ABSTRACT

CHEN, YING-ERH. Three Essays on A multiyear Crop Insurance Plan. (Under the direction of Barry K. Goodwin.)

This study focused on how to redesign MPCI and GRP so that they are more attractive to farmers. Here we propose multiyear MPCI and GRP that insurance terms are extended to more than a year. Our simulation results showed that the actuarially-fair rate for a multiyear insurance program was lower than the actuarially-fair rate for a single year insurance program when the correlation of yield distribution among years decreased. Our real data results also showed that the correlations of yields among years are not strong. Therefore, the proposed multiyear insurance program can be practical and will provide more interests for farmers to participate in the MPCI and GRP. We also discussed farmers’ welfare under different crop insurance plans. We are concerned about producers’ participation and producers’ behaviors if multiyear insurance plans become available. As optimal coverage levels can reflect both the decision to participate and producers’ behavior when buying insurance, we used empirical models to simulate a producer’s decisions given price and yield risks and with various degrees of risk aversion. We focused on three scenarios of risk aversion that represent the risk preferences commonly reported in the empirical literature, high risk aversion, and risk neutrality.
Three Essays on A Multiyear Crop Insurance Plan

by
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To my parents, Mr. Gin-Chang and Mrs. Yu-Li Chiang, and my husband, Dr. Ren-Hua Chung.
BIOGRAPHY

Ying-Erh Chen was born in 1977 in Taiwan. She received her bachelor degree in applied mathematics in 1999 from Providence University. She received her master degree in economics in 2003 from National Tsing Hua University. She started his doctoral work in economics at North Carolina State University in 2005.
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1. Introduction

Agricultural production suffers potential risks because of yield and price instabilities. These instabilities can result from various unpredictable factors, including natural disasters such as fire, drought, floods, and pest damage. Yield volatility causes price movements and also income instability for farmers. In order to help protect farmers from production, price and income risks, the Federal Crop Insurance Program provides various types of insurance.

Some insurance is based at the farm level, such as farm-level yield insurance (Multiple Peril Crop Insurance or MPCI), and farm-level revenue insurance (Crop Revenue Coverage (CRC) and Revenue Assurance (RA) coverage). The MPCI policy protects farmers against individual yield losses. Under this plan, insured farmers pay premiums based on crop yield for a specific geographical area, usually the county in which the farm is located. The Federal Crop Insurance Corporation (FCIC) provides indemnities when actual yields fall short of the farm’s insured yield. In 1985, the MPCI policy was changed to adopt actual production history (APH) for the insured unit in order to determine the farmers’ premiums. APH is based on the average of four- to ten-years of realized yields for the insured unit. More details of MPCI including the background of CRC and RA will be provided in the next chapter.

Other types of crop insurance are based on an index or on yields at an aggregate area level such as area-level yield insurance (the Group Risk Plan or GRP) and area-level revenue insurance (Group Risk Income Protection (GRIP)). In GRP, each farmer chooses a coverage level for the insured unit. Then the insurer predicts the county yield for the insured year.
based on that county’s data over a span of years using an adjustment for the yield trend for every insured farmer in that area. Finally, the insurer uses the expected county yield and coverage level in order to calculate a yield guarantee. The most distinct characteristic of GRP is that the farmers that are insured will obtain an indemnity when the county average yield is below the guaranteed yield regardless of the individual yield of the grower. Moreover, insured farmers under the GRP pay their premiums either after the crop has been harvested or when an indemnity payment is made, depending on which one is earlier. More details concerning GRP and GRIP will be provided in the next chapter.

Both the MPCI and GRP insurance programs are known to have had a historically low participation rate and poor performance in the 1980s and early 1990s (Goodwin, 1994; Ker and Goodwin, 2000; Goodwin and Smith, 1995; Glauber, 2004). Since the late 1990s, program participation has increased significantly, mainly because of government premium subsidies (Coble and Knight, 2002). This pattern is shown in Figure 1. To date, these crop insurance programs have achieved an 80% participation rate and government premium subsidy has reached $5,692 million dollars. Farmers may choose to expand production because the subsidy of crop insurance decreases the risk associated with planting. Concerns about the distorting effects of crop insurance on production resulting from increased subsidies have started to increase (Glauber, 2004). If current crop insurance programs can be redesigned to provide a lower premium rate in order to attract farmers to participate in these programs, less subsidy will be needed. Thus, both farmers and the government will benefit from this redesigned program. Farmers will pay a lower premium to mitigate yield, price or
revenue risk. The government will spend a lower cost of subsidy as subsidy is a proportion of the premium. Concerns about the distorting effects of crop insurance on production can be abated because of the lower subsidy as well. Therefore, redesigning current crop insurance programs with a lower premium rate is an important task to accomplish.
Figure 1 Summary of U.S. Crop Insurance Insured Acres and Subsidy

Source: USDA Risk Management Agency
One possible way to reduce the premium rate is to extend the current insurance plan from a single-year term to a multiyear term. In other words, the indemnity will be calculated based on the sum of yield or revenue in consecutive years. Our simulation results in Chapter 4 show that, when considering insurance programs for a multiyear term, the premium rate can be reduced if the crop yields in consecutive years are not perfectly positively correlated (i.e. the correlation coefficient < 1). These simulation designs will be described in Chapter 4. These simulation results motivate us to propose the multiyear MPCI, GRP and GRIP by considering the correlation of crop yields and prices in consecutive years.

There are several benefits other than lower premium rates if the current MPCI, GRP and GRIP period is extended for a longer period of coverage. First, farmers will not have to pay the total premium in the first year. In other words, farmers can pay a partial premium in the first year, whether they have yield loss for that year or whether they do not. When low risk farmers without a yield loss pay a partial premium in the first year, they will have more wealth or cash to allocate in the following year. When high risk farmers with a yield loss pay a partial premium in the first year, they will be less burdened by premiums and will have more ability to grow crops in the following year. If farmers have a severe loss in the first year, an indemnity will be paid to cover their production costs. Moreover, farmers who have a yield loss in the first year but do not have a yield loss in the second year will be capable of paying a premium after they earn benefits from selling yields in the second year of production. Therefore, farmers would have more time to collect the premium, and thus
diversify yield risk through a longer period insurance plan. These benefits would attract more farmers to participate the multiyear insurance plan.

The actuarially fair premium rate is a measure of the amount of the insurance premium that insured farmers have to pay as a percentage of total liability. A lower actuarially fair premium rate provides a better insurance policy for the insured farmer. The actuarially fair premium rate can be obtained when the expected insured loss is equal to the actuarially fair premium after subtracting administrative and program costs. These costs are omitted in eq(1).

To demonstrate:

\[
\text{actuarially fair premium rate} = \frac{\text{expected insured loss}}{\text{liability}} = \frac{\text{actuarially fair premium}}{\text{liability}} \tag{1.1}
\]

where

(1) \( \text{expected insured loss} = \text{prob(loss)expected(loss | loss occurs)} \)

(2) \( \text{Liability is the maximum possible loss.} \)

Though several alternative designs of insurance programs have focused on area yield insurance and revenue insurance in order to attract a higher number of farmers, none of these designs are intended to lower premium rates through multiyear insurance programs that consider correlation of yields in consecutive years. This study focuses on extending the periods of insurance programs (MPCI, GRP and GRIP) by considering the correlation of yields (MPCI and GRP) and the correlation of yield and price (GRIP) in consecutive years in order to decrease the actuarially fair premium rate. The extension of these programs would
thus lower the premium rates. The correlations of yields and prices between two consecutive years were investigated based on the Pearson’s correlation coefficient and copula methods. The relationship between the correlation and the actuarially fair premium rate was also studied based on simulations and data analyses. This relationship can provide a guideline as to how to make an insurance policy for multiyear MPCI, GRP and GRIP plans. We will describe a possible design for the multiyear insurance plan. We will also demonstrate that the proposed multiyear insurance plan may provide a more attractive insurance program than the single year MPCI, GRP and GRIP. Before we provide the details in the proposed insurance plans, we will first give a literature review of the current insurance programs in the following chapter.
2. Literature Review

2.1 Introduction of Current Crop Insurance Programs

Farmers face risks from drought, frost, insect infection and crop diseases. These types of uncertainties involving production result in income fluctuations for farmers. In order to stabilize farmers’ incomes, the Federal Crop Insurance Program (FCIP) introduced two types of insurance contracts for farmers: yield and revenue crop insurance contracts. Yield insurance protects farmers against crop yield losses. Revenue insurance, on the other hand, protects farmers against revenue losses resulting from a price decline, a yield decline or both. However, developing actuarially fair premium rates of revenue crop insurance is not straightforward as the joint distribution of the two random variables (i.e. price and yield) needs to be modeled in order to estimate the probability of loss, the expected loss and the premium.

Crop yield insurance contracts can be at the farm level or the area level. Multiple Peril Crop Insurance (MPCI) is the traditional farm-level yield crop insurance contract. In MPCI, each insured farmer must first provide the actual production history (APH) yield within a certain period of time (4-10 years) and must also choose a coverage level for the insured unit. The insurer then calculates the expected yield for the insured year based on the APH for each insured farmer. Finally, the insurer calculates the guaranteed yield from the APH, the coverage level and the predicted yield for each insured MPCI farmer. The guarantee yield is based on the APH yield multiplied by the level of coverage. When the realized yield for the insured farmer is below the guaranteed yield, the insured farmer will obtain an indemnity.
Farmers can select one of the yield guarantee percentages from 50% to 85% of their insurable yield in five-percent increments and may also select one of the three price guarantees determined by the FCIC forecasts of the expected prices. The top price election level was set at 90-100 percent of the expected market price. Three price election levels were available prior to 1984, and recently a price election between 30-100% has also become available. If realized yields fall below the selected coverage level, indemnities will be paid based on the result of the yield shortfall and the price guarantee. The yield shortfall is the difference between the realized yield and the guaranteed yield. This guaranteed yield is calculated by using the product of the yield guarantee percentage chosen by a farmer and the APH.

The expected loss and liability for the current MPCI and GRP contract can be derived as follows:

\[
\text{expected loss}(y) = \int_0^{\lambda \mu} f(y)dy [\lambda \mu - E(y \mid y < \lambda \mu)]
\]
\[
\text{liability} = \varphi \mu
\]

where

\[
E(y \mid y < \lambda \mu) = \frac{\int_0^{\lambda \mu} yf(y)dy}{\int_0^{\lambda \mu} f(y)dy}
\]

\(\varphi\) is the insured price per bushel  
\(\lambda\) is the insurance coverage rate for certain year  
\(\mu\) is the expected yield for insured year
A possible cause of poor performance for MPCI may be a result of hidden information by farmers. Insured farmers can change their farming behavior in order to obtain an indemnity. Farmers may decrease fertilizer, insecticide, herbicide and pesticide usage in order to affect their yields. Hence, yield shortfalls for insured farmers can be a result of an inability to monitor farmers’ practices. This problem is known as the moral hazard. In addition, farmers have more knowledge about their own crop yield distributions than the insurers, so they have the ability to compare the difference between the expected indemnity and the premium. As a result, farmers whose expected indemnity exceeds the premium are more likely to purchase crop insurance than those whose expected indemnity is lower than the premium. As farmers are more informed than insurers, due to hidden information, the insurance pool can be adversely affected. Due to this circumstance, crop insurance will experience a financial loss as the indemnity can be higher than the premium. This problem is known as adverse selection. Efforts to verify farm yield history and to adjust losses at the farm level result in high government costs for MPCI (Just and Pope, 2002).

Area-level insurance contracts gained support in 1994 because of the possible poor performance of MPCI and also due to high government administrative costs for individual plans. Under area insurance contracts, insurable yields and indemnities are based on the yield for a geographical area. The main advantage of area insurance is that it virtually eliminates the likelihood of moral hazard and may also diminish adverse selection. However, the main disadvantage of area insurance is that it does not protect farmers perfectly because of a possible weak correlation between area- and farm-level yields. When the correlation between
area- and farm-level yields is low, there is a possibility that farmers may experience a yield loss but are unqualified to obtain an indemnity based on area yields. This problem is known as basis risk.

The Group Risk Plan, or GRP, is one example of area insurance contracts. GRP allows producers to select one of the five coverage levels (70%, 75%, 80%, 85% and 90%) of the expected county yields. The expected county yield is calculated using the thirty years of county yield data from the National Agricultural Statistics Service (NASS) along with an adjustment for the yield trend. Indemnities are determined based on the product of the shortfall below the trigger yield selected by farmers along with the dollar value of the protection selected.

Although a yield insurance plan protects farmers from yield loss, it does not necessarily protect farmers from revenue loss. For example, farmers who do not have a yield loss may have a revenue loss due to a low crop price. Therefore, revenue insurance plans were proposed to accommodate this problem. Currently, available primary crop revenue insurance plans include Crop Revenue Coverage (CRC), Revenue Assurance (RA) coverage and Group Risk Income Protection (GRIP).

Crop Revenue Coverage guarantees farmers against crop loss based on their revenue. The guaranteed revenue is calculated as a coverage level (e.g. 50-85%) chosen by farmers multiplied by revenue, which is APH yield multiplied by the greater of base market price and
harvest market price. Payments will be made to farmers when the actual revenue (i.e. the harvest time yield multiplied by the harvest price) falls below the guaranteed revenue. The payment will be the difference between the guaranteed revenue and the actual revenue. When price decreases are offset by production increases or production decreases are offset by price increases and the actual revenue is not less than the guaranteed revenue, no payment will be made.

Revenue Assurance (RA) coverage is similar to CRC, but there are two main differences. The first difference is the determination of the guaranteed revenue. Under RA, farmers have two price options in the process of calculating the guaranteed revenue: the pre-planting price and the harvest price. The second difference is the flexibility of coverage levels when the pre-planting price option is chosen. Under CRC, farmers can choose 95 percent of the pre-planting price and can pay a lower premium. Under RA, farmers must insure 100 percent of the pre-planting price and must pay a higher premium.

RMA kept and combined the main features of the Crop Revenue Coverage and Revenue Assurance for the 2011 crop year for all crops with a 2011 crop year contract change date on or after April, 2010. Crop Revenue Coverage and Revenue Assurance with harvest price option are being placed by Revenue Protection, and revenue guarantee is based on the higher of the projected or harvest price (similar to CRC or RA with harvest price option). Revenue Assurance without harvest price option is being placed by Revenue Protection with harvest
price exclusion and revenue guarantee is based on the projected price only (similar to RA without harvest price option).

Group Risk Income Protection (GRIP) is similar to the concept of the Group Risk Plan (GRP), except that indemnity is determined based on county-level revenue rather than the expected county-level yields. The main difference between GRIP and the other revenue insurance plans such as CRC and RA is that the guaranteed revenue is based on the expected county-level revenue instead of the farm-level revenue. Under GRIP, insured farmers may select coverage levels between 70 to 90 percent of the expected county revenue. The guaranteed revenue under GRIP is calculated using the historic county yield multiplied by the harvest price (HPO) and also by coverage levels chosen by insured farmers. The price is the averaged futures price 5 days prior to planting. The actual county revenue is calculated as the actual county yield times a month-long average of the nearby futures price at the time of harvest. GRIP pays indemnities only when the actual county revenue falls below the guaranteed revenue chosen by the farmer.

### 2.2 Crop Insurance Plan Participation

Crop insurance participation was low in the 1980s and early 1990s as seen in Figure 1. Thus crop insurance participation was a major policy issue during this period. In 1986, participation in the program only reached 48.6 million acres, which was about 20% of the eligible acreage. Participation reached 101.3 million acres in 1990, which was about 40% of the eligible acreage. In 2008, participation reached over 80% with over 272 million acres
enrolled. Several studies of MPCI program participation incentives were completed using simulation methods and real data. These studies are described as follows.

Goodwin and Kastens (1993) showed that a higher premium rate had a significant negative effect on MPCI participation from cross-sectional wheat observations in Kansas in 1993. Smith and Baquet (1996) also obtained the same results from cross-sectional wheat farm observations in Montana in 1990. Coble et al. (1996) found that the premium elasticity was negative for wheat yields in 354 farms in Kansas between 1977 and 1990. Goodwin (1993) found that a higher premium had a negative effect on the proportion of eligible acres insured using a panel of 594 pooled annual, county-level corn observations in Iowa from 1985 to 1990. These results indicated that there was a negative relationship between premium and MPCI participation for farm- and county-level data, and also that farmers took premium rates into account when they made their insurance decisions.

Goodwin (1994) pointed out that adverse selection may be induced by the Federal Crop Insurance Corporation (FCIC)’s actuarial development of insurance premium rates. The FCIC determined insurance levels by using average yields calculated based on both insurance purchasers and non-purchasers. However, when farmers have a higher risk of yield loss, they are likely to purchase insurance. Therefore, adverse selection is induced. In order to solve this problem, APH was adopted by the FCIC in 1985 in order to determine the insurance yield level. Though adverse selection could be mitigated by adopting APH, the sole use of average farm yields of farms preceding 10 years of production data may poorly represent the
likelihood of loss as yield variation is not taken into account. On the other hand, in order to determine county-level premium rates, 35-40 years of experience will be examined and smoothing across county yield lines will be processed to reduce large differences across farms. Adverse selection may also be induced from the smoothing process as lower premium rates may be assigned to high loss risk counties while higher premium rates may be assigned to low loss risk counties. In addition, premium rates often cannot be adjusted flexibly because legislation limited the amount of increase of the premium rate. Adverse selection may also be induced because of a degree of premium rate rigidity.

Goodwin (1994) calculated empirical premium rates and FCIC rates in order to compare the differences among non-purchasers, insurance purchasers and the entire sample. Results suggested that insurance purchasers have a higher yield variation than non-purchasers. They also suggested that FCIC rates are significantly higher than the empirical rates in every case. Therefore, the current FCIC rate setting process may offer incentives for high risk farmers to participate, and thus may induce adverse selection. Goodwin (1993) then used some variables for farm characteristics such as net farm income, fertilizer and chemical expenditure per crop acre and a series of regional dummy variables including the average yields in order to see if the yield variation could be measured more accurately in the determination of premium rates. Results showed that these variables can predict yield variability better than the average yields by showing higher R Squares. Though these variables may provide useful information to predict yield variability, observable variables are quite limited. Therefore, the solution to reduce adverse selection is to use yield histories directly including the yield variation in
addition to the average yields because the average yields may imperfectly present loss probability.

Though these studies addressed the effect of premiums on MPCI participation incentives and although they pointed out the inherent problems of determining actuarially fair premium rates using the techniques mentioned above, little research has focused on an alternative insurance plan based on actuarially fair premium rate-setting in order to increase MPCI participation incentives. Current multiple peril (MPCI) and group risk (GRP) crop insurance plans are designed to mitigate monetary fluctuations resulting from yield losses for a specific year. However, yield realizations can vary from year to year and may depend on the correlation of yield realizations across years. Indemnities and actuarially fair premium rates, which are given by the expected loss divided by liability, for MPCI and GRP plans are related to yield realizations. If current MPCI and GRP are extended to include multiple periods of time so that poor yield realizations can be offset by another year’s better yield realizations, the actuarially fair premium rate is expected to decrease. Hence, the primary purpose of this dissertation is to propose a multiyear insurance plan which will also account for the correlation of yield and price distributions across years. We will discuss the details of the proposed plan in Chapter 4.

2.3 Modeling Yield and Price risk

Yield distributions are needed for yield insurance plans in order to calculate the probability of loss, the expected loss and the actuarially fair premium. The joint distribution of yield and
price is also needed for revenue insurance plans in order to calculate the probability of loss, the expected loss and the premium. Therefore, we will review several approaches in order to model yield and price distributions.

2.3.1 Parametric and Nonparametric Approaches

A variety of approaches for representing distributional structures have been proposed. These approaches can be classified into parametric and nonparametric approaches, depending upon whether they are assigned by a parametric distribution. The parametric approach estimates parameters in the distribution function by assuming that one knows the correct distributional family using the observed yield data. When a set of independent and identically distributed yield realizations are observed, one can use maximum likelihood in order to estimate the parameters for the distribution. For example, Botts and Boles (1958) used a normal distribution in order to estimate the yield risk. Gallagher (1987) used a gamma distribution instead of a normal distribution in order to model the soybean yield distribution, as the crop yield distribution is often asymmetrical and negatively skewed. The Beta distribution also has been widely used in the literature on the topic, as there is sufficient evidence of the existence of skewed data in the yield. (Nelson (1990), Borges, R., and W. Thurman (1994), Babcock and Hennessy (1996), Coble et al. (1996), Hennessy, Babcock and Hayes (1997)). In addition, the Weibull, the log-normal, the logistic, the Burr distribution, and mixtures of parametric distributions have also been used in order to model crop yields. As these parametric distributions vary in terms of their flexibility and in their ability to capture the characteristics of crop yields, their robustness for modeling yield densities is different. For
example, the log-normal distribution imposes positive skewness on the distribution, which is not typically expected for crop yields. When a dependence structure needs to be considered among random variables, the parametric copula approach is a good candidate since current parametric multivariate models usually have no closed form. We will introduce more details regarding copula functions in the next chapter.

