THE EFFECTS OF ADVERSE SELECTION AND EFFECTIVE COVERAGE LEVELS ON CROP INSURANCE PARTICIPATION

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ABSTRACT

The effects of crop insurance premium levels (adverse selection) and insurance coverage levels (effective coverage) on crop insurance participation are examined. A simulation of premium rates, coverage levels, and participation rates over time models the implications of random yield fluctuations using farm and county level data from Chouteau County, Montana, wheat producers. A statistical analysis measuring participation as a function of expected indemnity payments, effective coverage levels, and premium rates is conducted using cotton regional level data from the majority of the cotton producing states using a weighted ordinary least squares regression. The simulation shows that as rates increase (decrease) and coverage levels decrease (increase), participation levels decrease (increase). It also demonstrates that by indexing producers' insurable yields, participation rates stabilize. The regression results yield a significant, positive coefficient for the expected indemnity variable. However, contrary to expectations, the coefficient for effective coverage is insignificant and negative. The premium rate coefficient is insignificant and negative.

CHAPTER 1

INTRODUCTION

Agriculture is considered by most to be an inherently risky industry. Farmers are subject to production risks, stemming from nature's whimsical manner of producing disastrous events such as drought, flooding, and hail, among many other occurrences. The relative frequency of events is believed to generate significant yield instability.

This, however, is not the only uncertainty faced in agriculture. Farmers are subject to price risks as well as production risks. Both national and international market conditions affect the price that farmers receive for their commodities. However, local production may have little affect on the total world-wide amount of quantity available. As a result, low local production may have a negligible impact on price.

A useful tool to diminish risk and combat the effects of natural events beyond a producer's control is crop insurance. Insured correctly, producers have the ability to partially absolve themselves of risk.

The Market for Crop Insurance

A market for crop insurance will exist when there is both demand for and a supply of insurance contracts that interact to render a price for the contracts acceptable to producers and insurers. The producer's decision to purchase an insurance contract hinges on the

producer's net expected payout, the difference between the expected indemnities of and the premium to be paid for the contract. If the net expected payout is positive, risk averse and risk neutral producers will choose to insure. If the net expected payout is negative, as is the case in most of the private insurance markets, risk neutral producers will not insure. Only risk averse producers would choose to purchase insurance when premium price exceeds expected indemnities because risk averse producers place a premium on reducing risk and are willing to pay this premium in order to insure. Thus, the demand for crop insurance is really a consequence of risk aversion. In the case of crop insurance, the federal government subsidizes producer premiums. The resultant lower premium may increase the net expected payout enough to induce previously non-participating producers to purchase insurance.

As it turns out, there have been many attempts at establishing a private supply of crop insurance. These attempts, however, have not proved fruitful and have failed in general. Without a supply of insurance contracts, no market for insurance will exist.

Not surprisingly, a supply of crop insurance contracts has sprung up from the government sector. A major reason for this can be gleaned from the political economy literature. Becker (1983) asserts that special interest groups supply politicians with incentives, in the form of votes and campaign contributions, that entice the politicians into appeasing special interests. Heuth and Furtan (1994) state, "There is a clear, effective, political demand for protection from climatic and market risks by agricultural producers in a great number of countries of the world."

Gardner (1987) elaborates upon the subject. He points out that government support for programs varies with the ability of groups to generate political pressure. This support is

mostly a function of the size of a group and the group's geographic dispersion. Agricultural special interests such as the National Cotton Council and the National Association of Wheat Growers are sizable and well organized, leading the way for successful lobbies of Congress to provide government programs.

Current Crop Insurance

The Risk Management Agency (RMA) underwrites a primary insurance product and a number of experimental crop insurance alternatives. The principal insurance product, Multiple Peril Crop Insurance (MPCI), has been offered in various forms since 1939.

The crop insurance program has enjoyed modest success in the 1980's and 1990's in terms of the size of the program. Beginning in 1980, the onset of major changes to the program, MPCI was offered for 28 crops in 1676 counties. The number of crops covered increased to 51 in 1992, and the number of counties covered to 3026. In 1999, MPCI is offered for 100 crops to producers in 3026 counties (Atwood et al. 1999).

Despite the expansion of coverage offered by MPCI, however, one must be careful in evaluating the success of the crop insurance program. Generally, there are two statistics which measure the performance of crop insurance that are useful to examine. They are loss ratio and participation rate.[1] Loss ratio is equal to indemnities over premiums while the participation rate is the number of acres actually insured in the program divided by the total number of acres that could possibly be insured. A loss ratio greater than one implies

[1] Loss ratio should not be confused with loss cost ratio. Loss ratio is indemnities over premiums while loss cost ratio is indemnities over total liability. Liability is the amount of indemnity that would be paid if no crop was harvested.

performance that is less than actuarially neutral resulting in net losses to the government. A loss ratio equal to one implies actuarial neutrality and a loss ratio less than one implies net gains to the government. From the government's point of view, loss ratios less than one are preferable and in fact, the target loss ratio is currently set at 0.88 (Driscoll 1995).

"Ideally [for the government], the federal crop insurance program would enjoy high participation rates and provide most farmers with protection against losses but on average would require no subsidies,"(Goodwin and Smith 1995). Presently, the participation goal is fifty percent as set by the 1980 Federal Crop Insurance Act and a target loss ratio of 0.88 is used in computing insurance rates.

For several reasons, these goals have rarely been met. Apparently moral hazard and adverse selection play a large part in losses and in participation from year to year (Just and Calvin 1993; Smith and Goodwin 1994). Nevertheless, there are other explanations for losses and particularly for participation.

Effective Coverage

A producer's expected yield is the yield that is anticipated by the producer. This is mathematically equal to the mean of the producer's yield probability distribution function. It is generally assumed that a producer knows this yield with certainty. However, given a pool of heterogenous producers, it is difficult if not impossible for an insurance agent to detect each and every producer's true expected yield. Thus, the agent must assign an expected yield to each producer. The RMA does this using actual producer history (APH yields). An APH yield is the simple average of the most recent four to ten years of a farmer's

production. The APH yield is only an approximation of the producer's expected yield and errors can occur because the short set of data used in computing the APH yield may reflect periods of unusually bad or unusually good production.

Effective coverage can be defined as the percent coverage of a producer's expected yield. It is computed as the percent coverage election multiplied by the farm's APH yield and divided by the farm's expected yield, which is equivalent to insured yield over expected yield. For example, if a wheat producer chooses to insure 65 percent of his APH yield, has an APH yield of 30 bushels per acre, and his *true* expected yield is 35 bushels per acre, then the producer's effective coverage is:

$$\frac{65\% * 30\ bu/ac}{35\ bu/ac} = 55.7\% \tag{1.1}$$

As can be seen from the above example, a farmer's effective coverage may differ from the level of coverage chosen. *Ceteris paribus,* the lower the effective coverage level, the less likely the producer is to purchase insurance.

Of course, other variables also influence a farmer's insurance choice including the expected indemnity payout relative to the premium payment. Farmers with relatively high expected indemnity payment have a larger incentive to purchase insurance. The relationship between expected indemnity payouts and premiums necessary to trigger the purchase of insurance is dependent on the farmer's risk attitude. Since farms and farmers are heterogeneous, participation decisions will vary across farms. For a given level of risk aversion, farmers with low risk (low expected indemnity payment) might not buy insurance when farmers with high risk (high expected indemnity payment) would purchase insurance, even though both are facing the same insurance premium. Therefore, it is the heterogeneity

among producers in a given pool of risk, particularly with regard to production risk (expected indemnity payout), that leads to adverse selection. This adverse selection is difficult to empirically separate from the influence of expected coverage.

Current MPCI ratemaking procedures are usually based upon the last 20 years of indemnity payment. A series of above average yield years will result in lower premium rates because less indemnities than average were paid out over those years. As premium rates decline, participation will increase. At the same time, producers' APH yield increases will increase effective coverage levels and further encourage participation. Holding premium rates equal, if effective coverage increases, participation will increase stemming from the fact that the higher the coverage level, the higher are expected returns. This scenario would reverse itself for cases in which yields were repeatedly lower than average. The influences of adverse selection and effective coverage levels are thus compounding.

Participation continues to be a major concern of Congress and RMA, as evidenced by the 1994 Crop Insurance Reform Act (CIRA). It is clear that the intentions of CIRA were to decrease costly federal disaster programs while still providing farmers with consistent and reliable coverage when crop failures occurred (Goodwin and Smith 1995). Increased participation rates and/or more stable participation rates will lead to a decrease in disaster relief payments to the agricultural community because more producers will be insured against such disasters a greater percentage of the time.

In order to evaluate MPCI, factors affecting participation rates must be identified and studied. While attention has been given to participation rates in the crop insurance literature, no previous studies have focused on the relationship between effective coverage levels and

participation rates. By modeling the effects of effective coverage levels as well as other factors on participation rates, new insights may be gained.

