crop mix. For the equal acres farm, North Dakota has the highest optimal coverage level, followed by Kansas, and Mississippi and Illinois being the lowest. For the corn major farm, North Dakota has the highest optimal coverage level followed by Kansas, Illinois, and Mississippi. The wheat major Kansas farm has a higher optimal coverage level than the North Dakota wheat major farm. Only for the soybean major farm, both Illinois and Mississippi have an equal optimal coverage level, 1.20.

As in the single crop, in this multiple crop revenue case, optimal coverage levels are greater than 1.00 for all crop mixes across all geographical regions. This finding is similar with Deng, Barnett, and Vedenov (2007) for the single crop area yield product, GRP context.

Effects of Imposing Restriction on CAWFI Model

The optimal CAWFI is compared with the restricted CAWFI model where maximum scale and coverage level allowed in GRP are used to estimate restricted CAWFI certainty equivalent revenue. In this study, the optimal CAWFI was compared in single crop as well as multiple crop revenue contexts for all crops and crop mixes across states.

<u>Single Crop Farm: Optimal CAWFI vs. Restricted CAWFI</u>

In Kansas, North Dakota, Illinois, and Mississippi, certainty equivalent revenue for all crops in the farm were estimated. The certainty equivalent revenue for both optimal as well as restricted models was obtained. The focus here is to observe how restriction on scale and coverage level reduces the certainty equivalent revenue for the insured. The general expectation here was that putting a restriction on scale and coverage level would lower an insured's welfare and that relaxing a restriction may increase a farmer's welfare. These results have been presented in Table 11 below

Table 11

Single Crop: Optimal CAWFI vs. Restricted CAWFI

State	Crop	Optimal Scale for Optimal CAWFI	Optimal Coverage. Level for Optimal CAWFI	Max. GRP Scale for Restricted CAWFI	Max. GRP Coverage Level for Restricted CAWFI	Lower CER in Restricted CAWFI than Optimal CAWFI by (%)
Kansas	corn	2.74	1.35	1.5	0.9	-12.98
	Wheat	1.63	1.4	1.5	0.9	-10.77
North Dakota	Corn	2.59	1.3	1.5	0.9	-13.57
	Wheat	1.79	1.35	1.5	0.9	-5.44
Illinois	Corn	1.45	1.3	1.45	0.9	-4.78
	Soybean	1.46	1.4	1.46	0.9	-3.12
Mississippi	Corn	2.01	1.25	1.5	0.9	-9.61
	Soybean	2.32	1.5	1.5	0.9	-11.94

Note: CER stands for Certainty Equivalent revenue

Imposing constraint in choosing scale and coverage level in single crop county revenue has reduced farmers' certainty revenues ranging from 3.12% in Illinois soybean to 13.57% in North Dakota corn.

Evaluating crops across states, Mississippi corn has almost equal percentage of certainty equivalent revenue loss to Kansas wheat. Mississippi soybean is facing almost equal percentage of certainty equivalent loss to Kansas corn. In both states for both crops, loss percentages are very high. North Dakota wheat has a similar percentage of loss of certainty equivalent revenue as in Illinois corn while the percentage certainty revenue loss in North Dakota corn is very close to Kansas corn. As in area yield products, the imposition of restriction on scale and coverage level has reduced the farmer's expected utility in this single crop optimal CAWFI.

<u>Multiple Crops Farm: Optimal CAWFI vs. Restricted CAWFI</u>

Similar to single crop, this study estimated the certainty equivalent revenue for the optimal CAWFI as well as restricted CAWFI model in multiple crops. The certainty equivalent revenues were estimated for Kansas, North Dakota, Illinois, and Mississippi in all crop mixes. Prior expectation here was also the same as in the single crop revenue case that is relaxing restriction on CAWFI can increase farmer's expected utility. Based on certainty equivalent revenue, the percentage loss in restricted CAWFI models is presented in Table 12.