As the distributional choice may be incorrect, inaccurate predictions and inferences may occur. Therefore, a variety of nonparametric approaches have been developed in order to estimate crop yield distributions. The simplest estimator for a nonparametric approach is the histogram.

The parametric approach to modeling crop yield distribution is to select a parametric distribution. Then parameters for the distribution are estimated based on the observed yield data. A large amount of existing empirical evidence about crop yield distribution has confirmed negative skewness, which can be represented by the beta, gamma and Burr distributions. Therefore, if a parametric approach is adopted, one of these distributions can be the primary choice. On the other hand, the nonparametric approach does not assume a particular density distribution for a crop yield distribution, but rather it allows the data to select the best representation of crop yield distribution.

Given an observed series of yield realizations, one must choose an approximate distribution function to model the yield data. This approach is preferred when one has a strong
knowledge of the statistical distributions likely to describe yields, or when only a small amount of data are available. Applying an incorrect distribution function will result in biased estimates of the parameters in the distribution function and inaccurate insurance premium rates. When one is unsure of the approximate distribution function or when one is working with large amounts of data, the nonparametric approach may be preferred. Determination of the appropriate band width and placement of bins is a major task when using this approach. Hence, there is a trade-off between the parametric and nonparametric approaches.

### 2.3.2 Modeling Yield, Price, and Revenue Risk in Current Revenue Insurance Plans

In the revenue insurance plan, the determination of the actuarially fair premium rate is more complicated than the determination of yield insurance as yield and price risks both need to be considered. Therefore, in the process of calculating the premium rate, we need to consider the price distribution, the yield distribution and the correlation between price and yield.

The lognormal distribution is often used in order to model the price distribution. The expected price is the average of the daily price quotes for the futures contract for the harvest period observed in the planting period. The price volatility is usually calculated by applying the Black-Scholes options pricing formula to the price of the planting period put option on the harvest period future contract. The expected price and price volatility are used to estimate the mean and variance in the price distribution, respectively (Goodwin and Ker, 2002). The Beta distribution can be used to model the yield distribution. Then the revenue
distribution is modeled based on the joint distribution of price and yield. This distribution also accounts for the correlation between price and yield.


3. Copula and Dependence

Our main goal is to design multiyear insurance contracts based on the joint distributions of yield across years. We will demonstrate in Chapter 4 that the actuarially fair premium rate of a multiyear insurance contract depends on the degrees of correlation of yield across years. Therefore, modeling and estimating a correlation of joint distributions for yields in a multiyear insurance design is an important task. As joint distribution for two marginal distributions may not always have a closed form expression, modeling joint distributions can become complicated.

Several approaches have been proposed in order to model the correlation between distributions without explicitly modeling the joint distribution. One commonly used approach to modeling a multivariate distribution is based on non-parametric methods such as Kernel function (Zheng et al. 2008). However, in this approach the empirical distributions are restricted to observed data and a large amount of simulations are required in order to obtain a continuous distribution (Vedenov et al. 2008).

Another school of thought uses the inverse hyperbolic sine transformation (IHST) (Johnson 1949) in order to model non-normal distributions. The IHST method was extended to model multivariate non-normal distributions that account for skewness, kurtosis, heteroskedasticity and correlation (Ramirez 1997). However, this approach relies on a correlation matrix that measures the dependence structure. This structure may not be easy to obtain in practice (Vedenov et al. 2008).
Recently, the copula model has become a popular approach to modeling joint distributions (Vedenov et al. 2008, Tejeda et al. 2008). A copula provides flexibility as a dependence function that binds marginal distributions together in order to express joint distribution without sacrificing properties of marginal distributions. In other words, when one doesn’t know the form of the joint distribution, one can use a copula that adequately captures dependence structures of the data while reserving attractive properties of the marginal distributions. Therefore, one can use a copula in order to express a multivariate distribution in terms of marginal distribution, regardless of the form of the marginal distribution. Copula methods are also adopted in this study in order to model the joint distributions of yield. A more detailed review of copula methods will be given in section 3.2.

Pearson’s correlation coefficient by far is the most adopted dependence concept (Trivedi and Zimmer, 2007). Therefore, correlation of yield across years was estimated for farm- and county-level data based on Pearson’s correlation coefficient in Chapter 8. However, there are three limitations of the Pearson’s correlation coefficient (Trivedi and Zimmer, 2007). The first limitation is that Pearson’s correlation coefficient represents a weakness of correlation as a measure of dependence because, in general, a zero correlation does not imply independence. The second limitation is that it is not defined for some heavy-tailed distributions whose second moments do not exist. The third limitation is that it is not invariant under a strictly increasing nonlinear transformation. These limitations motivate us to use an alternative rank measure of dependence: such as Spearman’s rank correlation. We decided to use Spearman’s rank correlation in our copula approach. Different copula families
have their definitions for correlation coefficients. Thus, the estimated correlation coefficients from copula may not be straightforward to interpret. Therefore, in order to easily interpret the correlation coefficients, we transformed the dependence parameters estimated from the Copula approach to Spearman’s rank correlation in our multiyear insurance contract. We will introduce the definitions of Pearson’s and Spearman’s correlation coefficients and will review several commonly used Copula families in the following section.

### 3.1 Pearson’s Correlation Coefficient and Spearman’s Rank Correlation

Pearson’s correlation coefficient between a pair of variables $(X, Y)$ is defined as (Casella and Berger 2002)

$$
\rho(X, Y) = \frac{COV[X, Y]}{\sigma_X \sigma_Y}
$$

Where $COV[X, Y] = E[XY] - E[X]E[Y]$, $\sigma_X, \sigma_Y > 0$, $\sigma_X$ and $\sigma_Y$ denote the standard deviations of $X$ and $Y$.

When the pair $(X, Y)$ follows a bivariate normal distribution, $\rho(X, Y) = 0$ implies that $X$ and $Y$ are independent. In this case, zero correlation and independence are equivalent as the dependence structure is fully determined by the correlation.

Consider two random variables $X$ and $Y$ with continuous distributions $F_1$ and $F_2$, respectively. Spearman’s rho is the linear correlation between $F_1$ and $F_2$, which are integral transforms of $X$ and $Y$ and defined as (Jerome and Well 2003)

$$
\rho_S(X, Y) = \rho(F_1(X), F_2(Y))
$$
Spearman’s rank correlation is bounded on the interval [-1,1] and assumes the value zero under independence. This measure is based on the concept of concordance and discordance. The pair \((x_i, y_i), (x_j, y_j)\) are concordant if 
\[(x_i - y_i)(x_j - y_j) > 0\]
and are discordant if 
\[(x_i - y_i)(x_j - y_j) < 0.\]

3.2 Copula Function

The copula is a method for modeling the multivariate dependence structure among random variables, for which the marginal distributions are uniform distributions with a variable range between 0 and 1. As the copula method will be used in order to estimate correlation between yields and prices in our proposed insurance plans, we will introduce the copula approach in this chapter. When we need to fit variables to a bivariate copula, we need to calculate the individual CDF (cumulative density function) for the two random variables. As the CDFs all have uniform distributions with a variable range from 0 to 1 (which satisfies the assumption of the copula), we can use the CDF to fit the bivariate copula. The parameters are estimated by the maximum likelihood method. There are several copula families available, and each family also has some generator functions. Therefore, the choice of different copula models can result in different joint distributions. Model fitting criteria, such as the Akaike information criterion, can be used to select among alternative copula functions. In order to determine the most appropriate copula family, the Akaike information criterion (AIC) (Akaike 1974), which accounts for the number of parameters and likelihood estimates, for each copula family needs to be calculated. The copula family with the lowest AIC value can be used. In addition, the most appropriate generator function can be selected based on the
likelihood estimates for different generator functions in the same family. We will discuss additional details for copula selection criteria in section 3.5. In this section, we will introduce two copula families – the Archimedean Copula and the Normal Copula, and we will also introduce several generator functions for each family.

A copula C is a multivariate joint distribution whose marginals are all uniformly distributed on the interval [0, 1].

\[ C(u_1, ..., u_p) = \Pr(U_1 \leq u_1, ..., U_p \leq u_p) \]

Sklar (1959) demonstrated that there is always a p-dimensional copula C such that for all \( x \) in the domain of \( F \) where \( F \) is a p-dimensional distribution function with marginals \( F_1, ..., F_p \),

\[ F(x_1, ..., x_p) = C(F_1(x_1), ..., F_p(x_p)) \]

### 3.2.1 Archimedean Copula Family

An Archimedean copula with two random variables \( u \) and \( v \) is constructed as:

\[ C(u, v) = \varphi^{-1}(\varphi(u) + \varphi(v)) \]

where

1. \( \varphi \) is a continuous, strictly decreasing generator function from \([0, 1]\) to \([0, \infty]\)

   such that \( \varphi(1) = 0, \varphi'(t) < 0, \varphi'(t) > 0 \) for all \( 0 < t < 1 \).

2. \( \varphi^{-1} \) denotes the pseudo-inverse of \( \varphi \)
(3) C is the function from \([0, 1]\) to \([0, 1]\)

There are several generator functions in the Archimedean copula family, including the Clayton, Frank, and Gumbel Copulas. \(\theta\) is the parameter of copula in the following copula function:

(a) Clayton Copula:
A Clayton Copula takes the form:

\[
C(u, v; \theta) = (u^{-\theta} + v^{-\theta} - 1)^{-\frac{1}{\theta}} \text{ where } \theta \in (0, \infty)
\]

(b) Frank Copula:
A Frank copula is constructed as:

\[
C(u, v; \theta) = -\frac{1}{\theta} \log\left[1 + \frac{(e^{-\theta u} - 1)(e^{-\theta v} - 1)}{e^{-\theta} - 1}\right]
\]

where \(\theta \in (-\infty, \infty)\)

where \(\theta \neq 0\) (parameter of copula)

(c) Gumbel Copula:
A Gumbel Copula is constructed as:

\[
C(u, v; \theta) = \exp\{-[(-\log u)^{\theta} + (-\log v)^{\theta}]^{\frac{1}{\alpha}}\}
\]

where \(\theta \in [1, \infty)\)
3.2.2 Normal Copula Family

Another popular copula family is the normal copula family. Farlie-Gumbel-Morgenstern (FGM), Gaussian and t-Copula functions are included in the normal copula family. Their densities are described as follows:

(a) Farlie-Gumbel-Morgenstern (FGM) copula:

A Farlie-Gumbel-Morgenstern copula is constructed as:

\[ C(u, v) = uv + \theta uv(1-u)(1-v) \]

where \(-1 < \theta < 1\)

(b) Gaussian Copula:

\[ C(u, v) = \Phi^{-1}(u) \int_{-\infty}^{\Phi^{-1}(v)} \frac{1}{2\pi(1-R_{12}^2)^{1/2}} \exp\left\{ -\frac{s^2 - 2R_{12}st + t^2}{2(1-R_{12}^2)} \right\} ds \]

where \(\Phi^{-1}\) denotes the inverse of the distribution function of the univariate standard normal distribution and \(R_{12}\) is the linear correlation coefficient of the corresponding bivariate normal distribution.

(c) t-Copula:

\[ C(u, v) = \int_{-\infty}^{\Phi^{-1}(u)} \int_{-\infty}^{\Phi^{-1}(v)} \frac{1}{2\pi(1-R_{12}^2)^{1/2}} \exp\left\{ 1 + \frac{s^2 - 2R_{12}st + t^2}{\nu(1-R_{12}^2)} \right\}^{-\nu/2} ds \]

where \(R_{12}\) the same definition as in the Gaussian copula. \(t\) is the t distribution with the degree of freedom \(\nu\).
3.3 Types of Dispersion Structures

When implementing a three-year GRP program, we need to consider the pairwise correlations between years. These pairwise correlations can be organized using different dispersion structures. In this chapter, four types of dispersion structures were commonly used to fit the copula models: autoregressive of order 1 (Ar1), exchangeable (EX), Toeplitz (TOEP) and unstructured (UN) dispersion matrices. The corresponding dispersion matrix, or correlation matrices, when dimension is equal to 3 are as follows:

(1) Autoregressive of order 1 correlation matrix:

Ar1 imposes that the impact on crop yields for the current year diminishes in the following years.

\[
\begin{pmatrix}
1 & \rho_1 & \rho_1^2 \\
\rho_1 & 1 & \rho_1 \\
\rho_1^2 & \rho_1 & 1
\end{pmatrix}
\]

(2) Exchangeable dispersion structure:

EX imposes that the correlation among years does not vary over time.

\[
\begin{pmatrix}
1 & \rho_1 & \rho_1 \\
\rho_1 & 1 & \rho_1 \\
\rho_1 & \rho_1 & 1
\end{pmatrix}
\]

(3) Toeplitz dispersion structure:

TOEP imposes that the impact on crop yields is consistent when the intervals between years are the same.
\[
\begin{pmatrix}
1 & \rho_1 & \rho_2 \\
\rho_1 & 1 & \rho_2 \\
\rho_2 & \rho_2 & 1
\end{pmatrix}
\]

(4) Unstructured dispersion structure:

UN imposes that the correlations among years vary over time.

\[
\begin{pmatrix}
1 & \rho_1 & \rho_2 \\
\rho_1 & 1 & \rho_2 \\
\rho_2 & \rho_2 & 1
\end{pmatrix}
\]

### 3.4 Parameter Estimation- Full Maximum Likelihood (FML)

The FML method, which maximizes a likelihood function, is a method used to estimate the parameters of the copulas and the parameters for the marginal distribution functions simultaneously. The maximum likelihood estimation method maximizes the full likelihood function for the sample based on the multivariate data.

Consider the derivation of the likelihood for a bivariate model \((y_1, y_2)\). The marginal density function is 
\[ f_j(y_j \mid x_j; \beta_j) = \frac{\partial F_j(y_j \mid x_j; \beta_j)}{\partial y_j} \]

and the copula derivative is 
\[ \frac{\partial C_j((F_1(x_1; \beta_1), F_2(x_2; \beta_2); \theta))}{\partial F_j} \text{ for } j = 1, 2 \]

The copula density is 
\[ c(F_1, F_2) = \frac{d}{dy_2dy_1} C(F_1, F_2) = C_{12}(F_1, F_2)f_1f_2 \]

where 
\[ C_{12}((F_1 \mid x_1; \beta_1), (F_2 \mid x_2; \beta_2); \theta) = \frac{\partial C((F_1 \mid x_1; \beta_1), (F_2 \mid x_2; \beta_2); \theta)}{\partial F_1 \partial F_2} \]

and the log-likelihood function is
\[ L_N(y_1 | x_1, \beta_i), (y_2 | x_2, \beta_2); \theta) \]
\[ = \sum_{i=1}^{N} \sum_{j=1}^{2} \ln f_{j} (y_{ij} | x_{ij}; \beta_j) + \sum_{i=1}^{N} C_{ij} \left[ F_1 (y_{1i} | x_{1i}; \beta_1); F_2 (y_{2i} | x_{2i}; \beta_2); \theta \right] \]

FML estimates are obtained by solving the score equations \( \partial L_N / \partial \Omega = 0 \) where \( \Omega = (\beta_1, \beta_2, \theta) \). FML will be used for parameter estimation in our empirical analyses.

### 3.5 Copula Selection Criteria

As different copula functions exhibit different dependence patterns, one may wish to estimate several copulas and to know which one fits the data best. In this section we will discuss the details of empirical estimation of copula and copula selection criteria.

The first step in copula estimation is to specify univariate marginal distributions. This decision is of the upmost importance because we can model the dependence structure more precisely when the marginal distributions fit better.

Economic and statistical features can guide us in making this decision. For example, the maximum possible yield from crop production is limited by biological constraints. Therefore, a large empirical literature (Gallagher (1987), Nelson (1990), Borges, and Thurman (1994), Hennessy, Babcock and Hayes (1997), Babcock and Hennessy (1996), Coble et al. (1996)) reports that crop distributions are negatively skewed. Goodness-of-fit tests also should be used in order to test how well the marginal distributions fit the data. These tests can guide us in selecting the parametric form of the marginal distributions. The second step in copula
estimation is to specify a copula function, which can be selected based on the properties of the data. If only positive dependence is expected by the features of the data, the choice of a copula that only allows positive dependence may be appropriate. If one expects tail dependence, the choice of a copula that doesn’t allow this dependence would not be appropriate. Furthermore, likelihood estimates or other selection criteria can be used in order to decide which Copula model to choose.

A copula model with a single dependence parameter is non-nested. Maximum likelihood can be used to choose between non-nested parametric models. To choose between models with more than one parameter, either the Akaike information criterion (AIC) or the Bayesian information criterion (BIC) can be used. For example, Akaike Information criterion is equal to 2K-2ln(L), where K is the number of parameters and ln(L) is the maximized likelihood value. A copula function with a smaller AIC value indicates a better fit of the data. If all the copulas under consideration have the same number of parameters, choosing models based on AIC or BIC is equivalent to choosing the maximized log likelihood value (Trivedi and Zimmer, 2007). There is only one correlation parameter in a two-year insurance plan. Therefore, we will select the best copula function by using the maximized likelihood value. It is very likely to have two or more correlation parameters in a three-year insurance plan. Therefore, we will select the best copula function by using AIC in a three-year insurance plan.
4. Purpose of Multiyear Crop Insurance Plans

In this chapter and also in Chapter 5, we will introduce multiyear insurance plans. We will also explain the reasons why multiyear insurance plans should be proposed. We will also present simulation results in order to support that the proposed plans are practical. We will then describe the proposed plans in detail in Chapter 5.

4.1 Purpose of Multiyear Revenue and Yield Insurance Plans

A multiyear revenue insurance plan should be a more attractive option to both the Risk Management Agency (RMA) and to farmers for several reasons. For insured farmers, it will provide a lower actuarially fair premium rate than the current single year insurance program. We will use a two-year revenue insurance plan as an example in order to demonstrate the advantages of a multiyear revenue insurance plan over the current revenue insurance plan from the perspectives of insurers, farmers, and the RMA.

For insurers, the determination of indemnity depends on the actual revenue at periods 1 and 2. Therefore, a decrease in the actual revenue during one period can be offset by an increase in the actual revenue in the other period. The actual revenue has two components: price and yield. A decrease in price or yield may result in a decrease in the actual revenue. Yield shortfall in one period can be offset by an increase in yield in the other period or an increase in price in the same and/or the other period. Similarly, a decrease in price in one period can be offset by an increase in price in the other period or an increase in yield in the same and/or the other period. Therefore, for insurers, the expected loss of a multiyear revenue insurance
The premium rate for a multiyear revenue insurance plan can thus be lower than the current single-year plan except when the correlation of yield across years is perfectly positively correlated.

The multiyear revenue insurance plan proposed in this study will be constructed as a hybrid of single year and multiyear revenue insurance plan coverage. In other words, farmers will obtain a partial payment of indemnity in each year if their actual revenue in that year falls below a certain level. Also, farmers will obtain an indemnity at the end of the insurance year if the average of the actual revenue for two years falls below a certain level. The partial payment of indemnity will be made to mitigate revenue loss in each year. Therefore, farmers can be assured that the revenue loss will not bankrupt them as this partial payment of indemnity provides a safety net to protect farmers from revenue loss to some degree. If farmers have an operating loan from banks, they will be able to repay the loan and keep their good credit through this partial payment of indemnity. This plan will be more attractive to lenders as loans will be better collateralized. Therefore, farmers with good credit can continue to take out loans for production costs for the next period. For farmers, then, this proposed multiyear revenue insurance plan would also be more attractive than the current revenue insurance plan because of the lower premium rate and the partial payment of indemnity.
To the RMA, on the other hand, a lower cost may exist in a multiyear revenue insurance plan, though more random variables (price and yield in periods 1 and 2) need to be considered at a time. Moral hazard and adverse selection are two major problems in the crop insurance plan. The adverse selection effect is expected to be mitigated from a) pooling insured farmers into a more homogeneous risk pool using a more accurate classification of the insured parties or b) attracting more farmers to participate in this risk pool. As this multiyear revenue insurance plan will appear more attractive to farmers, it is expected that the participation rate will increase. The more farmers that participate in this multiyear insurance plan, the less adverse the pool will be. Therefore, adverse selection may be alleviated through the proposed multiyear insurance contract.

The multiyear yield insurance plan is also expected to have the same advantages as the multiyear revenue insurance plan over the current MPCI and GRP. As a yield loss in one year can be offset by a yield increase in the other year, the expected loss over two years can be reduced, which also lowers the premium rate. Also a partial payment of indemnity is paid to farmers who have severe loss in one year to cover their loss. Finally, the administrative cost is expected to be lower for a multiyear yield insurance plan than current MPCI and GRP. These properties also can attract more farmers to participate in the multiyear yield insurance plan.
4.2 Simulation

4.2.1 Relationship between the Actuarially Fair Premium Rate and Correlation Across Years

In this section, we will show simulation results for the actuarially fair rates based on different correlations of yields across years for the two-year and three-year yield crop insurance plans. For simplicity, we only simulated yield distributions for yield crop insurance plans. However, the results can be applied to revenue insurance plans as well. Several assumptions were made in these simulations. These assumptions are described as follows.