Objective of Thesis

The main purpose of this thesis is to examine the relationships between participation rates and effective coverage levels, expected indemnity payouts, and premium rates. Furthermore, specific methods of assigning coverage levels will be examined.

This will be done in two separate exercises. The first will be a simulation of MPCI performance over time for wheat producers in Chouteau County, Montana. The second exercise of the thesis will be to model the effects of effective coverage, expected indemnity payments, and insurance rates on participation using a weighted ordinary least squares (OLS) regression.

The simulation will evaluate the performance of MPCI over time using standard Monte Carlo procedures to generate random yield realizations through time. Participation rates will be computed and examined. This model will compute expected yield by the current, standard APH method and will generate rates using current MPCI ratemaking procedures.

Furthermore, in addition to simulating current MPCI practices, proposed changes in setting producer's insurable yields will be examined. As mentioned before, currently a producer's insurable yield is set by averaging the most recent four to ten years of production. A new method for setting insurable yields has been proposed and is called indexing. This method differs in that it averages the difference between the producer's yield and the average county yield over the most recent four to ten years of data and adds this average difference

to the long term expected county yield, which is computed as the average detrended county yield for a longer time period. Mathematically:

$$\hat{f}_t = \hat{c} + (\bar{y} - \bar{c}) \tag{1.2}$$

where $\hat{f}_t$ is the producer's insurable yield, $\hat{c}$ is the expected county yield, and $(\bar{y} - \bar{c})$ is the average deviation between farm yield and county yield for the years reported by the farm.

By indexing, a producer will not be penalized for bad years if yields were also unusually bad for the corresponding county. Conversely, a farmer will not be rewarded for a series of good years if the whole county also experienced bumper crops. This method will stabilize expected yields over time. The effect of indexing on participation rates will be analyzed by comparing the results from the simulated current APH method with the indexed method.

The second section of analysis involves estimating the demand for crop insurance for cotton producers in the United States with cross sectional data aggregated by risk region.[2] This will be done by employing a weighted OLS model. The hypotheses being examined is whether effective coverage, expected indemnity payouts, and premium rates influence participation rates.

The remainder of the thesis will be divided into four chapters. Chapter two will present a brief history of crop insurance which will be followed by a literature review in chapter three. Procedures and data will be presented in chapter four. Chapter five will be results and conclusions.

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[2] These are regions which have similar yield variability as determined by the Federal Crop Insurance Corporation (FCIC). The regions differ by crop and may cross state borders.

CHAPTER 2

HISTORY OF CROP INSURANCE IN THE U.S.[3]

Crop insurance in the United States has existed in various forms for at least a century. From 1899 through 1920, crop insurance was offered by private companies with no financial success. The Revenue Realty Guarantee Company was one of the first attempts at offering an "all-risk" insurance program to agricultural producers. In 1899, the company offered a bid of $5.00 per acre to purchase a producer's entire wheat crop regardless of yield. Documentation on this endeavor is lacking. However, the company discontinued business after only one year (Hoffman 1925).

In the late 1910's, three private crop insurance companies began offering insurance policies to producers in North and South Dakota, as well as Montana. Heavy losses were incurred from these contracts because of drought and also because areas covered were too small to effectively spread risk (Valgren 1922). Other reasons for losses were the presence of moral hazard and adverse selection. As Goodwin and Smith (1995) point out, monitoring was difficult and costly.

In 1920, a revenue product was introduced by the Hartford Fire Insurance Company. The insurance contract was to protect not only yield but also price. In testifying before

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[3] The paper by Kramer (1983) is an excellent synopsis of the early history of crop insurance and was largely followed and summarized.

Congress, the company's president reported that sharp price declines resulted in net losses of $1.7 million (Valgren 1922).

At the same time, Congress began to inquire as to the plausibility of crop insurance. Data from the United States Department of Agriculture (USDA), published in 1922, enumerated the various causes of crop loss from 1909-1918. Drought was responsible for the greatest amount of damage. Other causes of loss were frost, excessive moisture, diseases, pests, and winds. Hail damage, the only peril privately insured against other than fire, accounted for less than two percent of all crop failure (Valgren 1922).

In 1922, a resolution introduced by Senator McNary (R-Oregon) provided for the appointment of a select Senate committee whose purpose was to investigate crop insurance. The investigation was to focus on the costs and adequacy of private insurance, sufficiency of crop yield data, and the value of extending the scope of insurance (Senate Select Committee, *Investigation of Crop Insurance*).

Several different interests testified before the Senate and all agreed that a successful program would need to be national and that better data than what was currently available would be required. Even with these findings, Congress expressed interest in sponsoring crop insurance.

The USDA again conducted research on crop insurance in 1936. With more data provided by the Agricultural Adjustment Agency, it was concluded that an actuarial basis for the insurance of wheat could be established (Rowe 1938). Political support for the crop insurance program was enhanced by widespread droughts in 1934 and 1936. During the 1936 presidential race, President Roosevelt appointed an interagency committee to study the

possibility of government-sponsored crop insurance. Two days later, his opponent, Alf Landon, declared, "the question of crop insurance should be given the fullest attention."

In 1937, Roosevelt's committee recommended establishing a federal crop insurance program for wheat yields but not for price. However, the birth of crop insurance by the federal government was controversial. For example, editors of the *Christian Science Monitor* asked:

> Will the program become in effect an underwriting of high-risk farming areas which in fact ought to be retired from farming and put to grazing, forests or other use instead of burdening steadier farms with cutthroat competition in good years and a demand upon them for assistance in bad years?

Still, Congress persisted and in 1938 legislation created the Federal Crop Insurance Corporation (FCIC), a subsidiary of the USDA. The FCIC was given the responsibility of administering the first Multiple Peril Crop Insurance program, which was created under Title V in the 1938 Agricultural Adjustment Act. Since its outset, the history of federal Multiple Peril Crop Insurance can be divided into five periods: 1938-1944, 1946-1973, 1974-1980, 1980-1994, and 1994-1999.[4]

Period I: 1938-1944

Wheat growers harvesting crops in 1939 were the first to receive government crop insurance coverage. They were offered coverage levels between 50 and 75 percent of recorded average yield against most conceivable perils.

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[4] These distinctions were presented by Goodwin and Smith (1995) and Atwood et al. (1999).

The national loss ratio from this first experience was 1.52. Losses resulted partially from drought the first year. There were also fundamental flaws in the program's administration that contributed to the poor loss ratio. Farm level data was insufficient in many counties and inexperienced estimators relied too heavily on county level data leading to underestimated premiums. Furthermore, insurance contracts for wheat were completed late and were not sent out until after crops had been planted. This created an adversely selected pool because nearly half of the original applicants allowed their contracts to lapse (Clendenin 1942).

In order to reduce the high loss ratio, new premium calculations were adopted. Throughout the remainder of the period, however, losses remained high. During the next three years, the loss ratio averaged 1.65 prompting Congress to cancel the crop insurance program in 1943.

Period II: 1945-1973

In the late 1940's, steps were taken to address problems in the crop insurance program. Three-year contracts were introduced in order to deal with the problem of adverse selection. Requiring producers to sign up for three years at a time would discourage them from jumping into the program for a single year in anticipation of short term gains. Also, only county data was used to estimate premiums and only partial coverage was available to producers (Kramer 1983).

Beginning in 1945, MPCI was reintroduced for major crops such as wheat, cotton, flax, and others in which sufficient data was available. The 1945 and 1946 crop years

produced high losses, once again, stemming from problems previously incurred, including poor data and administrative problems (Atwood et al. 1999).

The high losses in 1945 and 1946 resulted in Congress reducing the program to an experimental phase. Harsher restrictions were placed upon the number of counties in which insurance would be available and on the number of farms that were required for a county to be insured (FCIC, *Report of the Manager, 1948*).

The program's experimental phase saw a surplus of premiums over indemnities in three of five years. The five-year average loss ratio was 0.97. Reserves, however, were not accumulating quickly enough. The three-year surplus was still not sufficient to cover one year of losses such as that of 1949 (FCIC, *Report of the Manager, 1953*).

In 1955, the FCIC reported that several high-risk counties in Colorado, New Mexico, and Texas would not be offered insurance beginning in 1956. The board of directors was convinced that no sound premiums could be established in these counties. If these counties had not been included in the program, premiums would have exceeded indemnities in each year after 1948 (FCIC, *Report of the Manager, 1956*).

The 1960's saw the FCIC concentrate on increasing coverage. In 1965, premiums were lowered to stimulate participation. Rate decreases had the desired effect as participation did indeed increase, but so did government cost. Indemnities exceeded premiums in 1967, 1968, and 1969 (FCIC, *Annual Report, 1969*, and *Annual Report, 1970*).