Table 12

Multiple Crops: Optimal CAWFI vs. Restricted CAWFI

State	Crop Mix	Optimal Scale for Optimal CAWFI	Optimal Coverage Level for Optimal CAWFI	Max. GRP Scale for Restricted CAWFI	Max. GRP Coverage Level for Restricted CAWFI	Lower CER in Restricted CAWFI than Optimal CAWFI by (%)
Kansas	Equal Acres	2.02	1.25	1.5	0.9	-9.15
	Corn Major	2.28	1.35	1.5	0.9	-10.36
	Wheat Major	1.87	1.35	1.5	0.9	-8.49
North Dakota	Equal Acres	1.98	1.35	1.5	0.9	-6.28
	Corn Major	2.21	1.45	1.5	0.9	-8.38
	Wheat Major	1.81	1.3	1.5	0.9	-4.48
Illinois	Equal Acres	1.29	1.2	1.29	0.9	-3.64
	Corn Major	1.32	1.3	1.32	0.9	-3.92
	Soybean Major	1.41	1.2	1.41	0.9	-3.56
Mississippi	Equal Acres	2.4	1.2	1.5	0.9	-11.27
	Corn Major	2.12	1.25	1.5	0.9	-9.95
	Soybean Major	2.85	1.2	1.5	0.9	-13.85

Note: CER stands for Certainty Equivalent revenue

The restriction imposed on farmers in selecting scale and coverage level in multiple crops optimal CAWFI has reduced certainty equivalent revenue by 3.56% in the soybean major farm in Illinois and by 13.85% in the soybean major farm in Mississippi.

In Kansas, the corn major farm has the highest certainty equivalent revenue loss percentage, followed by the equal acres farm and wheat major farm in Kansas. In North

Dakota, restricting scale and coverage level would decrease certainty equivalent revenue by 8.38% in the corn major farm, followed by the equal acres farm and wheat major farm. The results in Kansas and North Dakota have shown a similar pattern; however, the percentage loss in North Dakota is lower than in Kansas. Illinois farms have the lowest percentage loss for all crop mixes among all states. In Mississippi, the soybean major farm has the highest percentage of expected utility loss followed by the equal acres farm and corn major farm. Mississippi farms have a higher percentage loss as compared to Illinois for all crop mixes though both states have grown the same crops.

Restriction on scale and coverage level has yielded different percentages of loss in the same crop mixes across states. As in the single crop CAWFI, multiple crops CAWFI produces the similar results that imposing a restriction to the CAWFI model would reduce farmers' welfare. This result is consistent with the area yield product, GRP, where restriction on scale and coverage reduces farmers' expected utility.

Evaluation of Optimal CAWFI with No-Insurance and Whole Farm Insurance (CFWFI)

The optimal CAWFI's performance was evaluated against no-insurance program, restricted CAWFI program, or whole farm insurance based on farm-level yield (CFWFI). This study compares certainty equivalent revenue generated by each model and also compares expected indemnity payouts. The comparisons were made for single crop CAWFI as well as multiple crops CAWFI.

Evaluation in Single Crop Farm

The certainty equivalent revenue for Kansas, North Dakota, Illinois, and Mississippi for all crops was estimated with no program, optimal CAWFI, restricted CAWFI, or CFWFI, which have been presented in relative percentage in Table 13. In addition, to evaluate among these three models, expected indemnity for each models have also been estimated and presented in the same table.

Table 13

Single Crop: Optimal CAWFI vs. No-Insurance and 90% CFWFI

State	Crop	Ratio of CER in 90% CFWFI to No Program	Ratio of CER in Optimal CAWFI to No program	Ratio of CER in Restricted CAWFI to No Program	Ratio of Expected Indemnity in Optimal CAWFI to 90% CFWFI	Ratio of Expected Indemnity in Restricted CAWFI to 90% CFWFI
Kansas	Corn	1.23	1.23	1.08	3.84	0.28
	Wheat	1.31	1.32	1.18	2.36	0.75
North Dakota	Corn	1.28	1.27	1.12	2.86	0.35
	Wheat	1.11	1.12	1.06	3.76	0.57
Illinois	Corn	1.10	1.10	1.04	4.94	0.63
	Soybean	1.03	1.05	1.02	7.49	0.56
Mississippi	Corn	1.10	1.13	1.03	4.14	0.16
	Soybean	1.81	1.70	1.55	3.36	0.32