(a) The yield distribution for each year follows a Beta distribution with the shape parameters $\alpha = 2, \beta = 1.5$ and data ranging from 0 to 200.

(b) The correlation coefficient of yield distributions between the first year and second year varies between -1 and 1. The correlation coefficient of yield distributions among the first, second and third years is between -0.5 and 1.

(c) The farmer selects a 70% coverage level and the expected yield is 160.

Indemnity is paid if the average yield over two or three years is below the guaranteed yield, which is $0.7 \times 160 = 112$. Then the actuarially fair premium rates are calculated based on the loss function. Results are shown in Table 1. As demonstrated in Table 1, rate_{12} is the actuarially fair premium rate of the two-year yield insurance plan and rate_{123} is the actuarially fair premium rate of the three-year yield crop insurance plan; rho is the Spearman correlation coefficient of yield distributions among the first, second and third year.
Several conclusions can be made from Table 1: (1) the actuarially fair premium rates for two-year and three-year yield crop insurance plans are at the minimum (i.e. 0) when the correlation coefficients are close to -1 for a two-year plan and -0.5 for a three-year plan; (2) the actuarially fair premium rates for two-year and three-year yield crop insurance plans are at the maximum (.166 and .165, respectively) when the correlation coefficient is 1, which is the same as the actuarially fair premium rate of a one-year yield crop insurance plan; and (3) the actuarially fair premium rates of two-year and three-year yield crop insurance plans with rho<1 are lower than the actuarially fair premium rate for a single year.

We can use the Figure 2 to present these simulation results in order to demonstrate the relationship between correlations across years and the actuarially fair premium rate. We put the correlation coefficient of yields across years in the x-axis and the actuarially fair premium rate of multiyear yield insurance plans in the y-axis. The red curve represents the simulation results for a two-year insurance plan and the blue curve represents the simulation results for a three-year yield insurance plan. When yields between two years are perfectly positively correlated, the actuarially fair premium rate of a two-year yield insurance plan is at its maximum and is the same as the single year yield insurance plan (actuarially fair premium rate=0.165 of a single year yield insurance plan). This result also holds true for the three-year yield insurance plan. When yields among three years are perfectly positively correlated, the actuarially fair premium rate of a three-year yield insurance plan is also at its maximum and is the same as the single year yield insurance plan.
When the correlation of yields between two years decreases from perfectly positive to perfectly negatively correlated, the actuarially fair premium rate of a two-year yield insurance plan decreases from 0.16 to 0. When the correlation of yields among three years decreases from perfectly positively correlated to -0.5, the actuarially fair premium rate of a three-year crop yield insurance plan also decreases from 0.16 to 0. The simulation results demonstrated that a multiyear yield insurance plan can have a lower actuarially fair premium rate than current single-year yield insurance plans.
### Table 1 Simulation Result for Two-and-Three Year Yield Crop Insurance Plan

<table>
<thead>
<tr>
<th>Observation</th>
<th>rate_{12}</th>
<th>rate_{123}</th>
<th>Rho</th>
<th>Observation</th>
<th>rate_{12}</th>
<th>rate_{123}</th>
<th>Rho</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>N/A</td>
<td>-1</td>
<td>11</td>
<td>0.110</td>
<td>0.087</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0.030</td>
<td>N/A</td>
<td>-0.9</td>
<td>12</td>
<td>0.116</td>
<td>0.097</td>
<td>0.1</td>
</tr>
<tr>
<td>3</td>
<td>0.044</td>
<td>N/A</td>
<td>-0.8</td>
<td>13</td>
<td>0.122</td>
<td>0.097</td>
<td>0.2</td>
</tr>
<tr>
<td>4</td>
<td>0.055</td>
<td>N/A</td>
<td>-0.7</td>
<td>14</td>
<td>0.129</td>
<td>0.114</td>
<td>0.3</td>
</tr>
<tr>
<td>5</td>
<td>0.066</td>
<td>N/A</td>
<td>-0.6</td>
<td>15</td>
<td>0.133</td>
<td>0.121</td>
<td>0.4</td>
</tr>
<tr>
<td>6</td>
<td>0.074</td>
<td>0.007</td>
<td>-0.5</td>
<td>16</td>
<td>0.140</td>
<td>0.130</td>
<td>0.5</td>
</tr>
<tr>
<td>7</td>
<td>0.082</td>
<td>0.035</td>
<td>-0.4</td>
<td>17</td>
<td>0.144</td>
<td>0.137</td>
<td>0.6</td>
</tr>
<tr>
<td>8</td>
<td>0.091</td>
<td>0.052</td>
<td>-0.3</td>
<td>18</td>
<td>0.149</td>
<td>0.144</td>
<td>0.7</td>
</tr>
<tr>
<td>9</td>
<td>0.097</td>
<td>0.066</td>
<td>-0.2</td>
<td>19</td>
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</tr>
<tr>
<td>10</td>
<td>0.104</td>
<td>0.076</td>
<td>-0.1</td>
<td>20</td>
<td>0.162</td>
<td>0.158</td>
<td>0.9</td>
</tr>
</tbody>
</table>

Note: The rate for a single year plan is 0.165, which is the same as rates for multi-year plans when rho=1.
Figure 2 Relationship between the Actuarially Fair Premium Rate and Correlation of Yield Across Years
4.2.2 Relationship between the Actuarially Fair Premium and Correlation Across Years

In section 4.2.1, simulation results show that a lower actuarially fair premium rate can be reached by using a multiyear insurance plan. As only a 70% coverage level was chosen in the simulation shown in section 4.2.1, we will continue to use these simulations in order to compare the cost of a premium payment for multiyear insurance plans to two one-year plans based on the different values of coverage levels of total indemnity payment because farmers may select different coverage level than the one that we chose for the simulation. The simulation results discussed here are shown in Figures 3-10. In addition, as the correlation of yields across years may vary from farm to farm and county to county, we will also use simulations in order to compare the cost of premium payments for multiyear insurance plans to two one-year plans based on the different values of correlation. These results are shown in Figures 11-21. By examining Figures 3-21, one can see a clearer picture of how multiyear insurance plans can offer a lower premium payment through different levels of coverage levels. In Figure 3-10, we fixed the yield correlation and the relationship between the premium payment and coverage level of indemnity is therefore shown. In Figures 11-21, we fixed the coverage level of indemnity and the relationship between yield correlation and premium payment for two one-year plans and a multiyear plan are shown.

We made the following assumptions in our simulations:

a) The expected yield is 160 bu/A across two years.

b) Coverage levels of total indemnity=70%, 80%, 90%, and 100%.
c) Coverage level for partial payment of indemnity for a multiyear plan=50%.

d) The insured price is one dollar/bu.

e) For a three year plan, the correlation of yields between any two of the three years is the same.

For multiyear plans, the total indemnity is paid if the average yield over two or three years is below the guaranteed yield. This is calculated using the coverage level multiplied by the expected yield. Also a partial payment of indemnity is paid for a year if the realized yield for that year falls below the guaranteed yield. This is calculated by using the coverage level for partial payment of total indemnity multiplied by the expected yield. The x-axis represents the correlation of yields across years and the y-axis represents the premium payment.

As seen in Figure 3, when farmers choose the 70% coverage level in a one-year plan for a period of two years, the premium payment will be around $36.88-$37.32. The premium payment for a single-year plan for two years barely changed with different values of correlations as they are purchased independently each year. However, when farmers choose the 70% coverage level in a two-year plan, the premium will be between $1.35-$36.95, depending on the correlation of yields between the two years. When the correlation coefficient is -1, the two-year plan has the lowest premium payment. This is because the loss in one year can be offset perfectly by the gain in the other year in the two-year plan. In Figure 4, when farmers choose the 70% coverage level in a one-year plan for a period of three years, the premium payment will be around $55.46-$55.94. The premium payment did not change with correlation in this case as well due to the fact that the one-year plans are
purchased independently over a span of three years. However, when farmers choose the 70% coverage level in a three-year plan, the premium rate will fall to between $21.43-$55.73, depending on the correlation of yields. The premium payment is at its lowest when the correlation coefficient is -1. Therefore, the premium payment in a multiyear insurance plan is always less than the premium payment of a one year insurance plan for multiple years except when the correlation coefficient is 1. When the correlation coefficient for yields is 1, the premium payments are the same for both plans. This is because the offset of loss for a multiyear plan will not have an effect in this case.

We then selected different coverage levels ranging between 70% and 100% in order to investigate the relationship between the correlation of yield and premium payment. As seen in Figures 5 to 10, we also observed the same pattern as Figure 3 and 4 when coverage levels are at 70%. This demonstrates that the premium payment of a multiyear plan is always lower than the payment for one year plans regardless of coverage level. However, the difference in payments between the two plans becomes smaller when the coverage level increases. This is because the offset effect is minimized with a high rate of coverage. In addition, multiyear plans will guarantee a coverage level of 50% for partial payment of indemnity for each year.
Figure 3 Relationship between Premium Payment and Correlation between Two Years with 70% Coverage Level

Figure 4 Relationship between Premium Payment and Correlation Across Three Years with 70% Coverage Level
Figure 5 Relationship between Premium Payment and Correlation between Two Years with 80% Coverage Level

Figure 6 Relationship between Premium Payment and Correlation Across Three Years with 80% Coverage Level
Figure 7 Relationship between Premium Payment and Correlation between Two Years with 90% Coverage Level

Figure 8 Relationship between Premium Payment and Correlation Across Three Years with 90% Coverage Level
Figure 9 Relationship between Premium Payment and Correlation between Two Years with 100% Coverage Level

Figure 10 Relationship between Premium Payment and Correlation Across Three Years with 100% Coverage Level
Next we investigated the relationship between coverage level and premium payment by fixing the correlation of yields among years. In Figure 11, we can see that when the correlation of yields between two years is -1 and the coverage levels of total indemnity are between 70% and 100%, the premium payments of two one-year plans are between $30-$100 and the premium payments of two-year plans are between $0-$100. The premium payment for a two-year plan is also lower than the payment for two one-year plans with different coverage levels. The difference in the premium payments between the two plans becomes larger when the coverage level is smaller. This is consistent with the observations in Figures 3-10.

Then we also selected different correlation coefficients of yields among years (i.e. -0.5, 0, 0.5, 0.8, 1) to investigate the relationship between premium payment and coverage level in Figure 12-21. In conclusion, from Figure 11-21, given a fixed coefficient of correlation, a multiyear plan will always have a lower premium payment compared to single year plans when the correlation coefficient is <1. The multiyear plan has the same premium payment as the one year plans when the correlation coefficient is 1 due to the lack of the effects on offsetting losses. Also the difference in the premium payments between a multiyear plan and a one-year plan for multiple years becomes larger when both the correlation of yields and coverage levels are lower. Moreover, the multiyear plan will also guarantee a coverage level of 50% for partial payment of indemnity for each year. The simulation results in this chapter show the advantages of the proposed multiyear insurance plans over the current single-year
plan. In the next two chapters, we will give a detailed description of the contract design and implementation for the multiyear insurance plans.

Figure 11 Relationship between Premium Payment and Coverage Level between Two Years with Perfectly Negative Correlation
Figure 12 Relationship between Premium Payment and Coverage Level between Two Years with -0.5 Correlation

Figure 13 Relationship between Premium Payment and Coverage Level Across Three Years with -0.5 Correlation
Figure 14 Relationship between Premium Payment and Coverage Level between Two Years with Zero Correlation

Figure 15 Relationship between Premium Payment and Coverage Level Across Three Years with Zero Correlation
Figure 16 Relationship between Premium Payment and Coverage Level between Two Years with 0.5 Correlation

Figure 17 Relationship between Premium Payment and Coverage Level Across Three Years with 0.5 Correlation
Figure 18 Relationship between Premium Payment and Coverage Level between Two Years with 0.8 Correlation

Figure 19 Relationship between Premium Payment and Coverage Level Across Three Years with 0.8 Correlation
Figure 20 Relationship between Premium Payment and Coverage Level between Two Years with Perfectly Positive Correlation

Figure 21 Relationship between Premium Payment and Coverage Level Across Three Years with Perfectly Positive Correlation
5. Outline of A Multiyear Insurance Plan

5.1 Introduction of A Multiyear Insurance Plan

In this chapter, we will begin to describe the proposed multiyear insurance plan in detail. In a multiyear revenue insurance plan, like what is seen in current revenue insurance plans, farmers choose a coverage level. However, several differences exist between a multiyear revenue insurance plan and the current existing revenue insurance plans. The first major difference is that insurance is extended from a single term to multiple periods of time for the multiyear plan. The guaranteed revenue is calculated for each period in a way that is similar to the current Crop Revenue Coverage and Revenue Assurance plans. Next the guaranteed revenue for the multiyear plan is based on the average of the guaranteed revenue over a period of multiple years. In the last harvest period, when the average of the actual revenue over the specified period of time falls below the guaranteed revenue, payment will be made. The payment made will be the difference between the average of actual revenue over a specified period of time and the guaranteed revenue calculated over multiple periods of time. This way, when a decrease in revenue in period 1 is offset by increase in revenue in period 2 or vice versa, payment may not be made if the average revenue is more than the guaranteed revenue.

In this situation, farmers may not obtain as much of an indemnity payment as they do when purchasing single year plans over a period of years. To compensate farmers for a possible yield loss in either one of insured year, insured farmers will obtain a partial payment of an indemnity at a certain insured period in order to cover the cost of production if the actual
revenue during a specific insured period falls below a certain level in the proposed multiyear revenue insurance plan. In other words, a multiyear revenue insurance plan not only guarantees revenue for the total insured years, but it also guarantees revenue corresponding to variable costs of production in each insured year. We can take a two-year revenue insurance plan for example. Insured farmers choose a coverage level $\beta$ of revenues for an average across the two years of coverage. Thus, they will obtain a total indemnity when the actual revenue over two years falls below the guaranteed revenue (i.e. $\beta$ times the expected revenue). In addition, partial payment will be made in any given year when the actual revenue in that year falls below the variable costs of production. The partial payment will be equal to 100 percent of the variable costs of production. This way, at least the insured farmers can obtain their cost of production for multiple periods of time if they have actual revenue less than the guaranteed revenue. This will make a multiyear revenue insurance plan more helpful to farmers because insured farmers will not be worried that the total indemnity will fail to their loss of production in a certain year. This is the second major difference between the current revenue insurance plan and a multiyear revenue insurance plan.

5.2 How to Implement A Multiyear Insurance Plan in Practice

In this section, we will describe the specific details of a multiyear revenue insurance plan. We will define the determination of total indemnity and partial payment of total indemnity based on the cost of production when insured farmers’ actual revenues fall below the guaranteed revenue. We will also explain how a multiyear revenue insurance plan is developed in theory. Only the multiyear revenue insurance plan is introduced here. However, the design of a
multiyear yield insurance plan is similar to the design of a multiyear revenue insurance plan, except that the indemnity is determined based on production yields so that only distributions for yields need to be considered. The period of coverage for a multiyear insurance plan may be two or three years. Longer periods of coverage are not considered as modeling multiple correlated variables may be inappropriate given limited data. It may also be unrealistic for farmers to wait more than three years to obtain an indemnity.

5.2.1 Determination of Total Indemnity and Partial Payment of Total Indemnity in A Multiyear Revenue Insurance Plan

The total indemnity is paid when the average revenue over two years is less than the guaranteed revenue. We present the total indemnity determination of a two-year insurance plan in the following equation:

\[ R_i^A + R_2^A < \beta \cdot (E(R_i) + E(R_2)) \]

Where

\[ R_i^A = \text{actual revenue at year } i, i = 1, 2 \]

\[ E(R_i) = \text{expected revenue at year } i \]

\[ \beta = \text{coverage level}, \beta \leq 1 \]

The total indemnity is thus the difference between the sum of realized revenue over two years and the guaranteed revenue. Also, a partial payment of total indemnity will be made if the actual revenue in a certain year falls below a certain level. This partial payment of total indemnity is based on the cost of production and futures price. Partial payment of total
Indemnity is the difference between the threshold \((\gamma \mu_i)\) and the actual revenue \((R^A_i, R^A_2)\), where \(\gamma\) is the coverage level for the partial payment of total indemnity and \(\mu_i\) is the expected yield in year \(i\). Thus, partial payment of the total indemnity amount is determined by the values of \(\gamma, \mu_i, R^A_i, R^A_2\).

There are many approaches to setting up the level of \(\gamma\) for the government. The first solution that the government can choose in order to decide the coverage level of \(\gamma\) is to cover farmers’ short-term debt as farmers are usually dependent on short-term loans. We can consider variable production costs to determine the coverage level of \(\gamma\). Soil quality, elevation, quantity of inputs, operating practices and other factors may all affect production cost and thus production cost varies from farm to farm and crop to crop. Therefore, measuring a farm’s production cost accurately will require detailed farm records. However, this type of record keeping is expensive and is not easy to obtain. Hence, the estimated cost of production of a representative farm will be used for the multiyear revenue insurance plan discussed here. The predicted price reflects the expected market value and also the expected revenue (per bushel) for farmers. A long period of predicted price data and estimated cost of production (such as estimated cost of production of corn, corn silage, soybeans, alfalfa, and pasture in Iowa) are both publicly available. Therefore, the ratio of the estimated cost of production to predicted price can be an indicator to determine the coverage level. More specifically, the ratio \(\gamma\) can be calculated in the following equation: \(\gamma = \frac{\text{estimated variable cost}}{\text{predicted price}}\)
After the coverage level is obtained by using the estimated cost of production and predicted price, the threshold of partial payment of total indemnity in periods 1 and 2 will be the coverage level times actual revenue in periods 1 and 2, respectively.

Therefore, the estimated partial payment for the cost of production in periods 1 and 2 can be derived from the expected revenue in periods 1 and 2. Payment of the cost of production will be made by using this indicator. More specifically, the proposed two-year revenue insurance plan will guarantee insured farmers \( \gamma R_i^A \); b) \( \gamma R_2^A \); and c) \( \beta (E(R_i) + E(R_2)) \) and \( \gamma \) will be based on the cost of production.

Farmers may prefer a higher partial payment of indemnity, which means the higher level of \( \gamma \). However, government will be more burdened by having a higher partial payment of indemnity. The government, therefore, would prefer the lower level of \( \gamma \). The second solution to this problem is to consider the insurance cost for government and the benefits for farmers under different ranges of \( \gamma \). Through the consideration of cost and benefit with a different range of \( \gamma \), government should have a good estimate of how much it will cost and how well it will help farmers under a certain range of \( \gamma \).
5.2.2 Modeling Yield and Price Distributions and Correlation Between Price and Yield Across Years

In order to design a 2-year revenue insurance plan, we need to consider yield distributions for periods 1 and 2 and price distributions for periods 1 and 2 so that the expected revenue can be calculated for various years. In total we have to consider four random variables: two yield and two price random variables. As price and yield are rarely independent, the correlation of price and yield also needs to be considered. We also need to consider the correlation of price between two years and correlation of yield between two years.

Modeling yield distributions will be accomplished using a Beta distribution. Price will be modeled as a lognormal distribution. The parameters of mean and variance in the lognormal distribution will be estimated from the futures and option contracts, respectively, like as is done in current revenue insurance plans. The correlation of price between periods 1 and 2 will be estimated based on the observed futures prices between years. In addition, the correlation between yield and price in periods 1 and 2 will be estimated using the futures prices and the observed yield data. As a result, we can construct a four by four correlation matrix for the pair-wise correlation between the four variables. Then we can simulate two yield and two price distributions according to their marginal distributions and the correlation matrix. The expected revenue in periods 1 and 2, coverage level of the cost of production, the actuarially fair premium rate and the expected loss will be estimated from the joint distribution for the four variables.
6. Theoretical Demonstration of Multiyear Crop Insurance Plans

We have described the details for the two-year insurance plan in the previous section. We have also shown that the premium rate can be lower in a two-year insurance plan than in a one-year plan based on simulation results. In this section, we will demonstrate, in theory, the advantages of a two-year insurance plan over two independent one-year insurance plans. In short, a two-year insurance plan has features of a) possible partial payment of indemnity in each year and b) a total indemnity payment in the second year that will address losses over total revenues across a two-year span. Partial payment of indemnity will be made when the actual revenue falls below a predetermined threshold for each individual year. Indemnity payments will be made in the second year when the sum of actual revenue for both years falls below a predetermined threshold. We will assess this two-year insurance plan from both the farmer’s and government’s points-of-view.

From the government’s perspective, we need to consider whether the government needs to pay more indemnity in a two-year insurance plan compared to what they would need to pay for in two one-year insurance plans. We also need to address the difference in the amount of an indemnity payment between a two-year insurance plan and two one-year insurance plans.