New management in 1969 reviewed problems of the crop insurance program. Findings were of the flavor that losses resulted largely from coverage increases and rate reductions which supporting statistics did not justify. Shorter time periods used in calculating

rates tended to follow recent trends rather than long term averages. Thus, rates were often times lower than experience could justify (FCIC, *Annual Report, 1969*).

Several changes were made to the program in 1970 to correct these problems. These adjustments, including high loss program cancellations and premium adjustments for other crops, led to average loss ratio of only 0.6 through the 1973 crop year (Goodwin and Smith 1995).

Period III: 1974-1980

In the mid-1970's, the Agriculture and Consumer Protection Act of 1973 along with the Rice Production Act of 1975 enabled a disaster relief program. The disaster payments were very popular with producers because there was no premium cost to participate in the program.

However, major criticisms ensued. It was argued that the disaster program led to production in high-risk areas, insured against avoidable losses caused by poor management, and encouraged producers in arid regions to collect payments rather than plant under marginal conditions (Miller and Walter 1977). In the late 1970's, loss ratios fluctuated between a low of 0.5 in 1978 to a high of 3.29 in 1980, due mostly to changes in growing conditions (Goodwin and Smith 1995).

Period IV: 1980-1994

The main purpose of the Federal Crop Insurance Act of 1980 was to replace disaster aid with the more actuarially sound crop insurance program. Annual restrictions on expansion

were removed and new coverage levels of 50, 65, and 75 percent coverage were introduced, instead of the previous single coverage rate of 65 percent. The government would subsidize 30 percent of producer premiums for both the 50 and 65 percent coverage level. Any increase in coverage beyond the 65 percent level would have to be actuarially neutral. The subsidy paid to a producer selecting the 75 percent coverage level would be equal to the subsidy amount received had they chosen 65 percent coverage. In addition, the government would cover administrative costs. The other notable change in the crop insurance program was the difference in the marketing aspect of insurance. Private companies could now sell insurance in as many counties as they desired (Goodwin and Smith 1995).

Up until 1982, premium rates for individual producers were set using county level data and reflected the situation of average farms in the county. In 1983, a new rate-setting procedure based on an individual's actual production history was introduced. A producer's history of up to ten years could be used to determine their average yield, but individual farm variability was still ignored and farms with the same average yield were charged identical rates. Also in 1983, another new aspect came about called optional units. Whereas previously, farmers could only insure all of their acreage under one contract, now they could insure land in different sections separately, where each tract of land separately insured was called a unit. This benefitted large farms that previously were unlikely to experience losses on a large percentage of land in production (Goodwin and Smith 1995).

The loss ratio in the 1980's rose from an annual average of 1.21 (1981-1983) to 1.32 (1984-1990). The higher loss ratio was attributed to program expansion which insured more marginal areas as well as severe droughts in 1985 and 1988. The new innovations in the

insurance program, particularly optional units, also contributed to the increased loss ratio (Goodwin and Smith 1995).

The 1990 United States Food, Agricultural, Conservation and Trade Act (the 1990 Farm Bill) extended the 1980 program. MPCI was continued, but the focus switched from increasing participation to dealing with high loss ratios and taxpayers costs. A provision was also included allowing FCIC to introduce new types of insurance contracts on an experimental basis (Goodwin and Smith 1995).

Period V: 1994-1999

In 1994, the Crop Insurance Reform Act was passed by Congress. This legislation changed MPCI slightly by allowing more flexibility in yield and price electives and by changing subsidy calculation rules. The act also made it more difficult for Congress to pass ad hoc disaster relief bills. Furthermore, new innovations in crop insurance were to be pursued, including cost of production insurance and revenue insurance (Atwood et al. 1999).

The annual average loss ratio over this period dropped to 0.79, with only one out of five crop years resulting in a loss ratio greater than one. Insured acreage over this period approximately doubled the level of the late 80's and early 90's.

CHAPTER 3

REVIEW OF LITERATURE

Theory of Insurance

Insurance contracts have existed for many years underwriting risks that range from a person's health to whether or not the Loch Ness monster exists.[5] While crop insurance has not been around for quite as long, it has been experimented with for over a century. During this time, the structure of insurance contracts has been examined.

The foundation for the theory of insurance stems from Von Neumann and Morgenstern's *Theory of Games and Economic Behavior*. Published in 1944, this work describes the neoclassical theory of behavior under uncertainty and is the basis for most insurance demand research.

Von Neumann and Morgenstern demonstrated the theory of expected utility. They asserted that an agent who faces s possible outcomes will act as if they maximized their expected utility,

$$E(u) = \sum_{s=1}^{S} \pi_s u(x_s) \tag{3.1}$$

where π_s denotes the probability of the sth outcome, x_s denotes the expected value of the sth outcome, and $u(\,)$ is a well behaved utility function with $u' > 0$ and $u'' < 0$. It is important

[5] Borch (1990) provides an enlightening description of insuring the risk of whether or not the Loch Ness Monster exists.

to note that in this context, π_s is considered to be known with certainty to all parties involved.[6]

Consider the two-state model of a risk averse individual endowed with initial wealth, W (Laffont 1989). The individual is faced with two possible outcomes, one in which the individual experiences no loss and one in which a loss, L, occurs. The two states can be expressed mathematically by the following:

(3.2) State 1 - $w_1 = W$

(3.3) State 2 - $w_2 = W - L$.

The individual has the option of purchasing an insurance contract that would shelter the agent from a loss. Assuming the insurance provider is risk neutral, contract costs are zero, and the insurance market is competitive, the actuarially neutral insurance premium will be:

(3.4) $$\alpha = \pi L,$$

where α is the premium paid by the agent to the insurance provider and π is the probability of experiencing the loss, L. This premium will satisfy the zero-profit condition brought about by competition in an industry.

If the insurance provider sets a price, $q = \pi$ (from the zero-profit condition), for each unit of insurance purchased, z, the agent will choose z in order to maximize:

(3.5) $$\underset{z}{MAX}\ [(1-\pi)\ u(w_1)\ +\ \pi\ u(w_2)]$$

---

[6] Knight (1965) distinguishes risk from uncertainty. Risk refers to situations for which the probabilities of various outcomes are known completely by the agents while uncertainty implies that the probabilities are unknown.

subject to the constraints:

(3.6) $$w_1 = \mathrm{W} - qz$$

(3.7) $$w_2 = \mathrm{W} - \mathrm{L} + z - qz.$$

The first order condition is:

(3.8) $$(1 - \pi)\, q\, u'(\mathrm{W} - qz) = \pi(1 - q)\, u'(\mathrm{W} - \mathrm{L} + z - qz).$$

Since $q = \pi$, the equation simplifies to:

(3.9) $$u'(\mathrm{W} - qz) = u'(\mathrm{W} - \mathrm{L} + z - qz).$$

Assuming that second-order conditions are met, in order for the equality to hold and for utility to be maximized, the quantity of insurance purchased must exactly equal the amount of loss possible, mathematically: $z = \mathrm{L}$. Therefore, the insured agent would choose a coverage level which completely insures the risk. In other words, insurance is complete.

Casual observation of the real world may show that most agents are not insured completely. In *Wealth of Nations*, Adam Smith notes that, "[the insurance] premium must be sufficient to compensate the common losses, to pay the expenses of management, and to afford such a profit as might have been drawn from an equal capital employed in any common trade."

This statement implies that a fair insurance premium is composed of three parts: 1) expected claim payments; 2) administrative costs; and 3) opportunity cost or risk premium, a return to the insurer for bearing risk. Borch (1990) represents this as:

(3.10) $$\mathrm{P} = \mathrm{E} + \mathrm{A} + \mathrm{R}.$$

In this equation, P is premium, E is expected payments, A is administrative expense, and R is the risk premium.

If premiums were purely equal to expected payments, a risk averse agent would insure completely. As can be seen from the equation above, a premium is normally going to be greater than the expected payment. Thus, agents often purchase incomplete coverage.

Problems With Insurance Contracts

Estimating premium rates is a very difficult matter. Ideally, premium rates would be estimated individually, encompassing only the specific situation relevant to each producer. The majority of the time, however, estimating rates in this manner is infeasible because of the prohibitive costs involved in gathering information for each insured individual. As of yet, comprehensive data that will allow individual rates to be developed does not exist in crop insurance.

Two major considerations that arise from this problem are adverse selection and moral hazard. These two problems, spawned by asymmetric information, are cited as the major reason for the losses that plague the federal crop insurance program (Goodwin and Smith 1995).

Adverse selection is a situation in which individuals have loss probabilities that are not homogeneous and cannot be observed by the insurer. Assume the insurer develops a single set of rates that reflect the situation of an average producer. These rates are presented to all individuals in a risk pool. Individuals then decide whether or not to purchase insurance based on their individual evaluation of their risk. Since the individual is likely to possess more information about their situation than the insurer, the individual can more accurately assess their own risk. If a producer's probability of experiencing a loss is greater than or equal to

the risk implied by the insurance rate and the producer is risk neutral or risk averse, that producer will purchase insurance. However, a producer who faces lower risk than implied in the premium rate will not purchase an insurance contract.

