

HEDGING DOWNSIDE RISK TO FARM INCOME WITH FUTURES AND OPTIONS:
EFFECTS OF GOVERNMENT PAYMENT PROGRAMS AND FEDERAL CROP
INSURANCE PLANS

by

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(Under the Direction of Jack E. Houston)

ABSTRACT

The high proportion of government payments in total crop farm income and the purchase of subsidized crop insurance have changed the income distribution of U.S. crop farmers. As a result, the risk management behaviors of U.S. crop farmers are affected by these programs in terms of the use of private market risk management tools, such as futures and options. The objective of this research is to investigate the effects of the government payments and federal crop insurance policies on the usage of futures and options by crop farmers from a downside risk management perspective.

Acknowledgment of the effects of different government payment programs and crop insurance on hedging can benefit crop farmers so that they can adjust their positions in futures and options accordingly. Understanding such effects can be informative to policy makers in prioritizing government risk management policies.

This research contributes to the literature by proposing to use a downside risk hedge model, the second-order lower partial moment (LPM_2) hedge model, to evaluate the interaction of government and private risk management tools used by U.S. crop farmers.

This study also initiates the application of conditional kernel density method and the copula approach to the crop prices and yields simulating process. The conditional kernel density method generates county yields and farm yields with the same conditional pattern as revealed in the historical yield patterns. The copula simulation allows the crop yields and prices to attain more flexible joint distributions other than being restricted to the multivariate normal distribution.

Results in this study suggest that both yield insurance and revenue insurance creates more hedging demands for futures. But revenue insurance decreases the buying of put options at the same time. Loan deficiency government payments substitutes largely for the hedging role of put options while Counter cyclical payments substitutes futures hedge. This study also confirms that the optimal futures hedge in the downside risk hedge model is an under-hedged position compared to the optimal positions based on an expected utility hedge model. Hence, the downside risk hedge model provides a better explanation for the actual futures hedging behaviors of crop farmers.

INDEX WORDS: Downside risk, Hedging, Lower partial moments, Futures, Options,

Government payment programs, Federal crop insurance

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CHAPTER 1

INTRODUCTION

Price and production uncertainty generally comprise two main sources of risk to a crop producer's farming income. Common risk management strategies usually consider futures and options as the only risk management instruments to protect farmers from undesired low farm income resulting from lower crop prices at harvest. But U.S. crop producers, in addition to futures and options, have access to two additional types of government-supported means to manage the risk of low farm income: government payment programs and subsidized federal crop insurance plans.

1.1 Background

By limiting income risk faced by farmers, three major government payment programs – direct payments (DP), loan deficiency payments (LDP), and counter cyclical payments (CCP) – legislated in the current farm bill, the Food Security and Rural Investment (FSRI) Act, provide substantial income support to U.S. crop farmers. In 2005, these three government payments (DP, LDP, and CCP) totalled over \$14.3 billion, which accounts for almost 20% of the 73.8 billion net farm income of that year¹. For crop farmers, the percentage of these payments in net farm income would be even higher since they receive all of these payments but they contribute to the net farm income together with livestock farmers. Such a heavy proportion of income support

¹ Data source: Economic Research Service, U.S. Department of Agricultural.

http://www.ers.usda.gov/briefing/farmincome/data/GP_T6.htm

http://www.ers.usda.gov/briefing/farmincome/data/va_t1.htm

from government generally would reduce the possibility of sharp drops in income for the participating farmers and may affect the risk management behaviors of crop farmers.

In the past decade, subsidized federal crop insurance plans have become a promising way for U.S. crop farmers to manage price and production risk. This is evidenced by the fact that net insured acres, excluding acres under the free catastrophic insurance, have increased from about 105 million acres in 1995 crop year to 158 million acres in 2000 crop year and to over 217 million acres in 2005. Meanwhile, the premium subsidy has increased from \$436 million in 1995 to \$686 million in 2000 and to over \$2 billion in 2005². As an alternative risk management instrument, crop insurance policies increase the available tools in the risk management portfolios of crop farmers.

The effects of government-oriented risk management tools on the use of financial market risk management tools, such as futures and options, concern researchers for several reasons. First, such effects reveal the distortion of government intervention to private market decisions. Second, the large amount of government payments and federal insurance subsidies may lead to substantive influence on the use of futures and options, even if the marginal effects are trivial. Third, acknowledgement of such effects has practical meaning to crop farmers, because they could adjust their portfolios of risk management tools accordingly. Fourth, policy makers may be interested in such evaluations, because they would have more insights of potential policy alternatives, should they be forced to reform the existing government payments and insurance programs due to budget constraints, weaknesses in political lobbying strength, or pressure from international trade partners.

² Data from Summary of Business Report, Federal crop insurance Corp, RMA, USDA

1.2 Problem Statement

Although understanding the impacts of government payment programs and federal crop insurance plans on the use of futures and options would benefit both crop farmers and policy makers, very few studies examine such effects³. Among studies in the literature that examine such issues, the expected utility (EU) hedge model, which assumes that crop farmers hedge with futures and options to maximize expected utility, appears to be the only method used (Poitras, 1993; Hanson et al. 1999; Coble et al. 2000, 2004; Mahul 2003; Wang et al. 2004).

By making assumptions on the utility function and on the distribution of random variables, such as harvest-time yield, spot price, and futures price, optimal hedge ratios can be found numerically. Stochastic simulation and numerical optimization are normally used instead of analytically-derived optimal solutions, because government payments, crop insurance, and options in the risk management portfolio censors the portfolio at multiple points. Such kinks in payoffs restrict the differentiability required for analytical derivation (Coble et al., 2000). While the assumptions on the yield and prices distribution can be tested using historical data, the utility function is usually subjectively determined, since it requires special experiments to delineate any decision maker's utility function (Chavas, 2004). However, because the true utility function is not known, results obtained from a particular utility function may be misleading and lack generality (Sakong et al., 1993).

When examining the effects of government payments and/or insurance on hedging, most of the previous works consider the effects on futures only, but disregard the fact that put options may be used together with futures to achieve the optimal hedging. Should options be used

³ The special issue of European Review of Agricultural Economics in September 2004 claim producer hedging and insurance decisions under multiple uncertainties as a new issue about individual behavior towards risk.

together with futures by the crop farmers at the planting time when they attempt to hedge price risk to their crop at harvest? A few studies have suggested that options have a distinct role in the risk management portfolio under price and yield uncertainty or when cash prices received by farmers are truncated (Sakong et al., 1992; Moshini and Lapan, 1995; Hanson et al., 1999). Thus, futures and options should be considered together as available risk management instruments to the crop farmers.

To evaluate the effects of government payments and insurance on the optimal hedge ratios in futures and options, harvest-time values of several variables, including farm-level yield, spot price, futures price and market year average price, which partly determines the CCP, need to be simulated. Existing literature typically simulate such harvest-time realizations based on two key assumptions. One assumption is that these random variables have joint normal distribution, or at least they can be transformed to be joint-normally distributed. The problem with the joint normality assumption is that it is too restrictive, if there is no hypothesis test result to support such an assumption.

The second assumption usually made in previous works is that farm-level yield has the same distribution as county-level yield, except having a larger variance. Because county-level yield has a longer record than farm-level yield, such an assumption enables the researchers to get more reliable estimates regarding yield distribution and its relationship with other price variables by using county yields rather than much shorter, farm-level yield data. However, such assumptions may not be appropriate in that the constant variance assumption for farm-level yield contradicts the variance pattern reflected in the historical yield data. Figures 1.1-1.2 and tables 1.1-1.2 show that the variance of farm-level yields is not constant. Instead, the variance varies with the level of county yields.

To avoid subjectivity that may be introduced by any particular utility function used in the EU hedge model, two approaches can be implemented. One is to run the model with as many appropriate utility functions as possible and then check the consistency across the results. The other approach is to use a utility-free hedge model to investigate the same issue and to examine if there is consistency across the results from different hedge models. This study takes the second path and applies a downside risk hedging model — second-order lower partial moment (LPM₂) hedge model — to examine the effects of government payments and insurance on the use of futures and options. In order to allow for more flexibility in the joint distribution between yield and price and to accommodate the fact that farm-level yield variance is conditional on county yield, this study will apply the copula method and the conditional kernel density approach to simulate relevant yield and price distributions.

1.3 Objectives

The main objective of this study is to apply a utility-free, downside risk hedge model to investigate the effects of government payment programs and federal crop insurance plans on the optimal use of risk management tools in the financial market, such as futures and options. To accomplish the main objective, the following sub-objectives will be pursued:

1. To review the current non-ad hoc government payment programs and insurance products; to review the literature on the lower partial moments (LPM) risk measures and the associated LPM₂ hedge model.
2. To set up a portfolio payoff function, including payoffs from market hedge, federal crop insurance and government payments, for a representative crop farm which has information up to planting time.

3. To forecast the harvest-time farm yield, futures price, local cash price, and marketing year average price by applying copula Monte Carlo simulation and kernel smoothing methods.
4. To examine the effects of three types of government payments (DP, LDP, and CCP) and two insurance plans (the Actual Production History plan and the Crop Revenue Coverage plan) on the optimal hedge ratios using the second-order lower partial moment (LPM_2) decision criterion. The sensitivity of optimal hedge ratios to varying coverage levels of insurance, and to the bias in futures prices will be investigated. The effects of transaction costs incurred by trading futures contracts will be examined.
5. To examine the relationships between the optimal LPM_2 hedge ratios and optimal EU hedge ratios. A specific hypothesis to be tested is that farmers will hedge more in futures and less in put options under the EU decision criterion than under the LPM_2 hedge model with target payoff set at the mean value. Chapter 3 shows that the optimal hedge ratios in an LPM_2 hedge model balance between a smaller semivariance and a larger right skewness when the target payoff is set to mean value, while the hedge ratios in an EU hedge model trade off between a smaller variance and a larger right skewness. Thus, the decision maker might hedge more in the EU hedge model than in the LPM_2 hedge model.

1.4 Model Selection

Different from the expected utility decision criterion, which takes account of risk by maximizing the probability-weighted utility, the lower partial moment (LPM) hedge model directly minimizes a measurement of downside risk, which is the expected value of the certain power of the shortfall from a target payoff. The LPM hedge model requires no assumptions

about a utility function, but instead assumes that the risk management objective is to minimize the perceived risk which is measured by a function of the shortfall.

In addition to its utility-free feature, the LPM criterion seems to be more relevant than the expected utility approach when government payments and insurance are considered in the hedge portfolio. The ultimate purpose of the government payments and federal crop insurance plans is to protect crop farmers from receiving low farm incomes. Such a purpose is reflected by the often-cited “safety net” in the U.S. farm policy files. In other words, government payments are part of the set of safety measures established by the U.S. government to protect farmers from downside risk to their incomes. Federal crop insurance plans oppose low income by nature, because they base their value on the degree to which they limit downside risk. Following this line of reasoning, downside risk to farm income is clearly the concern of such government programs as government payments and federal crop insurance plans. Consequently, one can assume that downside risk to crop income is also the concern of farmers.

In order to make the results from an LPM hedge model comparable with the results from an EU model with commonly assumed preferences that $U' > 0, U'' < 0, U''' > 0$ ⁴, this study will focus on the LPM₂ hedge model — which minimizes the expected value of the squared shortfall from the target payoff — to examine the effects of government payments and insurance on hedge ratios (See details in Chapter 3).

⁴ Note that decreasing absolute risk averse preferences satisfy this set of conditions.

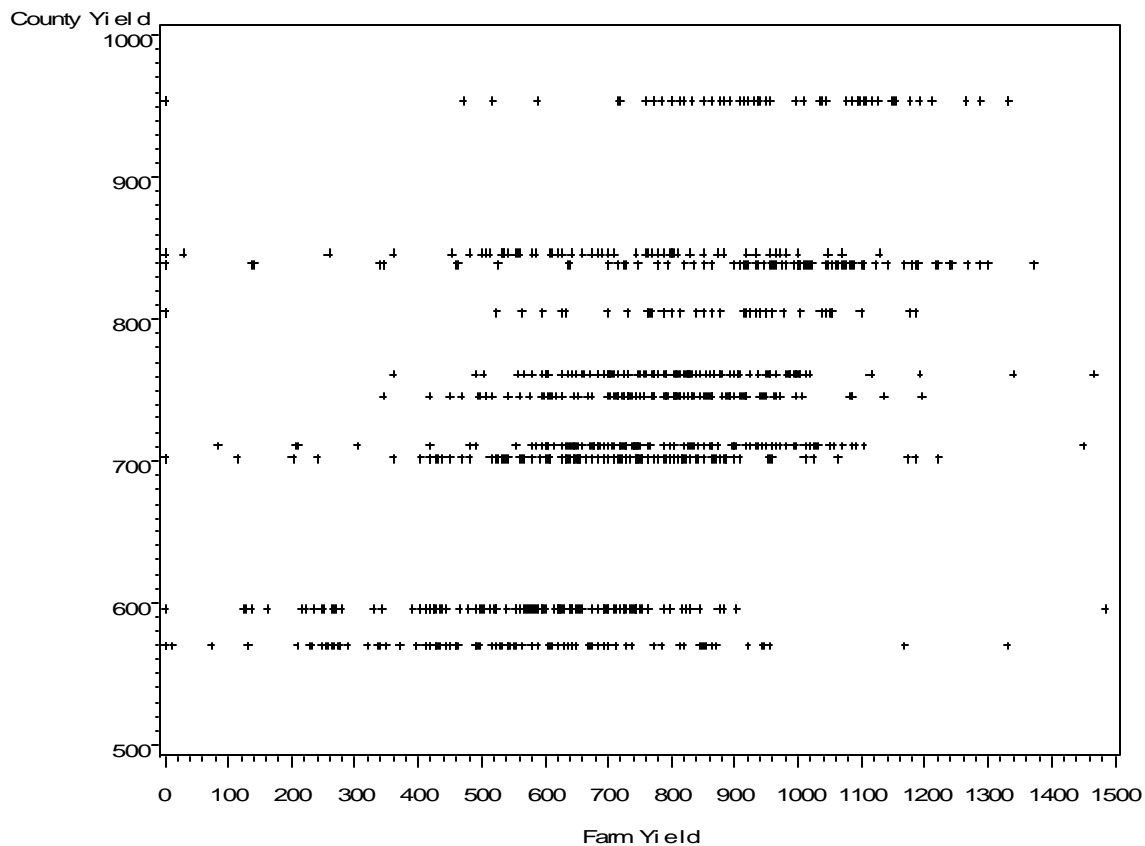


Figure 1.1 Cotton in Colquitt County: Conditional Farm-level Yields in 1991-2000 (in pounds)

Table 1.1 Standard Deviations of Farm-level Cotton Yields in Colquitt County in 1991-2000

Year	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
County yield (lb)	805	954	846	839	761	746	711	596	702	570
Std. Dev.	439	506	394	458	169	162	202	212	249	242

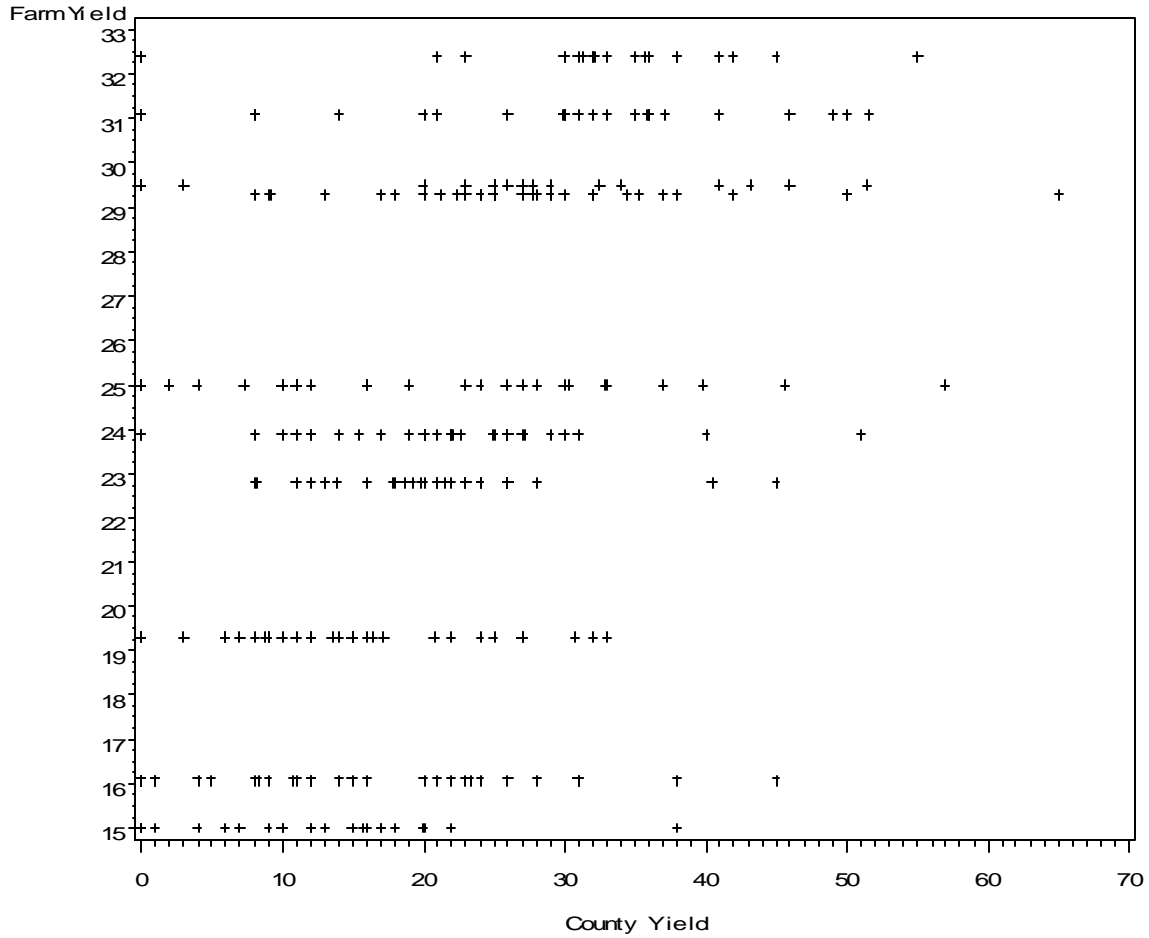


Figure 1.2 Soybean in Bulloch County: Conditional Farm-level Yields in 1991-2000 (in bushels)

Table 1.2 Standard Deviations of Farm-level Soybean Yields in Bulloch County in 1991-2000

Year	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
County yield (bu)	29.5	32.4	15.0	31.1	29.3	22.8	23.9	19.3	16.1	25.0
Std. Dev.	17.3	18.3	9.3	16.7	12.2	7.9	10.2	9.3	12.3	15.3

LPM_2 is also called the semi-variance when the target payoff is set to be the mean payoff. By minimizing the semivariance, the optimal LPM_2 hedge ratios tend to increase the right skewness of the payoff distribution of the hedge portfolio. By comparison, the Taylor expansion of the expected utility function at the mean payoff reveals that the optimal hedge ratios from an EU model would be a compromise between the smaller variance and the higher right skewness.

The fact that EU model favors smaller variance whereas LPM_2 hedge minimizes semivariance leads to the conjecture that the crop farmer will hedge less in futures under the LPM_2 model than under the EU hedge model. If the optimal hedge suggested by the LPM_2 criterion is smaller than what is suggested by the EU model, misspecification of the hedging objective would be another explanation for the limit use of futures by crop farmers.

1.5 Simulation Methods

To avoid the restrictive multivariate normal assumption on harvest-time price and yield variables, this study proposes to apply copula approach in simulation. A copula is a function that links the joint cumulative density function of multiple random variables with the marginal cumulative density function of each random variable. The copula function expresses the dependence among variables without assuming a specific functional form of the joint distribution. Sklar's theorem stated that each continuous copula function corresponds to one joint distribution of the random variables involved. Hence, by estimating the copula function for a vector of random variables, a certain joint distribution for the random variables is implicitly determined. But the advantage of the copula approach over the direct multivariate normal assumption is that the distributions of the individual variables need not to be normal or to be transformed normal. Another advantage is that the joint distribution behind the copula may be different from the multivariate normal distribution and may even be some joint distribution that doesn't belong to

any particular parametric distributions. Thus, the copula method adds more modeling flexibility in the sense that the simulated variables could have any individual distributions, and their joint distribution could be different from multivariate normal.

To simulate farm-yield with variance contingent on county-yield as observed in the historical yield data, conditional kernel density method is implemented. Conditional kernel density is a conditional density function derived based on a kernel density approach. By estimating the conditional density function and the corresponding conditional cumulative distribution function for the farm-level yield conditional on county-level yield, the simulated farm-level yield would present the pattern reflected in the historical yield data that the variance of farm-level yield changes with county yield.