We will discuss these issues in General Model 1 and in reduced Special Cases 1.1 and 1.2 in the following section. Compared to the currently used one-year insurance plan, a two-year insurance plan has two key features: a lower premium payment and a guaranteed partial payment of indemnity in either of the years if a loss occurs in that year. Let us now look at
the farmer’s perspective. Farmers are expected to have higher participation rates in a two-year plan due to a lower premium requirement with the same coverage level for a two-year insurance plan rather than two one-year insurance plans as seen in our simulation earlier. As we have demonstrated previously, the premium rate can be lower in a two-year insurance plan. Secondly, we will consider whether farmers are better off based on their time preference when the partial payment of indemnity of a two-year insurance plan is made. Moreover, farmers may face liquidity constraints in the capital market. Therefore, we will take the time preference of farmers as well as liquidity constraints into account in order to discuss the insurance outcome of the two-year insurance plan seen in General Model 2 and Special Cases 2.1 and 2.2.

6.1 General Model 1: Two-Year Crop Insurance Plan

The two-year crop insurance plan can be seen as two single year policies and also as one plan with two years of coverage because it will guarantee farmers against a yearly loss in each year and the overall loss in the second year. Payment made in each year that is based on the actual revenue in that year is called “partial payment of total indemnity.” Payment made in the second year that is based on the actual revenue for two years is called “the total indemnity payment.” It is necessary to mention that both partial payment of indemnity and total indemnity may be made in the second year. Before we move forward, we define the following terms:
$R_i$ : random variable for revenue in year $i$, $i=1,2$;

$R_i^A$ : the actual revenue in year $i$, $i=1,2$;

$\gamma$ : the coverage level for partial payment of indemnity determined by the insurer and $0 < \gamma < 1$;

$\beta$ : the coverage level for total indemnity payment decided by farmers and $0 < \beta < 1$;

$\mu_i$ : the expected revenue ($E(R_i)$) in year $i$ and $\gamma \mu_i$ is the threshold of partial payment of indemnity.

$Pay_i(R_i^A | \gamma)$ : the partial payment of indemnity made in year $i$, $i=1,2$;

$I_i(R_i^A, R_i^A | \gamma, \beta)$ : partial payment of indemnity and total indemnity payment made in year two;

$I_{2\text{-year}}$ : total payment for the two-year insurance plan

We can also express the conditions used in deciding whether the partial and total indemnity payments will be made in the following equations:

a.1) Partial payment of indemnity will be made if $R_i^A <\gamma \mu$

a.2) Total indemnity payment will be made in the second year if

$$R_1^A + R_2^A < \beta(E(R_1) + E(R_2)) = \beta(\mu_1 + \mu_2)$$

Based on these two conditions, the payment can be calculated as follows:

b.1) $Pay_i(R_i^A | \gamma) = \max(\gamma \mu_i - R_i^A, 0)$
b.2) 
\[ I(R_1^d, R_2^d | \gamma, \beta) = \max(\gamma \mu_2 - R_2^d, 0) + \max\{\beta(\mu_1 + \mu_2) - \max(R_1^d, \gamma \mu_1) - \max(R_2^d, \gamma \mu_2), 0\} \]

b.3) \[ I_{2-yr} = P \alpha |(R_1^d | \gamma) + I(R_1^d, R_2^d | \gamma, \beta) \]

We use Table 2 to show the difference in conditions in General Model 1 and Special Cases 1.1 and 1.2.

Table 2 General Model 1, Special Cases 1.1 and 1.2

<table>
<thead>
<tr>
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<th>Two-Year Insurance Plan</th>
<th>One-Year Insurance Plan</th>
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<tbody>
<tr>
<td>General Model 1</td>
<td>( \beta = 1, 0 &lt; \gamma &lt; 1 )</td>
<td>( \gamma = 1 )</td>
</tr>
<tr>
<td>Special Case 1.1</td>
<td>( \beta = 1, \gamma = 0 )</td>
<td>( \gamma = 1 )</td>
</tr>
<tr>
<td>Special Case 1.2</td>
<td>( \beta = 1, \gamma = 1 )</td>
<td>( \gamma = 1 )</td>
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We then use Figure 22, in which the x-axis is revenue in year one and the y-axis is revenue in year two, in order to demonstrate the indemnity area for partial and full indemnity payment. According to a.1) and b.1), partial payment of indemnity will be made if \( R_1^d < \gamma \mu_1 \) or \( R_2^d < \gamma \mu_2 \) when \( 0 < \gamma < 1 \). Therefore, in Figure 22, indemnity areas for partial payment of indemnity are “A+C+E+I+O” for year one and “I+J+K+L” for year two. Here we assume \( \beta = 1 \) throughout General Model 1 and Special Cases 1.1 and 1.2 for simplicity. However, this condition can be easily relaxed. According to a.2) and b.2), indemnity payment in year two will be made if \( R_1^d + R_2^d < \mu_1 + \mu_2 \) when \( \beta = 1 \). Therefore, indemnity areas for year two are “C+D+E+F+G+I+J+K+O”. According to b.3), indemnity areas in total are
“A+C+D+E+F+G+I+J+K+L+O” under $\beta = 1$ and $0 < \gamma < 1$. The actuarially fair premium rate of the two-year insurance plan can be calculated as:

\[
\text{actuarially fair premium rate} = \frac{\text{actuarially fair premium}}{\text{liability}} = \frac{\text{expected loss}}{\text{liability}} = \frac{\text{expected loss}}{2\varphi\beta\mu}
\]

where $\varphi$ is the insured price per bushel. We assumed that $\varphi = 1$ for simplicity.

In order to obtain the premium rate for the two-year insurance plan, we need to calculate the expected loss. In the meantime, we also need to obtain the amount of the expected loss for the government. As seen in the discussion above, indemnity areas are “A+C+D+E+F+G+I+J+K+L+O” under $\beta = 1$ and $0 < \gamma < 1$. In General Model 1, we will only calculate the expected loss for areas “A+L” and we will calculate the expected loss for
areas “C+D+E+F+G+I+J+K+O” later in Special Case 1.1. The actual revenue in year one falling inside area A means that $R_1^i < \gamma \mu_i$ and $R_1^i + R_2^i > \mu_1 + \mu_2$. On the other hand, the actual revenue in year two falling inside area L means that $R_2^i < \gamma \mu_2$ and $R_1^i + R_2^i > \mu_1 + \mu_2$. This means that the expected loss for areas “A+L” is

$$E(loss \mid \gamma > 0, \beta = 1) = \text{prob}(loss) E(loss \mid loss occurs)$$

$$= \text{prob}(R < \gamma \mu_1, R_1 + R_2 > \mu_1 + \mu_2) E(R_1 + R_2 \mid R_1 < \gamma \mu_1, R_1 + R_2 > \mu_1 + \mu_2)$$

$$+ \text{prob}(R_2 < \gamma \mu_2, R_1 + R_2 > \mu_1 + \mu_2) E(R_1 + R_2 \mid R_2 < \gamma \mu_2, R_1 + R_2 > \mu_1 + \mu_2)$$

where $f(R_1, R_2)$ is the joint pdf of $R_1$ and $R_2$.

Thus, we demonstrated that the two-year insurance plan can be a good substitute for two one-year insurance plans for farmers. From the government’s perspective, we also investigated the difference in the indemnity payment between the two-year insurance plan and two one-year insurance plans.
We will continue the assumption that $\beta = 1$ and $0 < \gamma < 1$ for the two-year insurance plan. We also assume $\gamma = 1$ in years one and two for two one-year insurance plans and we hold this assumption both in General Model 1 and in Special Cases 1.1 and 1.2. In other words, the indemnity payment of two one-year insurance plans will be made when $R_1^A < \mu_1$ for year one and $R_2^A < \mu_2$ for year two. We can then express the difference in indemnity payment $(X_G)$ between the two different plans in the following:

$$X_G = \text{total payment for two one-year insurance plans} - \text{total payment for the two-year insurance plan with partial payment of indemnity}$$

$$= I_{1-\text{yr}} - I_{2-\text{yr}}$$

where $I_{1-\text{yr}} = Pay_1(R_1^A | \gamma) + Pay_2(R_2^A | \gamma)$

We can select one coordinate of $(R_1^A, R_2^A)$ to show how to express the difference in indemnity payment with $(R_1^A, R_2^A)$ located in different areas (A+B+C+D+E+F+G+H+I+J+K+L+O) in Figure 22. For example, when the actual revenue for two years falls in area “A,” the total indemnity payment for two one-year insurance plans is $\mu_1 - R_1^A$ in year one because $R_1^A < \mu_1$ and $R_2^A > \mu_2$. The total indemnity payment for the two-year insurance plan is $\gamma \mu_1 - R_1^A$ because $R_1^A < \gamma \mu_1$ and $R_1^A + R_2^A > \mu_1 + \mu_2$. Therefore the difference in indemnity payment is $(\mu_1 - R_1^A) - (\gamma \mu_1 - R_1^A)$. We can calculate the difference in the indemnity payment for other areas as seen in the following:
From the calculations of $X_G$ above, we can obtain $X_G \geq 0$ when $\beta = 1, \theta < \gamma < 1$.

Therefore, we can conclude that indemnity payment for two one-year insurance plans is higher than the total indemnity payment in a two-year insurance plan. Differences in indemnity depend on $\mu_1, \mu_2, \gamma, R_1^A, R_2^A$ and the values of $\mu_1$ and $\mu_2$ depend on the correlation of revenues across years. Therefore, the differences in indemnity will depend on the correlation of revenues across years. This demonstrates that government would prefer a two-year insurance plan due to lower indemnity.

We will now discuss Special Case 1.1, in which the two-year insurance plan does not guarantee partial payment of indemnity in each of the two years ($\gamma = 0$) but only guarantees the sum of actual revenue for two years. We will also discuss the indemnity areas, the expected loss of a two-year insurance plan without partial payment of indemnity, and the difference in indemnity payment between a two-year insurance plan without partial payment of indemnity and two one-year insurance plans in Special Case 1.1.
6.2 Special Case 1.1: Comparing Two One-Year Plans with A Two-Year Crop Insurance Plan without Partial Payment of Indemnity

In Special Case 1.1, no partial payment of indemnity will be made ($\gamma = 0$) regardless as to whether the actual revenue in either year one or two falls below the threshold or whether it does not. More specifically, the two-year insurance plan only considers the sum of actual revenue over a period of two years in Special Case 1.1. We therefore keep the assumption that $\beta = 1$. As seen in the General Model 1, indemnity areas are “C+D+E+F+G, I+J+K+O” when $\beta = 1$. We can therefore calculate the expected loss of insurance for government when $\beta = 1$ using the following equation:

The Expected Loss for area “C+D+E+F+G, I+J+K+O”

$$E(loss \mid \gamma = 0, \beta = 1)$$

$$= prob(R_1 + R_2 < \mu_1 + \mu_2)E(R_1 + R_2 \mid R_1 + R_2 < \mu_1 + \mu_2)$$

$$= \int_{0}^{\mu_1+\mu_2} \int_{0}^{\mu_1+\mu_2-R_2} f(R_1, R_2)dR_1dR_2 \ E(R_1 + R_2 \mid R_1 + R_2 < \mu_1 + \mu_2) \quad (6.2)$$

As partial payment of indemnity is not guaranteed, partial payment of indemnity will not be made no matter how much the amount of actual revenue is in years one and two. According to a.1) and b.1), the following condition will hold:

$$Pay_i(R_i \mid \gamma = 0) = 0 \ \forall i \quad (6.3)$$

From eq(3), the total indemnity payment for Special Case 1.1 is

$$I_{2-YR} = Pay_i(R_i \mid \gamma) + I(R_1, R_2 \mid \gamma, \beta) = I(R_1, R_2 \mid \gamma = 0) \quad (6.4)$$
We can then calculate the difference in indemnity payment between two one-year plans and a two-year insurance plan without partial payment of indemnity. We define the difference in indemnity payment \( X_{S_i} \) as follows:

\[ X_{S_i} = \text{total payment for two one-year insurance plans} - \text{total payment for the two-year insurance plan without partial payment of indemnity} \]

\[ = I_{1-yr} - I_{2-yr} \]

\[ = I_{1-yr} - I(R_1, R_2 | \gamma = 0) \]

We have a summary of the difference in indemnity payment between two one-year insurance plans and two-year insurance plan with partial payment of indemnity in General Model 1. We can use the same calculations as we used in General Model 1 in order to obtain \( X_{S_i} \) in the following:

\[ X_{s_i} = \begin{cases} 
(\mu_i - R_i^A) - 0 & \text{if } (R_i^A, R_j^A) \in A,B \\
(\mu_i - R_i^A) - (\mu_i + \mu_2 - R_i^A - R_2^A) = R_2 - \mu_2 & \text{if } (R_i^A, R_j^A) \in C,D,O \\
[(\mu_i - R_i^A) + (\mu_2 - R_2^A)] - (\mu_i + \mu_2 - R_i^A - R_2^A) & \text{if } (R_i^A, R_j^A) \in E,F,I,J \\
(\mu_2 - R_2^A) - (\mu_i + \mu_2 - R_i^A - R_2^A) & \text{if } (R_i^A, R_j^A) \in K,G \\
(\mu_2 - R_2^A) - 0 & \text{if } (R_i^A, R_j^A) \in H,L 
\end{cases} \]

We can reach the conclusion that indemnity payment for two one-year insurance plan is still higher than the total indemnity payment in a two-year insurance plan because \( X_G \geq 0 \) when \( \beta = 1 \) and \( \gamma = 0 \) as seen in the calculation of \( X_G \) above. This conclusion is the same as the one that we obtained in General Model 1; the correlation of revenues across years also plays
a role in the difference in indemnity payment. In General Model 1 and Special Case 1.1, we discussed the two-year crop insurance plan both with and without partial payment of indemnity depending on the value of $\gamma$. We will continue to discuss another case corresponding to a different value of $\gamma$ in Special Case 1.2. When the two-year insurance plan guarantees partial payment of indemnity in each of the two years with $\gamma = 1$, General Model 1 will reduce to Special Case 1.2.
6.3 Special Case 1.2: One-and-Two-Year Insurance Plans

In Special Case 1.2, we will discuss the two-year insurance plan with partial payment of indemnity when \( \gamma = 1 \). According to a.1), partial payment of indemnity will be made when the actual revenue in any one of the two years falls below 100% of the expected revenue. More specifically, a.1), b.1) and b.2) will become the following:

Partial payment of indemnity will be made in year \( i \) if \( R_i < \mu_i, i = 1,2 \)

\[
Pay_i(R_i | \gamma = 1) = \max(\mu_i - R_i, 0), i = 1,2
\]

\[
I(R_i, R_2 | \gamma = \beta = 1) = \max(\mu_2 - R_2, 0) + \max(\mu_1 + \mu_2 - \max(R_1, \mu_1) - R_2, 0)
\]

In addition, as seen in General Model 1, indemnity areas are “C+D+E+F+G+I+J+K+O” when \( \beta = 1 \) and indemnity areas for partial payment of indemnity are “A+B+C+D+E+F+G+H+I+J+K+L+O” when \( \gamma = 1 \). Therefore, indemnity areas are “A+B+C+D+E+F+G+H+I+J+K+L+O” when \( \beta = 1 \) and \( \gamma = 1 \). Note that in the assumption for two one-year insurance plans, indemnity payment will be made when the actual revenue falls below the expected revenue where \( R_1 < \mu_1 \) in year one and \( R_2 < \mu_2 \) in year two. This means that we implicitly assume \( \gamma = 1 \) in years one and two for two one-year insurance plans. Therefore, indemnity areas for two one-year insurance plans with \( \gamma = 1 \) are exactly the same with the indemnity areas as a two-year insurance plan with \( \gamma = 1 \). These results suggest that the two-year insurance plan with \( \gamma = 1 \) is equivalent to two one-year insurance plans with \( \gamma = 1 \). Following the same discussion seen in General Model 1 and Special Case 1.1,
we can also calculate the expected loss of insurance for government when \( \beta = 1 \) and \( \gamma = 1 \) for the two-year insurance plan with \( \gamma = 1 \) in the following equation:

The Expected Loss for areas “A+B+C+D+E+F+G+H+I+J+K+L+O”

\[
E(loss \mid \gamma = 1, \beta = 1) = \int_{0}^{\infty} \int_{0}^{\infty} f(R_1, R_2) dR_1 dR_2 \ E(R_1 + R_2 \mid R_2 < \mu_2) \\
+ \int_{\mu}^{\infty} \int_{\mu}^{\infty} f(R_1, R_2) dR_1 dR_2 \ E(R_1 + R_2 \mid R_1 > \mu_1, R_2 < \mu_2)
\]

We discussed the difference in the indemnity payment in General Model 1 and Special Case 1.1. We will not discuss this in Special Case 1.2, however, because Special Case 1.2 is equivalent to two one-year insurance plans with \( \gamma = 1 \).
7. Farmers’ Welfare Based on Time Preference

In the previous chapter, we discussed the indemnity areas based on Figure 22, calculated the expected loss of insurance for a two-year insurance plan for government, and compared the difference in indemnity payment between one and two-year insurance plans in General Model 1 and Special Cases 1.1 and 1.2. In addition, we discussed how to decide the optimal coverage level for the partial payment of indemnity across a span of two years for the government. We have discussed these topics in order to demonstrate the main issues of a two-year insurance plan that government should address. A multiyear crop insurance plan is designed to help producers reduce intrayear income uncertainty through partial payment and multiyear income uncertainty through total indemnity. Therefore, we are interested in farmers’ welfare with a multiyear crop insurance plan when their welfare is measured by their expected income. In this chapter, we consider farmers’ welfare with and without a multiyear revenue crop insurance plan. Our welfare measure is based on the difference between the expected income for the two year revenue crop insurance plan and the expected income for the uninsured cases. Since our interest is producers’ welfare under a crop insurance plan, we assume that farm earnings is the only income resource from selling one single commodity and producers don’t use other risk management tools such as futures contract to protect their income. Producers’ preferences toward risk is also a factor to affect their welfare in each given situation and we focus on risk neutral producers here.

Since partial payment of indemnity may be made in each of the two years under certain conditions, it is important to investigate whether farmers are happier when partial payment of
indemnity is made in each of the two years than when partial payment of indemnity is made in the second year. This question is related to the time preference of farmers. In the following section, we will include time preference in order to investigate the outcomes of partial payment made in first and second year of a two-year insurance plan for farmers.

7.1 The General Discussion of Producers’ Welfare

We use the expected income to measure producers’ welfare and then we can compare the difference of expected income between with and without purchasing a multiyear revenue crop insurance. When a producer doesn’t purchase a crop insurance plan, his expected income for two years can be calculated as

\[
\mu_1 + \mu_2 = \int_0^\infty \int_0^\infty (R_1 + R_2) f(R_1, R_2) dR_1 dR_2
\]

When a producer purchases a two-year revenue crop insurance plan, his expected income for two years can be calculated as

\[
\mu_1^* = \text{prob}(R_i \in \gamma \mu_i) \gamma \mu_i + (1 - \text{prob}(R_i \in \gamma \mu_i)) E(R_i \mid R_i > \gamma \mu_i)
\]

\[
R_2^* = \begin{cases} 
\gamma \mu_2 & \text{if } (R_1, R_2) \in L \\
(1 - \gamma)\mu_1 + \mu_2 & \text{if } (R_1, R_2) \in C, E, I \\
\mu_1 + \mu_2 - R_1 & \text{if } (R_1, R_2) \in D, F, G, J, K \\
R_2 & \text{if } (R_1, R_2) \in A, B, O, M, N, H
\end{cases}
\]
\[ \mu_2^* = \frac{P(R_2 < \gamma \mu_2, R_1 + R_2 > \mu_1 + \mu_2) \gamma \mu_2}{\text{Area}^L} + \frac{P(R_1 < \gamma \mu_1, R_2 < (1 - \gamma) \mu_1 + \mu_2) \gamma \mu_1}{\text{Area}^C} \]
\[ + \int_{\mu_1 + \mu_2}^{\mu_1 + \mu_2 - R_1} \left( \mu_1 + \mu_2 - R_1 \right) R_1 (R_1) dR_1 dR_2 \]
\[ + \int_{(1 - \gamma) \mu_1 + \mu_2}^{\infty} R_2 f(R_1, R_2) dR_1 dR_2 \]
\[ + \int_{\mu_1 + \mu_2}^{\infty} R_2 f(R_1, R_2) dR_1 dR_2 \]

We then can compare \( \mu_1 + \mu_2 \) and \( \mu_1^* + \mu_2^* \) for the difference in the expected income between farmers not purchasing a two-year insurance plan and farmers purchasing the plan.

### 7.2 Insurance Outcomes and A Comparison of Utility

Since we would like to know if farmers prefer to obtain partial payment of indemnity in year one, we will compare the utility level with the partial payment of indemnity made in each of the two years and the total indemnity made in year two to both partial payment of indemnity and the total indemnity made in year two.

\( U(f(R_1, R_2)) \) and \( U(f^*(R_1, R_2)) \) are utility functions for farmers without and with a two-year crop insurance plan, respectively; \( f(R_1, R_2) \) and \( f^*(R_1, R_2) \) are the joint distribution function for farmers without and with a two-year crop insurance plan, respectively.