As a result of these circumstances, only producers whose risk is greater than or equal to the risk assumed by the insurer participate in the program. This leads to losses occurring more frequently than the insurer expected. A net loss to the insurer occurs because indemnities exceed premiums.

As long as detection of risk differences between producers is prohibitively expensive or the insurer is simply unable to detect risk differences among producers, the problem cannot be corrected by simply increasing premiums for high risk producers. If premiums were increased across the board, low risk producers would drop out of the program leaving only producers that are as much or more risky than the rates imply to participate in the program. This situation would conclude as before, with indemnities greater than premiums and net losses for the provider.[7]

Moral hazard is the other major problem vexing crop insurance. Moral hazard is the instance in which the existence of an insurance contract alters the probability distribution of a loss. This is basically stating that agents' behavior can affect the likelihood of loss.

In agriculture, the common viewpoint is that moral hazard usually manifests itself as a case of reduced inputs. Horowitz and Lichtenburg (1993) found that insured farms used more pesticides and almost twenty percent more nitrogen than did non-insured farms. A

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[7] It is unclear exactly what will happen to the loss ratio in this case. It may decrease but losses will most likely exceed premiums (Goodwin and Smith 1995). If enough risk averseness exists in the pool, it is possible that premiums may exceed indemnities.

chemical like nitrogen is very beneficial if sufficient moisture is received but can be detrimental if too little rain falls. Smith and Goodwin (1994) criticized the Horowitz and Lichtenburg study and by modeling insurance and chemical purchases jointly concluded that insured producers spend an average of $4.75 less per acre than do uninsured producers. Quiggin (1994) contended that moral hazard could increase the variability of crop yields using an example of producers being able to choose varieties of wheat seed which generate high yields but are particularly susceptible to drought or insects instead of more robust, lower yielding seed varieties.

It has been estimated that moral hazard has decreased the United States' annual wheat yields by over ten percent, or about 171 million bushels (Just and Calvin 1993). Other estimates have been smaller, putting losses from moral hazard at about two bushels per acre (Coble et al. 1993). These losses are difficult to avoid as long as the costs of monitoring such behavior are prohibitively high.

Another more minor problem exists in crop insurance. Quiggin (1994) points towards the absence of risk pooling as a complication in the crop insurance program. Whereas risks can be pooled in most instances, like life insurance and car insurance, agricultural risks cannot be pooled with other agricultural risks, even for areas as large as entire countries. Producers in a given area are likely to face the same adverse conditions, thus the occurrence of indemnities is connected. Quiggin notes that the problem could be alleviated by organizations (probably governments) with large portfolios offering insurance contracts. Alternatives may include the possibility of risks being pooled across large geographical areas (i.e. continents) or with other unrelated risks such as life insurance.

Econometric Demand Models For Crop Insurance[8]

The demand for crop insurance has been studied for over a half-century. Early studies focused mostly on the characteristics of insured farmers. Results of the work (Clendenin 1942; Jones and Larson 1965; Shipley 1967; Beeson 1971) suggested that producers who were in poor financial standing and who were less diversified were more likely to purchase crop insurance. Furthermore, it was noted that farmers who did not participate did so because of low coverage levels (Bray 1963; Starr 1963). Attitudes of farmers in the early 1960's reflected the belief that increasing yield trends spawned low coverage levels.

In the 1980's, economists began looking more specifically at the demand for crop insurance using a neoclassical demand function. Models used participation as a proxy for the quantity of insurance purchased and explained demand by employing several variables. Nieuwoudt et al. (1985), using pooled state-level data from 1965-81, noted that the expected rate of return was a significant component of the demand for insurance. Since the premium rate is a critical element of expected rate of return, its effects upon participation are implied in the effects of expected rate of return.

In 1986, Gardner and Kramer also reported that the expected rate of return was an important variable in explaining participation. They further concluded that more recent returns were more heavily weighted in the producer's participation decision. The report

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[8] Largely summarized from Goodwin and Smith (1995).

asserted that a premium subsidy of 30 percent would increase participation from 20 to 25.5 percent. These figures imply an elasticity of –0.92 for acreage.

It is generally agreed that the expected rate of return is significant and that the elasticity of demand is inelastic. Smith and Baquet (1993) further concluded that the elasticity differs depending on whether the rate of return is positive or negative for a given producer. Producers with higher risk (positive rate of return) were less influenced by premium changes. Thus, high risk producers' demand was more inelastic than was low risk producers.

There have been other variables used in estimating crop insurance demand including producer's age, farm financial statistics, off-farm income, livestock production (diversification), and government program participation. Goodwin (1994) argued that insurance purchases were influenced by the producers' expectations of governmental ad hoc disaster relief. He concluded that producers who believed they would receive protection from such programs were 16 percent less likely to purchase insurance.

The Mechanics of MPCI

Multiple Peril Crop Insurance is a yield-based insurance product for farmers. It is currently the main crop insurance product offered by the RMA, available for most crops and in most counties in which the crops are produced.

The goal of MPCI "is to determine rates which will, when applied to the exposures underlying the risks being written, provide sufficient funds to pay expected losses and expenses and maintain an adequate margin for adverse deviation," (Driscoll 1995).

The theory behind MPCI rates is called the Loss Cost (Pure Premium) Theory. This theory asserts that the actuarially neutral rate is equal to the total losses divided by the total liability (exposure) of the product:

$$Pure\ Premium = \frac{Total\ Losses}{Total\ Liability} \tag{3.11}$$

where losses and liability are expressed in dollars and liability is the maximum possible amount of indemnity paid for a given time period. This method is retrospective in the fact that it uses existing data from the past and predicts a rate for the future.

This rate is accurate only for the pool of insured producers for whom it was computed or producers who are similar. The data used in the procedure must be comparable over time and relate to loss potential. A further assumption is that all possible outcomes are represented in the data that is used.

MPCI rates are based on 20 years of county loss cost ratio data. In order for the set of loss cost ratios through time to be comparable, each loss cost ratio is converted to a 75 percent coverage basis. Furthermore, the four largest ratios are capped at the value of the 5th largest. A simple average of the 20 adjusted loss cost ratios is computed. This determines the average, non-catastrophic premium rate to be charged in a county.

RMA believes that catastrophic events such as state-wide flooding or severe drought cannot be accurately estimated at the county level. For this reason, catastrophic event coverage is computed at the state level. This is done to compensate for the four largest county loss cost ratios being capped. A weighted average in which the county loss cost premium is assigned a weight of three-fourths and the state-wide catastrophe premium is assigned a weight of one-fourth is the total average premium to be charged in a county. This rate is then

loaded for the government's target loss ratio of 0.88 as well as administrative expenses. After this, any rate adjustments needed for type and practice relativities are applied (i.e. dryland versus irrigated). These rates are smoothed over county lines to insure that there are not dramatic rate fluctuations between counties when there are no identifiable systematic differences in risk between the counties.

A curvilinear relationship between average yield and the degree of risk (premium rate) for a crop is used by RMA and is expressed by linear approximations which are used to differentiate between insurable yields. This allows rates to be spanned into discrete intervals, called R-spans, each of which is assumed to reflect similar risk throughout the entire R-span . R-spans divide the yields between 50 and 150 percent of a county's average into constant percentage segments. There are typically nine R-spans for a crop, but there may be up to thirty two.

CHAPTER 4

PROCEDURES AND DATA

Simulation Procedures

The simulation conducted in this thesis modeled the process by which MPCI rates were computed. Also modeled were the individual farmer's participation decisions. Combining these two aspects into one dynamic model allowed participation rates over time to be simulated. The purpose was to analyze how participation rates changed as coverage levels and premium rates changed. There were a total of 100 different simulations ran, each containing 100 years of simulated data. This was done in order for different random yield patterns to be represented.

Because of the small amount of data available for each farm (6 to 17 years), county level yield data were incorporated into the model to give a more accurate probability distribution of yield levels through time.

The first step in the simulation process was to compute each farm's actuarially neutral rate. This step assumed that all possible events were represented in the samples of county yields and farm yields (errors) being used.

Actuarially neutral rates for 65 percent coverage were computed for each farm and for each possible farm expected yield ranging from 1 to 100 bushels per acre in one bushel

increments, where farm expected yield is denoted as $E(f_i)$. This was done by computing the indemnity that would occur for every possible farm actual yield. The farm actual yield is computed as:

(4.1) $$\hat{f}_i = c_j + \bar{d}^f + e_k^f$$

where c_j is the county yield, $\bar{d}^f$ is the average difference between farm yield and county yield, and e_k^f is the farm error. There were 51 county yields and between 6 and 17 farm errors per farm, yielding between 306 and 867 possible actual yields for each farm.