Note: Scale and Coverage Level for Optimal and Restricted CAWFI are in table 5

The optimal CAWFI increases certainty equivalents relative to no-insurance program in all crops for the single crop revenue scenario. In the previous section, it was shown that optimal CAWFI outperforms restricted CAWFI. The restricted CAWFI's certainty equivalent revenue was also compared against no-insurance program. Results show that, in each crop in all four states, even restricted CAWFI's certainty equivalent revenues are greater than no-insurance program. The restricted CAWFI outperforms over no-insurance program by 2% in Illinois soybean farm and by 55% in the Mississippi soybean farm. That the restricted and optimal CAWFI are able to produce more certainty equivalent revenue compared with no-insurance program illustrates that CAWFI is a workable insurance product that can protect farmers from loss.

The certainty equivalent revenue in whole farm insurance based on farm-level yield (CFWFI) and optimal CAWFI were compared with no-insurance program for baseline. As CFWFI and optimal CAWFI were compared for some crops in some states, CAWFI performs better and for some other crops CFWFI performs better. For instance, optimal CAWFI in Kansas wheat outperforms by 1% more over no-insurance program than CFWFI, optimal CAWFI in North Dakota wheat also outperforms by 1% more than CFWFI over no-insurance program. That the optimal CAWFI produces higher certainty equivalents as compared with 90% CFWFI in most of the crops illustrates that optimal CAWFI can minimize the whole farm risk as equally as CFWFI.

Based on the actuarially fair rate of insurance premium, an evaluation was made across three models -- optimal CAWFI, restricted CAWFI, and 90% CFWFI. The expected indemnity for each model was compared for all crops in all states, considering 90% CFWFI as a baseline. The expected indemnities for optimal CAWFI are highest among these three models in each state for all crops, followed by 90% CFWFI, and restricted CAWFI having the lowest indemnity payouts.

In the single crop context, the expected indemnity in optimal CAWFI is 236% higher in Kansas wheat to 749% in Illinois soybean as compared with 90% CFWFI. Farmers would have to pay from more than two folds to more than seven folds for optimal CAWFI as compared with 90% CFWFI depending upon crop mix and state. However, the restricted CAWFI produces lower certainty equivalent revenue, but it can provide protection to farmers with fairly lower premiums as compared to 90% CFWFI.

Evaluation in Multiple Crops Farm

Optimal CAWFI, restricted CAWFI, and CFWFI under multiple crop scenarios were compared using the certainty equivalents and expected indemnity payouts for those models. Results are in Table 14.

Table 14

Multiple Crops: Optimal CAWFI vs. No-Insurance and 90% CFWFI

State	Crop Mix	Ratio of CER in 90%CFWFI to No Program	Ratio of CER in Optimal CAWFI to No Program	Ratio of CER in Restricted CAWFI to No Program	Ratio of Expected Indemnity in Optimal CAWFI to 90% CFWFI	Ratio of Expected Indemnity in Restricted CAWFI to 90% CFWFI
Kansas	Equal Acres	1.15	1.17	1.07	3.41	0.39
	Corn Major	1.18	1.19	1.08	4.09	0.34
	Wheat Major	1.15	1.17	1.08	4.41	0.44
North Dakota	Equal Acres	1.10	1.11	1.05	4.40	0.45
	Corn Major	1.15	1.16	1.07	4.43	0.40
	Wheat Major	1.07	1.09	1.04	4.66	0.48
Illinois	Equal Acres	1.03	1.06	1.02	5.67	0.52
	Corn Major	1.04	1.07	1.03	6.48	0.59
	Soybean Major	1.01	1.04	1.01	7.07	0.44
Mississippi	Equal Acres	1.09	1.15	1.03	4.20	0.14
	Corn Major	1.09	1.13	1.03	4.76	0.15
	Soybean Major	1.11	1.18	1.04	4.06	0.13