As farmers are risk neutral to revenues, the first derivatives with respect to \( R_1 \) and \( R_2 \) are positive \( \left( \frac{\partial U}{\partial R_i} > 0, i = 1,2 \right) \) and the second derivatives are equal to zero \( \left( \frac{\partial^2 U}{\partial R_i^2} = 0, i = 1,2 \right) \). In Figure 23, assume \( R_1^4 \) and \( R_2^4 \) fall inside areas “C, E” and the coordinate for \( (R_1^4, R_2^4) \) is...
(a, b) where $a < \gamma \mu_i$ and $b > \gamma \mu_2$. (a, b) is shown in purple circle point in Figure 23. In year one, since $R_i^d < \gamma \mu_i$, the partial payment of indemnity will be made according to a.1) and b.1). Therefore, in year one, we shift the coordinate $(R_i^d, R_2^d)$ horizontally from (a, b) to $(\gamma \mu_i, b)$. The red circle point is the position of $(\gamma \mu_i, b)$. In year two, since $R_2^d > \gamma \mu_2$, the partial payment of indemnity will not be made according to a.1) and b.1). In addition, in year two, as $R_i^d + R_2^d < \mu_i + \mu_2$, indemnity will be made according to a.2). As a result, we shift $(R_i^d, R_2^d)$ vertically to the point that lies on the line $R_i + R_2 = \mu_i + \mu_2$ in year two, which means that $(R_i^d, R_2^d)$ will shift vertically from $(\gamma \mu_i, b)$ to $(\gamma \mu_i, \mu_i + \mu_2 - \gamma \mu_i)$ in year two. The position of $(\gamma \mu_i, \mu_i + \mu_2 - \gamma \mu_i)$ is the green circle point. The utility curve passing $(\gamma \mu_i, \mu_i + \mu_2 - \gamma \mu_i)$ is the utility level with the partial payment of indemnity made separately in years one and two and the total indemnity made in year two. The utility level is calculated as

$$U(R_i^*, R_2^* = (1 - \gamma)\mu_i + \mu_2))$$

$$= \int_0^{(1-\gamma)\mu_i + \mu_2} \int_0^{(1-\gamma)\mu_i + \mu_2} f(R_1, R_2)\gamma \mu_i dR_1 dR_2 + \int_0^{(1-\gamma)\mu_i + \mu_2} f(R_1, R_2)((1-\gamma)\mu_i + \mu_2) dR_2$$

$$= \int_0^{(1-\gamma)\mu_i + \mu_2} \int_0^{(1-\gamma)\mu_i + \mu_2} f(R_1, R_2)\gamma \mu_i dR_1 dR_2 + \int_0^{(1-\gamma)\mu_i + \mu_2} f(R_1, R_2)((1-\gamma)\mu_i + \mu_2) dR_2$$

$$(7.1)$$

where $R_i^*$ and $R_2^*$ are revenue in year one and two with a two – year crop insurance plan

Now we need to discuss the situation where both the partial payment of indemnity and the total indemnity are made in year two. We keep the assumption that $R_i^d$ and $R_2^d$ fall inside area “C, E” and $(R_i^d, R_2^d)$=(a, b) where $a < \gamma \mu_i$ and $b > \gamma \mu_2$. Therefore, we also use the purple circle point to show the position of (a, b). In this case, the partial payment of indemnity and
the total indemnity are both made in year two and thus \((R_1^d, R_2^d)\) will shift vertically to the point lying on the line \(R_1 + R_2 = \mu_1 + \mu_2\) in year two, which means that \((R_1^d, R_2^d)\) will shift vertically from \((a, b)\) to \((a, \mu_1 + \mu_2 - a)\) in year two. The blue circle point is the position of \((a, \mu_1 + \mu_2 - a)\). The utility curve passing \((a, \mu_1 + \mu_2 - a)\) is the utility level with both the partial payment of indemnity and the total indemnity made in year two. The utility level which is the expected revenue passing \((R_1, \mu_1 + \mu_2 - R_1)\) is calculated as

\[
U(R_1^*, R_2^*) = (\mu_1 + \mu_2 - R_1)
\]

\[
= \int_{0}^{\mu_1 + \mu_2 - R_1} \int_{0}^{R_2} f(R_1, R_2)(\mu_1 + \mu_2 - R_1)dR_2dR_1 + \int_{0}^{\mu_1 + \mu_2 - R_1} \int_{0}^{R_2} f(R_1, R_2)(\mu_1 + \mu_2 - R_1)dR_2dR_1
\]

\[
= \frac{\mu_1 + \mu_2 - R_1}{1 + r_0}
\]

We then can compare the utility level of equation (7.1) and (7.2) for two schemes we described above.

Figure 23 Insurance Outcome with Time Preference
8. Empirical Results for Multiyear Yield and Revenue Crop Insurance Plan

In Chapter 4, the simulation results suggested that when the Spearman’s rank correlation of yields across years is not perfectly positively correlated, the actuarially fair rate can be lower in the multiyear yield insurance plan than the single-year plan. In this chapter, we used farm and county-level data for corn, soybean, barley, cotton and grain sorghum in several important producing counties and states to investigate the presence and level of correlation of yield across years from Pearson’s correlation coefficient estimates. Though we mentioned that the Pearson’s correlation coefficient may be weak as a measure of dependence, Pearson’s correlation coefficient results estimated from real data can be viewed as an indicator of whether multiyear insurance plan can possibly offer lower actuarially fair premium in real case because it’s a simple calculation. As long as the Pearson’s correlation coefficient from real data is not close to 1, we have good reason to believe that the implementation of multiyear insurance plan can offer a lower actuarially fair premium rate in practice. We will see that Pearson’s correlation coefficients estimates in section 8.3.1 and 8.3.2 suggest that yields are not significantly correlated in most cases across years on the farm and county-level data. Therefore, this motivates us to obtain better dependence parameter estimates than Pearson’s correlation coefficient from the copula approach and estimate the actuarially fair rates of multiyear insurance plans based on the Copula models in Chapter 9.

8.1 Data

The farm-level data used in this study were collected from the Risk Management Agency (RMA) of the USDA. We examined a) corn and soybeans in Iowa, Illinois, Ohio and Indiana;
b) barley in North Dakota, Montana; c) cotton in Texas; d) grain sorghum in Kansas and Nebraska; and e) wheat in North Dakota, Kansas, Montana, Oklahoma and Texas. This farm-level data set consists of yearly yields, insured acres of yield measured, the years of yield measured, county and state location, the type of insurance plan and practice for each insured farm. The beginning years and ending years of the farm data vary from farm to farm. The beginning years range from 1986 to 1989, and the ending years range from 1995 to 1997. Data which are not continuous for some farms were excluded from our analysis due to the difficulty of measuring correlation of yields between two years. A “transitory yield” is assigned to a farmer whose yield history is not sufficient to calculate actuarially fair premium in federal program. Transitory yields were excluded in our study.

Since each yield observation in this farm data is continuous for 10 years at the same location, we don’t have to consider the crop rotation practice issue in our analysis. All farms in this data set insured their crops on at least one occasion during the time period examined and the locations (county and state) for each insured farm were reserved in the data. This allowed us to aggregate farm-level yields under different insurance plans and practices for each county and state, and estimate yield correlation across years (Pearson’s correlation coefficient) on the county- and state-level. The aggregated farm-level data on the county- and state-level allowed us to (1) investigate the insured yield correlation on the county- and state-level across years; (2) compare insured yield correlation on the county level across years with yield (including uninsured and insured farms) correlation across years from county-level data; (3) investigate the level of spatial correlation of yield correlation across years among
counties and states. We used Table 3 to describe the farm data of corn, soybean, barley, cotton, grain sorghum and wheat in several states.

Table 3 Farm-Level Statistics for Selected States and Crops

<table>
<thead>
<tr>
<th>Crop</th>
<th>State</th>
<th>Number of counties</th>
<th>Number of observations</th>
<th>Crop</th>
<th>State</th>
<th>Number of counties</th>
<th>Number of observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn</td>
<td>Iowa</td>
<td>99</td>
<td>42,678</td>
<td>Barley</td>
<td>Idaho</td>
<td>14</td>
<td>193</td>
</tr>
<tr>
<td>Corn</td>
<td>Illinois</td>
<td>99</td>
<td>18,394</td>
<td>Barley</td>
<td>Montana</td>
<td>32</td>
<td>979</td>
</tr>
<tr>
<td>Corn</td>
<td>Indiana</td>
<td>88</td>
<td>4,780</td>
<td>Barley</td>
<td>North Dakota</td>
<td>45</td>
<td>2,158</td>
</tr>
<tr>
<td>Corn</td>
<td>Ohio</td>
<td>75</td>
<td>1,618</td>
<td>Grain Sorghum</td>
<td>Kansas</td>
<td>96</td>
<td>6,659</td>
</tr>
<tr>
<td>Cotton</td>
<td>Texas</td>
<td>94</td>
<td>11,191</td>
<td>Grain Sorghum</td>
<td>Nebraska</td>
<td>44</td>
<td>3,195</td>
</tr>
<tr>
<td>Soybean</td>
<td>Iowa</td>
<td>98</td>
<td>33,177</td>
<td>Wheat</td>
<td>Montana</td>
<td>20</td>
<td>7,486</td>
</tr>
<tr>
<td>Soybean</td>
<td>Illinois</td>
<td>100</td>
<td>9,416</td>
<td>Wheat</td>
<td>Kansas</td>
<td>103</td>
<td>20,647</td>
</tr>
<tr>
<td>Soybean</td>
<td>Indiana</td>
<td>83</td>
<td>2,783</td>
<td>Wheat</td>
<td>Oklahoma</td>
<td>45</td>
<td>5,543</td>
</tr>
<tr>
<td>Soybean</td>
<td>Ohio</td>
<td>45</td>
<td>1,756</td>
<td>Wheat</td>
<td>Texas</td>
<td>58</td>
<td>1,669</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>North Dakota</td>
<td>53</td>
<td>29,622</td>
</tr>
</tbody>
</table>

Other than analyzing the farm-level data for selected crops, we also analyzed county-level data. County corn yield data from 1928 to 2007 in Iowa, Illinois, Ohio, and from 1929 to 2007 from Indiana were obtained from the National Agricultural Statistical Service (NASS) of the USDA. The average county yield for 80 years in Iowa, Illinois and Ohio, and 79 years in Indiana were calculated, and the top ten production counties in these 4 states were chosen for analysis.

Production costs were collected for Idaho, Iowa, Illinois, Indiana, Kansas, North Dakota, Ohio, and Texas from the state extension Services. We used variable costs and futures to calculate coverage levels for partial payment. Table 4 shows the values of the variable costs.
in different states, futures prices and futures periods for different crops. Variable costs include fertilizer, seed, pesticide, dryer haul, machinery fuel, machinery repairs, hauling, and interest on pre-harvest variable costs in our study. Some states provide variable costs at different yield levels and only one of the yield levels was chosen in our study. We used futures prices from the Chicago Board of Trade for corn, cotton, soybean and wheat. Then the coverage levels of partial payment, which is also shown in Table 4, were calculated based on the variable cost divided by the futures.
### Table 4 Coverage Levels of Partial Payment for Selected States and Crops

<table>
<thead>
<tr>
<th>Year of budget</th>
<th>State</th>
<th>Commodity</th>
<th>Practices</th>
<th>Period of futures</th>
<th>Variable cost based on the yield level</th>
<th>Coverage level of Partial Payment</th>
</tr>
</thead>
<tbody>
<tr>
<td>2009</td>
<td>Iowa</td>
<td>Corn</td>
<td>Corn following corn</td>
<td>Dec/2010</td>
<td>145bu./ac 2.99/4.45</td>
<td>3=.67</td>
</tr>
<tr>
<td>2009</td>
<td>Illinois</td>
<td>Corn</td>
<td>Corn after corn</td>
<td>Dec/2010</td>
<td>175bu./ac 2.52/4.45</td>
<td>.56</td>
</tr>
<tr>
<td>2010</td>
<td>Indiana</td>
<td>Corn</td>
<td>Continuous corn</td>
<td>Dec/2010</td>
<td>149bu./ac 2.26/4.45</td>
<td>.50</td>
</tr>
<tr>
<td>2010</td>
<td>Ohio</td>
<td>Corn</td>
<td>Corn of conservation tillage</td>
<td>Dec/2010</td>
<td>150bu./ac 1.96/4.45</td>
<td>.44</td>
</tr>
<tr>
<td>2009</td>
<td>Texas</td>
<td>Cotton</td>
<td>Cotton for dry land</td>
<td>May/2010</td>
<td>400b./ac 0.28/.77</td>
<td>.36</td>
</tr>
<tr>
<td>2009</td>
<td>Iowa</td>
<td>Soybean</td>
<td>Herbicide tolerant soybeans</td>
<td>Nov/2010</td>
<td>50bu/ac 4.26/10.2</td>
<td>.41</td>
</tr>
<tr>
<td>2009</td>
<td>Illinois</td>
<td>Soybean</td>
<td>Soybean after corn</td>
<td>Nov/2010</td>
<td>51bu./ac 4.90/10.2</td>
<td>.48</td>
</tr>
<tr>
<td>2010</td>
<td>Indiana</td>
<td>Soybean</td>
<td>Rotation soybean</td>
<td>Nov/2010</td>
<td>49bu./ac 3.53/10.2</td>
<td>.34</td>
</tr>
<tr>
<td>2010</td>
<td>Ohio</td>
<td>Soybean</td>
<td>Soybean without tillage</td>
<td>Nov/2010</td>
<td>48bu./ac 3.60/10.2</td>
<td>.35</td>
</tr>
<tr>
<td>2009</td>
<td>North Dakota</td>
<td>Wheat</td>
<td>Spring wheat</td>
<td>Dec/2010</td>
<td>28bu./ac 3.59/6.11</td>
<td>.58</td>
</tr>
<tr>
<td>2008</td>
<td>Kansas</td>
<td>Wheat</td>
<td>Rotation wheat</td>
<td>Dec/2010</td>
<td>57bu./ac 3.20/6.11</td>
<td>.52</td>
</tr>
<tr>
<td>2009</td>
<td>Texas</td>
<td>Wheat</td>
<td>continuous wheat in dryland and grazed</td>
<td>Dec/2010</td>
<td>20bu./ac 2.47/6.11</td>
<td>.40</td>
</tr>
</tbody>
</table>

**Note 1:** Variable cost and predicted price are on a per-bushel basis.

**Note 2:** Coverage level of partial payment is equal to variable cost divided by the futures price estimate.

**Note 3:** The denominator is the futures price from Chicago Board of Trade.
8.2 Removing Time Trend for County Data

With the improvement of technology, crop yields increase over time. Thus, we need to remove the time trend for the yield data collected over different years. First we fit the time trend model for crop yields over years. The relationship between crop yield $y_t$ and time could be represented as

$$y_t = X_t \beta + e_t$$  \hspace{1cm} (8.1)

where $X_t$ represents the linear or nonlinear function of time.

If crop yields increase over time linearly, we can use the following trend model to fit the relationship between crop yield and time:

$$y_t = \beta_0 + \beta_1 t + e_t$$
where $X_t = (1, t)$ and $\beta = (\beta_0, \beta_1)$ \hspace{1cm} (8.2)

If crop yields grow quadratically, we can use the following trend model to fit the relationship between crop yields and time:

$$y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + e_t$$
where $X_t = (1, t, t^2)$ and $\beta = (\beta_0, \beta_1, \beta_2)$ \hspace{1cm} (8.3)

Regression analysis suggested that corn yields of county data in our analysis grow quadratically (i.e. the null hypothesis of $\beta_2=0$ is rejected), and thus eq (7) was adopted to remove the time trend. After we fit the time trend model for crop yield over time, we obtained trend-predicted yield data ($\hat{y}_t$) and deviation from the trend ($e_t$). Since lots of empirical studies support the idea that deviations from the time tend to be proportional to
crop yield, we use the following equation to normalize crop yields over time (Miranda and Glauber, 1997):

\[ \tilde{y}_t = \hat{y}_t (1 + \frac{e^{-}}{\hat{y}_t}) \]  \hspace{1cm} (8.4)

*where*

\( \hat{y}_t \) is detrended yield data of last observation
\( \tilde{y}_t \) is normalized yield data over time

### 8.3 Empirical Results

In this section, we will present the following: (1) Pearson’s correlation coefficients for yields of county data for each county between two consecutive years; and (2) Pearson’s correlation coefficients for the corn, soybean, barley, cotton, grain sorghum and wheat yields for each county between two consecutive years, after we aggregated the farm data to a county level; (3) Pearson’s correlation coefficient for the corn, soybean, barley, cotton, grain sorghum and wheat yield between two consecutive years, after we aggregated the farm data to a state level. In our results for p-values, p-values < 0.0001 were replaced by zero.

### 8.3.1 Pearson’s Correlation Coefficient for County Data

Each top ten production counties of corn were chosen from Iowa, Illinois, Indiana and Ohio. Corn for grain yields for these 40 counties grows quadratically during this period based on the regression analysis. Thus, equation (8.3) was applied to fit the time trend model. After detrending the normalized county yield data, Pearson’s correlation coefficients were calculated and the significance of the correlations between \( y_1 \) and \( y_2 \), which are yields
between two years, were tested. Pearson’s correlation coefficients and p-values are summarized in Table 5 and Table 6. In Iowa and Illinois, Pearson’s correlation coefficients are positive except in Scott County and Logan County, respectively. Positive Pearson’s correlation coefficients imply that an increase in yields in one year is associated with an increase in yields in another year or a decrease in yields in one year is associated with a decrease in yields in another year. In Indiana, Pearson’s correlation coefficients are negative except in Union County. Negative Pearson’s correlation coefficients imply that an increase in yields in one year is associated with a decrease in yields in another year. In Ohio, most of the counties have positive Pearson’s correlation coefficients. However, only the p-value for Carroll County in Indiana is significant when the significance level is equal to 0.05. This implies that the yields in one year are negatively correlated significantly with yield in another year with 0.05 significance level at Carroll in Indiana. No p-value in these counties is significant when the significance level is equal to 0.01 or 0.025. In other words, there is no significant correlation of yield across years in these 40 counties in Iowa, Illinois, Indiana and Ohio. From these Pearson’s correlation coefficients estimated from detrended normalized county data by using equation (8.4) in Iowa, Illinois, Indiana and Ohio, we can conclude that (1) yield across years are not positively correlated significantly when significance level is equal to 0.01 and 0.025; (2) yield across years are not negatively correlated significantly when significance level is equal to 0.01 and 0.025 except Union County in Indiana; (3) yield across years are not positively or negatively correlated significantly in Iowa and Ohio when significance level is equal to 0.01 and 0.025.
Table 5 Pearson’s Correlation Coefficient of Iowa Corn and Illinois Corn (County-Level NASS Data)

<table>
<thead>
<tr>
<th>Iowa</th>
<th>County</th>
<th>Correlation Coefficient (Significance Level)</th>
<th>County</th>
<th>Correlation Coefficient (Significance Level)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cedar County</td>
<td>0.012 (0.091)</td>
<td>Hamilton County</td>
<td>0.156 (0.168)</td>
</tr>
<tr>
<td></td>
<td>Scott County</td>
<td>-0.014 (0.089)</td>
<td>Wright County</td>
<td>0.215 (0.056)</td>
</tr>
<tr>
<td></td>
<td>Ground County</td>
<td>0.156 (0.179)</td>
<td>Webster County</td>
<td>0.197 (0.081)</td>
</tr>
<tr>
<td></td>
<td>Marshall County</td>
<td>0.137 (0.225)</td>
<td>Humboldt County</td>
<td>0.150 (0.184)</td>
</tr>
<tr>
<td></td>
<td>Hardin County</td>
<td>0.124 (0.274)</td>
<td>Boone County</td>
<td>0.161(0.155)</td>
</tr>
<tr>
<td>Illinois</td>
<td>County</td>
<td>Correlation Coefficient (Significance Level)</td>
<td>County</td>
<td>Correlation Coefficient (Significance Level)</td>
</tr>
<tr>
<td></td>
<td>Piatt County</td>
<td>0.080 (0.47)</td>
<td>De Kalb County</td>
<td>0.063 (0.537)</td>
</tr>
<tr>
<td></td>
<td>Macon County</td>
<td>0.071(0.533)</td>
<td>Sangamon County</td>
<td>0.123(0.277)</td>
</tr>
<tr>
<td></td>
<td>Logan County</td>
<td>-0.088 (0.439)</td>
<td>Warren County</td>
<td>0.131(0.247)</td>
</tr>
<tr>
<td></td>
<td>Christian County</td>
<td>0.00837 (0.941)</td>
<td>Champaign County</td>
<td>0.00 (0.994)</td>
</tr>
<tr>
<td></td>
<td>Moultrie County</td>
<td>0.222 (0.048)</td>
<td>Dewitt County</td>
<td>0.028 (0.802)</td>
</tr>
</tbody>
</table>
### 8.3.2 Pearson’s Correlation Coefficient and Autocorrelation for Farm Data

In this section, we present Pearson’s correlation coefficients for farm data at the state and county level in consecutive years for corn, soybean, barley, cotton, grain sorghum and wheat. In addition, we present autocorrelation for state level data based on the farm level data.