An indemnity, I, occurred if $\hat{f}_i < 0.65 * E(f_i)$ and was recorded as:

(4.2) $$I_i = 0.65 * E(f_i) - \hat{f}_i.$$

If $\hat{f}_i > 0.65 * E(f_i)$, then no indemnity was payed out and $I_i = 0$. Indemnities were computed for each possible farm yield realization. The actuarially neutral rate for each farm was the simple average of the recorded indemnity payments.

(4.3) $$\textit{neutral rate} = \frac{1}{n} \sum_{i=1}^{n} I_i$$

The main body of the simulation began by computing the average 65 percent rate for the insured pool. This rate, r_t, was calculated by taking the simple average of the twenty most recent loss cost ratios, where loss cost ratio is LCR_i.[9]

(4.4) $$r_t = \frac{1}{20} \sum_{i=t-20}^{t-1} LCR_i$$

In order to begin the simulation an average 65 percent rate of 7.58 percent was calculated.[10] As the simulation advanced in years, this rate was given a weight of $\frac{21-t}{20}$,

[9] Administrative loading and subsidies were ignored for the purpose of this simulation. Also, the highest four loss cost ratios were not capped at the value of the fifth highest as does FCIC. Leaving the high loss cost ratios was a substitution for the catastrophe loading practiced by FCIC which was not feasible to implement in this study.

[10] This was done by computing the actuarially neutral rate over all farms in the data.

where t is time, so that in year $t = 1$ its weight was one, in year $t = 20$ it was weighted as $\frac{1}{20}$, and in year $t = 21$ and beyond its weight was zero. This weighted average was added to the average LCR for the available years to derive the total average rate.

Once the average rate was derived, each farm's insurable yield, APH_i, was calculated by taking an average of the farm's previous six years of reported yields:

(4.5) $$APH_i = \frac{1}{n} \sum_{i=1}^{6} \hat{f}_i.$$

To begin the simulation, an initial insurable yield was calculated using the farm's actual data. As the simulation continued, each initial APH yield was weighted appropriately and combined with the realized farm yields generated in the simulation.

A rate was calculated for each farm given its APH yield, APH_i. This was done using a rate equation which expressed the relationship between yields and rates that was previously estimated and took the form:

(4.6) $$\ln(rate) = -0.683 - 0.038 * \ln(APH) - 0.059 * APH.$$ [11]

Throughout the simulation, the intercept term was adjusted up or down to reflect changes in the actuarially neutral rate computed from the loss cost ratios from year to year.

The farm's actuarially neutral rate was compared to the premium rate to be charged in the simulation. If $rate * (1 - subsidy) \leq 1.1 * neutral\ rate$ [12], the farm purchased insurance.

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[11] This is consistent with the practices of FCIC in providing MPCI rates. For a more detailed description of the derivation of the equation see Appendix A.

[12] Papers by Fraser (1988) and Atwood, Watts, and Baquet (1996) suggest that wheat producers will purchase actuarially neutral insurance that is loaded up to 10 percent above the neutral premium.

If not, the farm declined insurance. Participation was recorded as 0 if the farm did not purchase and 1 if the farm did purchase.[13]

Next, a farm actual yield, $\hat{f}_i$, was computed. For a given farm, a realized county actual yield, c_j, was randomly drawn from the pool of county yields. To this was added the farm's average deviation from the county, $\bar{d}$, as well as the farm error, e_k^f, which was randomly drawn from the farm's individual error pool.

(4.7) $$\hat{f}_i = c_j + \bar{d} + e_k^f$$

An indemnity of $I_i = 0.65 * APH - \hat{f}_i$ was recorded for each farm if $\hat{f}_i < 0.65 * APH$. If $\hat{f}_i > 0.65 * APH$, an indemnity of $I_i = 0$ was recorded.

This process of determining a farm's premium rate, participation, realized yield and indemnity was repeated for each farm in the simulation. With this done, total indemnities and total liability were computed for the set of farms participating and a loss cost ratio was computed. A participation rate was also computed by dividing the number of farms participating into the number of farms in total.[14]

This was the last step of the simulation for any one year. This process was then repeated one hundred times to simulate one hundred years of performance. Furthermore, the simulation was repeated one hundred times in total with different actual yield patterns in each simulation.

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[13]Farms were allowed to jump in and out of the program from year to year. Their realized yield was recorded and used in determining their *APH* yield no matter whether they participated or not.

[14]Farm sizes were modeled as one acre per farm.

This entire simulation was also conducted substituting the indexed APH yield method described in chapter one for the non-indexed APH yield method currently employed by FCIC.

Simulation Data

The data used in the simulation portion of this thesis were both farm and county level data. The county level data were county-adjusted regional (CAR) wheat estimates from Chouteau County, Montana, over a fifty one year period: 1947-1997.[15]

The farm level yield data consisted of observations from 1021 farms taken from Chouteau County. This data was provided by RMA and was for farmers who bought MPCI in 1997. Each observation consisted of the farm's reported yield from the previous 6 to 17 years as well as the corresponding county yield as reported by National Agricultural Statistics Service (NASS) for each year reported.

The farm level and county level yield data were used to decompose the difference between farm level yields and county level yields into county-wide variability and farm variability. This was done by first subtracting the county yield, c_t, from the farm yield, f_t, to compute the difference between farm and county yields, d_t^f,

(4.8) $$d_t^f = f_t - c_t.$$

The simple average of these differences was then computed,

(4.9) $$\bar{d}^f = \frac{1}{n}\sum_{i=1}^{n} d_i.$$

[15] A more detailed explanation of the CAR yield data is available in Appendix B.

By subtracting the average farm difference, $\bar{d}^f$, and the county yield for a given year from the farm yield for the same year, the farm level variability separate of any county variability can be computed:

(4.10) $$e_t^f = f_t - \bar{d} - c_t = f_t - (\bar{f} - \bar{c}) - c_t \,.$$ [16]

Regression Procedures

The maintained hypothesis of the regression was that participation is a function of effective coverage (*EC*), expected indemnity (*pay*), and the rate charged for MPCI (*mpci*), which is subsidized by the federal government. This is basically a demand function for crop insurance:

(4.11) $$part = \alpha + \beta_1 * ec + \beta_2 * pay + \beta_3 * mpci$$

The *ec* coefficient is expected to be positive asserting that as effective coverage increases, participation will increase. As stated before, if premium rates are held constant, an increase in effective coverage is analogous to an increase in expected indemnity. Increases in expected indemnity are expected to lead to more acres being insured. Following this line, the expected sign for *pay* is positive also. The *mpci* coefficient is expected to be negative as neoclassical demand theory would suggest.

An OLS regression weighted by NASS planted acres was employed. By estimating this regression, the effects of effective coverage, expected indemnity payment, and the premium rate can be estimated and tested for significance. This was done in order to

[16] The procedure set forth for estimating farm variability follows that of Atwood et al. (1997), Kmenta (1971), and Just and Weninger (1999).

complement the simulation portion of the study in hopes that matching results would be obtained. The expected signs of the regression variables concur with expectations for the simulation. If regression results are similar to those of the simulation, empirical confirmation of the simulation will be offered.

Regression Data

For the regression portion of the analysis, cross-sectional cotton data from 11 states was used. These states were: Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, Missouri, North Carolina, South Carolina, Tennessee and Virginia. Data for the additional cotton states - Arizona, California, Kansas, New Mexico, Oklahoma and Texas - is not yet available. The data was aggregated by risk region as determined by RMA. A total of 29 observations were used.

Participation (*part*) data was computed for 1997 by dividing the number of acres insured as reported by USDA into the number of acres planted according to NASS:

$$part = \frac{USDA\ Insured\ Acres}{NASS\ Planted\ Acres}. \tag{4.12}$$

Effective Coverage (*EC*) was determined by dividing the insured yield into the expected yield.:

$$EC = \frac{Insured\ Yield}{Expected\ Yield} = \frac{0.65 * \bar{Y}^f}{\hat{C} + (\bar{Y} - \bar{C})} \tag{4.13}$$

where insured yield is 65 percent of the average farm level *APH* yield, $\bar{Y}^f$, and expected yield is the average county predicted yield for 1998, $\hat{C}$, estimated from the appropriate regional trend line and adjusted for the average farm, $\bar{Y} - \bar{C}$.[17]

[17] Refer to Appendix B for explanation of predicted value.

The variable *pay* is computed as the ratio of Indexed Income Protection (IIP) to MPCI rates:

$$pay = \frac{IIP}{MPCI}. \tag{4.14}$$

Assuming IIP more accurately estimates the expected indemnity payment, then the sign of the pay variable is expected to be positive.[18]

IIP rates were calculated at Montana State University in 1998 for the 1999 crop year. The average IIP rate was calculated as an average of the rate paid by each farm in a region using 1997 farm data as reported by FCIC.

MPCI rates were provided by FCIC and were calculated in 1998 for the 1999 crop year. The average MPCI rate was calculated as an average of the rate paid by each farm in a region using 1997 farm data as reported by FCIC.