1.6 Organization of the Study

This dissertation is composed of six chapters. Chapter 2 first provides a review on the three government payment programs (DP, LDPs, and CCP) authorized by the current farm bill and two federal crop insurance plans (APH and CRC). Chapter 2 also provides a literature review on the hedging effects of government payments and federal crop insurance. Given that lower partial moment (LPM) risk measures and the lower partial moment hedge model have not been widely acknowledged in the agricultural economics field, Chapter 3 is devoted to review the development and theoretical justification of LPM risk measures, and to survey the major applications of the second-order lower partial moment (LPM_2) hedge model. Chapter 4 explains the data and methodology used in this study. Since one important contribution of this study is to adopt new methods to simulate harvest-time price and yield data, the procedures used in these methods, such as conditional kernel smoothing method and copula functions, are thoroughly

documented. Chapter 5 reports the empirical results and sensitivity analysis for various scenarios. Summary and discussions are provided in the chapter 6.

CHAPTER 2

LITERATURE REVIEW: GOVERNMENT PROGRAMS AND HEDGING EFFECTS

This chapter reviews the government programs including government payment programs under 2002 Farm bill and the prevailing federal crop yield and revenue insurance plans in the first two sections. The third session provides a discussion of the previous works on the hedging effects of the government programs. The issues with the existing research methods prompt the proposition of the hedge model to be developed in this study.

2.1 Government Payment Programs under 2002 Farm Bill

Since the first farm bill, the Agricultural Adjustment Act of 1933, U.S. government has been providing income supports to U.S. farmers through a variety of government programs. The commodity support provisions in the 2002 farm bill, Food Security and Rural Investment (FSRI) Act, include three primary types of payments: (1) direct payments, (2) loan deficiency payments, and (3) counter-cyclical payments. The direct payments (DP) are “decoupled” in the sense that the payments are not related to current year price or production but provide annual fixed income support to enrolled farmers. In particular, DP for any crop year in 2002-2007 is exactly known in advance. Thus, DP shifts the distribution of the farm income to the right but not change the shape of the distribution.

The loan deficiency payments (LDP) are a part of the marketing loan program (See Monke for details of other policies in the market loan program). LDP provides income benefits when market prices are below loan rates. Enrolled producers can receive the LDP equal to the

product of actual yield multiplied by the difference between the loan rate and local crop price. Hence, the size of LDP is affected by both the market price and the actual production.

By design, the LDP performs like a free put option to producers in that LDP compensates the producer for any difference between the current year market price and local loan rates and effectively provides a price floor at the local loan rate. Hence, it is natural to hypothesize that the availability of LDP might induce farmers to hedge less than they would without LDP.

The counter-cyclical payments (CCP) in the 2002 farm bill are triggered when the market year average price⁵ is below the target price less direct payment rate. The maximum CCP rate equals to the target price less the sum of the direct payment rate and the loan rate of LDP. The CCP is classified as a “decoupled” government subsidy since the total amount of CCP is not affected by the actual production but tied to program yield and units⁶. The payment mechanism of the CCP indicates that CCP provides an additional payment over LDP, and thus farmers will receive a price close to the target price (Wang et al., 2004). Anderson et al. (2003) pointed out that CCP is analogous to the difference between the value of one put option against the market year average price with a strike price equal to the target price minus the direct payment and the value of the other put option against local market price with a strike equal to the loan rate.

⁵ Market year average price is the weighted monthly national average price received by farmers with crop stocks sold in every month as weights.

⁶ In fact, farmers have the option to receive CCP up to three times within a marketing year. The first and second advance payments are based on estimated market year average price, and account for 35% of the estimated CCP each. The two payments are paid to farmers in October of the planting year and in February of the next year separately. The third payment which is due at the end of corresponding crop’s marketing year and will be the difference between the actual CCP for the marketing year and sum of two advance payments. In this study, the farmers are assumed to receive the estimated CCP at harvest in a lump sum.

2.2 Review of Selected Government Insurance Plans

Federal Crop Insurance Corporation (FCIC) provides U.S. producers with many insurance plans for a large variety of agricultural commodities. The characteristics of an individual insurance plan in the FCIC insurance products profile can generally be categorized according to (1) whether it insures against yield losses or against revenue losses, (2) whether the indemnity is triggered by losses at the farm level or at the county level, and (3) whether indemnity payments are based on a price selected at the time of signing up for the insurance or the higher of the price at sign-up and the price at harvest.

In this study, two insurance products, namely, Actual Production History (APH) and Crop Revenue Coverage (CRC) will be considered as the two alternative risk management tools in the risk management portfolio of the representative farmer who needs to decide on optimal hedge ratios at planting time⁷. APH and CRC are selected because they are the most popular policies purchased by crop farmers nationwide in recent years (Figure 2.1). Both APH and CRC have their indemnities triggered by farm-level losses.

The APH insurance plan, which is also known as Multiple Peril Crop Insurance, is the oldest crop insurance product. When the actual farm yield falls below a guaranteed yield level, an APH contract pays indemnity based on the difference between the two. The guaranteed yield equals a farmer-chosen coverage level times APH yield⁸. APH yield is a simple average of four to ten consecutive years of actual yields based on the farmer's production records⁹. Indemnities

⁷ This study will not consider insurance plans that are triggered by county-level losses due to data limitations.

⁸ The coverage level is also termed as farm-chosen yield election.

⁹ More details on how to calculate APH yield, see are provided by university extension at Iowa State University, available online at <http://www.exnet.iastate.edu/Publications/FM1826.pdf>.

are calculated by the product of the yield shortfall and an indemnity price. The indemnity price can be between 55% and 100% of the price set annually by RMA.

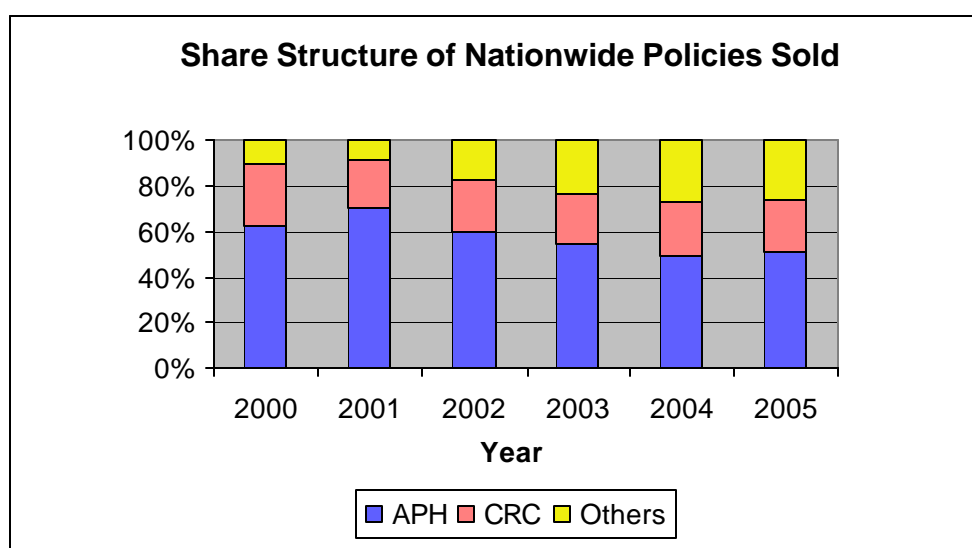


Figure 2.1 Shares of Nationwide Crop Insurance Policies

Data Source: USDA RMA <http://www.rma.usda.gov/data/sob.html>

CRC is a revenue insurance product which protects against low revenue resulting from low yields, low prices, or a combination of both. The CRC plan pays an indemnity whenever actual gross revenue falls below a revenue guarantee. The level of the guaranteed revenue under CRC is obtained by multiplying APH yield, the higher of the base price or harvest price, and the selected coverage level¹⁰. Hence, the level of guaranteed revenue will increase if the harvest price is greater than the base price. Both base and harvest prices are determined based on the prices of commodity futures contracts from the corresponding futures exchange. For example,

¹⁰ The available coverage levels for APH and CRC range from 50% to 85% with an increment of 5%.

the base price of cotton is determined by the daily average settlement price of the December contract on the New York Board of Trade during the period from January 15 to February 14. The harvest price is the average of the same December contract during November. For soybeans, the base price of soybean is the daily average of November contract on the Chicago Board of Trade during the month of February, while the harvest price is the average of November contract during October.

All the insurance plans provided by FCIC are currently subsidized by the U.S. government. In particular, the actual premium paid by farmers is just a certain percent of the total premium. The percentage paid equals $(1 - \text{premium subsidy factor})$ where the subsidy factor decreases as the coverage level increases¹¹.

2.3 Review of Literature Analyzing the Effects on Hedging

In literature, the effects of federal crop insurance plans and government payments programs under the current or previous farm bills on hedging have been address by a number of studies. Among these studies, the expected utility (EU) hedge model appears to be the only hedge model used (Poitras, 1993; Hanson et al. 1999; Coble et al. 2000, 2004; Mahul 2003; Wang et al. 2004). Thus, the use of a specific utility function to obtain the optimal solutions may result in lack of generality for most of the findings in the previous studies. Most of these studies investigated the effects of government payments and insurance on the use of futures only although it has been proven by Sakong et al. (1993) that the coexistence of both price and production risk induces the use of futures and options together in the optimal hedge.

¹¹ The table of subsidy factors and fees for different coverage level can be obtained from the USDA RMA website <http://www3.rma.usda.gov/apps/docbrowser/docbrowserA.cfm> .

Review of Effects of Government Payments on Hedging

Hanson et al. (1999) examined the effects of loan deficiency payments of the 1996 farm bill on actual hedging in futures and options. By using the maximum expected utility hedge model and assuming a logarithmic utility function, Hanson et al. found that the loan deficiency payments induce farmer to sell put options as well as buying futures at the same time. Since the LDP in 2002 farm bill has different loan rate and use actual yield but not program yield as in the 1996 farm bill to calculate the total payments, it is expected that the LDP in 2002 may have different effects on futures and put options from the loan deficiency payments under 1996 farm bill.

Coble et al. (2004) evaluated the effects of LDP of 2002 farm bill on the hedging demand for futures using an expected utility maximizing objective. By assuming bivariate normally distributed price and yield, no basis risk, and a risk-averse utility function in an analytical model, Coble et al. derived that the hedging demand for futures is negatively related to the change in the loan rate. That is, LDP has a substitution effect on futures hedging. Furthermore, Coble et al. pointed out that the degree of substitution of LDP for futures hedge is positively related to yield level. That is, the substitution effect is larger when the mean of the yield distribution is higher. This finding indicates that, the LDP will reduce the optimal futures hedge ratio by a larger amount when yield insurance is in the risk management portfolio than when it is not (Coble et al., 2004).

In order to investigate the effects of LDP on futures hedge under a more realistic situation that allows basis risk, non-normal joint distribution of yield, futures price and basis, Coble et al. used simulated data to solve optimal positions in futures for a representative farmer with CRRA

utility function¹². Results of Coble et al. showed that the effects of LDP on futures in the numerical model are consistent with analysis in the analytical model, namely LDP decreases futures hedging. However, the assumption of constant variance of the farm-level yield by Coble et al. does not comply with historical data. The assumption of joint normality for the transformed county yield and futures price may be too restrictive without testing. Failure to consider the use of options together with futures may bias their findings.

Wang et al. (2004) measured the effect of direct payments (DP) on futures hedging in an expected utility hedge model for a constant relative risk aversion (CRRA) utility function assumed for a representative farmer who grows winter wheat with spring barley and peas in rotation in Whitman County, Washington. Because the hedge ratios in the EU hedge model for a CRRA utility function are affected by wealth change, it is to be expected that Wang et al. found that the DP decreases the hedge ratio in futures by about 5%.

Wang et al. (2004) also analyzed the effects of LDP on the optimal hedge in futures. Results from Wang et al. showed that LDP substitutes the use of futures. Based on the analysis that CCP raises the price floor received by producers from near the loan rate to the level around the target price, Wang et al. (2004) investigated the effects of CCP on the use of futures by comparing the optimal hedge ratios before and after CCP is provided to the representative producer who already has LDP in his risk management portfolio. Results of the expected utility hedge model in Wang et al. showed that CCP has substitution effects on futures. However, such substitution effect is conditional on assumption of a low transaction cost associated with the futures hedge. If the transaction cost is too high, then LDP might substitute for the futures hedge completely and leave no chance to CCP to show its substitution effects on futures. Similar to the

¹² The utility function has the form of $U(W) = -W^{-1}$, where W is the end-of-season wealth.

study by Coble et al. (2004), Wang et al. assumed constant variance of the farm-level yield and joint normality for the county yield and transformed futures price in the simulation. Wang et al. investigated the effects of government payments on the hedging demand for futures only.

Anderson et al. (2003) presented another perspective from which CCP might interact with options. The analysis is partly inspired by the decoupled feature of CCP. For any producer who grows crops different from his program crop, his farm income from the planted crops is not protected by CCP despite that the producer might receive CCP for his program crop. The amount of CCP the farmer can receive is conditional on the market year average price of the program crop. If the price of futures contract of the program crop moves closely with the market price of the crop, then the farmer could actually buy call options to take advantage of the price increase and compensate the loss of CCP. By finding the optimal hedge in the expected utility hedge model, Anderson et al. (2003) showed that it is rational for producers to use call options to hedge at least a portion of the CCP under some conditions.

This study considers that the risk management decisions are made by the crop farmers at planting time, and that all the uncertainty will be resolved at harvest time. Thus, the relevant time span is from planting season to harvest season of the crop under discussion. Since the purchase of call options motivated by the CCP usually happens in post-harvest seasons, such effects will not be investigated in this research.

Review of Federal Insurance Effects on Hedging

Poitras (1993) pointed out that when crop producers face both price and production uncertainty, the analysis of the farmer's hedging problem should not ignore the possibility of using crop insurance. By assuming that the farmer managed the risk by optimizing the expected utility function, which was set as a function of the mean, variance and skewness of the end-of-

season wealth, Poitras obtained the analytical expression for the ratio of the value of futures contract hedged to the initial wealth. However, Poitras noted that the impact of the crop yield or revenue insurance on the futures hedge is not clear-cut, due to a number of potential offsetting effects.

Coble et al. (2000) examined the impacts of four insurance contracts, including APH and CRC, on the optimal hedge ratios of futures or put options separately. Hedging decisions of four representative risk-averse corn producers from four counties of different states were investigated to identify any regional difference. Based on the assumption that futures and options are alternative tools in the risk management portfolio, Coble et al. used a behavior model to analyze the effects of the APH plan on futures and put options separately.

The results of Coble et al. indicated that adding APH into the risk management portfolio always increases the futures hedge ratio regardless of the regional difference. When put options are allowed in the portfolio instead of futures, APH increases the hedge with put options for all the tested locations. Results of the sensitivity tests suggest that a higher coverage level of APH leads to a higher hedge ratio in futures or in put options.

Results from Coble et al. indicated that the effects of CRC on hedging demand for futures or put options are not as uniform as APH. In three out of four locations, CRC increased the use of futures. But in another three of the four locations, CRC decreased the hedging demand for put options. In addition, Coble et al. recognized that transaction costs imposed on hedging reduce the use of futures or put options, *ceteris paribus*. One interesting question to ask is whether the results from Coble et al. will be comparable to results from studies that have futures and options included simultaneously in the risk management portfolio, since Coble et al. modeled futures and options separately.

Wang et al. (2004) investigated the optimal hedging in futures and choice of crop insurance in the presence of government payments under the 2002 farm bill in the expected utility framework. Although Wang et al. didn't directly address the effects of crop insurance on hedging, results of their study indicated that when only futures but no options are considered in the risk management portfolio, the presence of APH insurance slightly increases hedging demand for futures, while CRC decreases futures hedging. Thus, Wang et al. identified the same positive effects that yield insurance has on futures as did Coble et al. (2004). However, regarding the impacts of revenue insurance on futures hedging, the two studies give quite different results.

Mahul (2003) examined the effects of crop yield and revenue insurance on the hedging demand with both futures and options in the portfolio. By including three straddles¹³ at three distinct strike prices in the portfolio, Mahul tested the hedging demand for options in terms of the use of straddles for a representative producer who maximizes his expected utility. The results showed that, given no insurance in the risk management portfolio, the producer will short futures but long straddles with positions in futures larger than in straddles. When the APH plan is included in the portfolio, the producer will increase hedging in futures but make almost no adjustment to straddles. The availability of the CRC decreases hedging demand for futures, but shows mixed effects on the use of three straddles. When straddles are left out of the portfolio, Mahul found that CRC decreases the futures hedge, which is consistent with Wang et al. (2004) but contradict Coble et al. (2000).

Regarding the impact of coverage level of APH on the hedging, Mahul found the same relationship as identified by Coble et al. (2000), i.e. hedging demand for futures increases as

¹³ A short (long) straddle can be constructed by selling (buying) one put and one call at the same strike price. It is well known that any one of the three, a put option, a call option and a future, can be replicated by the other two. Hence, positions in futures and straddles can be converted to positions in futures and put options only.

coverage levels increase. In addition, Mahul reported that hedging demand for options is almost insensitive to changes in APH coverage level.

Mahul expressed two concerns about his findings. One is that the transaction costs were ignored in the analysis even though transaction costs from trading multiple straddles together with futures might have a nontrivial influence on optimal futures and options hedge ratios (Mahul, 2003). In fact, many zero or close-to-zero hedge ratios and the opposite signs of the nonzero hedge ratios for the three straddles may indicate that assuming three straddles may be redundant. The other concern by Mahul is that the small size of the sample might have caused the distribution of the generated data to be far from the true joint distribution of price and yield since only eight pairs of price and yield data of the selected farm were used to estimate the distribution parameters.

In general, previous studies take the expected utility (EU) hedge model as the only method to investigate the hedging effects of government programs (Poitras, 1993; Hanson et al. 1999; Coble et al. 2000, 2004; Mahul 2003; Wang et al. 2004). These studies normally use stochastic simulation and numerical optimization instead of analytically-derived optimal solutions because including government payments, crop insurance, and options into the risk management portfolio makes the portfolio payoff non-continuous but censored at multiple points. Such kinks in payoffs limit the use of analytical derivation (Coble et al., 2000). Since a utility function needs to be subjectively specified to find the optimal hedging positions given that the true utility function is unknown, results obtained from a particular utility function may be lack of generality (Sakong et al., 1993).

When examining the effects of government payments and/or insurance on hedging, the previous works usually consider the effects on futures, but disregard the fact that put options may

be used together with futures to achieve the optimal hedging. However, Sakong et al. (1992) proved that when both price and yield are uncertain, options need to be added into the optimal hedge portfolio under an EU model. Moshini and Lapan (1995) suggested that options have a distinct role in the risk management portfolio under price and yield uncertainty. Hanson et al. (1999) showed that when effective cash price received by farmers is truncated, options are desired by the decision maker who maximizes his expected utility. Thus, futures and options should be considered together as available risk management instruments to the crop farmers. Note that the complexity of the resulting model may not allow for direct verification of analytical results when options are included in the hedging, but they can still be tested by means of the numerical approach.

To evaluate the effects of government payments and insurance on the optimal hedge ratios in futures and options, harvest-time values of several variables, including farm-level yield, spot price, futures price and market year average price, which partly determines the CCP, need to be simulated. Existing literature typically simulate such harvest-time realizations based on two key assumptions. One assumption is that these random variables have joint normal distribution, or at least they can be transformed to be joint-normally distributed (Hanson et al. 1999; Coble et al. 2000, 2004; Mahul 2003; Wang et al. 2004). The problem with joint normality assumption is that it is too restrictive, if there is no hypothesis test result to support such an assumption. Due to the limited historical data points, the multivariate normal assumption could not generally be tested with an acceptable power¹⁴. Instead, previous studies usually test the normality of yield and price variables (or transformed yield and price) separately. However, on one hand,

¹⁴ Power means the probability of rejecting the null hypothesis when the null hypothesis is not true. Many more data points are needed as the dimension of the distribution increases. For example, the number of data points that are enough to delineate a normal distribution may not be large enough to trace the bell of a bivariate normal distribution.

disagreement exists about the normality or log-normality of the crop yield distribution in literature (Sherrick et al., 2004). On the other hand, even if the marginal distributions are tested to be normal, the joint distribution is not guaranteed to be multivariate normal¹⁵.

The second assumption usually made in previous works is that farm-level yield has the same distribution as county-level yield, except a larger variance. Because county-level yield has a longer record than farm-level yield, such an assumption enables the researchers to get more reliable estimates regarding yield distribution and its relationship with other price variables by using county yield rather than much shorter farm-level yield data. But, such assumption may not be appropriate in that the constant variance assumption for farm-level yield contradicts the variance pattern reflected in the historical yield data (figures 1.1-1.2, tables 1.1-1.2).

To avoid subjectivity that may be introduced by any particular utility function used in the EU hedge model, this study proposes to use a utility-free downside risk hedge model, the second-order lower partial moment (LPM₂) hedge model, to examine the effects of government payments and insurance on the use of futures and options. In order to allow for more flexibility in the joint distribution between yield and price and to accommodate the fact that farm-level yield variance is conditional on county yield, this study will apply the copula method and the conditional kernel density approach to simulate relevant yield and price distributions.

Next chapter overviews the relationship between prevailing downside risk measures and lower partial moments (LPM) as well as the applications of LPM hedging strategies in existing literature.