Note: Scale and Coverage Level for Optimal and Restricted CAWFI are in table 6

The optimal CAWFI produces greater certainty equivalent revenue compared with no-insurance program in multi-crop revenue context, too. It produces 4% more certainty equivalent revenue in the soybean major farm in Illinois to 19% more in the corn major farm in Kansas. Not only that, even restricted CAWFI is producing 1% to 8%

more certainty equivalent revenue as compared with no-insurance program. These results show that CAWFI is a workable insurance product for multiple crop area revenue contexts, too.

The interesting result in multiple crop contexts is that optimal CAWFI outperforms 90% CFWFI in each state for all crop mixes. The gap is very narrow for all crop mixes in Kansas and North Dakota, i.e., 1% to 2% more, while it is wider in Illinois and Mississippi. In the equal acres farm in Mississippi, optimal CAWFI exceeds 90% CFWFI by 6% and by7% in the soybean major farm in Mississippi. This result shows that appropriate weight, optimal scale, and optimal coverage level assigned to CAWFI would be able to minimize basis risk equally as a farm-level product while estimating the multi-crop area revenue context.

However, the optimal CAWFI produces higher certainty equivalent revenue, the expected indemnity pay outs for this product is at least three fold to more than seven fold across states and farm types. The expected indemnities in optimal CAWFI are more than three fold in the equal acres farm in Kansas to more than seven fold in the soybean major farm in Illinois. To protect the farm revenue as equally with the 90% CFWFI, farmers with optimal CAWFI would have to pay at least three times the premium; this may go more than seven folds. The gap of expected indemnity is wider between optimal CAWFI and 90% CFWFI. It should be noted that these are actuarially fair premium rates. The higher transaction cost in CFWFI as compared with CAWFI may narrow this gap which is beyond this study.

The restricted CAWFI pays the lowest expected indemnity among these three models. The restricted CAWFI pays only 13% to 15% of 90% CFWFI's expected indemnity in different crop mixes in Mississippi, which is the lowest among all the states and farm types:34% to 44% of 90% CFWFI in Kansas, 40% to 48% of 90% CFWFI in North Dakota, and 44% to 59% of 90% CFWFI in Illinois.

Sensitivity Test on Optimal CAWFI Model

In this study, the analysis assumed all farmers were moderately risk-averse; however, all decision makers may not be moderately risk averse. Another assumption is that the revenue share of a crop on the farm is an appropriate weight, which seems logical but has not been proven yet. Therefore, sensitivity tests were conducted for these two assumptions.

Test on Weight of Optimal CAWFI Model

The revenue share of crops on the farm was used as an appropriate weight in CAWFI. In this case, CAWFI also used acres as a weight. The results are in Table 15. The optimal scale in using acreage share as a weight was obtained and is slightly higher than the optimal scale from revenue share as a weight. The optimal coverage levels for those respective scales in acreage share as a weight are at least equal or greater than the optimal coverage levels in revenue share as a weight. The certainty equivalents under both scenarios were compared.

Table 15

Effects of Weights in Optimal as well as Restricted CAWFI Model

			Kansas	North Dakota	Illinois	Mississippi
	Acreage share of Crops in Farm		50:50	50:50	50:50	50:50
Acreage Share as a weight	Optimal CAWFI	Scale	2.39	2.33	1.58	2.81
		Coverage Level	1.35	1.35	1.2	1.2
	Restricted CAWFI	Scale	1.5	1.5	1.5	1.5
		Coverage Level	0.9	0.9	0.9	0.9
	Revenue Share of Crops in Farm		75:25	65:35	62:38	65:35
Revenue Share as a Weight	Optimal CAWFI	Scale	2.02	1.98	1.29	2.4
		Coverage Level	1.25	1.35	1.2	1.2
	Restricted CAWFI	Scale	1.5	1.5	1.29	1.5
		Coverage Level	0.9	0.9	0.9	0.9
CER Ratio of Acreage share Optimal CAWFI to Revenue share Optimal CAWFI			1.0014	1.0002	1.0028	1.0060
CER Ratio of Acreage Share Restricted CAWFI to Revenue Share Restricted CAWFI			0.9998	0.9971	0.9981	0.9974