<table>
<thead>
<tr>
<th>County</th>
<th>Correlation Coefficient (Significance Level)</th>
<th>County</th>
<th>Correlation Coefficient (Significance Level)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Howard County</td>
<td>-0.415(0.216)</td>
<td>Rush County</td>
<td>-0.14(0.219)</td>
</tr>
<tr>
<td>Tipton County</td>
<td>-0.19(0.095)</td>
<td>Madison County</td>
<td>-0.106(0.452)</td>
</tr>
<tr>
<td>Carroll County</td>
<td>-0.228(0.043)</td>
<td>Benton County</td>
<td>-0.066(0.575)</td>
</tr>
<tr>
<td>Union County</td>
<td>0.023(0.839)</td>
<td>Grant County</td>
<td>-0.025(0.827)</td>
</tr>
<tr>
<td>Clinton County</td>
<td>-0.214(0.058)</td>
<td>Decatur County</td>
<td>-0.077(0.502)</td>
</tr>
<tr>
<td>Henry County</td>
<td>0.077(0.499)</td>
<td>Clark County</td>
<td>-0.198(0.079)</td>
</tr>
<tr>
<td>Lucas County</td>
<td>0.161(0.155)</td>
<td>Sandusky County</td>
<td>0.13(0.251)</td>
</tr>
<tr>
<td>Clinton County</td>
<td>-0.167(0.139)</td>
<td>Preble County</td>
<td>-0.174(0.123)</td>
</tr>
<tr>
<td>Fulton County</td>
<td>0.091(0.442)</td>
<td>Van Wert County</td>
<td>0.213(0.059)</td>
</tr>
<tr>
<td>Greene County</td>
<td>0.148(0.19)</td>
<td>Champaign County</td>
<td>-0.054(0.633)</td>
</tr>
</tbody>
</table>
Table 7 reports Pearson’s correlation coefficient and p-value for each crop and each state. States that have data with less than 15 counties available were excluded from our analysis since a few counties may not be representative for a state. The statistics indicate the differences across the states in correlation across years and the significance of correlation.

Table 7 Pearson’s Correlation Coefficient for Selected States and Crops

<table>
<thead>
<tr>
<th>Crop</th>
<th>State</th>
<th>Pearson’s Correlation Coefficient</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn</td>
<td>Iowa</td>
<td>-0.362</td>
<td>0.337</td>
</tr>
<tr>
<td>Corn</td>
<td>Illinois</td>
<td>0.230</td>
<td>0.550</td>
</tr>
<tr>
<td>Corn</td>
<td>Indiana</td>
<td>-0.090</td>
<td>0.817</td>
</tr>
<tr>
<td>Corn</td>
<td>Ohio</td>
<td>-0.072</td>
<td>0.853</td>
</tr>
<tr>
<td>Soybean</td>
<td>Iowa</td>
<td>-0.283</td>
<td>0.460</td>
</tr>
<tr>
<td>Soybean</td>
<td>Illinois</td>
<td>-0.036</td>
<td>0.926</td>
</tr>
<tr>
<td>Soybean</td>
<td>Indiana</td>
<td>0.256</td>
<td>0.506</td>
</tr>
<tr>
<td>Soybean</td>
<td>Ohio</td>
<td>-0.119</td>
<td>0.759</td>
</tr>
<tr>
<td>Barley</td>
<td>Montana</td>
<td>0.375</td>
<td>0.319</td>
</tr>
<tr>
<td>Barley</td>
<td>North Dakota</td>
<td>0.113</td>
<td>0.772</td>
</tr>
<tr>
<td>Cotton</td>
<td>Texas</td>
<td>-0.253</td>
<td>0.510</td>
</tr>
<tr>
<td>Grain Sorghum</td>
<td>Kansas</td>
<td>-0.300</td>
<td>0.431</td>
</tr>
<tr>
<td>Grain Sorghum</td>
<td>Nebraska</td>
<td>0.307</td>
<td>0.421</td>
</tr>
<tr>
<td>Wheat</td>
<td>Kansas</td>
<td>-0.481</td>
<td>0.189</td>
</tr>
<tr>
<td>Wheat</td>
<td>Montana</td>
<td>0.587</td>
<td>0.096</td>
</tr>
<tr>
<td>Wheat</td>
<td>North Dakota</td>
<td>0.554</td>
<td>0.121</td>
</tr>
<tr>
<td>Wheat</td>
<td>Oklahoma</td>
<td>-0.066</td>
<td>0.864</td>
</tr>
<tr>
<td>Wheat</td>
<td>Texas</td>
<td>-0.730</td>
<td>0.025</td>
</tr>
</tbody>
</table>

From Table 7, only Illinois corn and Indiana soybean has positive correlation coefficient among Iowa, Illinois, Indiana and Ohio. This difference may suggest that (1) Illinois and Indiana have high land quality suitable to grow corn and soybean, respectively so that yields for Illinois corn and Indiana soybean are more stable within these two states; (2) moral hazard and adverse selection may result in (a) unstable corn yield in Iowa, Indiana and Ohio; (b) unstable soybean yield in Iowa, Illinois and Ohio.
For barley in Table 7, Montana and North Dakota barley are stable across years and this may suggest that (1) the natural condition such as precipitation, weather and soil are beneficial to barley in the northern west part of the US; (2) moral hazard and adverse selection may not affect yield significantly in these states.

For cotton and grain sorghum in Table 7, Texas cotton, and Kansas and Nebraska grain sorghum show negative correlation which implies yield increases in one year but decreases in another year. This may suggest that (1) weather and soil conditions are similar in some level because these three states are located in the central part of the United States; (2) the unstable yield may result from moral hazard and adverse selection.

From Table 7, we can also see that Kansas, Oklahoma and Texas wheat show negative correlation of yield between two years and Montana and North Dakota wheat show positive correlation. The results are not surprising since Montana and North Dakota are geographically similar and Kansas, Oklahoma and Texas are also neighbor states. Also moral hazard and adverse selection may also play a role deciding the correlation.

In summary, Pearson’s correlation coefficients for Illinois corn, Indiana soybean, Montana and North Dakota barley, Montana and North Dakota wheat at the state level are all positive from Tables 9, but none of them are significantly correlated at level 0.05. Texas wheat is the only crop that shows negatively significant (p-value=0.0255) at the state level. The correlation results in Tables 7 can provide a guideline for government agency to prioritize
states and crop to implement the multiyear insurance plans. For example, the actuarially fair rate for Texas wheat can be much lower based on the multiyear insurance plan than single year plan due to the significantly negative correlation.

Next, we show Pearson’s correlation coefficients for these six crops at the county level based on the farm-level data through the following correlation maps. The following figures provide Pearson’s correlation coefficient and p-value results for farm data in graphical form for each state at the county level. We used four colors in the maps to show four levels of Pearson’s correlation coefficients. Moreover, we used histograms to show p-value results for most counties in the Appendices.

For Iowa corn in Figure 24, Pearson’s correlation coefficient increases from the western to eastern Iowa. From Figure 42 the average annual precipitation increases from the western to eastern Iowa. Figure 24 and 42 suggest that (1) precipitation may be a key factor to influence yield stability of Iowa corn; (2) Iowa corn is more stable in eastern Iowa than west and thus Iowa corn may prefer to grow under average annual precipitation between 34-38 inches based on the precipitation map.

For Illinois corn and soybean, correlation levels of Illinois corn and soybean in the central Illinois vary from county to county from Figure 26 and 27. The corn and soybean mean yield from 1972-2007 from department of agricultural and consumer economics at University of Illinois in northwest, northeast, west, central, east, west southwest, east southeast, southeast
and southwest Illinois is distinct. This suggests that Illinois has widely varying land quality especially in the central Illinois. The varying land quality in the central Illinois may suggest that yield in this area are more likely to be unstable.

For Indiana corn, counties in the central and southwestern Indiana mostly have negative and positive correlation, respectively from Figure 28. The annual average precipitation trends across Indiana increases from the northern to the southern Indiana from Figure 42. For Indiana soybean, counties in the northwestern Indiana mostly have negative correlation from Figure 29 and the average annual precipitation is lowest in this area from Figure 42. Therefore, for Indiana corn and soybean, unstable yield may result from less precipitation.

For Ohio corn, (1) counties in the central Ohio mostly have positive correlation and these counties belong to the same level of average annual precipitation; (2) counties in the northwest and southeast mostly have negative correlation and these counties belong to two different levels of average annual precipitation from Figure 30 and 42. This result may suggest that Ohio corn is more unstable when precipitation is much less in the northwestern or much more in the south western Ohio.

For Montana barley, the correlation of the upper and lower parts in central Montana is positive and the correlation of the middle part in central Montana is negative from Figure 32. The spatial pattern of correlation is very similar with average annual precipitation from Figure 42. Figure 32 and 42 suggest that (1) Montana barley may be mostly influenced by
precipitation; (2) Montana barley may not prefer to grow with 18-40 inches of average annual precipitation. For Montanan wheat, all counties in the north eastern Montana are with positive correlation from Figure 33 and the elevation of this area is around 1800-3000 ft from Figure 43. This may suggest that Montana wheat is preferred to grow in this level of elevation.

For Nebraska grain sorghum, counties in the southeastern Nebraska mostly have negative correlation and these counties belong to two different levels of average annual precipitation from Figure 34 and 42. This may imply that unstable yield results from significantly lower or higher precipitation. For North Dakota barley, counties in the northern North Dakota mostly have negative correlation from Figure 35 and these counties belong to the same level of temperature range from Figure 44. This may suggest that insufficient light or lower temperate for barley growth result in yield instability in the northern North Dakota.

For North Dakota wheat, Figure 36 suggests that most western counties have positive correlation of yield between two years and most eastern counties have negative correlation. Average annual precipitation increases from the western to eastern North Dakota from Figure 42. Thus the stability of North Dakota wheat may be influenced by precipitation.

For Kansas grain sorghum, counties in the northeastern Kansas mostly have negative correlation and these counties have the same level of average annual precipitation from Figure 37. This suggests that too much average annual precipitation in this area is not
beneficial for Kansas grain sorghum and thus Kansas grain sorghum is not stable in this area.
For Kansas wheat, counties in the southwestern Kansas have positive correlation from Figure 38 and the central-downstream of the Arkansas River goes through that area. Since average annual precipitation is lowest in the western Kansas, this suggests that Kansas wheat in this area may obtain enough water from the Arkansas River so that wheat yield is stable.

For Oklahoma wheat, counties in the central Oklahoma mostly have positive correlation which belong to the same elevation level (1200-1800 ft) from Figure 39 and 44. This may suggest that Oklahoma wheat prefers to grow under this level of elevation. For Texas cotton, counties with positive correlation are mostly located in eastern Texas from Figure 40. The average annual precipitation in eastern Texas is higher than west Texas from Figure 42 and this suggests that Texas cotton may be influenced by the precipitation.

For Texas wheat, counties with positive correlation are mostly located in northeastern Texas from Figure 41 whose region falls in the same level of annual daily average temperature between 55.1-60.0 F. This may suggest that temperature may play an important role for Texas wheat. However, many yield data for cotton and wheat on the farm-level for many counties in Texas are not available. The conclusion needs to be further verified when more yield data are available.
Figure 24 Correlation Result for Iowa Corn (Farm-Level Data)

Figure 25 Correlation Result for Iowa Soybean (Farm-Level Data)
Figure 26 Correlation Result for Illinois Corn (Farm-Level Data)

Figure 27 Correlation Result for Illinois Soybean (Farm-Level Data)
Figure 28 Correlation Result for Indiana Corn (Farm-Level Data)

Figure 29 Correlation Result for Indiana Soybean (Farm-Level Data)
Figure 30 Correlation Result for Ohio Soybean (Farm-Level Data)

Figure 31 Correlation Result for Ohio Soybean (Farm-Level Data)
Figure 32 Correlation Result for Montana Barley (Farm-Level Data)

Figure 33 Correlation Result for Montana Wheat (Farm-Level Data)
Figure 34 Correlation Result for Nebraska Grain (Farm-Level Data)
Figure 35 Correlation Result for North Dakota Barley (Farm-Level Data)

Figure 36 Correlation Result for North Dakota Wheat (Farm-Level Data)
Figure 37 Correlation Result for Kansas Grain (Farm-Level Data)

Figure 38 Correlation Result for Kansas Wheat (Farm-Level Data)
Figure 39 Correlation Result for Oklahoma Wheat (Farm-Level Data)

Figure 40 Correlation Result for Texas Cotton (Farm-Level Data)
Figure 41 Correlation Result for Texas Wheat (Farm-Level Data)
Figure 42 Annual Precipitation Map in the United States from 1971 to 2000

Figure 43 Elevation Map for Montana
Figure 44 Mean Daily Average Temperature Map in the United States from 1961 to 1990

Figure 45 Elevation Map for Oklahoma
### Table 8 Autocorrelation Coefficient for Selected States and Crops (Farm Level Data)

<table>
<thead>
<tr>
<th>Crop</th>
<th>State</th>
<th>Autocorrelation</th>
<th>Durbin-Watson D</th>
<th>Confidence Interval</th>
<th>Pr&lt;DW</th>
<th>Pr&gt;DW</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn</td>
<td>Iowa</td>
<td>0.358</td>
<td>1.283</td>
<td>(0.354939, 0.361061)</td>
<td>&lt;0.0001</td>
<td>1</td>
</tr>
<tr>
<td>Corn</td>
<td>Illinois</td>
<td>0.678</td>
<td>0.644</td>
<td>(0.673337, 0.682663)</td>
<td>&lt;0.0001</td>
<td>1</td>
</tr>
<tr>
<td>Corn</td>
<td>Indiana</td>
<td>0.707</td>
<td>0.587</td>
<td>(0.697851, 0.716149)</td>
<td>&lt;0.0001</td>
<td>1</td>
</tr>
<tr>
<td>Corn</td>
<td>Ohio</td>
<td>0.508</td>
<td>0.984</td>
<td>(0.492277, 0.523723)</td>
<td>&lt;0.0001</td>
<td>1</td>
</tr>
<tr>
<td>Soybean</td>
<td>Iowa</td>
<td>0.306</td>
<td>1.338</td>
<td>(0.295019, 0.316981)</td>
<td>&lt;0.0001</td>
<td>1</td>
</tr>
<tr>
<td>Soybean</td>
<td>Illinois</td>
<td>0.538</td>
<td>0.925</td>
<td>(0.531482, 0.544518)</td>
<td>&lt;0.0001</td>
<td>1</td>
</tr>
<tr>
<td>Soybean</td>
<td>Indiana</td>
<td>0.644</td>
<td>0.712</td>
<td>(0.632011, 0.655989)</td>
<td>&lt;0.0001</td>
<td>1</td>
</tr>
<tr>
<td>Soybean</td>
<td>Ohio</td>
<td>0.423</td>
<td>1.154</td>
<td>(0.407907, 0.438093)</td>
<td>&lt;0.0001</td>
<td>1</td>
</tr>
<tr>
<td>Barley</td>
<td>Montana</td>
<td>0.290</td>
<td>1.420</td>
<td>(0.269787, 0.310213)</td>
<td>&lt;0.0001</td>
<td>1</td>
</tr>
<tr>
<td>Barley</td>
<td>North Dakota</td>
<td>0.043</td>
<td>1.913</td>
<td>(0.029385, 0.056615)</td>
<td>&lt;0.0001</td>
<td>1</td>
</tr>
<tr>
<td>Cotton</td>
<td>Texas</td>
<td>0.554</td>
<td>0.892</td>
<td>(0.548021, 0.559979)</td>
<td>&lt;0.0001</td>
<td>1</td>
</tr>
<tr>
<td>Grain</td>
<td>Kansas</td>
<td>0.353</td>
<td>1.293</td>
<td>(0.345250, 0.360750)</td>
<td>&lt;0.0001</td>
<td>1</td>
</tr>
<tr>
<td>Grain</td>
<td>Nebraska</td>
<td>0.274</td>
<td>1.452</td>
<td>(0.262811, 0.285189)</td>
<td>&lt;0.0001</td>
<td>1</td>
</tr>
<tr>
<td>Wheat</td>
<td>Kansas</td>
<td>0.126</td>
<td>1.748</td>
<td>(0.121598, 0.130402)</td>
<td>&lt;0.0001</td>
<td>1</td>
</tr>
<tr>
<td>Wheat</td>
<td>Montana</td>
<td>0.166</td>
<td>1.668</td>
<td>(0.158690, 0.173310)</td>
<td>&lt;0.0001</td>
<td>1</td>
</tr>
<tr>
<td>Wheat</td>
<td>North Dakota</td>
<td>0.402</td>
<td>1.195</td>
<td>(0.398325, 0.405675)</td>
<td>&lt;0.0001</td>
<td>1</td>
</tr>
<tr>
<td>Wheat</td>
<td>Oklahoma</td>
<td>0.337</td>
<td>1.326</td>
<td>(0.328505, 0.345495)</td>
<td>&lt;0.0001</td>
<td>1</td>
</tr>
<tr>
<td>Wheat</td>
<td>Texas</td>
<td>0.562</td>
<td>0.875</td>
<td>(0.546656, 0.577344)</td>
<td>&lt;0.0001</td>
<td>1</td>
</tr>
</tbody>
</table>

Note: 1. Pr<\text{DW} is the p-value for testing positive autocorrelation, and Pr>\text{DW} is the p-value for testing negative autocorrelation; 2. Pr<\text{DW}=<0.0001, Pr>\text{DW}=1
Yield in this current year could be influenced by yield in the past year. Therefore, we used autoregressive integrated moving average (ARIMA) model to calculate the autocorrelation when we pooled farm level data for each selected state. Table 8 summaries the autocorrelation, Durbin-Watson D statistics and confidence intervals for the selected states and crops. In Table 8, for the selected crops and states, yields are positively correlated across years. The autocorrelation in these selected states is below 0.60 except Illinois corn, Indiana corn, and Indiana soybean.

In summary, in this chapter we provided comprehensive estimates of Pearson’s correlation coefficients for yields between two years at the state and county level based on the farm-level data. The correlation coefficients can be very different among states for different crops. However, only Texas wheat shows significantly negative correlation. We also investigate correlation patterns at county level within each state. We can also see correlation patterns vary from state to state, mostly due to geographic locations and weather patterns. Based on the histograms of p-values provided in the Appendices, most of the correlation is not significant. Our simulation results in the previous chapter suggested that the multiyear insurance plan has advantages over current plans when the correlation coefficient is less than 1. Hence, the results in this chapter provide solid evidence that the proposed multiyear insurance plan will have lower actuarially fair premium rate than current single year plans in practice. Moreover, our estimates can provide a guideline for government agency to decide and prioritize counties or states and crop types to implement the multiyear insurance plans.
In the next chapter, other than estimating correlations of yields between two consecutive years using the sample Pearson’s correlation coefficient, we also estimated the correlations using the copula method. The copula method implicitly models the marginal distributions and thus may provide better estimate of the correlation than Pearson’s correlation coefficient, which is estimated directly from the sample. We used the Beta margins to fit to the Normal, Clayton and Frank Copulas under certain correlation structures for two and three-year GRP.

In this chapter, we will show how to implement a multiyear crop insurance for Adair County in Iowa in the following three sections. In section 9.1, we (1) follow the statistical methods we discussed in Chapter 8 in order to obtain the detrended normalized data; (2) process the Goodness-of-Fit test of Normal and Beta distribution for detrended normalized data; (3) use FML (Full Maximized Likelihood) to estimate parameters of Copula and marginal distribution simultaneously as we discussed in Chapter 3; (4) use likelihood values and AIC rules we stated in Chapter 3 to select the copula function which fits the data best for a two- and three-year insurance plan. In section 9.2, we will describe how to establish the coverage level of partial payment. In section 9.3, we will demonstrate a multiyear insurance contract design example (Adair County in Iowa) based on the results we obtained from sections 9.1 and 9.2.

9.1 Empirical Results of Copula Estimation

The Goodness-of-Fit test showed that a Beta distribution was appropriate for yields. Thus we specified Beta distribution as the marginal distribution in the first step of copula estimation. We then considered Frank, Clayton and Normal Copulas in order to estimate the parameters of Beta distribution and the copula function simultaneously by the use of FML. As these three copulas have the same number of parameters in a two-year insurance plan, we selected the best model based on their likelihood value. For a three-year insurance plan, where copulas can have different numbers of parameters based on the correlation matrix structure,
we selected the best model based on their AIC values. The Frank Copula has the highest likelihood value and the lowest AIC value among the three copulas in both two- and three-year insurance plans, respectively. Based on these results, in this section we simulated a joint yield distribution with two marginal beta distributions based on the correlation we obtained from the Frank Copula function. We then estimated the actuarially fair premium rates for a two-year crop insurance plan using the joint yield distributions. We also used the same process in order to estimate actuarially fair premium rates for a three-year insurance contract. These results are shown in Table 11.