¹⁵ Let X_1 and Z be independent standard normal random variables, and define $X_2 = \text{sign}(X_1) |Z|$, where the *sign* function returns 1 if $X_1 \geq 0$ and returns -1 if $X_1 < 0$. In this case, both X_1 and X_2 are standard normal, but the vector \mathbf{X} , of which they are components, is not joint-normal. (http://www.riskglossary.com/link/joint_normal_distribution.htm)

CHAPTER 3

REVIEW OF LPM RISK MEASURES AND LPM HEDGING

Because the lower partial moment criterion has thus far had its primary applications in finance literature, this chapter reviews the LPM risk measures and the LPM hedge literature in the first two sections. Because the LPM_2 hedge model is proposed to be used to investigate the effects of government programs on the optimal hedge in futures and options, instead of expected utility model, this chapter will also present an analytical comparison between LPM_2 hedge ratios and the expected utility (EU) hedge ratios.

3.1 LPM Risk Measures

Downside Risk Measures LPM and Stochastic Dominance

Using LPM as downside risk measures originated in the investment literature. Roy (1952) proposed to apply the safety-first rule to make investment decision under uncertainty. Roy's safety-first rule determines the optimal investment portfolio by minimizing the probability of the investment return falling below some target threshold return while maintaining a specified expected return. Thus, Roy's portfolio selection criterion reflects a downside risk measure which defines risk as the shortfall relative to the threshold return. This risk measure is in contrast with the traditional risk measure, variance, which counts both the upside potential and the downside misfortune from the expected return as risk.

Fishburn (1977) suggested to measure risk with an $a - t$ model in the form

$Risk = \int_{-\infty}^t (t - x)^a dF(x)$, where $a > 0$ and $F(x)$ is the cumulative distribution function. Fishburn's

risk measure is motivated by the observation that decision makers in the investment context usually associate risk with failure to attain at least a target return.

Bawa (1978) generalized Roy's downside risk measure by constructing a set of downside risk measures, called lower partial moments, in the form

$$LPM_n = \int_{-\infty}^{\bar{p}} (\bar{p} - \tilde{p})^n dF(\tilde{p}) \quad (3.1)$$

with $n \geq 0$. LPM_0 is equivalent to Roy's down-side risk measure. If n is a positive integer, LPM_n represents the probability-weighted n^{th} -power of the shortfall below a target payoff \bar{p} . Thus, Bawa's LPM risk measures are equivalent to risk measured by Fishburn's $a - t$ model.

The theoretical justification of the LPM criterion in determining an optimal investment portfolio resides in the relationship between LPM risk measures and stochastic dominance. Stochastic dominance rules rank the alternative investment portfolios based on the payoff distribution of the portfolios. The n^{th} -order stochastic dominance is defined as follows.

Given two portfolios X and Y, and their respective cumulative payoff distribution F and G , if $F^{(n)}(t) \leq G^{(n)}(t)$ for $t \in R$, then X dominates Y by the n^{th} -order stochastic dominance.

Here $F^{(n)}(t) = \int_{-\infty}^t F^{(n-1)}(u) du$, $F^{(1)} \equiv F(t)$, $n \geq 2$, and $F(t)$ is the cumulative distribution function

(Levy, 1998).

In particular, the first-, second-, and third-order stochastic dominance are defined as follows (Levy, 1998).

Definition 3.1

If $F(t) \leq G(t)$ for all values of t and if at least at some t^* that $F(t^*) < G(t^*)$, then portfolio X dominates portfolio Y by first-order stochastic dominance (X FSD Y).

Definition 3.2:

If $\int_{-\infty}^t F(u)du \leq \int_{-\infty}^t G(u)du$, (or $F^{(2)}(t) \leq G^{(2)}(t)$) for all t and the inequality holds at least at some t^* , then portfolio X dominates portfolio Y by second-order stochastic dominance (X SSD Y).

Definition 3.3:

If $\int_{-\infty}^t \int_{-\infty}^z F(u)dudz \leq \int_{-\infty}^t \int_{-\infty}^z G(u)dudz$, (or $F^{(3)}(t) \leq G^{(3)}(t)$) for all t and the inequality holds at least at some t^* , and $\int_{-\infty}^b F(u)du \geq \int_{-\infty}^b G(u)du$, where b is the upper bound of t , then portfolio X dominates portfolio Y by third-order stochastic dominance (X TSD Y) ¹⁶.

The n^{th} -order stochastic dominance is consistent with expected utility maximization for all utility functions satisfying $(-1)^k U^{(k)} \leq 0$ ($k = 1, 2, \dots, n$, $U^{(k)}$ is the k^{th} derivative of function U). (Yamai and Yoshida, 2002; See pp.116-117 of Levy, 1998 for the proof). Because the utility functions discussed in the economics and finance literature are usually assumed to satisfy nonsatiation ($U' > 0$), risk-aversion ($U'' < 0$) and decreasing absolute risk aversion (a necessary condition is $U''' > 0$), the relationship between FSD, SSD, TSD and the expected utility with such properties are given by the following theorems.

Theorem 3.1:

If and only if X FSD Y, then $E_F U(X) \geq E_G U(Y)$ for all the utility functions with $U' > 0$, and strict inequality exist for at least some U_0 with $U'_0 > 0$. (See pp.48-49 of Levy, 1998 for the proof.)

¹⁶ That $\int_{-\infty}^b F(u)du \leq \int_{-\infty}^b G(u)du$ is equivalent to $E_F(X) \geq E_G(Y)$ can be proved by applying integrating by parts (Levy, 1998).

Theorem 3.2:

If and only if X SSD Y , then $E_F U(X) \geq E_G U(Y)$ for all the utility functions with

$U' > 0$ and $U'' < 0$, and strict inequality exist at least for some U_0 with $U'_0 > 0$ and $U''_0 < 0$. (See

pp.69-72 of Levy, 1998 for the proof.)

Theorem 3.3:

If and only if X TSD Y , then $E_F U(X) \geq E_G U(Y)$ for all the utility functions with $U' > 0$, $U'' < 0$

and $U''' > 0$ and at least for some U_0 . (See pp.92-96 of Levy, 1998 for the proof.)

Both Fishburn (1977) and Bawa (1978) noted that LPM_n criterion are consistent with $(n+1)^{th}$ order stochastic dominance rule for $n = 0, 1, 2$. That is:

If X FSD Y , then $LPM_0(X) \leq LPM_0(Y)$ for all levels of the target payoff;

If X SSD Y , then $LPM_1(X) \leq LPM_1(Y)$ for all target payoffs;

If X TSD Y , then $LPM_2(X) \leq LPM_2(Y)$ for all target payoffs.

By means of integrating by parts, Ingersoll (1987) proved that

$F^{(n+1)}(t) = \frac{1}{n!} LPM_{n,t}$ (See Appendix A). Thus, LPM_n criterion is consistent with $(n+1)^{th}$ order

stochastic dominance. Because $(n+1)^{th}$ order stochastic dominance and the expected utility

criterion result in the same ranking for all the utility functions with $(-1)^k U^{(k)} \leq 0$ ($k = 1, 2, \dots,$

n), LPM_n criterion is also consistent with the expected utility criterion if the expected utility

criterion results in the same ranking across all the utility functions U satisfying $(-1)^k U^{(k)} \leq 0$ (k

$= 1, 2, \dots, n$). In particular, LPM_2 is consistent with the expected utility criterion when the

expected utility criterion yields the same ranking for all the utility functions with $U' > 0$, $U'' < 0$,

and $U''' > 0$, of which the usually desired decreasing absolute risk aversion utility functions are

members (Harlow and Rao, 1989).

Relationship of LPM and Other Prevailing Risk Measures

Value-at-Risk is perhaps one of the most widely used financial risk measures among practitioners (Harris and Shen, 2006). For a given time horizon T and a confidence level P (such as $P = 0.95, 0.99$), Value-at-Risk (VaR) is the loss that is exceeded with probability $1-P$ over the time horizon T (Duffie and Pan, 1997)¹⁷. Thus, VaR can be understood as the converse of LPM_0 because VaR represents the amount to be lost with a given probability while LPM_0 is the probability of a target amount to be lost. If the target payoff in LPM_0 is set to be the VaR, then LPM_0 is the probability corresponding to the VaR. Consequently, the portfolio selected by the VaR rule, which chooses the portfolio with the highest $(1-P)^{\text{th}}$ quantile of its payoff distribution, is the same as the portfolio determined by minimizing LPM_0 if the target payoff set to the highest VaR of all the portfolios. Similar to LPM_0 , VaR has been proven to be consistent with first-order stochastic dominance (Yamai and Yoshida, 2002).

Another popular risk measure in the financial world, which is also related to LPM risk measures, is the expected shortfall. Expected shortfall is also termed as conditional VaR, since it is the probability-weighted payoff below a specified quantile divided by the probability corresponding to the quantile. The expected shortfall is perhaps a more applicable risk measure than VaR, since it takes the magnitude of the payoff (or loss) into account. Expected shortfall has been proved to be consistent with second-order stochastic dominance (Yamai and Yoshida, 2002). Thus, expected shortfall is consistent with LPM_1 . In other words, if one portfolio X has a smaller LPM_1 than portfolio Y for any target payoff, then portfolio X has the smaller expected shortfall of the two portfolios.

¹⁷ For the loss distribution of the portfolio, VaR corresponds to the upper quantile; for the market value distribution of the portfolio, VaR corresponds to the lower quantile.

In the hedging literature, a number of studies have focused on the LPM_2 criterion (e.g, see Eftekhari, 1998; Lien and Tse, 2000; Chen et al. 2003; Turvey and Nayak, 2003). One appealing feature of LPM_2 is that it is consistent with TSD and therefore consistent with the expected utility criterion if the expected utility criterion results in the same rankings for all the utility functions having nonsatiation ($U' > 0$), risk-aversion ($U'' < 0$), and $U''' > 0$ which includes decreasing absolute risk aversion utilities. Moreover, LPM_2 is equal to the semivariance when the target payoff in LPM_2 is set at the expected payoff, and thus LPM_2 is the exact downside risk measure comparable to variance, which treats both upside and downside deviations from the expected payoff as risk. If the distribution of the portfolio payoff is symmetric, then using LPM_2 as a risk measure would be equivalent to using variance and result in the same ordering of risky portfolios (Eftekhari, 1998). But for an asymmetric portfolio payoff distribution, a downside risk measure such as LPM_2 is more intuitive than variance.

3.2 Review of LPM Applications in Hedging

LPM Model and Hedging Strategies

Lower partial moment (LPM) risk measures have been applied in the hedging context. There are generally two paths taken by the literature to incorporate LPM risk measures into a hedge model. The first way is to minimize LPM directly, based on the assumption that the risk management objective is to minimize risk. A number of research papers have investigated the properties of the optimal hedge ratios in such LPM hedge models which take the form:

$$MinLPM_n = Min \int_{-\infty}^c [c - (r_p - hr_f)]^n dF(r_p - hr_f) \quad (3.2)$$

where r_p , r_f are returns from spot and futures market, respectively;

c is the target return and h is the hedge ratio and

$F(r_p - hr_f)$ is the cumulative distribution function of the hedge portfolio.

When $n=2$, (3.2) is the LPM₂ hedge model.

Eftekhari (1998) applied the numerical search method to determine the minimum LPM₂ hedge ratio, because no analytic solution to the minimization of LPM₂ exists. Specifically, the returns of the hedge portfolio for any hedge ratio within a pre-specified range were calculated and compared to determine the optimal LPM₂ hedge ratio. In Eftekhari's work, the target return was set to zero and the distribution of returns from the hedge portfolio was assumed to be discrete uniform. By comparing the mean return and LPM₂ of the hedge portfolios obtained from the minimum variance hedge with those under the LPM₂ hedge for FTSE-100 stock index¹⁸ data from 1985 to 1994, Eftekhari found that the LPM₂ hedge yielded a higher mean return and LPM₂ in most years, if the hedge ratios are recalculated every year based on return data of the previous year.

Lien and Tse (1998) proved that when futures market is unbiased and distribution of spot and futures returns is bivariate normal, the LPM₂ hedge ratio is the same as minimum variance hedge ratio, which is also the optimal hedge ratio under the expected utility framework for any utility function.

Lien and Tse (2000) also calculated the optimal LPM₂ hedge ratio for the Nikkei Stock Average index. Unlike Eftekhari, who assumed a discrete uniform distribution for the hedge portfolio, Lien and Tse estimated the empirical distribution of returns from the hedge portfolio

¹⁸ FTSE-100 is short for the Financial Times Stock Exchange (FTSE) 100 Index, which is a capitalization-weighted index of the 100 most highly capitalized companies traded on the London Stock Exchange. This index was developed with a base level of 1000 as of January 3, 1984 and it often serves as a benchmark for European stocks. FTSE-100 index futures are traded on Euronext.liffe, where LIFFE stands for London International Financial Futures and Options Exchange. LIFFE was acquired by Euronext NV (an amalgamation of the Paris, Amsterdam, Brussels and Lisbon exchanges) on 24 December 2001.

using the kernel density method. Lien and Tse also analyzed the effects of target return on LPM₂ hedge ratio. The results from their comparative analysis showed that the investor will hedge more as the target return in the LPM₂ increases. Consistent with the study by Eftekhari, Lien and Tse detected significant difference between minimum variance hedge ratio and the LPM₂ hedge ratio. As a result, they emphasized that the risk concept of the hedger should be ascertained before designing the optimal hedging strategy.

The work by Turvey and Nayak (2003) is one of the few studies that examine the LPM₂ hedge ratios for agricultural commodities. Turvey and Nayak numerically search for the minimum LPM₂ hedge ratios for wheat and live cattle based on daily price data from the cash and futures markets. In agreement with earlier studies, empirical results from Turvey and Nayak showed divergence between the LPM₂ hedge ratio and minimum variance hedge ratio. However, unlike the Lien and Tse (2000) study, Turvey and Nayak found that a higher target return doesn't always yield a larger LPM₂ hedge ratio. Findings from Turvey and Nayak may not be comparable to those by Lien and Tse, because Turvey and Nayak used the price levels in their model rather than returns defined as the percent price change by Lien and Tse.

Other Hedge Models Applying LPM Risk Measures

In addition to the LPM hedge model, there are other hedge models that use LPM as the risk measure but assume a different hedge objective from risk minimization. Chen et al. (2003) developed a mean-LPM₂ hedge model where the optimal hedge ratio is obtained by maximizing a risk-return function

$$\text{Max } U(r_p - hr_f) = \text{Max} E(r_p - hr_f) - \int_{-\infty}^c [c - (r_p - hr_f)]^2 dF(r_p - hr_f) \quad (3.3)$$

where r_p and r_f are returns from spot positions and futures positions, respectively.

Chen et al. prefer the mean-LPM₂ hedge model over LPM₂ hedge model since the third-order stochastic dominance (TSD) criterion is equivalent to minimum LPM₂ criterion only when all candidate portfolios have equal mean returns. However, the present study will use LPM₂ hedge model instead of mean-LPM₂ hedge model for two reasons. First, the hedging objective of Chen et al. is rather arbitrary, because the tradeoff ratio between mean and risk is set to one without any theoretical justification. Second, under the assumption that the futures market is unbiased, i.e. $E r_f = r_p$, mean return of the hedge portfolio is unrelated to the hedge ratio. Thus, the optimal mean-LPM₂ hedge ratio is the same as the optimal hedge ratio from LPM₂ hedge model.

By substituting LPM₂ for variance in the constant relative risk aversion (CRRA) location-scale function developed by Nelson and Escalante (2004)¹⁹, Mattos and Garcia (2005) obtained a downside risk hedge model in the form of

$$MaxEU = Max\left(\frac{1}{\mathbf{m}^2 - \mathbf{g}LPM_2}\right), \quad (3.4)$$

where \mathbf{m} is the expected return of the hedge portfolio, and \mathbf{g} is the coefficient of constant relative risk aversion. Mattos and Garcia argued that such replacement is motivated by the fact that LPM₂ is a downside risk measure and has more intuitive appeal than variance. However, such modification is again subject to arbitrariness, due to lack of theoretical justification.

¹⁹ Escalante and Nelson (2004) showed that when the portfolio payoff satisfies location-scale condition, the optimal results that directly maximize the expectation of a CRRA utility function with normally distributed portfolio payoff are similar to the results that maximize the CRRA

mean-standard deviation function in the form of $\frac{1}{\mathbf{m}^2 - \mathbf{g}\mathbf{s}^2}$.

3.3 Relationship between LPM₂ Hedge Ratios and EU Hedge Ratios

When the target payoff is set to be the mean payoff, the optimal LPM₂ hedge ratios may tend to increase the right skewness of the payoff distribution of the hedge portfolio. The reason is that the optimal LPM₂ hedge ratios are solutions that minimize the lower part of the expected variation relative to the mean.

How EU hedge ratios affect the payoff distribution of the hedge portfolio depends on many conditions, such as the absence of production risk and the presence of unbiased futures prices²⁰. Under the assumptions of no production risk, unbiased futures prices, and linearity of the relationship of cash prices with futures prices, the optimal hedge ratios from the EU hedge model in such conditions is the same as the optimal hedge ratios under a minimum variance hedge model (Lence, 1995; Lien and Tse, 2002). By examining the Taylor expansion of the expected utility function at the mean payoff of the portfolio as in (3.5), one important implication can be drawn: if the utility function is continuous, risk averse, and has at least up to third-order derivatives, then optimal hedge ratios that maximize EU tend to limit the variance of the portfolio payoff but favor the right skewness of the payoff distribution. Thus, optimal hedge ratios from an EU model would be a compromise between the smaller variance and the higher right skewness (Lapan et al. 1991).

$$\begin{aligned}
 EU(\mathbf{p}) &= \int_{\mathbf{p}} U(\mathbf{m}_p + \mathbf{d}) f(\mathbf{d}) d\mathbf{d} \\
 &= U(\mathbf{m}_p) + \frac{1}{2} U''(\mathbf{m}_p) E(\mathbf{p} - \mathbf{m}_p)^2 + \frac{1}{3!} U'''(\mathbf{m}_p) E(\mathbf{p} - \mathbf{m}_p)^3 + \dots + \frac{1}{(n-1)!} U^{n-1}(\mathbf{m}_p) E(\mathbf{p} - \mathbf{m}_p)^{n-1} \quad (3.5) \\
 &+ \frac{1}{n!} E[U^n(\mathbf{p} + \mathbf{e}\mathbf{d})\mathbf{d}^n],
 \end{aligned}$$

²⁰ Lapan et al. (1991), Sakong et al. (1993), Mochini and Lapan (1995) defined that the futures price is unbiased if the expectation of the end-of-period futures price equals the current price of a futures contract.

where $0 < e < 1$ and \mathbf{m}_p is the mean of income \mathbf{p} .

Although both the LPM₂ hedge and the EU hedge have preference for right skewness of the payoff distribution of the hedge portfolio, the analysis that the EU model favors smaller variance whereas the LPM₂ hedge minimizes semivariance may indicate that the crop farmer will probably hedge less in futures but more in options under the LPM₂ model than under the EU hedge model.

In the next chapter, the risk management portfolio available to a representative crop farmer under various scenarios will be set up. The approaches applied to simulate the desired harvest-time prices and yield data will be explained in details.

CHAPTER 4

MODEL SPECIFICATIONS AND DATA SIMULATION

There are two sections included in this chapter. The first section of this chapter discusses and explains the assumptions and components to build the LPM₂ hedge model for several portfolios that include futures, put options, crop insurance and/or government payments. The second part clarifies the process to generate the desired data for numerical optimization. Because LPM₂ hedge model is the model proposed by this study and it has not been used previously to investigate the planting-time hedge decision by crop farmers, this chapter will concentrate on establishing the LPM₂ hedge model. Compared to the LPM₂ hedge model, an EU hedge model requires the same portfolio and probability information but a different objective function. Therefore, once the LPM₂ hedge model is set up and solved, optimal hedge ratios for the EU hedge model can be easily obtained as an extension.

4.1 LPM₂ Hedge Model for the Representative Crop Farmer

The Representative Crop Farmer

Due to the availability of Georgia's farm-level yield data, the hedging decision of a representative cotton farmer in Colquitt county of Georgia and of a representative soybean farmer in Bulloch county of Georgia will be investigated. Colquitt and Bulloch counties are

selected because of their high acreage devoted to cotton/soybean production²¹ and their larger numbers of farmers with more than six years of continuous records during the 1991-2000 period.

The representative farmer in a county is synthesized in such a way that for any year, the mean of the yield distribution equals the county yield, but the actual yield could be any actual farm-level yield realized in the county. It has been shown that the dispersions of farm-level yield around county yield vary from year to year (figures 1.1-1.2). This indicates that the representative farm defined above should have variance conditional on the county yield.

Other assumptions made for the representative producer are as follows. First, the crop producer is assumed to make a one-time hedge through the crop year. That is, the crop farmer takes hedge positions in futures and options at planting time, and later offsets his positions in futures and/or options at harvest. This assumption rules out the scenario that the crop farmer sets hedge positions at multiple time points from planting to harvest. Specifically, both the cotton and soybean representative farmers are assumed to take on hedge position on the last trading day in March, 2006. The cotton farmer will lift the hedge in November 2006, while the soybean farmer will close the hedge in mid-October.