Note: ratios are obtained from their respective certainty equivalent revenues (CER)

The acreage share as a weight in CAWFI has increased the optimal scale for all regions in equally distributed crop acres in the farm. Moving toward the acreage weight instead of revenue weight, higher weights are imposed to lower value of crops in each state. For example, in Kansas, the revenue share of crops is 75:25 ratio where assigning equal 50:50 weights to each crop in acreage share as a weight increases imposes the higher weights to lower value crop. This might be one of the possible reasons that could have pushed optimal scale up in acreage share as a weight in CAWFI.

The optimal CAWFI with acreage share as a weight has produced a slightly higher certainty equivalent revenue as compared with the optimal CAWFI with revenue share as a weight in equally distributed acres of crops in the farm in all states. However, the difference is so small (less than 0.60%) that it does not alter the CAWFI's performance over no-insurance program or 90% CFWFI. The restricted CAWFI with acreage share as a weight was compared with restricted CAWFI with revenue share as a weight in the equally distributed acres of crops in the farm across four states. Using acreage share as a weight has reduced CAWFI's performance slightly as compared with revenue share as a weight in the restricted model though the difference is slim. It confirms that the revenue share of crops in the multiple crops farm can also provide better weight to the optimal CAWFI as equally as with acreage share as a weight while in restricted the CAWFI case, the revenue share might be considered a better weighting mechanism. Therefore, farmers can use acreage share or revenue share as a weight in optimal CAWFI.

Test on Risk Aversion Coefficient of Optimal CAWFI Model

For the optimal CAWFI, other things remaining constant, the risk-aversion coefficient was varied and the certainty equivalent revenue was estimated for the optimal CAWFI along with no-insurance program and CFWFI. The expected indemnity pay outs in optimal CAWFI and 90% CFWFI at risk-aversion Levels 1 and 3 were also estimated.

The results are in Table 16. In the relative ratio of optimal CAWFI over no-insurance program, CFWFI was compared at two different risk-aversion levels. The reason of doing this is to observe whether CAWFI results vary across risk aversion coefficients or not.

Table 16

Effect of Risk Aversion Coefficient on Optimal CAWFI Model

	Optimal Scale	Optimal Coverage Level at Risk Aversion 1	Optimal Coverage Level at Risk Aversion 2	Optimal Coverage Level at Risk Aversion 3	Ratio of CER at r=1 to CER at r=3 in Optimal CAWFI
Kansas	2.02	1.25	1.25	1.35	1.0707
North Dakota	1.98	1.3	1.35	1.35	1.0570
Illinois	1.29	1.2	1.2	1.25	1.0107
Mississippi	2.4	1.2	1.2	1.25	1.0385

This test was conducted in equally distributed acres of crops in multiple crop farming in Kansas, North Dakota, Illinois, and Mississippi. In this study, the effort was to observe the effects of risk-aversion levels on optimal-coverage levels of the model. In Kansas, Illinois, and Mississippi, optimal coverage levels have not changed while moving from risk-aversion coefficient 1 to 2but have increased by 5% while moving from risk-aversion coefficient 2 to 3. In North Dakota, optimal coverage level increased by 5% while moving from risk-aversion coefficient 1 to 2 but remained the same while moving from risk-aversion coefficient 2 to 3. Because of the change in risk-aversion coefficient from 1 to 3, the optimal coverage level of the model has increased by 5% in each state.