Table 1: Regression Data Descriptive Statistics (n=29)

Variable	Mean	Standard Deviation	Minimum	Maximum	Coefficient of Variation
part	0.22602	0.26674	0.00000	1.00000	1.18020
ec	0.61491	0.03135	0.54213	0.68486	0.05099
pay	0.66970	0.35640	0.09848	1.61750	0.53218
mpci	0.06946	0.01459	0.05030	0.10959	0.21006

[18] IIP is an alternative rating method to MPCI. The rating procedure is a more data intensive procedure which combines 50 years of county level data with the smaller data set of farm yields. IIP estimates a probability distribution of yields for the farm level and calculates the actuarially neutral rate by using a Monte Carlo simulation drawing from the probability distribution function.

CHAPTER 5

RESULTS AND CONCLUSIONS

Simulation Results

The simulation model was conducted to examine participation levels and the effects of adverse selection and effective coverage upon them. The results emerging from the simulation are consistent with the predictions precipitated by casual observation and logic. The premium rates and coverage levels generated are moving averages and might not always reflect the true underlying mean of the loss probability distribution or the yield probability distribution. Inefficient premium rate and coverage level calculations due to a short data set lead to adverse selection and effective coverage effects. However, it is difficult to sort out the effects of effective coverage from adverse selection because premium rates and coverage levels change simultaneously. Nonetheless, the argument that effective coverage and adverse selection do indeed affect participation rates is supported. Dramatic swings in participation rates can be observed following years of above or below average county yields which result in changes in both premium rates and effective coverage levels.

The effects of adverse selection and effective coverage can be seen by examining graphs one and two, which show the simulated county yield series and simulated participation rates with 0 percent subsidy for non-indexed APH yields from simulation 11. The first

Figure 1: County Yield Series For Simulation 11

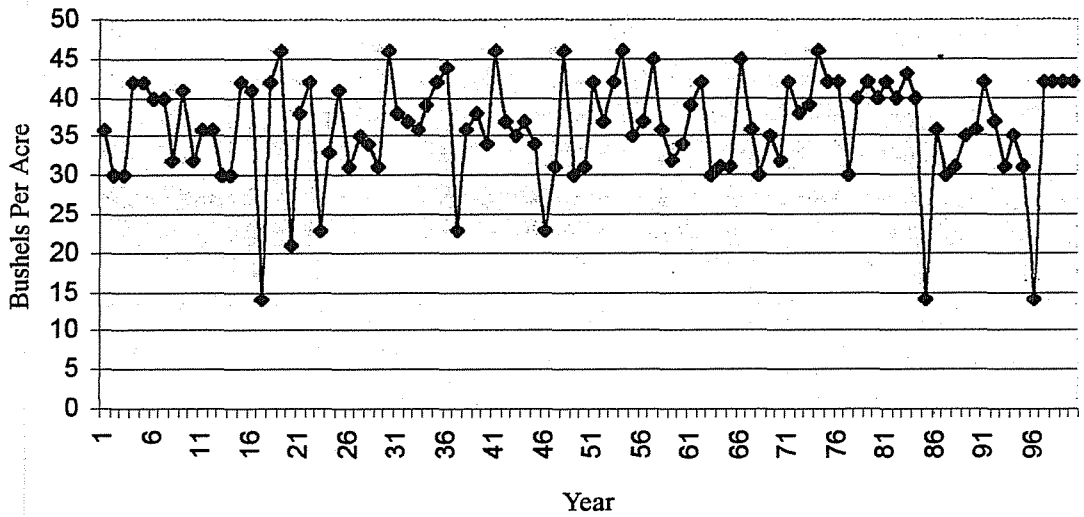
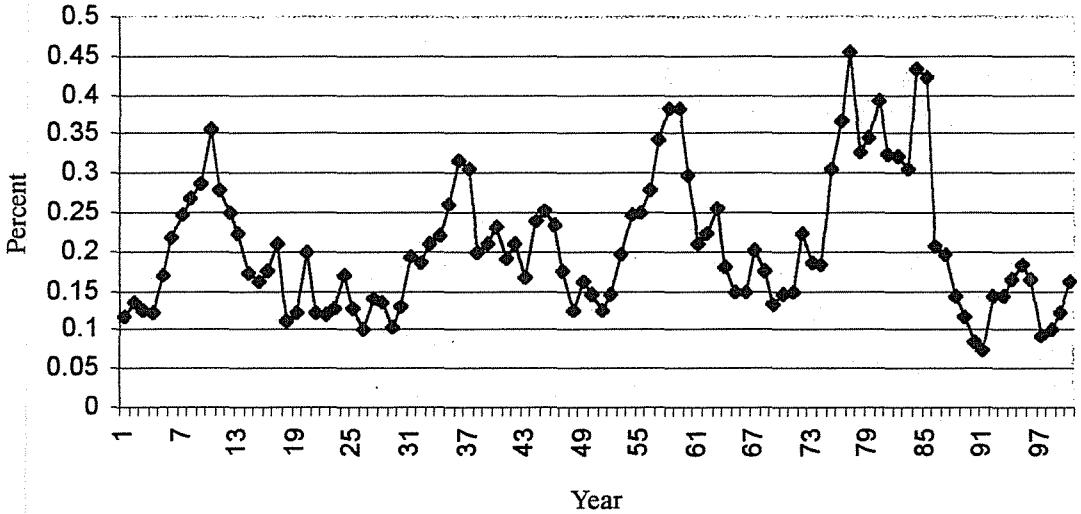


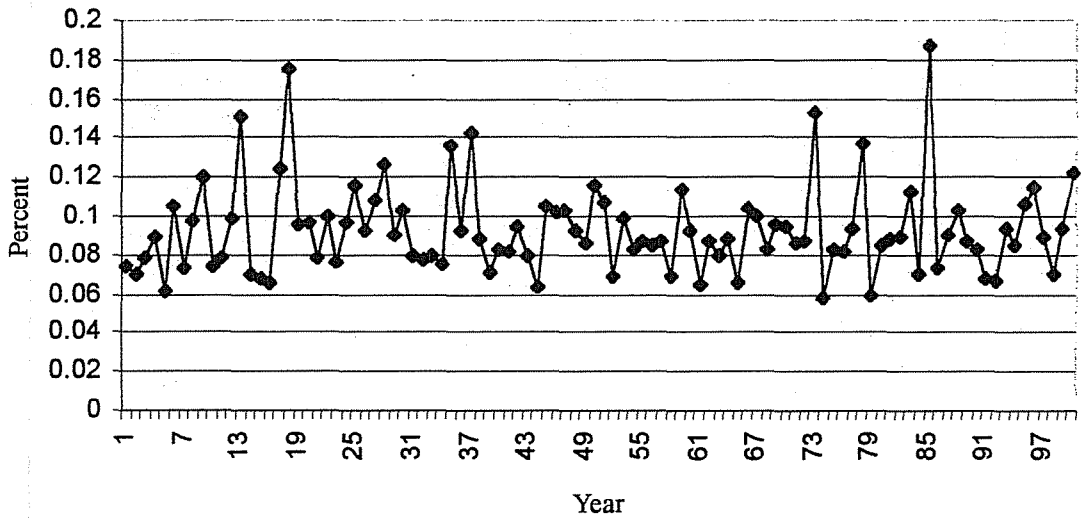
Figure 2: Participation Rate for Simulation 11



extreme yield event of 14 bushels per acre, some 22 bushels below the long term, detrended county average yield, produced a relatively high loss cost ratio of 17.5 percent, observed in

graph three. This high loss cost ratio in and of itself was enough to drive the average premium rate up almost half of a percent from 8.65 percent to 9.15 percent, thus discouraging relatively more producers from participating. At the same time, coverage levels were decreased, further driving producers from the program. The participation rate the following year took a drastic hit falling from 21 percent to just 11 percent.

Figure 3: Loss Cost Ratio for Simulation 11



Through the period of years 17 to 29, five years had slightly higher than average yields. Conversely, several years were extremely poor including yields of 14, 21, and 23 bushels per acre, which more than offset the above average years. Viewing this period as a whole, it can be seen that from years 18 to 30, the participation rates stayed well under the long term average of 20.7 percent. This result stems from the high loss cost ratio of 17.5 percent in year 17. This extreme loss ratio continued to keep premium rates high. Also, the magnitude of the yield hits in below average years depressed coverage levels.

Later in the simulation, a series of unusually high yields occurred. From the years 72 through 85, only one yield was below the long term county average. During this period, participation rates rose to levels in excess of 30 percent, even reaching above 40 percent in several years.

In year 86, a county average yield of 14 occurred. This drove participation rates in year 87 down to 20.8 percent from 42.4 percent. Successive yields further decreased coverage levels and participation levels declined even more to a low of 6.66 percent in year 92.