Second, the representative farmer is assumed to have a portfolio composed of income from selling crops at spot market as well as from four risk management instruments –futures, options on futures, federal crop insurance and government payments. To simplify the analysis regarding government payments, the representative farmer is assumed to produce a single commodity for which he is qualified to receive government payments. Third, the representative farmer makes his/her hedging decision at planting time by utilizing information available at that time. Such information includes parameters determined by the policy makers regarding the

²¹ In 2005, Bullock has the largest number of harvested soybean acres in Georgia; Colquitt has the second largest number of harvested cotton acres. (GA Statistics System in 2005-2006 Georgia County Guide).

federal crop insurance and government payments, and the estimation of the yield and price distribution at harvest. Fourth, the hedge decision for every acre of the crop planted is assumed to be independent of total acres planted. That is, the hedge portfolio based on one acre of the planted crop can be analyzed for simplicity.

Modifications to the Existing LPM₂ Hedge Model

The hedging problems examined so far by the LPM₂ hedging literature have considered price uncertainty as the only source of risk. But for crop farmers to make hedging decisions at planting time to protect their harvest income, unknown harvest yield is another factor that contributes to the uncertainty to their hedge portfolio. Therefore, the existing LPM₂ hedge model must be modified to include both price and production variables.

The presence of production uncertainty generally calls for the use of options together with futures (Sakong, 1993). Thus, options will be included in the LPM₂ hedge model in this study, and the optimal hedge ratio in options will be determined simultaneously with the optimal hedge ratio in futures.

Hedge Portfolio in the Base Scenario

When there are no insurance plans and government payments are available to the representative farmer, the representative farmer is assumed to use only futures and options to manage risk. The net value of the hedge portfolio at harvest is

$$\mathbf{p} = py + h_x (f_0 - f_1)Ey + h_z [\max(f_1 - k, 0) - v_z]Ey - C(Ey). \quad (4.1)$$

Here py is the revenue from selling the crop for cash at harvest, where p is the harvest cash price and y is the farm yield at harvest. Production cost C is assumed to be determined by the expected farm yield Ey , and therefore is known at planting time. The production costs of per acre crop planted in 2006 were decided based on the cost estimated by the Extension at University of

Georgia²². h_x and h_z are the hedge ratios for futures and options. h_x (or h_z) is measured as the ratios of yields hedged with futures contracts (or options contracts) to the expected farm yield. Positive (negative) h_x means to sell (buy) futures contracts. Positive (negative) h_z means to buy (sell) put options contracts. For example, if $h_x = 0.5$, the interpretation should be that the farmer hedge 50% of the expected yield on futures market with futures contracts. Conversely, $h_x = -0.5$ means that the farmer speculates in the futures market with the crop amount equal to 50% of his expected production. An implicit assumption to such a definition of hedge ratios is that the farmer can purchase any fraction of a standard futures contract or options contract. f_0 and f_1 are the prices of the close-to-harvest futures contract at planting and at harvest, respectively. For cotton, f_0 and f_1 are the prices of December contract, while for soybean, they are prices of November contract. k is the strike price of the put options, and v_z is the premium that the farmer pays to have the put options. Harvest cash price p , harvest farm-level yield y and futures price at harvest f_1 are not known at planting and will be simulated based on historical data. The assumption of unbiased futures and options prices will be imposed by simulating f_1 in such a way that $Ef_1 = f_0$ and by setting option premium $v_z = E(\max(f_1 - k, 0))$.

Hedge Portfolio Including APH or CRC Insurance Plan

To investigate the impacts of federal crop insurance plans on the use of futures and options, insurance is added to the hedge portfolio in 4.1. The two most used crop insurance plans, yield insurance plan APH and revenue insurance plan CRC, are considered as the alternative insurance policies that the representative farmer will choose from. To focus on the effects of crop insurance on the demand for hedging in futures and options contracts, the representative farmer

²² Source: <http://www.ces.uga.edu/Agriculture/agecon/printedbudgets.htm>

is not given the choice to determine the coverage level and price election in the insurance plans. However, sensitivity tests of coverage level of the APH or CRC insurance plan on the demand for futures and options will be performed, and the results will be discussed in chapter 5.

The value of the hedge portfolio including APH plan is given by

$$p_{APH} = py + h_x(f_0 - f_1)Ey + h_z[\max(f_1 - k, 0) - v_z]Ey + NV_{APH} - C(Ey) \quad (4.2)$$

where $NV_{APH} = p_{APH} \cdot \max(dy_{APH} - y, 0) - v_{APH}$. The y_{APH} is the APH yield of the representative farmer and is calculated by averaging the ten-year county yields from 1996 to 2005. Such a way to obtain APH yield is consistent with the former assumption for the representative farm that the mean of the farm yield distribution is equal to the county yield. The coverage level d is arbitrarily set at 70%. The effects of coverage level on hedge ratios will be examined and the results will also be discussed in the next chapter. If the harvest yield y is less than the insured yield dy , then the farmer gets an indemnity payment equal to the product of yield shortfall and indemnity price p_{APH} . Indemnity price is the price determined by Risk Management Agency (RMA)²³ of U. S. Department of Agricultural (USDA) multiplied by a price election factor selected by the insured farmer. The representative farmer in this study is assumed to choose price election factor of 100%. For cotton insurance in Colquitt in 2006, p_{APH} is \$0.53/lb. For soybeans in Bulloch in 2006, p_{APH} is \$5.15/bushel.

The actual APH insurance premium v_{APH} charged to the insured farmer is set by RMA according to a set of parameters including the farmer's APH yield and selected coverage level. To make the insurance premium consistent with the data simulated in this study, the actuarial fair premium is used, which is obtained by setting $v_{APH} = E(p_{APH} \cdot \max(dy_{APH} - y, 0))$.

²³ RMA provides a premium calculator which can be used to check the price used by RMA at the link <http://www.rma.usda.gov/tools/premcalc.html>.

When CRC is purchased by the representative farmer, the payoff from the hedge portfolio at harvest is

$$\mathbf{p}_{CRC} = py + h_x(f_0 - f_1)Ey + h_z[\max(f_1 - k, 0) - v_z]Ey + NV_{CRC} - C(Ey) \quad (4.3)$$

with $NV_{CRC} = \max[\mathbf{d} \max(f_{CRC0}, f_1)y_{APH} - f_1y, 0] - v_{CRC}$. The coverage level \mathbf{d} is still set at 70%.

For cotton, f_{CRC0} is defined as the daily average settlement price of December contract from January 15 to February 14 of 2006. For soybean, f_{CRC0} is the average of daily futures price of the November contract in February 2006. Premium v_{CRC} is calculated as the actuarial fair premium, which is, $v_{CRC} = E(\max[\mathbf{d} \max(f_{CRC0}, f_{CRC1})y_{APH} - f_1y, 0])$.

According to RMA, the subsidized insurance premium can be obtained by multiplying the actuarial fair premium by (1-subsidy factor). Therefore, the effects of premium subsidy on the optimal hedge ratio can be examined by comparing the hedge ratios under actuarial fair premium with those under the subsidized premium. The impacts of subsidy rate on the hedge ratios will be reported in next chapter.

Hedge Portfolio Including DP, LDP, CCP

Direct payments (DP) are fixed in 2002-2007 and paid annually to the eligible farmers enrolled in the government programs. Thus, when DP is added to the hedge portfolio, it increases the harvest value of the hedge portfolio by the amount, $DP = p_{DP} \cdot y_{DP}$, which is already known at the planting time. p_{DP} and y_{DP} are the direct payment rate and the base yield fixed from 2002 through 2007. The portfolio with futures, options and DP has payoffs as

$$\mathbf{p} = py + h_x(f_0 - f_1)Ey + h_z[\max(f_1 - k, 0) - v_z]Ey + DP - C(Ey) \quad (4.4).$$

Because DP is known at planting, the target payoff in the LPM₂ hedge model with DP in the portfolio is set as $E(py) + DP$. Since DP increases the actual portfolio income and the target (expected) portfolio income by the same amount, DP has no effects on the LPM₂ hedge ratios.

Loan Deficiency payments (LDP) are triggered when the market price is lower than the loan rate set by USDA. Thus, LDP received by the eligible farmer for per-acre yield can be expressed as $LDP = \max(p_{LDP} - p, 0) \cdot y$.

The amount of Counter Cyclical Payments (CCP) paid to eligible farmers is calculated as $CCP = \max[p_{CCP} - p_{DP} - \max(p_{MYA}, p_{LDP}), 0] \cdot y_{DP}$. The p_{CCP} is the target price set in 2002 farm bill. The p_{MYA} is the market year average price, which is not known for certain until the end of the crop marketing year. However, in order to evaluate the effects of CCP on the representative farmer's hedging demand for futures and options at planting, p_{MYA} is forecasted based on the simulated futures price in this study.

To identify the effects of the LDP and the CCP on hedge ratios, respectively, the two government payments are added to the portfolio (4.4) one by one, with the LDP added first. Such an order is justified by the design of the CCP, which has a target price higher than the loan rate in LDP and would provide extra price-risk protection in conjunction with LDP. The representative farmer's portfolio, including DP and LDP, is given by

$$p_{LDP} = py + h_x(f_0 - f_1)Ey + h_z[\max(f_1 - k, 0) - v_z]Ey + DP + LDP - C(Ey). \quad (4.5)$$

When the impacts of CCP are under investigation, the hedge portfolio is given by

$$p_{CCP} = py + h_x(f_0 - f_1)Ey + h_z[\max(f_1 - k, 0) - v_z]Ey + DP + LDP + CCP - C(Ey). \quad (4.6)$$

By adding net value of APH or CRC (i.e., NV_{APH} , or NV_{CRC}) into (4.4), (4.5) and (4.6), the hedge portfolios including both insurance and government payments are obtained as follows:

$$\mathbf{p}_{DPAPH} = py + h_x(f_0 - f_1)Ey + h_z[\max(f_1 - k, 0) - v_z]Ey + DP + NV_{APH} - C(Ey)$$

(4.7)

$$\mathbf{p}_{DPCRC} = py + h_x(f_0 - f_1)Ey + h_z[\max(f_1 - k, 0) - v_z]Ey + DP + NV_{CRC} - C(Ey)$$

(4.8)

$$\mathbf{p}_{LDPAPH} = py + h_x(f_0 - f_1)Ey + h_z[\max(f_1 - k, 0) - v_z]Ey + DP + LDP + NV_{APH} - C(Ey)$$

(4.9)

$$\mathbf{p}_{LDPCRC} = py + h_x(f_0 - f_1)Ey + h_z[\max(f_1 - k, 0) - v_z]Ey + DP + LDP + NV_{CRC} - C(Ey)$$

(4.10)

$$\mathbf{p}_{CCPAPH} = py + h_x(f_0 - f_1)Ey + h_z[\max(f_1 - k, 0) - v_z]Ey + DP + LDP + CCP + NV_{APH} - C(Ey)$$

(4.11)

$$\mathbf{p}_{CCPCRC} = py + h_x(f_0 - f_1)Ey + h_z[\max(f_1 - k, 0) - v_z]Ey + DP + LDP + CCP + NV_{CRC} - C(Ey)$$

(4.12)

The specific values of parameters in APH, CRC, DP, LDP and CCP are listed in Table 4.1.

The LPM₂ hedge model used in this study takes the form

$$\text{MinLPM}_2 = \text{Min}_{h_x, h_z} \int_{-\infty}^{\bar{p}} (\bar{p} - \mathbf{p})^2 dF(\mathbf{p}), \text{ where } \bar{p} \text{ is the target payoff of the hedge portfolio. The EU}$$

hedge model has the objective function given by $\max_{h_x, h_z} EU = \max_{h_x, h_z} EU(\mathbf{p} + ow)$, where U is

assumed to be a constant relative risk-averse utility function of the form $U(\cdot) = \frac{1}{1-r} (\cdot)^{1-r}$. The ow

is the original per-acre farm wealth, which is set to \$800 so that it is large enough to guarantee

the harvest wealth $w_I = ow + \mathbf{p} > 0$. The value of the risk aversion coefficient r is set to 2, the

well accepted value by previous studies (Coble et al. 2000, 2004; Mahul, 2003; Wang et al. 1998,

2004; Hauser et al. 2004).

By substituting the value of the hedge portfolio under different scenarios into the hedge model, numerical optimization methods can be used to find the corresponding optimal hedge ratios. By comparing the optimal hedge ratios in the presence of insurance or government payments with the hedge ratios from the base scenario, the effects of federal crop insurance or government payments on hedging demand for futures and options can be evaluated. In addition, by comparing the change in hedge ratios between the base scenario and the scenario with only crop insurance with the change in hedge ratios between the scenario of only government payments and the scenario including both crop insurance and government payment, the interaction between the effects of crop insurance and the effects of government payment on the use of futures and options can be ascertained.

The LPM_2 and EU hedge ratios are compared under scenarios with DP and APH or CRC in the portfolios. Inclusion of DP can increase the mean of the payoffs to be positive. The target payoffs in the LPM_2 hedge models for these scenarios with DP are set as the expected value of the hedge portfolio (4.4), which is $E(py) + DP - C(Ey)$.

The impacts of transaction cost associated with hedging on the use of futures have been discussed under the EU hedge model (Coble et al. 2000, 2004; Wang et al. 2004). The effects of transaction cost on the optimal LPM_2 hedge ratios can be examined by comparing the optimal hedge ratios with and without transaction costs. Sensitivity tests on how LPM hedge ratios vary with the levels of target payoff will also be performed and the results will be presented in next chapter.

Table 4.1 Summary of Parameters in APH, CRC, DP, LDP, and CCP

Crop	¹ Cotton (Colquitt, GA)	Soybean (Bulloch, GA)
Coverage level <i>d</i>	70%	70%
APH yield y_{APH}	768 (lb)	23.5 (bu)
APH price p_{APH}	\$0.53/lb	\$5.15/bu
CRC price f_{CRC0}	\$0.60/lb	\$6.19/bu
Base yield y_{DP}	707 (lb) ⁴	19.2 (bu) ⁵
³ DP rate p_{DP}	\$0.0667/lb	\$0.44/bu
² Loan rate p_{LDP}	\$0.52/lb	\$5.03/bu
³ CCP target p_{CCP}	\$0.724/lb	\$5.80/bu

Note :

¹ Rates listed are for the upland cotton of a specific grade.

(http://www.fsa.usda.gov/FSA/printapp?fileName=pf_20060301_insup_en_cottdcp06.html&newsType=prfactsheet)

² <http://www.fsa.usda.gov/FSA/webapp?area=home&subject=prsu&topic=lor>

³ <http://www.ers.usda.gov/Briefing/FarmPolicy/programprovisions.htm>

⁴ Average of the county yields from 1981 through 1985.

⁵ Average of the county yields over 1998-2001 times the ratio of the national average yield during 1981-1985 to the national average yield during 1998-2001.

4.2 Simulation of Harvest-Time Yield and Price Data

In order to make the hedge decision at planting, the representative farmer needs to know the dependence and the harvest-time marginal probability distributions of four random variables – farm-level yield, local market price, futures price, and market year average price – in addition to the information known for certain at planting, such as the parameter values determined by USDA or the farm bill for the crop insurance and government payments.

Existing studies usually assume a multivariate normal distribution for the transformed yield and price data, based on the normality test results that each of the transformed historical yield and price data can not be rejected to be marginally normal (Coble et al. 2000, 2004; Wang et al, 2004; Hauser et al. 2004). However, the joint normality assumption is overly restrictive, as random variables with marginal normal distributions can have joint distributions other than multivariate normal. To allow more flexible dependence structures between yield and price than the multivariate normal distribution, this study proposes to use the copula function to represent the relationship among yield and price variables. Specifically, two types of copula functions, Gaussian copula and Frank copula are used to simulate data. Different types of copulas, together with different parameter value included in the copula function, result in different joint distributions.

Another innovation of this study regarding data simulation is to apply a conditional kernel density approach to simulate farm-level yield. Due to the short period of the available farm-level yields (a yield record of maximum 10 years for each individual farm), in the previous studies, farm-level yield were usually substituted by the rescaled longer county yield series with the scale to be the ratio of farm yield standard error over county yield standard error. This way of augmenting farm yield assumes that farm-level yield has the same distribution as county-level

yield except a larger variance. However, historical data shows that farm yield variance varies with level of county yield rather than being constant (Figure 1.1-1.2). To generate farm yield data with variance contingent on county yield, this study applies conditional kernel density approach to the simulation.

General Simulation Methods and Historical Data

In figure 4.1, a flowchart illustrates the general steps to simulate the random values of four variables, futures price at harvest (f_I), harvest local cash price (p), market year average price (p_{MYA}) and the representative farm's yield at harvest (y_f), which are necessary in order to solve the hedge models. The most important two steps in the simulation are first to generate harvest-time futures price and county yield with the copula method, and then to simulate farm yield based on the generated county yield. In the next two sections, detailed simulation algorithms for harvest-time futures price, county yield and farm yield will be provided. After futures price at harvest is simulated, harvest-time cash price and market year average price will be generated based on their linear relationships with futures price indicated by the historical data.

Farm yield data for cotton in Colquitt county and farm yield data for soybeans in Bulloch county of Georgia from year 1991 to 2000 were obtained from RMA of USDA. Farm-level yield data were used to estimate the empirical conditional farm yield distribution. County-level yield of cotton in Colquitt county from year 1950 to 2005 and county-level yield of soybean in Bulloch county from year 1959 to year 2005 were collected on the website of the NASS of USDA. County yield data were used to estimate the empirical distribution of county yield as well as to estimate the correlation between yield and futures price²⁴.

²⁴ Speaking more exactly, this is the correlation between detrended county yield and the difference of logarithm of futures price at harvest and at planting that will be estimated because

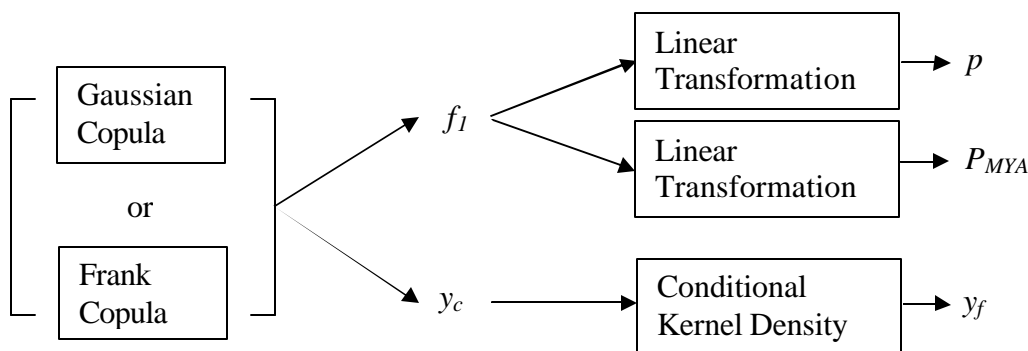


Figure 4.1 Simulation Flowchart

Note: y_c is the simulated county yield; y_f is the farm yield; f_I is futures price; p is the cash price; and p_{MYA} is the estimated market year average price.

Daily average futures prices at planting and at harvest were calculated based on the cotton futures data from the New York Board of Trade (NYBOT) from 1978 to 2006 and from soybean futures data from Chicago Board of Trade (CBOT) from 1979 to 2006²⁵. Harvest-time cash price was approximated by the average price received by Georgia producers collected by USDA from 1978 to 2005 for cotton and from 1979 to 2000 for soybeans²⁶. Market year average prices from 1978 to 2005 were obtained from NASS of USDA²⁷. Cash prices and market year average prices in 2006 are simulated based on their linear relationships with harvest-time futures prices, respectively. First, parameters in the linear regression of historical cash prices on harvest-time futures prices were estimated by ordinary least square (OLS). Then, cash price in 2006 was

significant correlation is detected between the two variables for cotton but is not found between detrended county yield and futures price at harvest.

²⁵ Specifically, cotton price of the December futures contract in March and in November were averaged, respectively; soybean prices of November futures in February and in October were averaged, respectively.

²⁶ Data source:

<http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1002>

²⁷ Data source: http://www.nass.usda.gov/QuickStats/Create_Federal_Indv.jsp

simulated by the predicted cash price plus a random shock drawn from the assumed normal residual distribution. Market year average prices were simulated in the same way.

Copula Simulation of County-level Yield (y_c) and Futures Price (f_I)

In statistics, copula is a function that connects the marginal distributions to the joint cumulative distribution (Nelson, 1999).