### 9.1.1 Detrended Normalized Data and Goodness-of-Fit Test

I used equation (8.3) and (8.4) in Chapter 8 in order to detrend and normalize corn yield data for Adair in Iowa. The parameter estimates for detrended data are shown in Table 9. After I obtained the detrended normalized data, I used the Goodness-of-Fit Tests for both Normal and Beta Distributions in order to see which distribution supports the detrended normalized data. The tests are rejected at the 0.05 significance level so that the detrended normalized data don’t have a normal distribution. As seen in Table 10, the tests cannot be rejected at the 1% and 5% significance levels, so the detrended normalized data may follow a Beta Distribution.
Table 9 Parameter Estimate for Detrended Data of Adair County in Iowa

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter Estimate</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>32.48</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>T</td>
<td>0.530</td>
<td>0.0938</td>
</tr>
<tr>
<td>( t^2 )</td>
<td>0.013</td>
<td>0.0008</td>
</tr>
</tbody>
</table>

Table 10 Goodness-of-Fit Test for Normal and Beta Distribution

<table>
<thead>
<tr>
<th>Goodness-of-Fit Test for Normal Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test</td>
</tr>
<tr>
<td>Kolmogorov-Smirov</td>
</tr>
<tr>
<td>Cramer-von Mises</td>
</tr>
<tr>
<td>Anderson-Darling</td>
</tr>
<tr>
<td>Chi-Square</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Goodness-of-Fit Test for Beta Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square</td>
</tr>
</tbody>
</table>

9.1.2 Copula Estimation and Selection

In order to model the dependence structure of joint distribution for the two-year insurance plan, we used the “Copula” package (Yan, 2006) provided in R to model the copula distributions. We used several copula functions (Normal, Clayton and Flank Copulas) with Beta marginals in order to estimate the parameters of both Beta distributions and copula
parameters simultaneously. We then selected the copula that best fit the data according to
their maximized log likelihood values and also Akaike's Information Criterion (AIC) for two-
and three-year insurance plans, respectively. In the following Tables, $\alpha_1$, $\alpha_2$, $\alpha_3$, $\beta_1$, $\beta_2$
and $\beta_3$ are estimated shape parameters for Beta Distributions; $\rho_1$, $\rho_2$, $\rho_3$ are Spearman’s
correlation coefficients. The spearman’s correlation coefficients were calculated based on
samples simulated under the copula parameters, which were estimated using the Adair
County yield data in Iowa.

For the three-year plan, we used the Beta distributions as marginal distributions to fit the
Normal, Clayton and Frank Copula Models with an autoregressive of order 1 correlation
structure: Exchangeable dispersion structure, Toeplitz dispersion structure and Unstructured
dispersion structure. We only present the Frank Copula fitting results with Beta marginals
and the UN correlation structure under the three-year GRP as this fitting has the lowest AIC
values among copula models with different correlation structures.
Table 11 Estimation Results of Copula Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter estimate</th>
<th>Standard error</th>
</tr>
</thead>
<tbody>
<tr>
<td>α₁</td>
<td>9.18</td>
<td>1.45</td>
</tr>
<tr>
<td>β₁</td>
<td>5.55</td>
<td>0.86</td>
</tr>
<tr>
<td>α₂</td>
<td>9.09</td>
<td>1.44</td>
</tr>
<tr>
<td>β₂</td>
<td>5.48</td>
<td>0.85</td>
</tr>
</tbody>
</table>

Spearman’s correlation($\rho$) 0.083

Maximized log likelihood -98.27

Estimation results for Frank Copula with Beta marginals and UN Correlation structure under three-year GRP

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter estimate</th>
<th>Standard error</th>
</tr>
</thead>
<tbody>
<tr>
<td>α₁</td>
<td>9.14</td>
<td>1.45</td>
</tr>
<tr>
<td>β₁</td>
<td>5.56</td>
<td>0.86</td>
</tr>
<tr>
<td>α₂</td>
<td>9.07</td>
<td>1.45</td>
</tr>
<tr>
<td>β₂</td>
<td>5.53</td>
<td>0.86</td>
</tr>
<tr>
<td>α₃</td>
<td>9.00</td>
<td>1.44</td>
</tr>
<tr>
<td>β₃</td>
<td>5.48</td>
<td>0.85</td>
</tr>
</tbody>
</table>

ρ₁ 0.013
ρ₂ 0.015
ρ₃ 0.014

AIC=294.54

9.2 Simulation Analysis

Based on the results in section 9.1, in this section we simulated a joint yield distribution with two marginal beta distributions based on the correlation that we obtained from the copula function. We then estimated the actuarially fair premium rates for two-year crop insurance
plans from the joint yield distributions. We also used the same process to estimate actuarially fair premium rates for three-year insurance contracts. These results are shown in Table 12.

After we obtained the coverage levels for partial payments as seen in Table 4, we demonstrated how partial payments can help farmers repay their debt when they have a yield loss in either one of the two years or a loss in both years. The results are shown in Table 12. The period of data shown in this table spans from 1926 to 2005. The Spearman’s correlation coefficient between two years is 0.083 estimated by using the Frank Copula. Next we simulated a joint yield distribution with two marginal beta distributions that have a 0.083 correlation between years. In order to view the parameters of beta distributions estimated by the Frank Copula, please see Table 12. The estimated actuarially fair premium rate based on the simulated model is $0.008 for a two-year insurance contract. We assumed that the expected yield is 155 bushels per acre and the coverage level for the total indemnity is 70%. As shown in Table 4, the coverage level for partial payment is 67% in Iowa (corn). We assumed that the realized yield is 90 and 135 bushels per acre in the first and second insured years, respectively, and that the insured price is $2.50 per bushel. The average size of a corn farm in Iowa is 242 acres (Goodwin, 2009). As yield in the first insured year is below the guaranteed yield, farmers are eligible to obtain a partial payment of $837,9.25, as demonstrated in Table 12. We also assumed that these farmers have a loan equal to the total variable cost. Therefore debt is the product of the total cost per acre times the farm size, which is equal to $109,831.70. We expected these farms to be engaged in the futures market. Therefore, the expected revenues will be the product of the futures price times yield per acre
and times farm size, which is equal to $96,921. As a result, farmers are able to repay their loans based on the partial payment and the expected revenue.

We also included an example of the three-year contract in Table 12. The Spearman correlation coefficients estimated from the Frank Copula are 0.013 between years one and two, 0.015 between years one and three and 0.014 between years two and three. The estimated actuarially fair premium rate is 0.0084 based on the simulated model. The assumptions that we made for the two-year insurance contract also hold true for the three-year insurance contract. These assumptions include the amount of expected yield, the coverage levels of total indemnity and also partial payment, the amount of yield in the first and second years, the insured price and the size of the farm. We further assumed that the realized yield in the third year is 100 bushels per acre. As the amount of yield in the first and third insured years is below the guaranteed yield, farmers will obtain a partial payment in these two insured years of $8,379.25 in the first year and $2,329.25 in the third year. In the third insured year, the sum of the realized yield is higher than the guaranteed yield. Therefore, farmers will not obtain total indemnity. Insured farmers may prefer higher two-year coverage and lower single year coverage level. Therefore, we also simulated a two-year coverage level of 80% and a single-year coverage level of 40% shown in Table 13. When farmers select higher two-year coverage level, the actuarially fair premium rate increases from 0.008 to 0.01. Farmers will not obtain partial payment in either one of the years because the single year coverage (40%) is low. We also demonstrated the actuarially fair premium
rates using the same assumptions that we made above with different coverage levels of total indemnity. This information is shown in Table 14.

Table 12 Adair County in Iowa (Corn) for Two-and-Three-Year Insurance Contract (70% Two-Year Coverage and 67% Single Year Coverage)

<table>
<thead>
<tr>
<th></th>
<th>Two-Year Insurance Contract</th>
<th>Three-Year Insurance Contract</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spearman’s rank correlation</td>
<td>0.083</td>
<td>0.013 (1&amp;2), 0.015 (1&amp;3), 0.014 (2&amp;3)</td>
</tr>
<tr>
<td>Parameter of Beta Distribution</td>
<td>(α₁, β₁) = (9.18, 5.55)</td>
<td>(α₁, β₁) = (9.14, 5.56)</td>
</tr>
<tr>
<td></td>
<td>(α₂, β₂) = (9.09, 5.48)</td>
<td>(α₂, β₂) = (9.07, 5.53)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(α₃, β₃) = (9.00, 5.48)</td>
</tr>
<tr>
<td>Actuarially fair premium rate</td>
<td>$0.0083</td>
<td>$0.0084</td>
</tr>
<tr>
<td>Expected yield</td>
<td>155</td>
<td>155</td>
</tr>
<tr>
<td>Coverage level of guaranteed yield for two-(and three) year insurance contract</td>
<td>70%</td>
<td>70%</td>
</tr>
<tr>
<td>Guaranteed yield for two(three) years</td>
<td>217 (=2*70%*155)</td>
<td>325.5 (=3*70%*155)</td>
</tr>
<tr>
<td>Coverage level of partial payment</td>
<td>67% (from Table 1)</td>
<td>67% (from Table 1)</td>
</tr>
<tr>
<td>Guaranteed yield in each year</td>
<td>103.85 (=67%*155)</td>
<td>103.85 (=67%*155)</td>
</tr>
<tr>
<td>Assumed yield in year 1 &amp; 2 (2 &amp; 3)</td>
<td>90, 135</td>
<td>90, 135, 100</td>
</tr>
<tr>
<td>Partial payment</td>
<td>$8379.25 (=2.5*(103.85-90)*242) in year 1</td>
<td>(1) $8379.25 (=2.5*(103.85-90)*242) in year 1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2) $2329.25 (=2.5*(103.85-100)*242) in year 3</td>
</tr>
<tr>
<td>Total indemnity</td>
<td>0 (101.17 + 135 &gt; 217)</td>
<td>0 (325 &lt; 101.17 + 135 + 101.17)</td>
</tr>
<tr>
<td>Short-term Debt</td>
<td>$109831.7 (=3.13<em>145</em>242)</td>
<td></td>
</tr>
<tr>
<td>Expected revenues in year 1</td>
<td>96921 (=4.45<em>90</em>242)</td>
<td></td>
</tr>
</tbody>
</table>

Note 1: Yield is on a per acre basis.

Note 2: Total indemnity will not be paid in the third insured year because the sum of realized yield is higher than the guaranteed yield.
Table 13 Adair County in Iowa (Corn) for Two-and-Three-Year Insurance Contract (80% Two-Year Coverage and 40% Single Year Coverage)

<table>
<thead>
<tr>
<th></th>
<th>Two-Year Insurance Contract</th>
<th>Three-Year Contract</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actuarially fair premium rate</td>
<td>$0.010</td>
<td>$0.004</td>
</tr>
<tr>
<td>Expected yield</td>
<td>155</td>
<td>155</td>
</tr>
<tr>
<td>Coverage level of guaranteed yield for two-(and three) year insurance contract</td>
<td>80%</td>
<td>80%</td>
</tr>
<tr>
<td>Guaranteed yield for two(three) years</td>
<td>248(=2*80%*155)</td>
<td>372(=3*80%*155)</td>
</tr>
<tr>
<td>Coverage level of partial payment</td>
<td>40%</td>
<td>40%</td>
</tr>
<tr>
<td>Guaranteed yield in each year</td>
<td>62(=40%*155)</td>
<td>62(=40%*155)</td>
</tr>
<tr>
<td>Assumed yield in year 1 &amp; 2 (&amp;3)</td>
<td>90, 135</td>
<td>90,135, 100</td>
</tr>
<tr>
<td>Partial payment</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Total indemnity</td>
<td>13915=2.5(248-225)242</td>
<td>28435=2.5(372-325)242</td>
</tr>
<tr>
<td>Short-term Debt</td>
<td>$109831.7(=3.13<em>145</em>242)</td>
<td></td>
</tr>
<tr>
<td>Expected revenues in year 1</td>
<td>96921(=4.45<em>90</em>242)</td>
<td></td>
</tr>
</tbody>
</table>

Table 14 Actuarially Fair Premium Rate under Different Coverage Level of Total Indemnity (67% Single Year Coverage Level)

<table>
<thead>
<tr>
<th>Actuarially Fair Premium Rate for Two-Year Insurance Contract</th>
<th>Actuarially Fair Premium Rate for Three-Year Insurance Contract</th>
<th>Coverage level for the Total Insured Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>$0.013</td>
<td>$0.009</td>
<td>80%</td>
</tr>
<tr>
<td>$0.031</td>
<td>$0.022</td>
<td>90%</td>
</tr>
<tr>
<td>$0.070</td>
<td>$0.061</td>
<td>100%</td>
</tr>
</tbody>
</table>

The contract design of a multiyear insurance plan has been explained in previous chapters and it has been shown that premiums can be lower for farmers through multiyear insurance plans. The multiyear insurance plan was proposed in order to help farmers stabilize their incomes through possible lower premium cost and also through partial payments that would be made over the course of one or both years of coverage. A multiyear insurance plan sets up the coverage level of partial payment for each insured year according to variable costs and futures price for each crop in each state. Farmers can then select the coverage level of total indemnity. Longer insured years, a lower actuarially fair premium rate and partial payment of total indemnity are three essential elements contained in the multiyear plan. These elements are used to stabilize farmers’ income by reducing the impact of agricultural risks (yield and price risks) and by increasing the attractiveness of a multiyear insurance contract to farmers. However, the producers’ demand for a multiyear crop insurance contract is not yet clear. Issues concerning producers’ demand can be addressed based on whether or not producers will purchase multiyear insurance contracts, and, if they do, what coverage level they will choose.

In this chapter, we will analyze producers’ choices based on a representative producer facing certain risk factors such as yield and price risks. Given his risk situation and preference, we will analyze producers’ demand by selecting a coverage level of total indemnity in order to maximize his expected utility of profits. In other words, we are concerned about producers’
decision to participate in this type of plan and also producers’ behavior in deciding a coverage level of total indemnity. Producers are likely to participate in multiyear insurance plans when they think that these plans can help them to manage risks well. As an optimal coverage level can reflect the decision to participate and can also reflect producers’ behavior in purchasing insurance, we used the optimal coverage level to evaluate the two-year insurance plan in this chapter.

10.1 Conceptual Framework

First we introduce a negative exponential utility function (Hennessy, 1998)

\[ U(\pi) = -e^{-\lambda \pi} + \alpha \pi \]

\( \lambda \) and \( \alpha \) are risk parameters that can be selected to represent risk aversion levels. \( \pi \) represents profit. The measure of absolute risk aversion is \( \rho[\pi] = -U''(\pi)/U'(\pi) \) and \( U'' \), \( U' \) are the second and first derivatives of the utility function, respectively. Therefore, the associated absolute risk aversion measure is \( \rho[\pi] = \lambda^2 e^{-\lambda \pi} / (\lambda e^{-\lambda \pi} + \alpha) \). Hennessy (1998) imposed two restrictions on the risk preference parameters: (1) \( \lambda > 0 \), (2) \( \alpha \geq 0 \). When \( \alpha = 0 \), the producer represents a CARA risk attitude; and when \( \alpha > 0 \), the producer represents a DARA risk attitude.

Kramer and Pope (1981) found the upper and lower bound of risk aversion coefficients using 12 groups of participants in their studies. They discovered that risk aversion coefficients range from \( 3 \times 10^{-2} \) to \( 1 \times 10^{-3} \) for risk neutrality and risk aversion. Rister, Skees and Black (1984) obtained the range of the coefficient of absolute risk aversion from \( 1 \times 10^{-5} \) to \( 1 \times 10^{-8} \).
for risk neutrality and risk aversion. McSweeney and Kramer (1986) used various levels of risk aversion to evaluate the efficiency of across-compliance strategies. Here the absolute risk aversion coefficient ranged from 0 to 6*10^{-4}. McSweeney and Kramer therefore reported the relative risk aversion parameters. Babcock, Chalfant and Collender (1987) estimated risk aversion parameters ranging from 3*10^{-3} to 3*10^{-5} for slight and moderate risk aversion and then chose appropriate risk aversion coefficients according to Binswanger’s categories of slight, moderate and intermediate levels of risk aversion. Hennessy (1998) chose the value of $\lambda$ ranging from 6.4*10^{-5} to 1.5*10^{-4} and the value of $\alpha$ ranging from 0 to 1.2*10^{-8}.

The estimated values of relative risk aversion for risk averse agents in the literature differ widely. Meyer and Meyer (2005) adjusted several reported estimates of relative risk aversion in order to compare these estimates with one another. They found that the reported relative risk aversion coefficient is close to one but greater than one and that it is constant or increasing slightly. In contrast, Kramer and Pope estimated a maximum value of 1525. In our simulation, we will consider CARA preference and will adjust the parameters of absolute risk aversion to obtain a value of relative risk aversion that is close to one.

10.2 Modeling Framework

Our goal is to choose the coverage level of total indemnity that will maximize the expected utility of profit when the utility is in negative exponential form. We adopted the values of risk aversion that were reported in previous studies. We modeled yield and price distributions $(y_1, y_2, p_1, p_2)$ and used the copula method to construct a four by four correlation matrix for
yield and price \((y_1, y_2, p_1, p_2)\) distributions. Therefore, four correlated yield and price distributions were simulated, and we repeated drawing random values of yields and prices from the estimated distributions for one million replications. We then calculated the expected utility of profits based on these values and also on the given risk parameters.

An expected utility function can be written as:

\[
EU(\pi) = \frac{1}{N} \sum_{i=1}^{N} \left[ -e^{-\lambda \pi(z_i)} + \alpha \pi(z_i) \right]
\]

Where profits are given by:

\[
\pi(z_i) = (p_i q_i^1 - \sum_{j=1}^{N} w_j^i + P_i P_i^j) x + (p_i^2 q_i^2 - \sum_{j=1}^{N} w_j^2 + P_i P_i^2 + T_i(z_i)) x - PC(z_i)
\]

Where \(i\) denotes the realized values for the \(i^{th}\) replicate; \(z_i\) is the coverage level of total indemnity; \(w_j^i\) is the per acre production cost of input \(j\) in the \(k^{th}\) insured year; \(q_i^k\) is the random yield per acre in the \(k^{th}\) insured year; \(p_i^k\) is the random price in the \(k^{th}\) insured year; \(PC\) is the premium cost which is equal to the expected loss; \(PP^k\) is the partial payment of total indemnity in the \(k^{th}\) insured year, which is a function of output, prices and coverage level of partial payment. It is given by the greater of zero or the difference in the output and guaranteed output in the \(k^{th}\) insured year; \(TI\) is the total indemnity, which is a function of output, prices and coverage level of partial payment and total indemnity. More specifically, we can express \(PP^k\), \(PC\), and \(TI\) in the following:
\[ PP^k = \max(0, \gamma \mu - q_i^k) \alpha, k = 1,2 \]
\[ PC = E(\text{loss} \mid \text{loss occurs}) \]
\[ TI = (\max(0, 2z - \max(\gamma \mu, q_i^1) - \max(\gamma \mu, q_i^2)))\varphi \]
\( \varphi \) is insured price and we assume \( \varphi = 1 \), \( \mu \) is estimated yield, 
\( \gamma \) is coverage rate of partial payment, \( z \) is coverage rate of total indemnity.

In order to select the coverage level of total indemnity for different degrees of risk averse producers, we considered three hypothetical scenarios. In particular, we considered scenarios where: (1) the risk aversion coefficients are \( \lambda = 1 \times 10^{-4} \) and \( \alpha = 5 \times 10^{-7} \), which are common in the empirical literature on the subject; (2) producers have CARA preference and a high degree of risk aversion; (3) producers are risk neutral.

10.3 Data

We used yield data at the county-level for corn, soybean and wheat in Adair (Iowa) and Buffalo (Nebraska) counties from the NASS of the USDA from 1959-2004. Specifically, we considered corn for grain and winter wheat. As seen in the previous chapter, it is reasonable to assume that crop yield follows a Beta distribution. We also followed a common assumption that price follows a log-normal distribution. We used monthly average close futures data from 1959-2004 from the Chicago Board of Trade (CBOT) and adopted historical volatility reported on the website of the New York Board of Trade to model a log-normal price distribution. Production costs were collected from the State Extension Service. The net return from the 2005 crop budgets and returns of Iowa and Kansas are -$81 for corn, $-43 for soybean and -$85 for wheat per acre. However, 12.6 million acres of corn and 10.2 million acres of soybean were planted in 2005 as seen in NASS statistics, which shows that
some farms have cost advantage. Therefore, we followed Goodwin’s procedure (2009) and performed our simulations under the assumption that 60% of production costs were provided by the budgets. Farm size statistics were obtained from the 2002 Agricultural Census.