This may conclude that moving from moderately risk-averse to highly risk-averse decision makers, optimal CAWFI's coverage level may change.

The certainty equivalent revenue of optimal CAWFI based on the optimal scale and optimal coverage level for risk-aversion coefficients 1 and 3 was estimated and are presented in relative ratio in the last column of Table 16. The ratios are deviating from 1% in the Illinois farm to 7% in Kansas farm. These deviations are so small that they would not alter the results.

CHAPTER VI

CONCLUSIONS

The concept of GRP was extended to single as well as multiple crops revenue context in this study, and a CAWFI model was designed. This model was tested on representative farms in four states, Kansas, North Dakota, Illinois, and Mississippi, producing three crops, corn, wheat and soybean. The selection of revenue percentage of crop in the farm as an appropriate weighting mechanism was an important effort to customize area revenue into farm revenue, minimizing basis risk exposure on the CAWFI model.

This study searched for the optimal scale and optimal coverage level and designed an optimal CAWFI model. In optimal CAWFI, farmers are allowed to optimize their revenue, choosing scale and coverage levels as needed. The optimal scales in most of the crops in single crop contexts are beyond the GRP maximum scale 1.50 and coverage levels are beyond 100%. A similar story can be found in multiple crops contexts where scale is greater than 1.50 in many crop mixes and coverage levels are greater than 100% for all crop mixes in all states. Both restricted and optimal CAWFI outperforms no-insurance programs, suggesting that CAWFI is a workable insurance product.

Imposing restriction on scale as per GRP provision and also on coverage level, a restricted CAWFI was designed. A farm-level product CFWFI at 90% coverage level was also estimated. That the certainty equivalent in restricted CAWFI is lower than optimal CAWFI in all crops and crop mixes across states suggests that relaxing the restriction on CAWFI can increase farmers expected utility. In the single crop context, optimal CAWFI produces a higher certainty equivalent than CFWFI in most of the crops across states. In multiple crop contexts, optimal CAWFI is able to produce a higher certainty equivalent over CFWFI in all four states for all crop mixes. This may show that optimal CAWFI minimizes basis risk equally with currently available CFWFI.

However, expected indemnity pay outs for optimal CAWFI are from more than three fold to more than seven fold as compared with CFWFI in multiple crop contexts, and from more than four fold to more than seven fold in single crop contexts, depending on geographical regions and crops as well as crop mixes. Farmers have to pay three to seven times more premiums in optimal CAWFI to obtain the same level of risk protection as in CFWFI.

Finally, the sensitivity test confirms that varying risk-aversion coefficients in optimal CAWFI or considering acreage share as an appropriate weight would not change the decisions.

In this study, the assumption of constant relative risk aversion (CRRA) utility function of wealth has been made to estimate expected utility. The CRRA utility function may not hold all the time for all the decision makers. There might be some exceptions where decision makers may show increasing relative risk aversion (IRRA) utility function where expected utility increases as the amount of initial wealth. In the same way, there might be some cases where decision makers may show decreasing relative risk aversion (DRRA) utility function over wealth where expected utility decreases as the amount of initial wealth increases. Therefore, further work in this model taking some other utility function except CRRA would be recommended to show robustness of the CAWFI for under all types of utility functions.

In addition to this, the CAWFI model was tested only in four geographical regions in three major field crops. This study can be extended to more regions covering many crops to generalize the results. In this study, whole farm insurance based on farm-level yield has been considered as a baseline model to compare with optimal CAWFI. This study can also be extended to compare this optimal CAWFI model with commodity-specific revenue coverage products like Crop Revenue Coverage (CRC) because in this study, whole farm insurance based on farm-level yield was taken as a baseline to compare with CAWFI.

In practice, insurance products are offered with farm programs like ACRE and SURE, which were not in this study. This study can also be extended, considering all of those farm support as well as price/income support programs together with optimal CAWFI, which may assist in determining the overlapping effects of optimal CAWFI with farm-support programs.

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