Definition 4.1:

Suppose that H is a joint cumulative distribution function (CDF) on \mathcal{R}^m with marginal CDFs, F_1, \dots, F_m , then $U_1 = F_1 \sim Unif[0, 1], \dots, U_m = F_m \sim Unif[0, 1]$ and the joint distribution function of U_1, \dots, U_m is a copula C such that

$$\begin{aligned} C(u_1, \dots, u_m) &= P(U_1 \leq u_1, \dots, U_m \leq u_m) = P[X_1 \leq F_1^{-1}(u_1), \dots, X_m \leq F_m^{-1}(u_m)] \\ &= P[X_1 \leq x_1, \dots, X_m \leq x_m] = H(x_1, \dots, x_m) \end{aligned} \quad (4.13)$$

Technically, copulas are joint distribution of unit uniform variates by defining a mapping from $[0, 1]^m$ to $[0, 1]$. But, since the unit uniform variates (e.g. F_1, \dots, F_m) are usually viewed as the probabilities of other variates (e.g. X_1, \dots, X_m), the copula actually represents the joint distribution by separating it into two contributions: the marginal distributions of the individual variables and interdependency of the probabilities (Gary, 2002). When the individual variates are independent, i.e. $P[X_1 \leq x_1, \dots, X_m \leq x_m] = P[X_1 \leq x_1] \cdot \dots \cdot P[X_m \leq x_m]$, the corresponding copula is an independence copula. A bivariate independence copula is a product copula in the form of $C(u_1, u_2) = u_1 u_2$, where $u_1, u_2 \sim Uniform(0, 1)$. (4.14)

According to the Sklar's theorem (Nelson, 1999), for any continuous multivariate CDF, there is a unique copula; conversely, for any copula, there is a joint distribution with marginal distributions of corresponding dimensions. By associating the marginal CDF with the joint CDF, copula fully described the dependence among the variables X_1, \dots, X_m (Chen and Huang) without

explicitly specifying the joint cumulative functional form. When the goal is only to know the dependence between individual variables, but not to find the exact joint distributional form, copula method provides a way to estimate the associations between variables without knowing their joint distribution (Cherubini et al., 2004). Since more types of copula functions are known than the types of joint distribution functions, the individual variables are allowed to have more joint distributional relationships by following copula methods than by assuming the joint distribution explicitly.

The need to model the distribution of harvest-time yields and prices and the distributional flexibility associated with the copula method motivate this study to use copula simulation. Among the many well-known copulas, two copulas, Gaussian copula and Frank copula were selected to model the dependence between the county yields and the futures prices. The purpose of selecting two copulas is to (i) demonstrate that a variety of joint distributions of yields and prices can exist other than the bivariate normal and (ii) provide a sensitivity analysis of the results. Appendix C shows that both Gaussian copula and Frank copula provide better fit than the bivariate normal assumption with respect to the relationship between the county yields and futures prices. However, this study does not assert that these two copulas make the best fits to the relationships between the sample yields and prices (For copula selection criteria, see Gary, 2002).

Bivariate Gaussian copula takes the form

$$C_G(u, v) = \Phi_{\mathbf{r}}(\Phi^{-1}(u), \Phi^{-1}(v)) \quad (4.15)$$

where $\Phi_{\mathbf{r}}$ is the bivariate normal CDF with the Pearson's coefficient \mathbf{r} , representing the linear correlation between the two variables X_1 and X_2 ; Φ is the normal CDF; u and v are variates from two independent Uniform (0, 1) distributions. When the two marginal variables have normal

distributions, a bivariate Gaussian copula is equivalent to a bivariate normal CDF, which means $C_G(\Phi(x_1), \Phi(x_2)) = \Phi_r(x_1, x_2)$ (See proof on p. 113 of Cherubini et al., 2004).

Frank copula is a one-parameter copula function of the form

$$C_F(u, v) = -\frac{1}{\mathbf{q}} \ln \left(1 + \frac{(\exp(-\mathbf{q}u) - 1)(\exp(-\mathbf{q}v) - 1)}{\exp(-\mathbf{q}) - 1} \right), \mathbf{q} \neq 0 \quad (4.16)$$

When the \mathbf{r} in Gaussian copula and \mathbf{q} in Frank copula are positive (negative), the marginal distributions coupled by the copulas are positively (negatively) associated.

In this work, the two marginal distributions coupled by the Gaussian copula or Frank copula are the distribution of county yield F_{y_c} and the marginal distribution of the logarithm difference between the futures prices at harvest and at planting, F_{dlnf} . County-level yields must be simulated because the representative farm's yields are modeled as conditional on the county yields. The marginal distribution of $(dlnf)$ is used here because, on the one hand, this differenced variable has a significant negative correlation with county yields. On the other hand, it can be used to generate harvest-time futures price f_I when the planting-time futures price f_0 is known. Significant dependence between y_c and $(dlnf)$ found in historical data determines the sign and magnitude of \mathbf{r} in Gaussian copula and \mathbf{q} in Frank copula.

Regression analysis on the soybean county-level yield of Bulloch county showed no linear trend in time. Therefore the county yield and farm yield of Bulloch county soybean production were used for the simulation without detrending.

Ordinary least squares analysis revealed that cotton yields of Colquitt county from 1950 to 2005 have a significant linear trend. To account for the temporal component, a simple detrending procedure was implemented by scaling yields from year 1978 through 2005 to year 2006. The detrended county yields were then calculated as:

$$y_c^{\text{det}} = y_{ct} + \hat{\mathbf{b}}(2006 - t) \quad (4.17)$$

where $\hat{\mathbf{b}}$ is the estimated coefficient for the year variable in the linear trend regression. Although the 6 to 10 years of available farm-level yield is unlikely to represent the underlying yield distribution for each farm (Deng et al.), all the farm-level yield information within a county could be used to estimate the yield distribution of a representative farm in the county by assuming that the yield of the representative farm could be equal to any farm yield harvested in the county in a specific year. By further assuming that every year's farm yield is multiplicatively conditional on that year's county yield, random pseudo yields of the representative farm in 2006 were generated as

$$y_f^{\text{det}} = y_c^{\text{det}} \cdot \frac{y_{ft}}{y_{ct}},$$

where t is any year of 1991-2000. To simplify notation, detrended county yield and detrended farm yield will be also represented by y_c and y_f in the rest of the study.

In the agricultural economics literature, yield distributions have been modeled by both parametric methods and nonparametric approaches (Ker and Goodwin, 2000; Wang et al. 2004). This study applied a nonparametric kernel density approach to estimate the empirical distribution of the detrended county yields. In particular, for any y_c^* , the empirical cumulative probability was estimated by

$$\hat{F}(y_c^*) = P(y_c \leq y_c^*) \approx \int_0^{y_c^*} \frac{1}{n} \sum_{i=1}^n K_h(y - Y_{ci}) dy \quad (4.18)$$

where $\frac{1}{n} \sum_{i=1}^n K_h(y - Y_{ci})$ is the kernel density estimator. Y_{ci} represents the detrended historical

county yields, K_h is defined as $K_h(\cdot) = (1/h)K(\cdot/h)$, h is the bandwidth or smoothing parameter

which determines the smoothness of the estimated density, and $K(\cdot)$ is referred to as the kernel and is usually chosen to be a unimodal probability density function that is symmetric around zero (Wand and Jones, 1995). In this study, the Epanechnikov density function was used as the

$$\text{kernel with } K(x) = \frac{3}{4}(1-x^2)1\{|x| < 1\} \quad (4.19).$$

Jones et al. (1996) provided a survey for bandwidth selection methods. This study used the bandwidth determined by the Sheather-Jones plug-in method to determine the bandwidth for y_c .

$\hat{F}(y_c^*)$ was calculated by applying Simpson's rule of numerical integration (Miranda and Fackler, 2002).

Futures prices have been specified by the lognormal distribution in the literature (Coble et al. 2000, 2004; Hauser et al. 2004). Since $dlnf (= \ln f_1 - \ln f_0)$ calculated with historical cotton and soybean futures data passed several normality tests (Tables 4.2 and 4.3), this study assumes ($dlnf$) to be normally distributed with mean and variance determined by the historical data. That is, $F_{dlnf} = \Phi(\hat{\mathbf{m}}_{dlnf}, \hat{\mathbf{s}}_{dlnf})$. Once planting time futures price f_0 is known, harvest futures price can be simulated by $f_1 = f_0 \cdot \exp(d \ln f)$.

Table 4.2 Normality Tests of $dlnf$ for Cotton Futures 1978-2005

Normality test	Distribution	Test statistic	P-value
Shapiro-Wilk	W	0.9533	0.240
Kolmogorov-Smirnov	D	0.1268	0.150
Cramer-von Mises	W-Sq	0.0646	0.250
Anderson-Darling	A-Sq	0.4448	0.250
$\hat{\mathbf{m}}_{dlnf}$	-0.025	$\hat{\mathbf{s}}_{dlnf}$	0.174

Note: $dlnf = lnf_1 - lnf_0$, f_0 and f_1 are the March and November daily average of the futures prices in December contract, respectively.

Table 4.3 Normality Tests of $dlnf$ for Soybean Futures 1979-2005

Normality test	Distribution	Test statistics	P-value
Shapiro-Wilk	W	0.9486	0.199
Kolmogorov-Smirnov	D	0.1155	0.150
Cramer-von Mises	W-Sq	0.0576	0.250
Anderson-Darling	A-Sq	0.3964	0.250
$\hat{m}_{d \ln f}$	-0.027	$\hat{S}_{d \ln f}$	0.167

Note: $dlnf = lnf_1 - lnf_0$, f_0 and f_1 are the February and October daily average of the futures prices in November contract, respectively.

Three major steps are involved to simulate interdependent variables with copulas. First, the parameters in the selected copula need to be estimated. This study applies maximum likelihood method to estimate the parameters in the Gaussian copula and the Frank copula. The second step is to generate unit uniform variates based on the estimated copula. Different copulas will have different algorithms to generate unit uniform variates. The third major step is to simulate variates of desired variables (e.g. county yield and transformed futures price) by substituting the generated uniform variates from the second step into the appropriate inverse cumulative distributions.

When the Gaussian copula is selected, the following steps are taken to generate detrended county yield y_c and harvest-time futures price f_1 :

1. Generate two independent random numbers z_{1i}, z_{2i} , from Normal (0, 1)
2. Compute the nonparametric correlation Spearman's r_s , between detrended y_c and $dlnf$ for cotton from 1978 to 2005 and for soybean from 1979-2005, and then calculate the

corresponding Pearson's correlation coefficient based on the formula²⁸ $\hat{r} = 2 \sin(\mathbf{p}\hat{r}_s / 6)$.

If the joint distributions is normal, r_s and \mathbf{r} calculated directly from data will be equal (Fackler).

3. Set $x_{1i} = z_{1i}$ and $x_{2i} = \hat{\mathbf{r}}z_{1i} + \sqrt{1 - \hat{\mathbf{r}}^2}z_{2i}$, then (x_{1i}, x_{2i}) has a bivariate normal distribution

with zero mean vector and variance-covariance matrix $\begin{bmatrix} 1 & \hat{\mathbf{r}} \\ \hat{\mathbf{r}} & 1 \end{bmatrix}$

4. Set $dlnf_i = (z_{1i} + \hat{\mathbf{m}}_{dlnf})\hat{\mathbf{S}}_{dlnf}$, then $f_{1i} = \exp(dlnf_i)f_0$
5. Set $u_i = \Phi^{-1}(x_{2i})$, then y_{ci} can be generated through $y_{ci} = F^{-1}(u_i)$ or $\hat{F}(y_{ci}) = u_i$.

When the Frank copula is used, a different algorithm must be implemented to simulate harvest-time county yield and futures:

1. For every pair of observed $(y_c, dlnf)$, set $\hat{u} = \hat{F}(y_c)$, and $\hat{v} = \Phi^{-1}[(d \ln f - \hat{\mathbf{m}}_{dlnf}) / \hat{\mathbf{S}}_{dlnf}]$.
2. For each pair of $(y_c, dlnf)$, set $\hat{c} = (n + 1)/N$ if there are n other pairs of $(y_c, dlnf)$ that have both the values of y_c and $dlnf$ no more than the values of y_c and $dlnf$ in the current pair. N is the sample size, which is 28 for cotton and 27 for soybeans.
3. Find $\hat{\mathbf{q}}$ in Frank copula by fitting the nonlinear model

$$\hat{c} = -\frac{1}{\hat{\mathbf{q}}} \ln \left[1 + \frac{(\exp(-\hat{\mathbf{q}}\hat{u}) - 1)(\exp(-\hat{\mathbf{q}}\hat{v}) - 1)}{\exp(-\hat{\mathbf{q}}) - 1} \right].$$

4. Simulate two independent random number z_{1i}, z_{2i} from Uniform (0, 1).

²⁸ Note that the Spearman's r_s is invariant to monotonic transformation of the correlated variables while Pearson's \mathbf{r} doesn't have such property. Consequently, the simulated y_c and $(dlnf)$ will have the same Spearman correlation as that between the historical y_c and $(dlnf)$, but don not remain the same Pearson's linear correlation (Fackler).

5. Set $x_{1i} = z_{1i}$ and $x_{2i} = -\frac{1}{\hat{q}} \ln \left[1 + \frac{z_{2i} (1 - \exp(-\hat{q}))}{z_{2i} (\exp(-\hat{q}z_{1i}) - 1) - \exp(-\hat{q}z_{1i})} \right]$.
6. Set $dlnf_i = \hat{\mathbf{s}}_{dlnf} \Phi^{-1}(x_{1i}) + \hat{\mathbf{m}}_{dlnf}$, then $f_{1i} = \exp(dlnf_i)f_0$.
7. y_{ci} is simulated by $y_{ci} = F^{-1}(x_{2i})$ or $\hat{F}(y_{ci}) = x_{2i}$.

By following the above algorithms, 10,000 pairs of (y_c, f_i) were simulated from the Gaussian copula and from Frank copula, respectively. In order to investigate the hedging decision under the unbiased futures price assumption, the mean of the simulated futures price was adjusted to equal the futures price at planting time (Wang, et al. 2004). Hedging decisions under biased futures price will also be examined after enlarging or shrinking the mean of the simulated futures by a certain percent. All the parameters estimated to the generated y_c, f_i, p , and p_{MYA} data series are listed in table 4.4 for cotton and table 4.5 for soybeans.

Both Gaussian copula and Frank copula are applied to simulate yield and price data for cotton. But only the Gaussian copula is used to simulate soybean yield and price data, since no significant dependence between the differenced soybean futures price and county yields is detected. Zero dependence between differenced soybean futures and county yield makes the simulation applying Frank copula no different from the simulation using Gaussian copula because in this case both copulas become the independence copula (3.14).

Simulation of Farm-level Yield

As shown by Figures 1.1 and 1.2 in chapter one, the distribution of farm yields is conditional on the level of county yield. To incorporate this relationship between farm yields and county yields into the simulated yield data, conditional kernel estimation was applied to simulate farm yield based on the generated county yield from Gaussian copula or Frank copula.

Table 4.4 Estimated Parameters for Simulating Cotton County Yields and Prices

Parameters in Simulation	Coefficient Estimation	P-value
$r_s(\mathbf{r})$	-0.331(-0.345)	0.0852
\mathbf{q}	-1.353	0.0197
b_{0_p}	9.420	0.0330
b_{1_p}	0.795	<.0001
Residual $\mathbf{s}_{_p}$	4.088	
$b_{0_{MYA}}$	8.286	0.0635
$b_{1_{MYA}}$	0.798	<.0001
Residual $\mathbf{s}_{_MYA}$	4.177	

Note: r_s is the Spearman correlation used to calculate Pearson correlation coefficient \mathbf{r} in the Gaussian copula simulation.

\mathbf{q} is the parameter in the Frank copula.

p is simulated based on the linear regression

$$p = b_{0_p} + b_{1_p}f_1 + e_1, e_1 \sim \text{Normal}(0, \mathbf{s}_{_p}).$$

p_{MYA} is simulated based on linear regression

$$p_{MYA} = b_{0_{MYA}} + b_{1_{MYA}}f_1 + e_2, e_2 \sim \text{Normal}(0, \mathbf{s}_{_MYA}).$$

Table 4.5 Estimated Parameters for Simulating Soybean Yields and Prices

Parameters in Simulation	Coefficient Estimation	P-value
r_s	-0.268	0.1765
\mathbf{q}	-0.003	0.9955
b_{0_p}	0.540	0.0180
b_{1_p}	0.871	<.0001
Residual $\mathbf{s}_{_p}$	0.173	
$b_{0_{MYA}}$	0.943	0.0027
$b_{1_{MYA}}$	0.820	<.0001
Residual $\mathbf{s}_{_MYA}$	0.262	

Note: Since the Spearman correlation coefficient r_s is not significant at $\alpha = 0.1$, zero correlation is assumed for futures price and county yield.

\mathbf{q} is the parameter in the Frank copula, which is not significantly different from 0.

p is simulated based on the linear regression

$$p = b_{0_p} + b_{1_p}f_1 + e_1, e_1 \sim \text{Normal}(0, \mathbf{s}_{_p}).$$

p_{MYA} is simulated based on linear regression.

$$p_{MYA} = b_{0_{MYA}} + b_{1_{MYA}}f_1 + e_2, e_2 \sim \text{Normal}(0, \mathbf{s}_{_MYA}).$$

The conditional cumulative distribution function of farm yield given county yield is given by

$$F_{y_f|y_c} = P(y_f < y_f^* | y_c = y_c^*) = \frac{P(y_f < y_f^*, y_c = y_c^*)}{P(y_c = y_c^*)} \quad (4.20)$$

By using bivariate kernel density method (Wand and Jones, 1995) and then applying Simpson's rule to integrate over the range of y_f (APPENDIX B), the joint cumulative probability in the numerator of (4.20) can be calculated by

$$\hat{P}(y_f < y_f^*, y_c = y_c^*) = \int_0^{y_f^*} \frac{1}{n} \sum_{i=1}^n K_{h_f}(y_f - Y_{fi}) K_{h_c}(y_c^* - Y_{ci}) dy_f \quad (4.21)$$

where $K_{h_f}(\cdot) = (1/h_f)K(\cdot/h_f)$, $K_{h_c}(\cdot) = (1/h_c)K(\cdot/h_c)$, and K is the Epanechnikov kernel in (4.19). Bandwidth h_f was determined by the simple normal reference method (Bowman and Foster, 1993), and bandwidth h_c was the same as the bandwidth in (4.18), which was used for estimating the univariate density and cumulative probability of y_c .

The denominator in (4.20) was estimated by

$$\hat{P}(y_c = y_c^*) = \int_{\min y_f}^{\max y_f} \frac{1}{n} \sum_{i=1}^n K_{h_f}(y_f - Y_{fi}) K_{h_c}(y_c^* - Y_{ci}) dy_f \quad (4.22)$$

Given the estimated $\hat{F}_{y_f|y_c}$, a random realization of y_f corresponding to a specific y_c generated from copula approach can be obtained in two steps. First, generate a random number u from Uniform (0, 1). Then find the y_f such that $y_f = \hat{F}_{y_f|y_c}^{-1}(u)$. The simulated farm yields were adjusted to make their mean value equal to the mean of the simulated county yield because the representative farm is assumed to have mean yield equal to the county yield²⁹.

²⁹ The y_f is adjusted by multiplying the ratio of mean (y_c)/mean(y_f).

The basic statistical measures of the 10,000 simulated yields and prices, y_c , y_f , f_1 , p and p_{MYA} , are listed in tables 4.6-4.9 for cotton and tables 4.10-4.11 for soybean. The 3D density maps of simulated county yield and farm yield are presented in figure 4.2 and figure 4.3 for cotton data and in figure 4.4 for soybean data. These density maps show that the variance of the farm yields changes with the levels of county yields.

The derivative-free numerical optimization procedure, the Nelder-Mead algorithm, was used (Miranda and Fackler, 2002) to solve for the minimum LPM_2 hedge ratios. Because the LPM_2 for the hedge portfolio is generally not a globally convex function of the hedge ratios, a grid search approach is used to locate the local minimum LPM_2 hedge ratios first and then based on the grid search results, the global optimal LPM_2 hedge ratio can be quickly found. For the EU hedge model, the BFGS (Broyden, Fletcher, Goldfarb, & Shano) algorithm was used in search for the optimal hedge ratios (Miranda and Fackler, 2002). Model optimization results under various scenarios are reported and discussed in next Chapter.

Table 4.6 Gaussian Copula: Basic Statistics of the Simulated Cotton Yields and Prices

Statistics	County Yield (lb.)	Farm Yield (lb.)	Future Price (cent)	Cash Price (cent)	P_{MYA} (cent)
Mean	848	848	58.52	55.88	54.99
Std Dev	143.94	—	10.15	9.01	9.11
Skewness	-0.001	—	0.568	0.416	0.434
Kurtosis	-1.035	—	0.715	0.436	0.498
Min	566	8	26.18	29.98	26.91
Q1	716	668	51.40	49.57	48.68
Q3	966	1040	64.61	61.50	60.72
Max	1142	1726	110.15	100.04	101.51

Note: Variance, skewness and kurtosis of farm yield are not listed because farm yield distribution is contingent on the level of county yield; P_{MYA} is the market year average price; Q1, Q3 are 25% and 75% quantile, respectively.