10.4 Simulation Analysis

Random variables in this simulation model are futures price for two years and county yield for two years. We used the same method to estimate the correlation of prices across years that we used in previous chapters. Similarly, we can estimate the correlation of yield and price in the first and second year. Given these correlations of yield and price across a span of years, as well as the correlation between yield and price in the first and second years that is estimated by using the copula method, we simulated correlated yield and price distributions.

Note that only one positive parameter is allowed in the Archimedean family in Copula, which is not realistic for our data. Therefore, we found the best copula function for our study from the Elliptical family (normal and t copula), which allows for positive and negative parameters. We only selected normal copula from the Elliptical family in order to estimate the parameters of yield and price distributions and correlation simultaneously as a t-distribution approximates to a normal distribution when the sample size is large. In addition, we only selected UN structure without assuming certain relationships between correlation parameters among four variables (two yield and price) to model the joint distribution as AR1, EX and TOEP structures (for more details of dispersion structures, please see section 3.3) assume certain relationships between correlation parameters that are
not reasonable in our case. For example, the EX structure assumes the correlation is the same between any two of the four random variables, which may not be true for the correlations between prices and between yields.

Price and yield distributions are simulated for multiyear crop insurance under three scenarios with coverage levels of total indemnity between 0-100% and 10% increments for each crop. Two different thresholds for total indemnity were also used. The threshold for total indemnity is the average yield. The average yield was calculated from 1959 to 2004 for each crop. The value of coverage levels of partial payment provided in Chapter 8. Production costs are shown in Table 15 and average farm sizes are shown in Table 16. These were fixed in our simulation. We changed various parameters of risk attitudes in order to see how coverage levels of total indemnity can vary.
Table 15 Production Cost Statistics

<table>
<thead>
<tr>
<th>Year of Budget</th>
<th>State</th>
<th>Commodity</th>
<th>Practices</th>
<th>Production Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>2004</td>
<td>Iowa</td>
<td>Corn</td>
<td>Following soybean</td>
<td>413.43</td>
</tr>
<tr>
<td>2005</td>
<td>Iowa</td>
<td>Corn</td>
<td>Following soybean</td>
<td>414.40</td>
</tr>
<tr>
<td>2004</td>
<td>Iowa</td>
<td>Soybean</td>
<td>Herbicide tolerant after corn</td>
<td>292.27</td>
</tr>
<tr>
<td>2005</td>
<td>Iowa</td>
<td>Soybean</td>
<td>Herbicide tolerant after corn</td>
<td>300.32</td>
</tr>
<tr>
<td>2005</td>
<td>Kansas</td>
<td>Wheat</td>
<td>Wheat-follow rotation</td>
<td>159.00</td>
</tr>
</tbody>
</table>

Table 16 Farm Size Statistics from 2002 Census

<table>
<thead>
<tr>
<th>State/ Crop</th>
<th>Farms/Acres</th>
<th>Implied Average Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iowa Corn</td>
<td>52,806</td>
<td>242</td>
</tr>
<tr>
<td></td>
<td>11,761.4</td>
<td></td>
</tr>
<tr>
<td>Iowa Soybean</td>
<td>48,752</td>
<td>233</td>
</tr>
<tr>
<td></td>
<td>10,418.6</td>
<td></td>
</tr>
<tr>
<td>Kansas Wheat</td>
<td>24,236</td>
<td>343</td>
</tr>
<tr>
<td></td>
<td>8,080.82</td>
<td></td>
</tr>
</tbody>
</table>

10.5 Empirical Results

We followed the procedures described in section 10.3 to estimate the parameters of yields and prices and the correlation of yields and prices across years from the normal copula under the UN structure simultaneously. We then simulated correlated yields and prices for Iowa corn, Iowa soybean and Nebraska wheat. We also selected the optimal coverage level from the maximized estimated utility under three different scenarios and two thresholds. Then we reported the parameter estimates of a Beta yield distribution and the log-normal price
distribution as well as the correlation estimates of yields and prices as seen in Table 17. In each case, we showed the optimal coverage level, partial payment in each year, total indemnity in the second year, profits and absolute ($\rho_A$) and relative ($\rho_R$) risk aversion coefficients at the maximized expected utility. In each scenario, we examined 100% of average yield for thresholds of total indemnity and kept the assumption of $1 of insured price. Lastly we examined how risk attitudes affect coverage level from the first to the third scenario.

The simulation results for optimal coverage levels based on the different scenarios described above are shown in Table 18. In the first scenario, we examined that a representative producer has a risk preference commonly seen in the existing empirical literature when production cost is set at 60% of the value of the budget. As shown in table 18, the representative producer in the case of Iowa corn, Iowa soybean and Nebraska wheat always selected the maximum available coverage (100%) of two-year insurance plan to maximize his expected utility of profits.

In the second scenario, we considered a representative producer who is more averse to risk. In this scenario we maintained production costs assumptions at 60% of the value reported in the budget. In the case of Iowa corn, Iowa soybean and Nebraska wheat, the representative farmer selects a 100% coverage level. The relative risk aversion coefficient for a representative producer of Iowa corn is around 4.70, of Iowa soybean around 1.90 and of Nebraska wheat around 9.25. This scenario shows a stronger risk aversion degree than in
other scenarios. The result that a representative producer with a stronger risk aversion prefers full coverage under an actuarially fair premium rate is consistent with the classic result.

In the third scenario, we assumed that the producers are risk neutral. In the case of Iowa corn, a representative producer selected 20% for the threshold of 100% of average yield. In the case of Iowa soybean, a representative producer selected 40%. In the case of Nebraska wheat, a representative producer selected 10% for the threshold of 100% of average yield. As expected, a representative farmer with a risk neutral attitude selected a lower coverage level than a representative farmer with a risk averse attitude.

Overall, a representative producer with similar preferences to those reported in the empirical literature and with a strong degree of risk aversion always prefers full coverage (100%). A representative farmer with a risk neutral attitude will always choose the lower coverage level. A representative producer of Nebraska wheat has the strongest degree of relative risk aversion (9.25) while a representative farmer of Iowa corn, Iowa soybean and Nebraska wheat is assumed to have a high risk aversion preference among the three scenarios.

We used three scenarios from the range of risk aversion attitude that were reported in the empirical literature available in order to see if farmers will choose to participate in two-year crop insurance. The correlation coefficient of yields across years that includes Iowa corn, Iowa soybean and Nebraska wheat is between -0.13 and 0.43. This is not close to one and thus the actuarially fair premium rate is lower than the rate seen in the single year insurance
plan. When the producers acknowledge that the actuarially fair premium rate differs between a single year insurance plan and a two-year insurance plan, the producers will always choose to participate in the two-year insurance plan and in most cases will select full coverage level to maximize their utility level. Farmers with a risk neutral attitude will always choose a lower coverage level. Our simulation indicated that the available coverage level range for a two-year insurance plan insurance contract may be set between 10%-100% by policy makers.

In addition, we used the same three scenarios from the range of risk aversion attitude but the premium rate is between 120% and 140% of the actuarially fair premium rate to see farmers’ participation rate of multiyear crop insurance plan. The results are shown in Table 19. The optimal coverage level for Iowa corn is 90% when the premium rate is 125%, 130%, 135% and 140% of the actuarially fair premium rate in the first and second scenario. For Iowa soybean, the optimal coverage level is 90% when the premium rate is 120%, 125%, 130%, 135% and 140% of the actuarially fair premium rate in the first scenario; a representative farmer still prefers full coverage level when the premium rate is 120%, 125%, 130%, 135% and 140% of the actuarially fair premium rate.
Table 17 Beta Yield Distribution, Log-Normal Price Distribution, Correlation Parameter Estimates and Price Volatility

<table>
<thead>
<tr>
<th>Variable</th>
<th>Adair County (Iowa) Crop: Corn</th>
<th>Adair County (Iowa) Crop: Soybean</th>
<th>Buffalo County (Nebraska) Crop: Wheat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Yield</td>
<td>148.16</td>
<td>42.68</td>
<td>84.77</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameter Estimate</th>
<th>$\alpha_1$</th>
<th>$\beta_1$</th>
<th>$\alpha_2$</th>
<th>$\beta_2$</th>
<th>$\mu_1$</th>
<th>$\mu_2$</th>
<th>Price Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_1$</td>
<td>11.42</td>
<td>6.12</td>
<td>11.22</td>
<td>5.88</td>
<td>5.449</td>
<td>5.442</td>
<td>0.18</td>
</tr>
<tr>
<td>$\gamma_2$</td>
<td>-0.13</td>
<td>1</td>
<td>-0.12</td>
<td>-0.27</td>
<td>1</td>
<td>0.66</td>
<td></td>
</tr>
<tr>
<td>$p_1$</td>
<td>-0.32</td>
<td>-0.12</td>
<td>1</td>
<td>0.66</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p_2$</td>
<td>-0.35</td>
<td>-0.27</td>
<td>0.66</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameter estimate</th>
<th>20.70</th>
<th>11.18</th>
<th>19.47</th>
<th>10.38</th>
<th>6.23</th>
<th>6.22</th>
<th>0.19</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_1$</td>
<td>1</td>
<td>-0.25</td>
<td>-0.09</td>
<td>-0.2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma_2$</td>
<td>-0.25</td>
<td>1</td>
<td>0.03</td>
<td>-0.04</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p_1$</td>
<td>-0.09</td>
<td>0.03</td>
<td>1</td>
<td>0.72</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p_2$</td>
<td>-0.20</td>
<td>-0.04</td>
<td>0.72</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameter Estimate</th>
<th>5.57</th>
<th>5.88</th>
<th>5.23</th>
<th>5.82</th>
<th>5.74</th>
<th>5.73</th>
<th>0.21</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_1$</td>
<td>1</td>
<td>0.43</td>
<td>-0.18</td>
<td>0.006</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma_2$</td>
<td>0.43</td>
<td>1</td>
<td>-0.38</td>
<td>-0.22</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p_1$</td>
<td>-0.18</td>
<td>-0.38</td>
<td>1</td>
<td>0.66</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p_2$</td>
<td>0.006</td>
<td>-0.22</td>
<td>0.66</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: $\alpha_1$, $\beta_1$, $\alpha_2$ and $\beta_2$ are two shape parameters of the beta distribution in the first and second year. $\mu_1$ and $\mu_2$ are mean value of the log-normal distribution in the first and second year.
Table 18 Simulation Result for Selected Crops and States for Two-Year Insurance plan with the Actuarially Fair Premium Rate

<table>
<thead>
<tr>
<th>Variable</th>
<th>Iowa Corn (Adair)</th>
<th>Iowa Soybean (Adair)</th>
<th>Nebraska Wheat (Buffalo)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Threshold: 100% of Average Yield</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Scenario 1: ( \lambda = 1 \times 10^{-4}, \alpha = 5 \times 10^{-7} )</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coverage Level</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Partial Payment in Year One</td>
<td>$86.190</td>
<td>$0.0003</td>
<td>$423.454</td>
</tr>
<tr>
<td>Partial Payment in Year Two</td>
<td>$82.652</td>
<td>$0.0009</td>
<td>$547.966</td>
</tr>
<tr>
<td>Total Indemnity</td>
<td>$3,028.242</td>
<td>$654.347</td>
<td>$14,935.28</td>
</tr>
<tr>
<td>Profits</td>
<td>$47,336.69</td>
<td>$19,073.89</td>
<td>$92,466.09</td>
</tr>
<tr>
<td>( \rho_A(\text{profit}) )</td>
<td>5.9E-05</td>
<td>9.03E-05</td>
<td>1.90E-05</td>
</tr>
<tr>
<td>( \rho_R(\text{profit}) )</td>
<td>1.9849</td>
<td>1.4585</td>
<td>0.8776</td>
</tr>
<tr>
<td><strong>Scenario 2: CARA, ( \lambda = 1 \times 10^{-4} ) (high risk aversion)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coverage Level</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Profits</td>
<td>$47,370.12</td>
<td>$19,099.41</td>
<td>$92,512.10</td>
</tr>
<tr>
<td>( \rho_A(\text{profit}) )</td>
<td>1E-04</td>
<td>1E-04</td>
<td>1E-04</td>
</tr>
<tr>
<td>( \rho_R(\text{profit}) )</td>
<td>4.7370</td>
<td>1.9009</td>
<td>9.2512</td>
</tr>
<tr>
<td><strong>Scenario 3: Risk neutrality (( \lambda = 0 ), ( \alpha = 5 \times 10^{-7} )</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coverage Level</td>
<td>20%</td>
<td>40%</td>
<td>10%</td>
</tr>
<tr>
<td>Profits</td>
<td>$47,400.93</td>
<td>$19,124.87</td>
<td>$92,516.67</td>
</tr>
<tr>
<td>( \rho_A(\text{profit}) )</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>( \rho_R(\text{profit}) )</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
</tbody>
</table>
Table 19 Simulation Result for Selected Crops and States for Two-Year Insurance Plan with Different Level of Premium Rate

<table>
<thead>
<tr>
<th></th>
<th>Iowa Corn (Adair)</th>
<th>Iowa Soybean (Adair)</th>
<th>Nebraska Wheat (Buffalo)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Premium rate</td>
<td>Coverage Level</td>
<td>Coverage Level</td>
</tr>
<tr>
<td>Scenario 1: $\lambda = 1 \times 10^{-4}$, $\alpha = 5 \times 10^{-7}$</td>
<td>120% of the actuarially fair premium rate</td>
<td>100%</td>
<td>90%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>125%~140% with 5% increments of the actuarially fair premium rate</td>
<td>90%</td>
</tr>
<tr>
<td>Scenario 2: CARA, $\lambda = 1 \times 10^{-4}$ (high risk aversion)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scenario 1: $\lambda = 1 \times 10^{-4}$, $\alpha = 5 \times 10^{-7}$</td>
<td>120%~140% with 5% increments of the actuarially fair premium rate</td>
<td>90%</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scenario 2: CARA, $\lambda = 1 \times 10^{-4}$ (high risk aversion)</td>
<td>120%~140% with 5% increments of the actuarially fair premium rate</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scenario 1: $\lambda = 1 \times 10^{-4}$, $\alpha = 5 \times 10^{-7}$</td>
<td>120%, 140% of the actuarially fair premium rate</td>
<td>90%</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scenario 2: CARA, $\lambda = 1 \times 10^{-4}$ (high risk aversion)</td>
<td>120% and 125% of the actuarially fair premium rate</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>130%, 140% of the actuarially fair premium rate</td>
<td>90%</td>
</tr>
</tbody>
</table>
10.6 Summary

In this chapter, we evaluated the two-year insurance plan by investigating the optimal coverage level. Our main concern centers around producers’ behavior when making a decision to participate and also to purchase insurance coverage given varying attitudes toward risk. We used the copula method to model the joint distribution of yields and prices across years and simulated farmers’ decisions with different degrees of risk aversion. Specifically, we have focused on three scenarios which cover the risk aversion coefficient commonly reported in the available empirical literature, high risk aversion, and risk neutral attitude. Our simulation results suggested that producers chose to participate in a two-year insurance plan, and in most cases producers chose a full coverage level to maximize their utility level. The simulation results suggested that multiyear crop insurance should be considered seriously as an alternative to current crop insurance programs. The simulation results also suggested that the available coverage level may be set between 10%-100% by the policy maker.
11. Conclusion

Here we proposed multiyear insurance plans, which are expected to have lower actuarially fair premium rates than current single-year insurance plans. Based on our simulation results, the correlation structure of crop yields across years plays an important role in the design of crop insurance contracts. Risk crop insurance programs, such as MPCI and GRP, have been characterized as having low participation rates because many farmers are not attracted to these types of programs. Several empirical studies showed that a decrease in premium rates can attract farmers to participate in the program. However, few researchers have focused on the design of insurance contracts for multiyear terms. Our simulation results showed that actuarially fair premium rates will decrease in two-year and three-year insurance plans when the correlation coefficient of yields between consecutive years decreases. As long as the correlation is not positively perfect (i.e. the Pearson’s correlation coefficient is not equal to 1), the actuarially fair premium rate for multiple year insurance contracts is lower than rates seen in single year insurance contracts.

Detailed designs of the multiyear insurance plans are also described in Chapters 4, 5 and 6. In addition to the feature of lower actuarially fair premium rates in multiyear plans, one other positive aspect is that farmers will obtain partial payment in order to cover their variable cost of production. If farmers have yield or revenue loss in a particular year, yield or revenue loss will not bankrupt them because of the partial payment in the plan. Lower actuarially fair premium rates and partial payment are expected to help farmers reduce the negative effect resulting from agricultural risks and help farmers return their short-term debt.
In order to demonstrate that our proposed insurance plans are practical, we then used county and farm level data for corn in Iowa, Illinois, Indiana and Ohio in order to calculate the Pearson’s correlation coefficients. For county data, we chose the top ten productive counties in Iowa, Illinois, Indiana and Ohio. Based on the real data analyses, the correlation coefficients are generally small. Therefore, when the proposed multiple year insurance plan is implemented in these states, the actuarially fair premium rate will be lower than the rate currently seen in single year insurance plans.

We then presented the Pearson’s correlation coefficients of yields and p-value between two consecutive years on the state and county levels. We used color maps to present the Pearson’s correlation coefficient of yields and histograms to present p-values in consecutive years at the county level based on the farm data. Most counties in Iowa have negative Pearson’s correlation coefficients based on the farm level data; p-value results showed that corn yields are not significantly correlated between consecutive years in Iowa, Illinois, Indiana and Ohio. The data analyses based on county and farm data showed that mostly there is no significant correlation of yields between different years. According to our simulation results, when the proposed multiyear insurance plans are applied to these states, they are expected to have lower actuarially fair premium rates than what is found in current single year insurance plans.

Since copula provides flexibility as a dependence function that binds marginal distributions together in order to express joint distribution without sacrificing properties of marginal distributions, copula methods were also adopted in our studies in order to model joint
distributions of yield. We used several copula functions to model joint distribution of yield across years and then selected the best copula function by using a maximum likelihood value and the AIC rule for two- and three- year insurance plans, respectively. After we selected the best copula function, we simulated joint distributions of yield and estimated the actuarially fair premium rate. We followed the methods we described above to show how two- and three- year insurance plans work by using specific county level data (Adair county in Iowa). We also showed that partial payments can help farmers return their short loan and stabilize their income in specific numeric values.

We are concerned about producers’ participation and producers’ behaviors if multiyear insurance plans become available. As optimal coverage levels can reflect both the decision to participate and producers’ behavior when buying insurance, we used empirical models to simulate a producer’s decisions given price and yield risks and with various degrees of risk aversion. We focused on three scenarios of risk aversion that represent the risk preferences commonly reported in the empirical literature, high risk aversion, and risk neutrality.

Our simulation results of Iowa corn (Adair county), Iowa soybean (Adair county) and Nebraska wheat (Buffalo county) showed that producers will choose to participate in the two-year insurance plan and in most cases producers will select a full coverage level. As expected, producers who are risk neutral will select a lower coverage level than the other scenarios examined. We also found that producers of Nebraska wheat have the highest risk aversion coefficients. Our simulations also provide an indicator for policy makers that the
available coverage level should be set between 10%-100% for a two-year insurance plan. We used the optimal coverage level to evaluate the two-year plan through producers’ decision to participate and also farmers’ behaviors when buying two-year insurance plans. Our simulations should be viewed as strong evidence that producers place high values on two-year insurance plans and consider two-year insurance plans as good risk management. Policy makers should seriously consider the fact that multiyear insurance plans can be a great alternative to the current insurance programs available.
References


Appendices

Figure 46 Histogram of P-Values of Iowa at County Level (Crop: Corn)

Figure 47 Histogram of P-Values of Illinois at County Level (Crop: Corn)
Figure 48 Histogram of P-Values of Indiana at County Level (Crop: Corn)

Figure 49 Histogram of P-Values of Ohio at County Level (Crop: Corn)
Figure 50 Histogram of P-Values of Iowa at County Level (Crop: Soybean)

Figure 51 Histogram of P-Values of Illinois at County Level (Crop: Soybean)
Figure 52 Histogram of P-Values of Indiana at County Level (Crop: Soybean)

Figure 53 Histogram of P-Values of Ohio at County Level (Crop: Soybean)
Figure 54 Histogram of P-Values of North Dakota at County Level (Crop: Barley)

Figure 55 Histogram of P-Values of Montana at County Level (Crop: Barley)
Figure 56 Histogram of P-Values of Texas at County Level (Crop: Cotton)

Figure 57 Histogram of P-Values of Kansas at County Level (Crop: Grain)
Figure 58 Histogram of P-Values of Nebraska at County Level (Crop: Grain)

Figure 59 Histogram of P-Values of Kansas at County Level (Crop: Wheat)
Figure 60 Histogram of P-Values of Montana at County Level (Crop: Wheat)

Figure 61 Histogram of P-Values of North Dakota at County Level (Crop: Wheat)
Figure 62 Histogram of P-Values of Oklahoma at County Level (Crop: Wheat)

Figure 63 Histogram of P-Values of Texas at County Level (Crop: Wheat)