Participation rate fluctuations, such as the ones described herein, were observed in each of the 100 separate simulations. It is clearly the case that as low yields drop out of the APH time horizon, participation increases. Conversely, as above average yields are discarded in favor of lower, more recent observations, participation decreases. Also, as excessively low or high loss cost ratios drop from the average rate calculation, participation rates change. These fluctuations in participation rates stem directly from the changes in effective coverage levels and rates levels brought about by yield cycles.

Participation results from the simulation are presented in table two. Increasing the subsidy level resulted in expanded participation. These increases in participation rates can be viewed by noticing the upward shifts in participation between the participation rate graphs for different subsidy levels. It is also worth noting that as subsidy levels increase, the mean participation rate for indexed APH yields catches and surpasses the mean participation rate of non-indexed APH yields. At a subsidy level of 80 percent, participation rates average 90 percent for non-indexed APH yields and 94 percent for indexed APH yields. As participation

nears 100 percent, above average participation rate fluctuations are dampened out for non-indexed APH yields, but below average fluctuations are not.

Table 2: Simulation Participation Rates For 0-80 Percent Subsidy Levels

Subsidy Level	Non-Indexed Mean	Non-Indexed Standard Deviation	Indexed Mean	Indexed Standard Deviation
00 %	20.91 %	0.0806 %	19.87 %	0.0135 %
20 %	29.83 %	0.1013 %	28.71 %	0.0145 %
40 %	43.22 %	0.1259 %	42.42 %	0.0166 %
60 %	63.76 %	0.1468 %	64.39 %	0.0283 %
80 %	90.50 %	0.0981 %	94.17 %	0.0244 %