Table 4.7 Gaussian Copula: Pearson Correlation of Simulated Cotton Yields and Prices

	County Yield	Farm Yield	Future Price	Cash Price	P_{MYA}
County Yield	1.000	0.504	-0.335	-0.290	-0.295
Farm Yield	0.504	1.000	-0.174	-0.147	-0.152
Futures Price	-0.335	-0.174	1.000	0.893	0.884
Cash Price	-0.290	-0.147	0.893	1.000	0.789
P_{MYA}	-0.295	-0.152	0.884	0.789	1.000

Table 4.8 Frank Copula: Basic Statistics of the Simulated Cotton Yields and Prices

Statistics	County Yield (lb.)	Farm Yield (lb.)	Futures Price (cent)	Cash Price (cent)	P_{MYA} (cent)
Mean	850	850	58.52	55.88	54.99
Std Dev	143.89	—	10.24	9.11	9.17
Skewness	-0.029	—	0.528	0.355	0.389
Kurtosis	-1.040	—	0.473	0.306	0.362
Min	569	1	25.87	23.37	25.68
Q1	717	669	51.24	49.67	48.74
Q3	967	1047	64.78	61.63	60.59
Max	1142	1729	110.61	98.24	100.50

Note: Variance, skewness and kurtosis of farm yield are not listed because farm yield distribution is contingent on the level of county yield; P_{MYA} is the market year average price; Q1, Q3 are 25% and 75% quantile, respectively.

Table 4.9 Frank Copula: Pearson Correlation of Simulated Cotton Yields and Prices

	County Yield	Farm Yield	Future Price	Cash Price	P_{MYA}
County Yield	1.000	0.502	-0.214	-0.197	-0.193
Farm Yield	0.502	1.000	-0.109	-0.098	-0.098
Future Price	-0.214	-0.109	1.000	0.896	0.886
Cash Price	-0.197	-0.098	0.896	1.000	0.793
P_{MYA}	-0.193	-0.098	0.886	0.793	1.000

Table 4.10 Gaussian Copula : Basic Statistics of the Simulated Soybean Yields and Prices

Statistics	County Yield (bu.)	Farm Yield (bu.)	Futures Price (dollar)	Cash Price (dollar)	P_{MYA} (dollar)
Mean	23.7	23.7	6.19	5.93	6.02
Std Dev	5.49	—	1.03	0.91	0.88
Skewness	-0.075	—	0.544	0.519	0.494
Kurtosis	-0.609	—	0.667	0.620	0.592
Min	10.7	0	2.87	3.05	3.34
Q1	19.5	13.8	5.47	5.30	5.41
Q3	27.7	30.8	6.81	6.50	6.55
Max	36.4	73.2	11.35	10.56	10.53

Note: Variance, skewness and kurtosis of farm yield are not listed because farm yield distribution is contingent on the level of county yield; P_{MYA} is the market year average price; Q1, Q3 are 25% and 75% quantile, respectively.

Table 4.11 Gaussian Copula: Pearson Correlation of Simulated Soybean Yields and Prices

	County Yield	Farm Yield	Future Price	Cash Price	P_{MYA}
County Yield	1.000	0.424*	-0.003	0.001	-0.003
Farm Yield	0.424*	1.000	-0.013	-0.010	-0.011
Future Price	-0.003	-0.013	1.000	0.982*	0.953*
Cash Price	0.001	-0.010	0.982*	1.000	0.936*
P_{MYA}	-0.003	-0.011	0.953*	0.936*	1.000

Note: Correlation coefficient with * is significant at $\alpha = 0.1$

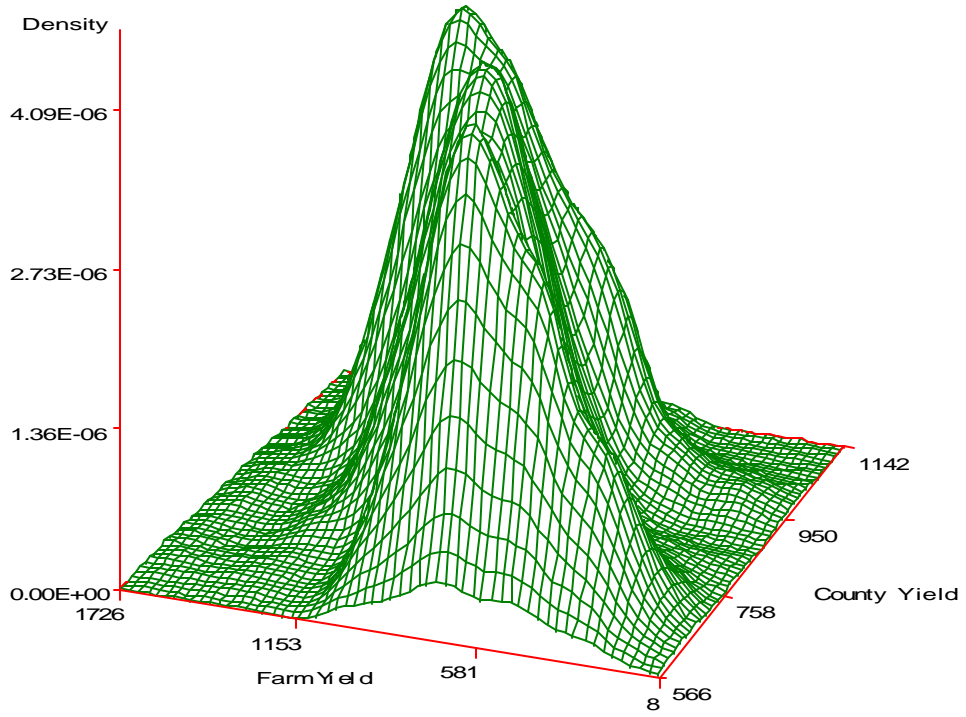


Figure 4.2 Density Plots of Simulated Farm and County Cotton Yields (Gaussian Copula)

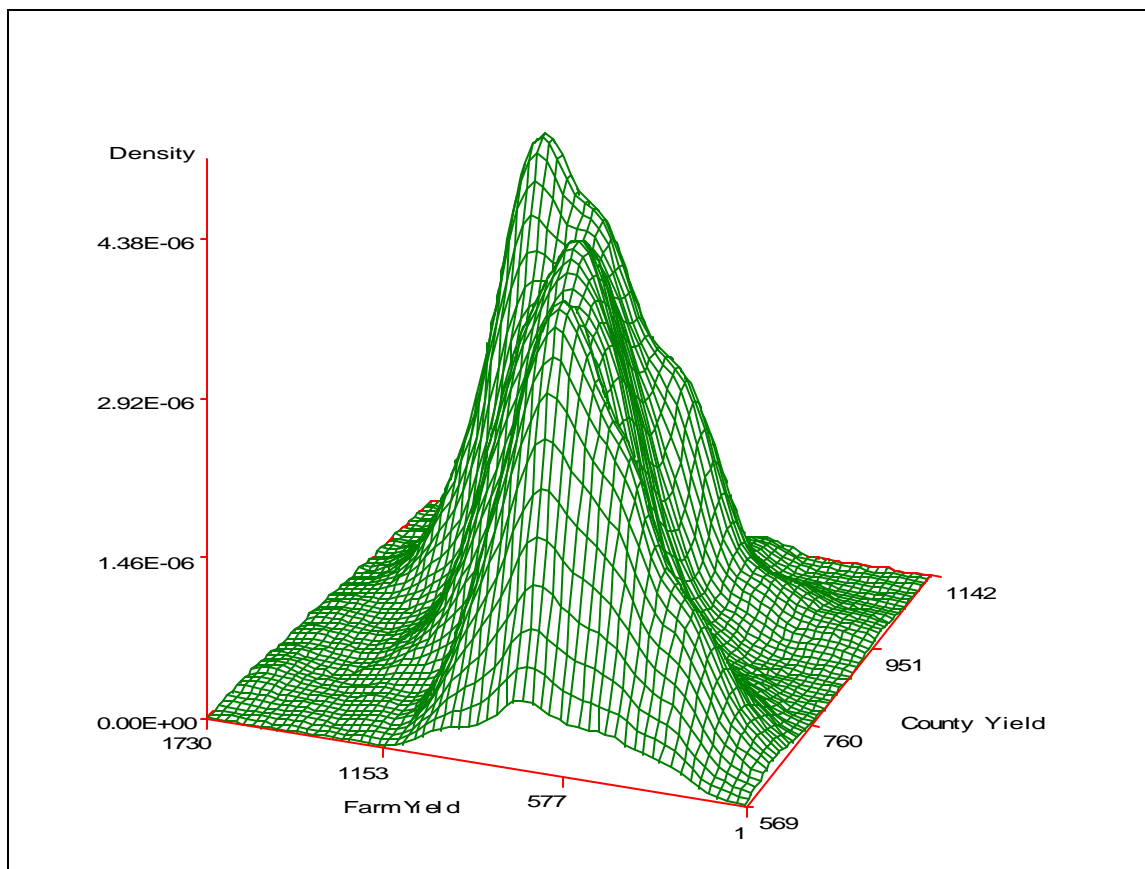


Figure 4.3 Density Plots of Simulated Farm and County Cotton Yields (Frank Copula)

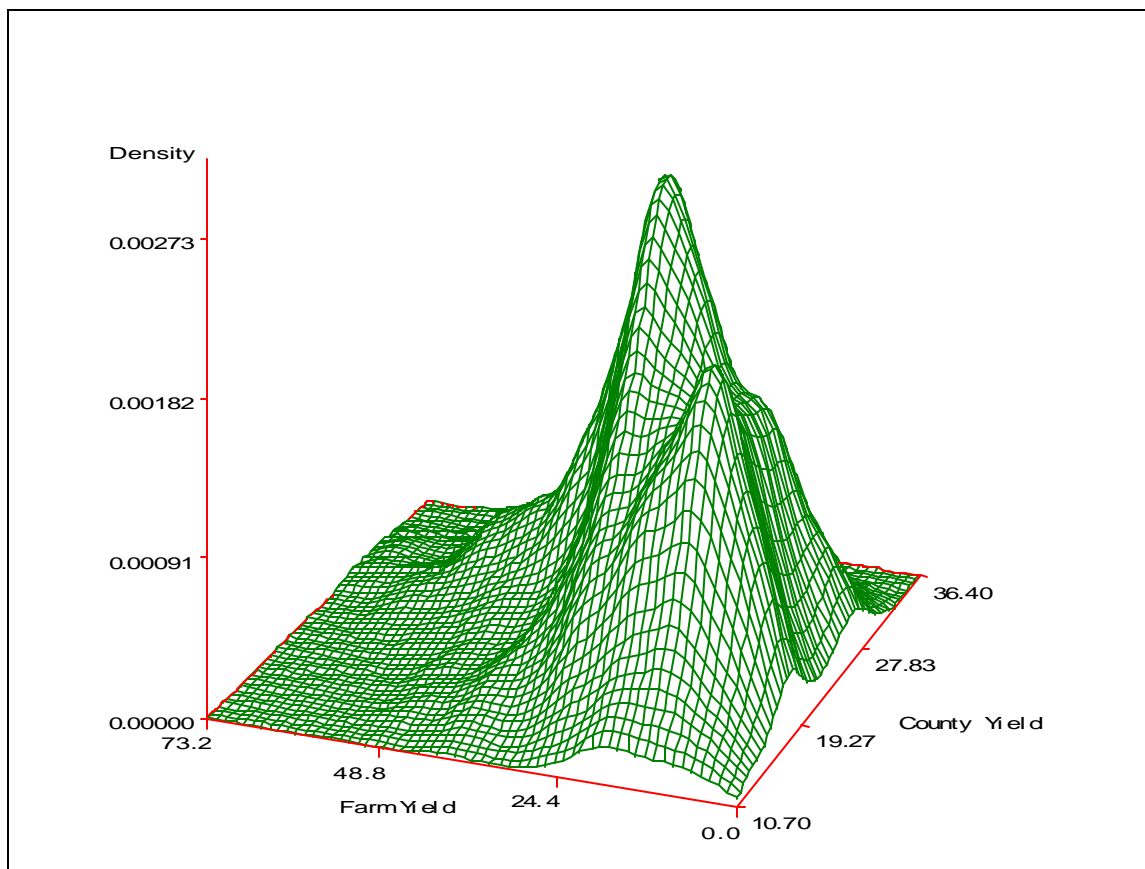


Figure 4.4 Density Plots of the Simulated Soybean Farm and County Soybean Yields (Gaussian Copula)

CHAPTER 5

SIMULATION RESULTS AND ANALYSIS

The impacts of crop yield and revenue insurance and of government payments on the optimal hedge ratios are reported and analyzed in this chapter. Sensitivity tests regarding the parameters used in the simulation are implemented and discussed.

5.1 Effects of Insurance and Government Payments on Hedging

Tables 5.1 and 5.2 report LPM₂ optimal hedge ratios and the LPM₂ risk measures under different scenarios and for both cotton and soybean data, respectively. Hedge ratios h_x and h_z are the ratios of the hedged yield to the expected yield on a per-acre basis. A positive h_x is an indication to sell futures at planting time, while a positive h_z is a signal to buy put options in the spring. In the base scenario, the crop farmer manages risk with only futures and put options. The availability of government payments and federal insurance programs reduce the downside income risk faced by crop farmers as the risk measure LPM₂ decreases.

By comparing the hedge ratios in the base case with the hedge ratios with APH in the portfolio in addition to futures and options in tables 5.1 and 5.2, it appears that more futures are sold when APH is in the risk management portfolio than when it is not. The result that APH promotes hedging demand for futures is consistent with the results of Coble et al. (2000) and Wang et al. (2004). However, the previous works did not consider options as a risk management tool to be used together with futures. This study shows that the positive relationship between APH and a futures hedge remains when put options are used together with futures as the hedging

instruments. This positive relationship can be intuitively understood, given the negative correlation between harvest-time crop yield and price. APH indemnity is triggered when harvest-time crop yield drops below the yield guarantee. The lower the yield, the higher is the APH indemnity. In other words, APH is more valuable when the crop yield is lower. If the crop price and yield are negatively correlated, then APH is more valuable when the harvest price is higher.

Figure 5.1 shows that a positive relationship can be fitted between the payoffs of APH and cash price. The positive relationship between the value of APH and the crop price implies that owing APH is similar to having a long position in futures or call options. Because a long call can be replicated by a long position in futures and a long position in put options, when the crop farmer has APH insurance, his payoff distribution could be similar to the payoff distribution when he has long positions in futures and maybe in put options. Thus, the crop farmer with APH in his portfolio would optimally sell more futures and buy fewer put options compared to the crop farmer with no APH. The actual effects of APH on the use of put options are not uniform but vary with the simulated data. When both futures and put options are in the portfolio, APH shows mixed effects on put options. This differs from the results by Coble et al. (2004) that suggested APH increases hedging in put options when the use of futures is excluded.

Inclusion of CRC in the portfolio increases the hedging demand for futures but decreases the hedging in put options. The price replacement feature of CRC and the negative correlation between harvest-time price and yield indicate that the indemnity of CRC tends to be triggered when the harvest-time crop price is higher than planting-time price. Unlike APH, which only protects against the risk of low yield, CRC may also pay indemnity when the harvest-time price drops so low that the revenue from selling the crop falls below the revenue guarantee in spite of a high yield. Since CRC may pay indemnities at both high and low crop prices, the value of CRC

against cash price might resemble a quadratic curve that opens up. Figure 5.2 shows that the value of CRC for simulated cotton data is parabolic in cash price. Thus, the payoff of CRC may be analogous to the combination of long position in futures and in put options. As a result, when the crop farmer has CRC in his portfolio, he tends to sell more futures and put options than when he has no CRC to achieve the optimal minimum LPM_2 portfolio. These effects of CRC on futures and options are comparable to those found by Coble et al. (2000), who assumed that futures and put options are alternative hedging tools. However, the positive effect of CRC on the futures hedge is contrary to Mahul (2003) and Wang et al. (2004). Mahul found that CRC decreases hedging in futures regardless of whether options are used or not. This divergence could result from the difference in the types of portfolio settings modeled, since Mahul used three straddles together with futures, while this study examines only the use of put options together with futures. Wang et al. detected a negative effect of CRC on futures when they gave no consideration to the use of put options. The results of Wang et al. might be biased by the omission of put options from the portfolio.

The availability of LDP to the crop farmer appears to slightly increase hedging with futures but considerably reduce the purchase of put options. The substitution effect of LDP for put options is consistent with the analysis that LDP is an implicit free put option provided to farmers. This finding is consistent with the empirical finding of Hanson et al. (1999) from an EU hedge model. With LDP in the portfolio, the hedger actually appropriates the value provided by LDP by buying fewer put options.

It is possible that the substitution effect of LDP for put options could be so strong that the decision maker shifts from hedging to speculating by means of selling put options. For example, in table 5.1, when LDP is added to the base portfolio, the hedge ratio in put options changes from

0.26 to -0.23 , and the total percentage of the hedged expected yield changes from 40% to negative 8%. This suggests that LDP over protects the crop farmer and converts him from a net hedger to a net speculator in futures/put options. The weak substitution effect of LDP for futures differs from the results of Coble et al. (2004) and Wang et al. (2004). Neither of these studies included put options in the portfolio, and both found that LDP could largely reduce the futures hedging positions.

The effects of CCP are assessed by comparing the hedge ratios from the case (FOD + LDP + LCP) with those from the scenario (FOD + LDP). CCP decreases the hedging demand for futures, but shows mixed effects on put options for the two crops, cotton and soybeans. However, the aggregate effects of CCP on futures and put options are the same for all datasets in the sense that CCP decreases hedging with the given market tools. The finding that CCP replaces futures to protect farmers against price risk is consistent with previous research by Wang et al. (2004). Anderson et al. (2003) found that CCP is analogous to the difference between a put option against the market year average price with a strike price equal to the target price minus the direct payment and the value of the other put option against local market price with a strike equal to the loan rate. In other words, CCP roughly resembles the trading strategy to buy one put options with a higher strike price and sell the other put option with a lower strike price, since the target price of CCP less the direct payment is higher than the loan rate. CCP in cotton data from a Frank copula in Figure 5.3 gives further evidence that payoffs of CCP are analogous to the bear spread strategy in options trading. The downward sloping part of CCP against cash price in figure 5.3 may decrease the hedging use for commodity futures.

By comparing the scenarios including both insurance and government payments, the scenarios including either insurance or government payments, with the scenario having only

futures, options and DP, the interaction effect of insurance and government payment on the use of futures and put options can be assessed. For example, in table 5.1, APH increases the futures hedge ratio by 0.01, and LDP increases the hedge in futures by 0.03, if they are included in the portfolio alternatively. The inclusion of both APH and LDP in the hedge portfolio increases the hedging demand for futures by 0.04. This indicates that there is no interaction between APH and LDP in terms of their effects on the optimal futures hedge. Following the same approach, it can be concluded that LDP has almost no interaction with APH and CRC. This finding differs from Coble et al. (2004), who, by ignoring the hedging role of put options, found that the existence of APH will increase the substitution effect of LDP for futures hedging. Contrary to LDP, the interactive effects of CCP with APH and CRC on the use of futures and put options are non-trivial and vary by crop and by county.

Comparing hedge ratios for cotton from different copulas in table 5.1, the optimal hedge ratios for cotton data simulated from two different copula assumptions are different, even though they are computed based on the same historical data. This suggests that the assumed joint distribution (or, equivalently, copula function) is an important factor affecting the optimal hedge ratios. However, as far as effects of government payments and crop insurance plans on the optimal hedge ratios are concerned, many of the results are consistent across the different copula functions. Thus, although the exact hedge ratios may not be used to guide actual hedging practice, the effects detected by this study provide valuable information for both crop farmers and policy makers.

In addition to disclosing the effects of government payments or crop insurance on use of futures and options, the results in tables 5.1 and 5.2 suggest that CRC is more efficient than APH for downside risk reduction. Including CCP decreases risk more than LDP. CRC has the largest

downside risk reduction effects among the four government income support programs. Hence, if there is budget competition among the programs, CRC should be given the highest priority among the four government payments and federal insurance programs discussed. Conversely, APH is the least competitive of the four programs in terms of downside risk reduction.

5.2 Optimal LPM₂ Hedge Ratios vs EU Hedge Ratios

Optimal hedge ratios for the LPM₂ model and the EU model for three scenarios including DP and APH/CRC are reported in tables 5.3 through 5.5. The effects of crop insurance policies and government payments on the hedging in futures and put options from the two models are consistent in terms of the signs of the effects. Thus, whether the LPM₂ hedge model or the EU hedge model is used to evaluate such effects, the directions of the impacts are observed to be the same.

However, the sums of the hedge ratios in futures and put options from the LPM₂ model are all smaller than aggregated hedge ratios from the EU model. In other words, the farmer hedges a smaller percentage of his expected production if he uses an LPM₂ model to estimate the optimal hedge ratio instead of EU model. These results do not reject the hypothesis that model misspecification may be another reason for the fact that the observed hedge in futures by farmers is less than the predicted hedge by the EU model. If the hedging objective is to minimize perceived risk to the farming income, but not to maximize the expected utility, then the crop farmers would seem to under-hedge when they are judged by the EU model.

Result presented in tables 5.3 to 5.5 strongly suggest that the hedge ratios in futures under an LPM₂ model are no greater than the futures hedge under an EU model, and that hedge ratios in put options under the LPM₂ hedge model are usually larger than the hedge ratios from the EU hedge model. That put options are preferred by the LPM₂ model compared to the EU model

could be explained by the evidence that the asymmetric payoff distribution of put options is consistent with the skewed distributions of the hedge portfolios that the LPM₂ hedge model generally yields.

By comparing the basic distributional statistics of the hedge portfolios, it can be seen that when the means of the hedge portfolio are the same, the hedge portfolios from the LPM₂ model always have a larger right skewness, a higher minimum payoff, and a higher maximum payoff than the portfolios from the EU hedge model. Although the EU hedge model yields portfolios with a smaller standard deviation than the LPM₂ model, any farmer who wants to hedge against extremely low income events may prefer the hedging strategies resulting from the LPM₂ hedge.

5.3 Impacts of futures Bias and Transaction Cost on Hedging

The impacts of perceived bias in futures prices on the optimal LPM₂ hedging positions is examined for the base scenario. Table 5.6 reports the optimal hedge ratios with and without futures price bias. The scenario of zero percent bias means no futures price bias; that is, $f_0 = Ef_1$. Negative bias means that the futures price at planting is lower than the expected futures price at harvest; i.e. $f_0 < Ef_1$. If the futures bias is assumed to be -2%, then $Ef_1 = f_0 / (100\% - 2\%)$. On the contrary, positive bias means that the futures price at planting is higher than the expected futures price at harvest; i.e. $f_0 > Ef_1$. Positive-biased futures prices are simulated by following the same method as for negative bias.

As expected, the negative bias of the planting time futures price suppresses the hedging demand for futures and could even convert the hedger to a speculator in the futures market. In contrast, a positive bias in the futures price induces more use of the futures hedge. The substitution effect between futures and put options may be caused by the assumption that put options are fairly priced, although futures prices are biased.

Table 5.1 Optimal LPM₂ Hedge Ratios under Different Scenarios for Cotton

Scenarios	Cotton Gaussian Copula			Cotton Frank Copula		
	h_x (chg ¹)	h_z (chg)	LPM ₂	h_x (chg*)	h_z (chg)	LPM ₂
Futures + Options (FO)	0.14	0.26	12938.40	0.32	0.16	13050.90
FO + APH	0.27 (0.13)	0.17 (-0.09)	8581.96	0.40 (0.08)	0.13 (-0.03)	8728.21
FO + CRC	0.38 (0.24)	-0.10 (-0.36)	7359.03	0.49 (0.17)	-0.14 (-0.30)	7496.41
Futures + Options + DP (FOD)	0.14	0.26	12938.40	0.32	0.16	13050.90
FOD + LDP	0.15 (0.01)	-0.23 (-0.49)	11524.61	0.33 (0.01)	-0.33 (-0.49)	11608.38
FOD + APH + LDP	0.29 (0.15)	-0.31 (-0.57)	7193.42	0.42 (0.10)	-0.36 (-0.52)	7305.56
FOD + CRC + LDP	0.41 (0.27)	-0.63 (-0.89)	5945.73	0.52 (0.20)	-0.67 (-0.83)	6043.53
FOD + LDP + CCP ²	-0.34 (-.49)	-0.02 (0.21)	5961.11	-0.19 (-0.52)	-0.09 (0.24)	6045.10
FOD + APH + LDP + CCP	-0.14 (-.28)	-0.15 (-0.41)	2543.40	-0.05 (-0.37)	-0.16 (-0.32)	2617.18
FOD + CRC + LDP + CCP	0.03 (-.11)	-0.60 (-0.86)	1724.34	0.10 (-0.22)	-0.60 (-0.76)	1774.64

Note: h_x , h_z are hedge ratios in futures and put options, respectively.

Positive h_x means sell futures at planting time and positive h_z means buy put options at planting time.

Mean, Min, Max are values in dollars on a per acre basis.

¹ Numbers in parenthesis are changes in hedge ratios compared to the base scenario FO.

² Numbers in parenthesis are changes in hedge ratios compared to the scenario (FOD+LDP).

Table 5.2 Optimal LPM₂ Hedge Ratios under Different Scenarios for Soybean

Scenarios	Soybean Gaussian Copula		
	h_x (chg ¹)	h_z (chg)	LPM ₂
Futures + Options (FO)	0.35	0.27	2409.64
FO + APH	0.44 (0.09)	0.20 (-0.07)	1332.20
FO + CRC	0.64 (0.29)	-0.28 (-0.55)	1068.90
Futures + Options + DP (FOD)	0.35	0.27	2409.64
FOD + LDP	0.39 (0.04)	0.04 (-0.23)	2373.34
FOD + APH + LDP	0.47 (0.12)	-0.05 (-0.32)	1293.61
FOD + CRC + LDP	0.69 (0.34)	-0.55 (-0.82)	1029.27
FOD + LDP + CCP ²	0.37 (-0.02)	-0.33 (-0.37)	2156.64
FOD + APH + LDP + CCP	0.45 (0.10)	-0.42 (-0.69)	1113.73
FOD + CRC + LDP + CCP	0.67 (0.32)	-0.93 (-1.20)	863.31

Note: h_x , h_z are hedge ratios in futures and put options, respectively.

Positive h_x means sell futures at planting time and positive h_z means buy put options at planting time.

Mean, Min, Max are values in dollars on a per acre basis.

¹ Numbers in parenthesis are changes in hedge ratios compared to the base scenario FO.

² Numbers in parenthesis are changes in hedge ratios compared to the scenario (FOD+LDP).

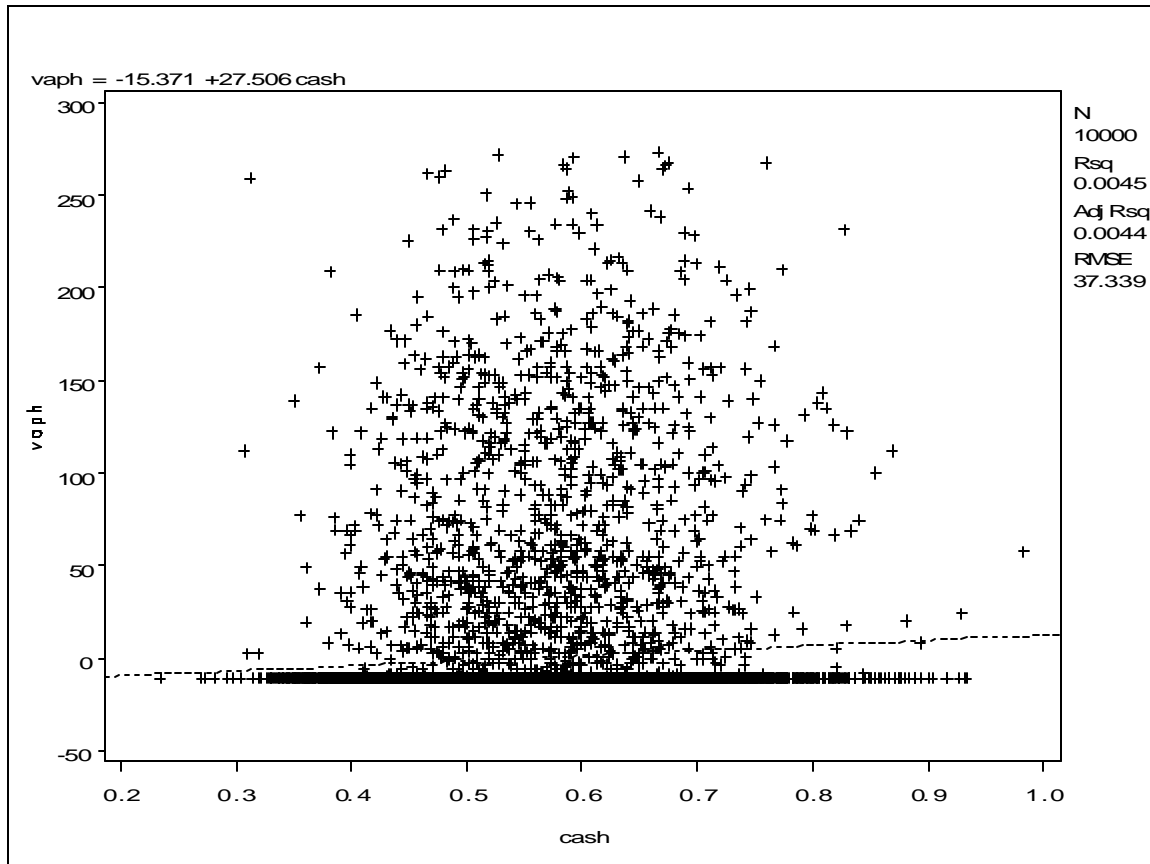


Figure 5.1 The Positive Relationship between the Value of APH and Cash Price in the Simulated Cotton Data (Frank Copula).

Note: the slope of the fitted line has P-value <0.0001.

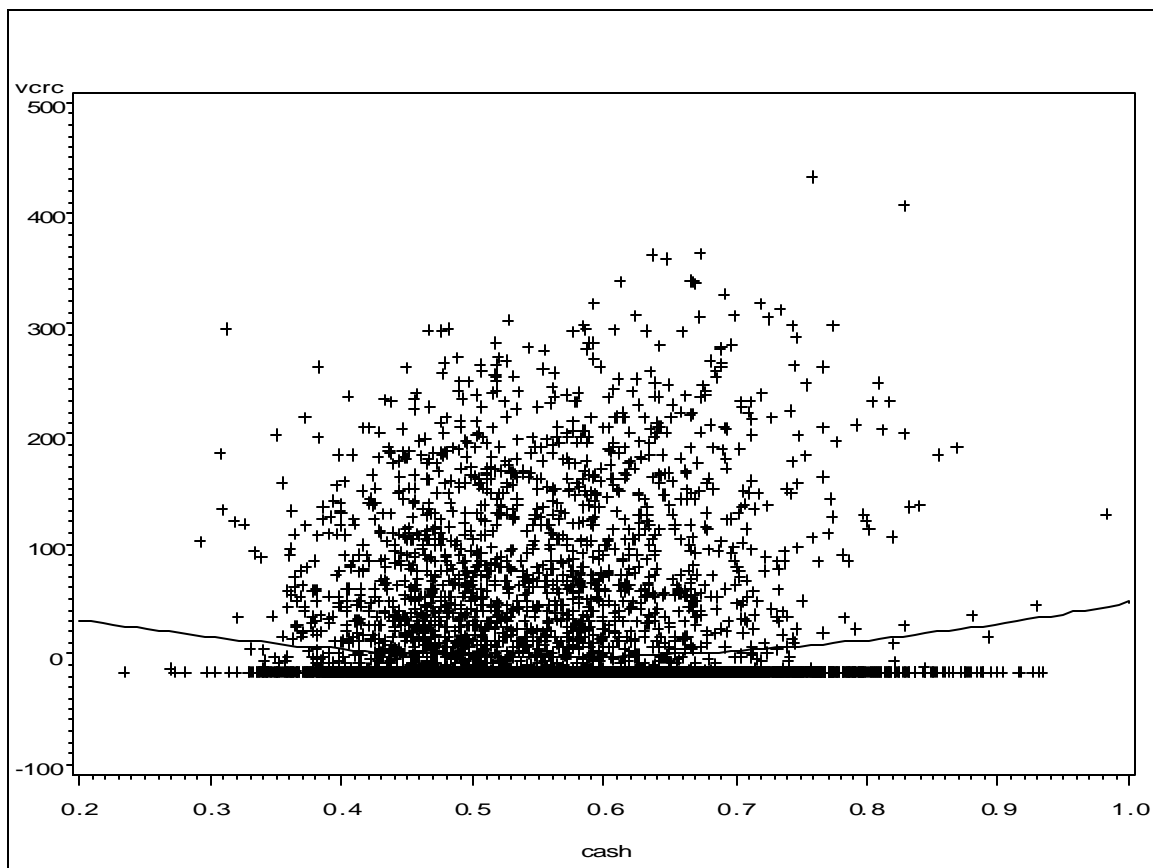


Figure 5.2 The Quadratic Relationship between the Value of CRC and Cash Price in the Simulated Cotton Data (Frank Copula)

Note: All three parameters of the fitted quadratic curve have P-value < 0.0001 .

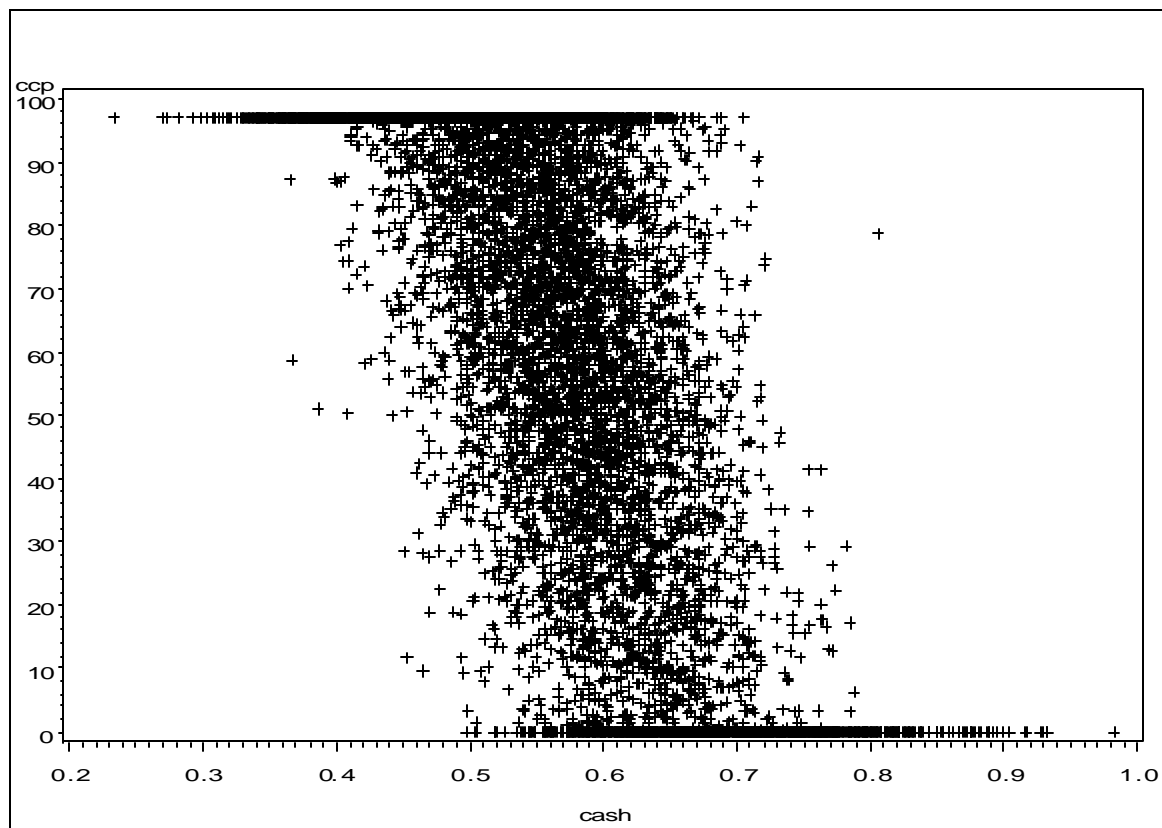


Figure 5.3 The Bear-spread Shaped Payoffs of CCP in the Simulated Data for Cotton (Frank Copula)

Table 5.3 Optimal Hedge Ratios from LPM and EU Model (Base)

Futures+Options+DP	Cotton Gaussian Copula		Cotton Frank Copula		Soybean Gaussian Copula	
	LPM ₂	EU	LPM ₂	EU	LPM ₂	EU
h_x	0.14	0.18	0.32	0.33	0.35	0.61
h_z	0.26	0.23	0.16	0.16	0.27	0.20
Mean	44.06	44.06	46.24	46.24	9.27	9.27
Std Dev	163.40	163.12	163.84	163.73	76.54	76.10
Skewness	0.147	0.132	0.118	0.112	0.712	0.654
Kurtosis	0.459	0.439	0.362	0.361	0.753	0.656
Min	-445.03	-449.66	-497.47	-500.19	-162.07	-182.07
Q1	-59.21	-59.03	-59.28	-59.07	-49.21	-48.23
Q3	148.97	148.55	150.20	149.87	51.89	51.58
Max	882.65	847.24	834.67	832.09	473.56	450.84

Note: h_x , h_z are hedge ratios in futures and put options. A positive h_x means sell futures at planting time and a positive h_z means buy put options at planting time. The set of statistics measures the distributional properties of the outcomes of the hedge portfolio.

Table 5.4 Optimal Hedge Ratios from LPM and EU Model (APH)

Futures+Options+DP +APH	Cotton Gaussian Copula		Cotton Frank Copula		Soybean Gaussian Copula	
	LPM ₂	EU	LPM ₂	EU	LPM ₂	EU
h_x	0.27	0.34	0.40	0.46	0.44	0.70
h_z	0.17	0.16	0.13	0.13	0.20	0.10
Mean	44.06	44.06	46.24	46.24	9.27	9.27
Std Dev	143.94	143.57	144.86	144.45	64.68	64.25
Skewness	0.662	0.637	0.637	0.612	1.349	1.283
Kurtosis	0.376	0.305	0.230	0.185	2.007	1.822
Min	-206.04	-224.62	-249.61	-267.24	-93.59	-116.09
Q1	-69.73	-69.38	-69.50	-68.77	-44.79	-42.21
Q3	137.27	137.75	138.62	139.48	41.55	41.19
Max	847.50	833.87	807.14	793.93	456.47	433.77

Note: h_x , h_z are hedge ratios in futures and put options. Positive h_x means sell futures at planting time and positive h_z means buy put options at planting time. The set of statistics measures the distributional properties of the outcomes of the hedge portfolio.

Table 5.5 Optimal Hedge Ratios from LPM and EU Model (CRC)

Futures+Options+DP +CRC	Cotton Gaussian Copula		Cotton Frank Copula		Soybean Gaussian Copula	
	LPM ₂	EU	LPM ₂	EU	LPM ₂	EU
h_x	0.38	0.44	0.49	0.55	0.64	0.82
h_z	-0.10	-0.07	-0.14	-0.10	-0.28	-0.20
Mean	44.06	44.06	46.24	46.24	9.27	9.27
Std Dev	137.39	136.98	138.43	137.91	60.80	60.41
Skewness	0.813	0.787	0.794	0.763	1.555	1.494
Kurtosis	0.573	0.504	0.447	0.394	2.630	2.451
Min	-192.43	-193.88	-186.97	-195.43	-54.70	-71.90
Q1	-70.96	-68.71	-68.35	-65.65	-38.23	-36.52
Q3	132.02	131.87	132.46	133.00	36.74	36.39
Max	828.41	816.23	792.02	778.49	438.04	421.60

Note: h_x , h_z are hedge ratios in futures and put options. Positive h_x means sell futures at planting time and positive h_z means buy put options at planting time. The set of statistics measures the distributional properties of the outcomes of the hedge portfolio.

Transaction costs involved in trading futures and options is another factor that could affect the use of futures and options. Following previous research (Coble et al. 2000, 2004; Wang et al. 2004), the transaction cost is assumed to be mainly composed of two parts: commission and interest forgone on the margin deposits. Commission is assumed to be \$20 for per round term. Since commission is known and certain, as long as the farmer decides to take positions in futures and options at the planting time, it doesn't affect the difference between the expected income and the actual income. As a result, such commission doesn't change LPM₂ optimal hedge ratios. The margin requirement for trading futures is \$900 per contract for cotton futures contract (NYBOT) and \$750 per contract for soybean futures (CBOT)³⁰. Because many brokers allow the investor to earn interest on the margin balance, the opportunity cost on the margin deposit is determined by the interest difference between the market competitive interest rate and the interest rate adopted by the futures exchange for the margin deposits.

This study assumes a 4% interest rate loss on the margin deposits annually. If the hedging period is assumed to be 8 months, then the opportunity cost of one dollar margin deposit is $(4\% \times 2/3)$ dollars. The interest loss on per unit crop hedged is calculated by multiplying the interest rate by the margin deposit for per unit crop hedged, which is 1.8 cents for hedging every pound of cotton and 0.15 dollar for every bushel of soybeans.

The optimal hedge ratios with transaction costs on futures contracts are reported in table 5.7. The effects of transaction costs can be obtained by comparing table 5.7 with tables 5.1 and 5.2 for the corresponding scenarios and crops. Not surprisingly, the introduction of transaction cost decreases the hedging demand for futures, but the negative effects of the transaction cost on futures hedge are generally smaller than the negative effects of CCP on the futures hedge.

³⁰ The initial margin and maintenance margin are the same for both cotton futures and soybean futures contract.

Table 5.6 Optimal LPM₂ Hedge Ratios under Biased Futures Markets

Bias	Cotton Gaussian Copula		Cotton Frank Copula		Soybean Gaussian Copula	
	h_x	h_z	h_x	h_z	h_x	h_z
Futures+Options						
-2%	-0.23	0.69	-0.32	1.13	-0.57	1.69
-1%	-0.16	0.70	0.03	0.63	-0.12	0.98
0	0.14	0.26	0.32	0.16	0.35	0.27
1%	0.44	-0.18	0.62	-0.29	0.84	-0.47
2%	0.52	-0.18	0.93	-0.73	1.35	-1.21

Table 5.7 Effects of Transaction Cost of Trading Futures and Options on the Optimal LPM₂ Hedge Ratios

Scenarios	Cotton Gaussian Copula		Cotton Frank Copula		Soybean Gaussian Copula	
	h_x	h_z	h_x	h_z	h_x	h_z
Futures + Options +DP (FOD)	0.11	0.30	0.30	0.19	0.32	0.31
FOD + APH	0.25	0.21	0.38	0.16	0.41	0.23
FOD + CRC	0.36	-0.07	0.47	-0.11	0.62	-0.25
FOD + LDP	0.13	-0.19	0.31	-0.29	0.36	0.09
FOD + APH + LDP	0.27	-0.29	0.40	-0.33	0.45	-0.01
FOD + CRC + LDP	0.40	-0.61	0.50	-0.64	0.67	-0.52
FOD + LDP + CCP	-0.32	-0.06	-0.17	-0.13	0.34	-0.28
FOD + APH + LDP + CCP	-0.13	-0.17	-0.03	-0.19	0.43	-0.38
FOD + CRC + LDP + CCP	0.02	-0.58	0.08	-0.58	0.65	-0.90

Note: Transaction cost is calculated as the interest forgone on the margin.

Margin requirement is \$900/ contract for cotton futures contract and is \$750/contract for soybean futures.

The LPM₂ hedge ratios are not affected by DP since DP increases the actual income and the expected income by the same amount.

5.4 Effects of Insurance Coverage and the Premium Subsidy

The sensitivity of the optimal hedge ratios in futures and put options to varying insurance coverage levels are tested by comparing the optimal hedge ratios under three coverage levels. The results are listed in table 5.7. Note that whether the crop insurance (APH or CRC) has positive or negative impacts on the futures and put options hedge ratios, such effects are amplified as the coverage level increases. That is, the higher the coverage level, the stronger the effects the crop insurance has on the hedge ratios. For example, the complementary effect of APH on futures hedge increases as the coverage level increases from 60% to 80%. However, the magnitude of the change in effects is not constant for every 10% increase in the insurance coverage level.

Although premium subsidies provide an important way for the government to encourage crop farmers to purchase the crop insurance, the results in table 5.7 indicate that the premium subsidies do not have much influence on the effects of APH or CRC on the use of futures and put options. In fact, the maximum effect of the subsidies changes the hedge ratios by as little as 5% of the expected yield. This result suggests that crop insurance premium subsidies may not have notably impacted the hedging decision of the crop farmers, although such subsidies have already amounted to billions of dollars per year. Conversely, the government subsidies in the form of LDP and CCP would greatly change the hedging demands by the cotton and soybean producers.

Table 5.8 Optimal LPM₂ hedge ratios for alternative insurance coverage levels and premium subsidy rates

Insurance guarantee level (Premium subsidy rate)	Cotton Gaussian Copula		Cotton Frank Copula		Soybean Gaussian Copula	
	h_x	h_z	h_x	h_z	h_x	h_z
DP + Futures + Options + APH						
60%	0.225	0.197	0.372	0.141	0.416	0.202
70%	0.268	0.174	0.401	0.129	0.436	0.195
80%	0.319	0.153	0.431	0.123	0.461	0.182
DP + Futures + Options + APH with premium subsidy						
60% (0.64)	0.222	0.197	0.369	0.140	0.403	0.200
70% (0.59)	0.265	0.173	0.397	0.128	0.417	0.192
80% (0.48)	0.317	0.150	0.426	0.122	0.439	0.178
DP + Futures + Options + CRC						
60%	0.301	0.036	0.429	0.009	0.564	-0.143
70%	0.381	-0.097	0.488	-0.137	0.643	-0.281
80%	0.477	-0.280	0.552	-0.303	0.734	-0.450
DP + Futures + Options + CRC with premium subsidy						
60% (0.64)	0.298	0.030	0.425	-0.013	0.551	-0.167
70% (0.59)	0.381	-0.112	0.486	-0.150	0.630	-0.321
80% (0.48)	0.482	-0.307	0.553	-0.328	0.723	-0.502

Note: premium subsidy rates are obtained from the actuarial files of risk management agency (RMA), USDA.

5.5 Sensitivity of the Optimal Hedge Ratios to Target Income

The sensitivity of the LPM₂ optimal hedge ratios to varying levels of target income per acre is examined by increasing (decreasing) the target net income by 20% and 50% for the base scenario. The results of such sensitivity tests in table 5.9 show that increasing the target payoff in the LPM₂ hedge model induces the optimal hedge ratio in futures to increase slightly. But the effects on put options appear to depend on the specific crop and county combination and could lead to a slightly higher or a lower use of put options. The insensitivity of the optimal LPM₂ hedge ratios to the target income indicates that even if the target income can not be determined precisely, the optimal hedge ratios would not be substantively different.

Table 5.9 Optimal LPM₂ Hedge ratios at Varying Target Income Levels in Base Scenario

Target Income	Cotton		Cotton		Soybean Gaussian	
	Gaussian Copula		Frank Copula		Copula	
	h_x	h_z	h_x	h_z	h_x	h_z
0.5*($Epy_f - C$)	0.12	0.262	0.29	0.163	0.34	0.263
0.8*($Epy_f - C$)	0.13	0.261	0.31	0.157	0.35	0.265
$Epy_f - C$	0.14	0.259	0.32	0.158	0.35	0.266
1.2*($Epy_f - C$)	0.15	0.257	0.33	0.159	0.36	0.266
1.5*($Epy_f - C$)	0.16	0.255	0.34	0.157	0.37	0.267

Note: p is cash price, y_f is farm yield, C is production cost

CHAPTER 6

SUMMARY AND CONCLUSIONS

6.1 Summary

The prevalence of two typical risks in crop farming activities, production uncertainty and price uncertainty, induces hedging demands for both futures and options by crop farmers. This study extends earlier work on the interaction of government payments, federal crop insurance plans, and the hedging demands of U.S. crop farmers for futures and options by examining the effects of government supported risk management tools on the joint use of futures and put options in a downside risk hedging model.

The high proportion of government payments in total crop farm income and the purchase of subsidized crop insurance have changed the income distribution of crop farmers. Thus, the risk management behavior of crop farmers is greatly influenced by these programs with respect to their use of private market risk management tools, such as futures and options. On one hand, acknowledging the effects of government payment programs and crop insurance on hedging will assist crop farmers to adjust their positions in futures and options appropriately. On the other hand, evaluations of such effects will help policy makers to better understand the impacts of potential changes in related policies.

The research literature until recently has viewed the expected utility (EU) hedge model as the only approach used to examine the effects of crop insurance policies and government payments on the use of futures and options. Inclusion of crop insurance, government payments, and options into the risk management portfolio acts to censor the portfolio payoffs at multiple

points, and thus restricts the differentiability required for analytical derivation. As a result, stochastic simulation and numerical optimization methods have been the preferred techniques for evaluating these effects. However, because the true utility function is not known, results obtained from a subjectively-selected utility function may be misleading and lack generality.

To avoid these drawbacks of EU hedge model, this study uses a utility-free downside risk hedge model, the second-order lower partial moment (LPM_2) hedge model, to investigate the relationships between the government-subsidized risk management tools and market risk management instruments. In addition to its utility-free feature, the LPM_2 hedge model is more relevant than the EU model when the government payments and insurance are considered in the hedge portfolio. This stems from the purpose of the government payments and federal crop insurance plans, which is to provide protection against low farm income. Theoretically, the LPM_2 criterion is consistent with third-order stochastic dominance. Since the third-order stochastic dominance exists if and only if the expected utility criterion yields the same rankings for all the utility functions with the properties of $U' > 0$, $U'' < 0$, and $U''' > 0$, LPM_2 is consistent with the expected utility criterion under the same conditions.

This study evaluates the effects of government payments and crop insurance in the LPM_2 hedge model for a representative cotton and soybean farmer in Colquitt/Bulloch county of Georgia. The representative farmer in a county is synthesized in such a way that for any year, the mean of the yield distribution equals the county yield, but the actual yield could be any actual farm-level yield realized in the county. The target income in the LPM_2 model is set at the mean of the income distribution.

Several portfolios are formulated for the representative farmer to assess the effects of government payments and crop insurance on the optimal hedge ratios in futures and put options.

The portfolio in the base scenario includes only futures and options. The remaining portfolios are created by including APH, CRC, DP, LDP, and CCP separately or jointly into the base portfolio. Since CCP provides extra income protection to crop farmers in conjunction with LDP, CCP comes into the portfolio only when LDP is already in the portfolio.

To solve for the optimal hedge ratios required to evaluate the effects of crop insurance and government payments on hedging, the harvest-time futures price, cash price and yield are simulated. This study applies the copula method to simulate the county yields and futures price. Compared to the traditional simulation method based on a multivariate normal assumption, copula simulation has the advantage of flexibility in two aspects. First, copula simulation allows the joint distribution of the individual variables to be some known, or even unknown, joint distribution other than a multivariate normal distribution. Second, the marginal distributions of the individual variables need not to be, or be transformed to, normal distributions.

Two copulas, a Gaussian copula and a Frank copula, are used to simulate cotton futures prices and county yields. Given that the Gaussian copula and the Frank copula are the same under the condition that the individual variables are independent, only Gaussian copula is applied for simulating soybean data, because since no significant interdependence was detected between historical soybean county yields and the transformed futures prices.

County yields and futures prices used in this study are obtained by three major steps in copula simulation. First, the parameters in the selected copula are estimated. This study applies maximum likelihood method to estimate the parameters in the Gaussian copula and the Frank copula. Second, unit uniform distributed variates with the same dependence as presented in the historical county yield and futures price are simulated according to the estimated Gaussian and Frank copula. Different copulas generally have different algorithms to generate unit uniform

variates. Third, variates of county yield and transformed futures price are simulated by substituting the generated uniform variates from the second step into the appropriate inverse cumulative distribution functions.

To simulate farm-level yield with variance conditional on the level of county yield, as presented in the historical data, conditional cumulative kernel estimation is applied to generate farm yields based on the generated county yields from the Gaussian copula or the Frank copula. The other two variables, cash price and market year average price, are simulated based on their linear relationship with futures price.

6.2 Conclusions

The inclusion of government programs and federal crop insurance in the hedging portfolio has always reduced the downside income risk to crop farmers. The effects of crop insurance and government payments on the use of futures and options are evaluated by comparing the optimal hedge ratios in various scenarios with the base scenario.

In the LPM₂ hedge model, inclusion of APH insurance in the portfolio increases the hedging demand for futures, because the negative correlation between harvest-time price and yield indicates a positive relation between the value of APH and the price. However, the effects of APH on the use of put options are mixed. Such findings about APH extend the results in earlier works by including put options together with futures in the potential risk management portfolio. These results suggest that APH has a positive effect on the futures hedge regardless of the use of put options.

The CRC revenue insurance policy consistently increases the hedging position of futures but decreases the hedging positions of put options. The effect of CRC on the futures hedge is consistent with the previous work by Coble et al. (2000), but conflicts with the results of Mahul

(2003) and Wang et al. (2004). The inconsistency might result from the omission of put options by Wang et al. and the use of a straddle but not put options directly by Mahul.

Direct payments have no effects on the LPM_2 hedge ratios because it increases both the actual farm income and the expected income by the same amount. The availability of LDP to the crop farmer marginally increases the hedge ratio in futures but considerably reduces the purchase of put options. The substitution effect of LDP for put options is consistent with the analysis that LDP is an implicit free put option provided to farmers. It is also consistent with the empirical finding of Hanson et al. (1999) from an EU hedge model. The protection provided by LDP could even convert the crop farmer from a hedger into a speculator. CCP decreases the hedging demand for futures, but shows mixed effects on put options across the two crops, cotton and soybeans. The joint effects of CCP on futures and on put options suggest that CCP substitutes the aggregated hedging demands for the private market risk management tools.

Regarding the interaction of the selected insurance policies and government payments on the use of futures and put options, LDP has almost no interaction with APH and CRC. Conversely, the interactive effects of CCP with APH and CRC on the use of futures and put options are non-trivial and mixed.

The insurance policies and government payments evaluated in the EU model have the same directional influences as they are in the LPM_2 hedge model. However, the LPM_2 model may be preferred by crop farmers, because the payoff distribution of the hedge portfolio from the LPM_2 hedge model has a higher minimum value, a higher maximum value and a higher right skewness compared to the hedge portfolio of equal mean from the EU hedge model.

Compared to the EU hedge model, the LPM_2 model also yields a consistently smaller optimal proportion of the expected production to be hedged with futures and put options. Such a

result confirms the hypothesis that model misspecification is likely another reason for the fact that the observed hedging in futures by farmers is less than the predicted hedge by using the EU model. If the hedging objective is to minimize the perceived risk to farm income, but not to maximize the expected utility, then crop farmers would appear to under-hedge from the perspective of the EU model.

The finding that the LPM₂ hedge model generally yields a lower hedge in futures but a higher hedge in put options compared to the EU hedge model may result from the reality that the asymmetric payoff distribution of put options is consistent with the more skewed distributions of the hedge portfolios that the LPM₂ hedge model generally yields.

Perceived biases in the seasonal futures prices are shown to have effects on the hedging demand for futures. A lower (higher) futures price at planting compared to the expectation of the futures price at harvest decreases (increases) the hedge ratios in futures. Transaction costs associated with trading in futures are assumed to be composed of commissions and interest forgone on margin deposits. By model design, the commissions would not affect the optimal hedge ratios. However, transaction costs incurred by the interest loss of margins decreases the hedging demand for futures.

Sensitivity tests of varying insurance coverage levels on hedge ratios suggest that the higher the coverage level, the stronger the effects that the crop insurance policies will have on the hedge ratios. The small effects of insurance premium subsidy rates on the hedge ratios indicate that, compared with government subsidies in terms of LDP and CCP, the crop insurance premium subsidies may have little impact on the hedging decisions of the crop farmers even though such subsidies have amounted to billions of dollars per year. On the contrary, the government subsidies in the form of LDP and CCP have more substantial effects on the hedging

demands for futures and options. The robustness of the optimal LPM₂ hedge ratios to the target incomes indicates that even if the target income can not be determined precisely, the optimal hedge ratios would vary minimally.

6.3 Suggestions for Future Research

Possible extensions to this study can be made in several directions. First, this study has not allowed crop farmers to decide whether to buy insurance or not. Future research could investigate the interactions of futures, options and insurance by allowing the producer to determine his/her positions jointly over all the feasible risk management tools. Second, this study calculates the payoffs of government payments according to the parameter values in the current farm bill. The effects of changes in the parameter values of the government payments on hedging could be investigated to gain a better understanding of the relationships between government payments and the use of futures and options. Third, this study used the actuarially fair premiums for the crop insurance rather than the actual premiums charged by these insurance plans. To use the actual premiums might make the model a better representation of the real portfolio risk management problem faced by crop farmers. Fourth, in the process of data simulation, the bandwidths used in the conditional kernel density estimation are determined based on the simple normal reference criterion. Because the empirical distribution obtained from the kernel density approach usually is very sensitive to the selection of the bandwidths, other bandwidths selection criteria may be tested to determine the robustness of the numerical results to the empirical conditional distribution of the farm yields.

In summary, this study makes two primary contributions to the agriculture economics literature. First, this dissertation developed a downside risk hedge model, the LPM₂ hedge model, to evaluate the interactions of government and private risk management tools used by U.S. crop

farmers. The LPM₂ hedge model is a more suitable model than the existing EU hedge model to investigate the interactions among risk management tools because the LPM₂ hedge model focuses on the downside risk management and does not have the limitation of utility subjectivity of the EU hedge model. Second, this study initiated the application of the conditional kernel density method and the copula approach in simulating the crop prices and yields. Such simulation techniques can be extended to model joint distributions of various variables of research interest.

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APPENDICES

A

The relationship between lower partial moment and stochastic dominance rules are briefly proved by the following steps.

First, define the repeated integrals of a probability distribution.

Define

$$F(Z) \equiv F_0(Z) \equiv \int_a^Z f(t)dt, \quad F_n(Z) \equiv \int_a^Z F_{n-1}(t)dt.$$

$$\text{For example } F_1(t) = \int_a^Z F(t)dt, \quad F_2(t) = \int_a^Z F_1(t)dt.$$

Second, by the definition of stochastic dominance, distribution F weakly stochastic dominate distribution G to the nth order if and only if

$$F_{n-1}(Z) \leq G_{n-1}(Z), \forall a \leq Z \leq b \quad (\text{A1a})$$

$$F_k(b) \leq G_k(b), \text{ for } k = 1, 2, \dots, n-2. \quad (\text{A1b})$$

Third, integrating by parts, the nth-order lower partial moment can be rewritten as a multiplier of nth order repeated integrals of a probability distribution.

$$\begin{aligned}
LPM_n(F; Z) &= \int_a^Z (Z-t)^n f(t) dt = F(t)(Z-t)^n \Big|_a^Z + n \int_a^Z (Z-t)^{n-1} F(t) dt \\
&= nF_1(t)(Z-t)^{n-1} \Big|_a^Z + n(n-1) \int_a^Z (Z-t)^{n-2} F_1(t) dt \\
&\quad \vdots \\
&= n! \int_a^Z F_{n-1}(t) dt = n! F_n(Z)
\end{aligned} \tag{A2}$$

In each step of A2, the lead term is zero since $F_i(a) = 0$ and $(Z-Z)^i = 0$.

Therefore, the sufficient and necessary conditions for distribution F to stochastically dominate G to the nth order, (A1a) and (A1b), can also be stated as

$$LPM_{n-1}(F; Z) \leq LPM_{n-1}(G; Z), \forall a \leq Z \leq b \tag{A3a}$$

$$LPM_k(F; b) \leq LPM_k(G; b), \text{ for } k = 1, 2, \dots, n-2. \tag{A3b}$$

B

Simpson's rule which approximates the function to be integrated with the piece-wise quadratic polynomials, was used to calculate conditional probability such that

4.21 and 4.22 can be approximated by

$$\begin{aligned}\hat{P}(y_f < y_f^*, y_c = y_c^*) &= \int_0^{y_f^*} \frac{1}{n} \sum_{i=1}^n K_{hf}(y_f - Y_{fi}) K_{hc}(y_c^* - Y_{ci}) dy_f \\ &\approx \sum_{j=1}^l w_j \left[\frac{1}{n} \sum_{i=1}^n K_{hf}(y_{fj} - Y_{fi}) K_{hc}(y_c^* - Y_{ci}) \right]\end{aligned}\quad (4.21A)$$

and

$$\begin{aligned}\hat{P}(y_f < y_f^*, y_c = y_c^*) &= \int_0^{y_f^*} \frac{1}{n} \sum_{i=1}^n K_{hf}(y_f - Y_{fi}) K_{hc}(y_c^* - Y_{ci}) dy_f \\ &\approx \sum_{j=1}^l w_j \left[\frac{1}{n} \sum_{i=1}^n K_{hf}(y_{fj} - Y_{fi}) K_{hc}(y_c^* - Y_{ci}) \right]\end{aligned}\quad (4.22A)$$

where l is an odd number of the nodes that divide the interval $[0, y_c^*]$ into $(l-1)$ subintervals of equal length h_s with $h_s = y_c^*/(l-1)$; w_j is the weight associated with each node with $w_1 = w_l = h_s/3$ and, otherwise, $w_j = 4h/3$ if j is even and $w_j = 2h/3$ if j is odd (Miranda and Fackler, 2002).

C

The values of log-likelihood functions for the detrended cotton yields and the log difference of futures prices are calculated in table c.1 based on three alternative density functions of bivariate normal distribution, Gaussian copula and Frank copula (C1- C3).

$$f(x, y) = \frac{1}{2\mathbf{p}\mathbf{s}_x\mathbf{s}_y\sqrt{1-\mathbf{r}^2}} \exp\left(\frac{(x-\mathbf{m}_x)^2/\mathbf{s}_x^2 + (y-\mathbf{m}_y)^2/\mathbf{s}_y^2 - 2\mathbf{r}(x-\mathbf{m}_x)(y-\mathbf{m}_y)/\mathbf{s}_x\mathbf{s}_y}{2(1-\mathbf{r}^2)}\right) \quad (\text{C1})$$

$$f(u, v) = \frac{1}{2\mathbf{p}\sqrt{1-\mathbf{r}^2}} \exp\left(\frac{(\Phi^{-1}(u))^2 + (\Phi^{-1}(v))^2 - 2\mathbf{r}\Phi^{-1}(u)\Phi^{-1}(v)}{2(1-\mathbf{r}^2)}\right)$$

(C2)

$$f(u, v) = \frac{-\mathbf{q}(e^{-\mathbf{q}} - 1)e^{-\mathbf{q}(u+v)}}{((e^{-\mathbf{q}u} - 1)(e^{-\mathbf{q}v} - 1) + e^{-\mathbf{q}})^2} \quad (\text{C3})$$

\mathbf{r} is the Pearson's correlation between the detrended county yields and the log difference of futures prices, $u, v \sim Unif(0,1)$, and \mathbf{q} is the estimated parameter in Frank copula.

Table C.1 Log-likelihood

Distribution	Bivariate Normal	Gaussian Copula	Frank Copula
Log-likelihood	-166.691	-75.1412	1.63606

Since Frank copula and Gaussian copula have higher log-likelihood value than the bivariate normal assumption, Frank copula and Gaussian copula provide a better fit to the county yields and futures prices than the bivariate normal distribution assumption for the case of cotton yields and futures prices in Colquitt county.