Figure 4: Comparison of Participation Rates at 0% Subsidy

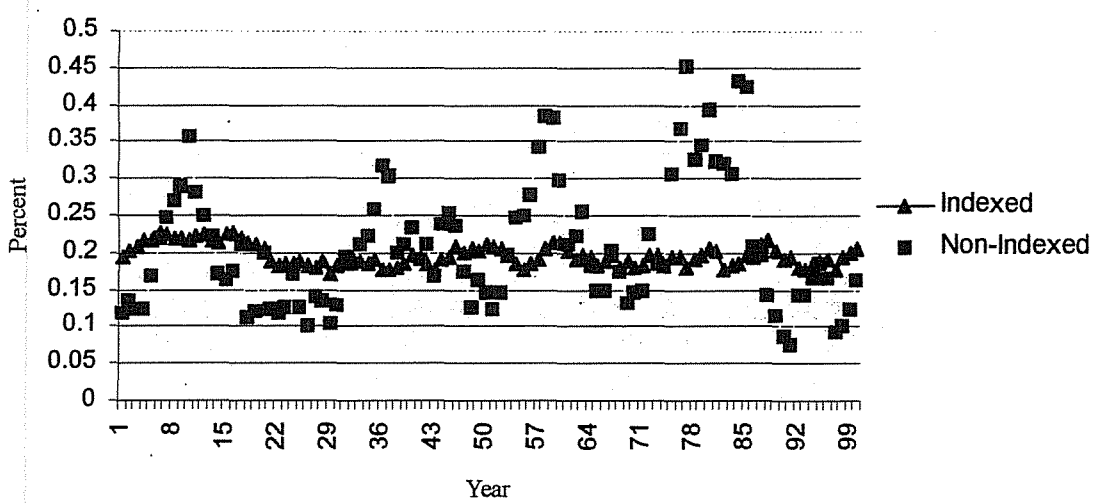


Figure 5: Comparison of Participation Rates at 20 % Subsidy

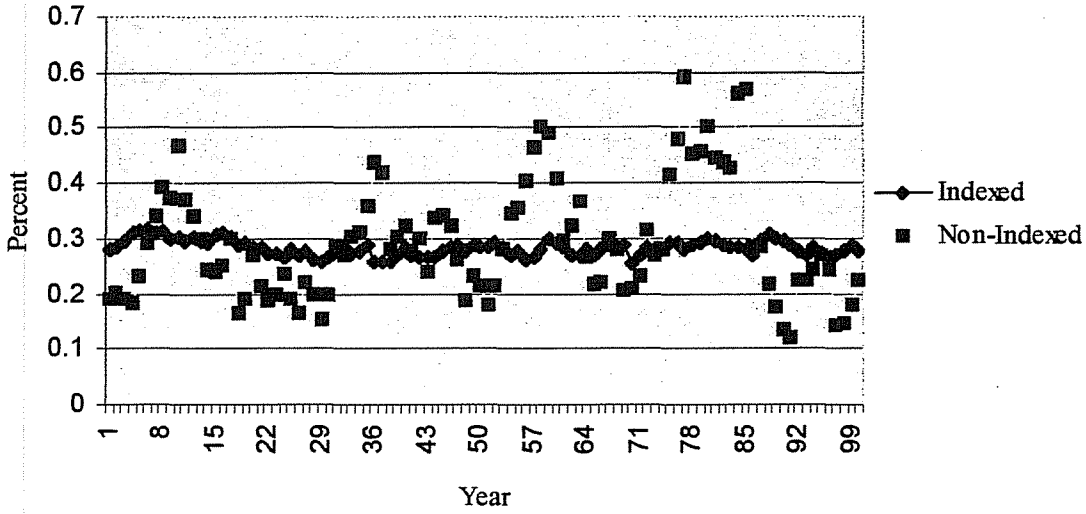


Figure 6: Comparison of Participation Rates at 40% Subsidy

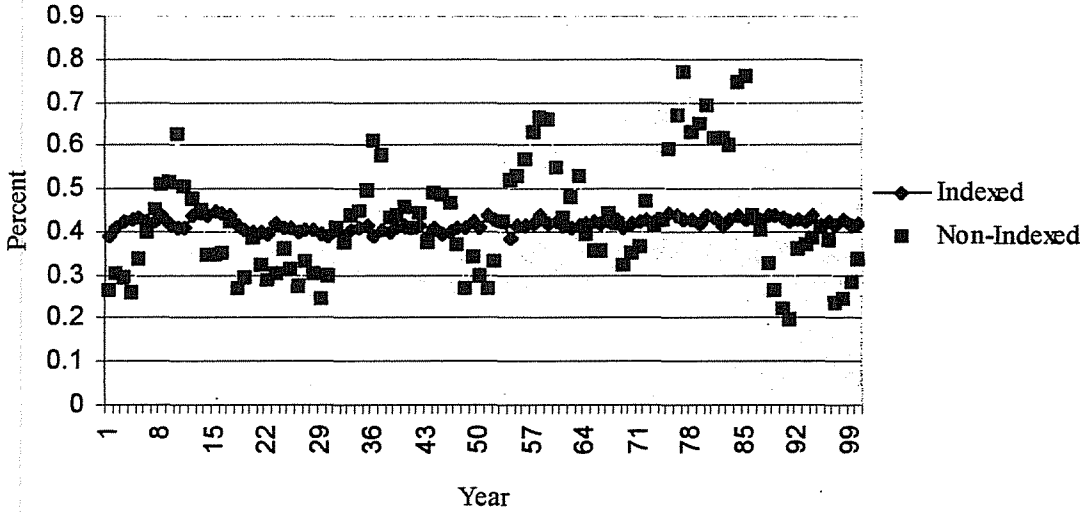


Figure 7: Comparison of Participation Rates at 60% Subsidy

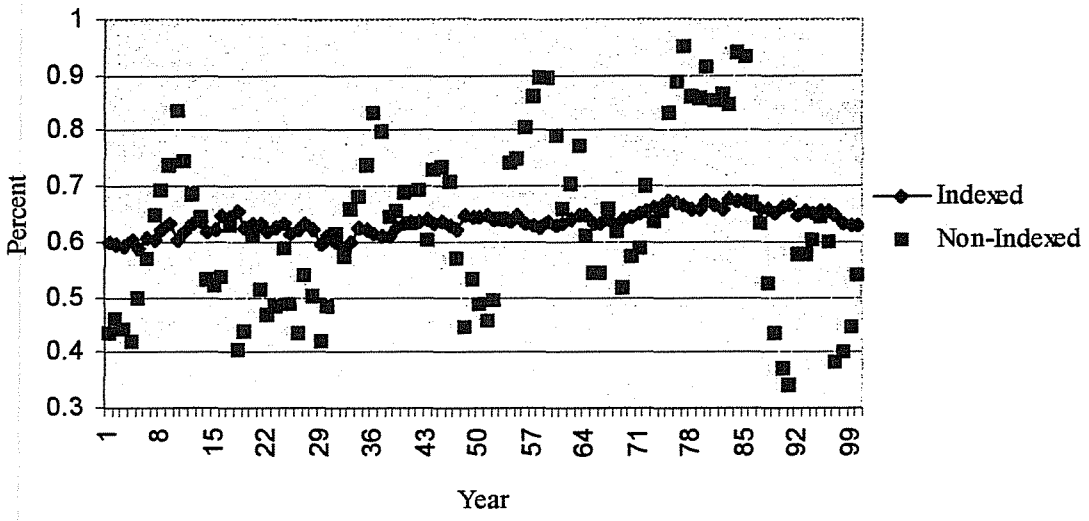
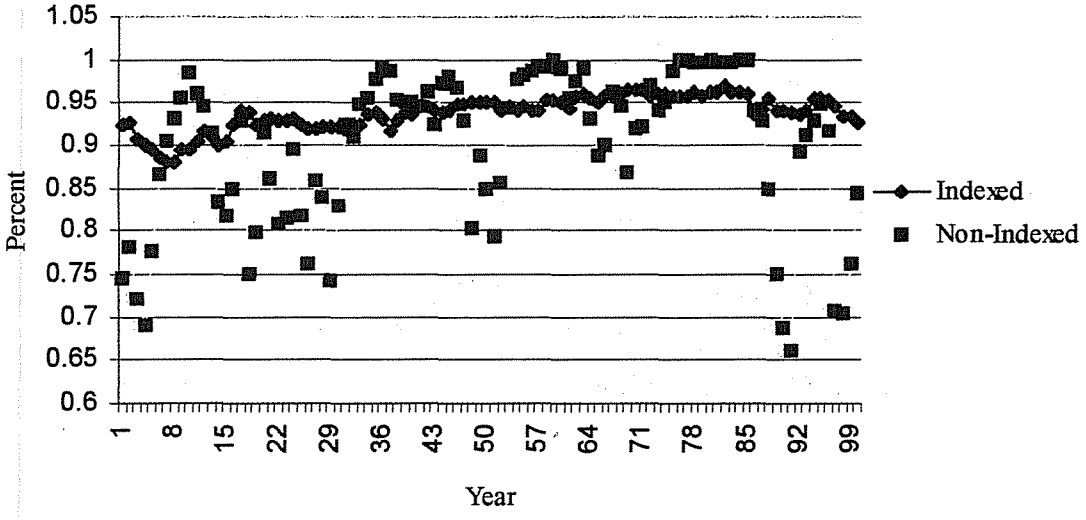


Figure 8: Comparison of Participation Rates at 80% Subsidy



Indexing APH yields appears to stabilize participation in the program. At every subsidy level, the difference between average participation rates for indexed APH yields versus non-indexed APH yields was negligible. The standard deviation, however, was notably different. This suggests that indexing APH yields may considerably stabilize participation rates in the crop insurance program.

By examining graph four, one can see how indexing producer APH yields leveled out participation rates. Whereas early on participation rates dropped far below average without indexing, participation rates using indexed APH yields were much more stable. Changes of no greater than 1.6 percent were observed in indexed participation rates unlike non-indexed participation rate changes of up to 9.7 percent. Results very similar to these were observed in the latter stages of the participation as well. Participation rates stayed about at the average using indexed APH, but were much higher using non-indexed APH yields.

These results demonstrate how indexing APH yields generates insurable yields which are closer to the producer's true expected yield. If effective coverage levels are overstated, relatively more producers would participate than would if coverage levels matched those which were used to develop the premium rates. Conversely, if effective coverage is understated compared to the rate being charged, relatively fewer producers would participate, the number of which participate depending on the individual producers' level of risk averseness.[19] By accounting for yield events that are above or below average at the county

[19] Producers who are risk averse may still participate but risk neutral producers would not. Different levels of risk averseness for each producer were not assigned in the simulation model since they cannot be accounted for with the data being used. However, one would expect the level of risk averseness to play an important role in the producer's participation decision.

level and taking these fluctuations out of a producer's APH yield, the APH yield is much more stable than it would be without indexing. Being able to insure yield levels which are closer to the producer's true expected yield stabilizes participation rates.

The stabilizing effects of indexing APH yields can also be demonstrated by comparing the standard deviations of each farm's APH yield and premium rate paid for both non-indexed APH yields and indexed APH yields.[20] Graphs nine and ten are histograms of the farm level APH yield standard deviation for non-indexed and indexed APH yields, respectively. The histograms for each have similar shapes, but the means are quite different. The average standard deviation of farm non-indexed APH yields is 4.74 bushels per acre while the average standard deviation of farm indexed APH yields is 3.99 bushels per acre. This shows that on average, each farm's standard deviation was decreased by almost 16 percent.

Similarly, graphs eleven and twelve show histograms of the standard deviation of premium rates paid by each farm for non-indexed and indexed APH yields, respectively. As seen in table 3, the average standard deviation of each farm's non-indexed APH yield premium rate paid is 1.863 percent while the average standard deviation of each farm's indexed APH yield premium rate is 1.520 percent. This shows that on average, the standard deviation of each farm's premium rate was decreased by 18.4 percent.

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[20] The farm level APH yield standard deviation was computed using the last 94 years of each simulation, giving a total of 9400 observations per farm. The standard deviation of the premium paid for each farm was computed using the last 80 years of each simulation for a total of 8000 observations per farm. Each APH yield and premium paid was included regardless of whether or not the farm participated in a particular year.

Figure 9: Average Farm Standard Deviation of Non-Indexed APH Yield

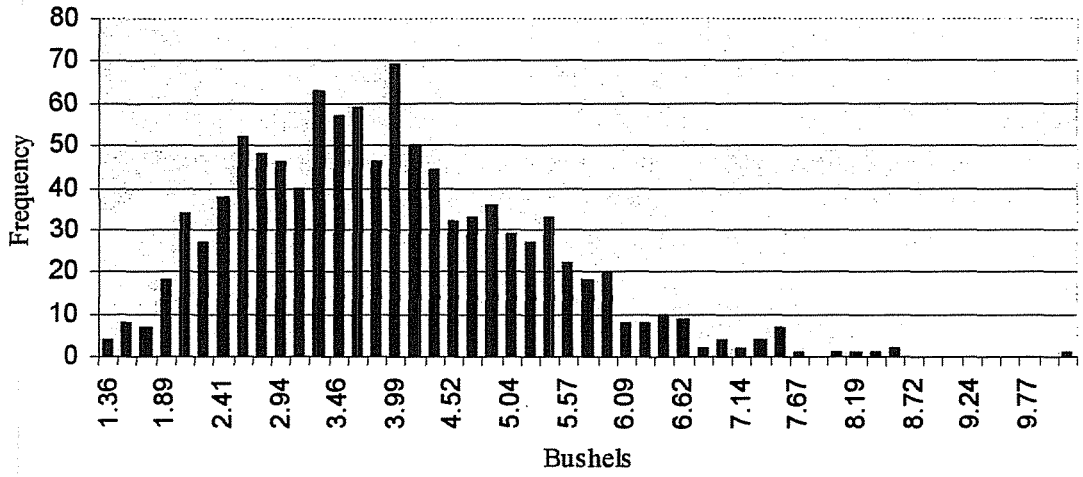

Figure 10: Average Farm Standard Deviation of Indexed APH Yield

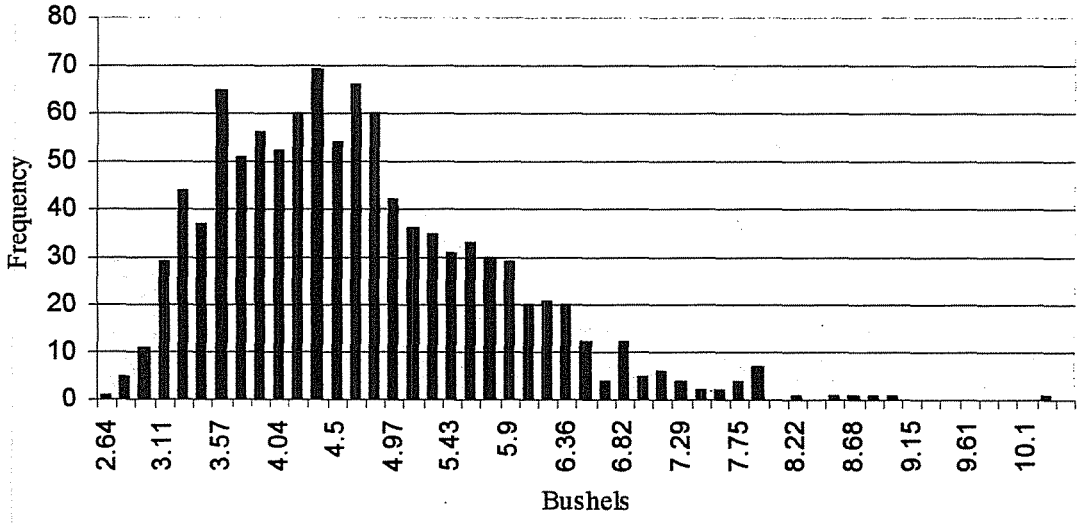

Figure 11: Average Farm Standard Deviation of Non-Indexed Premium Rate

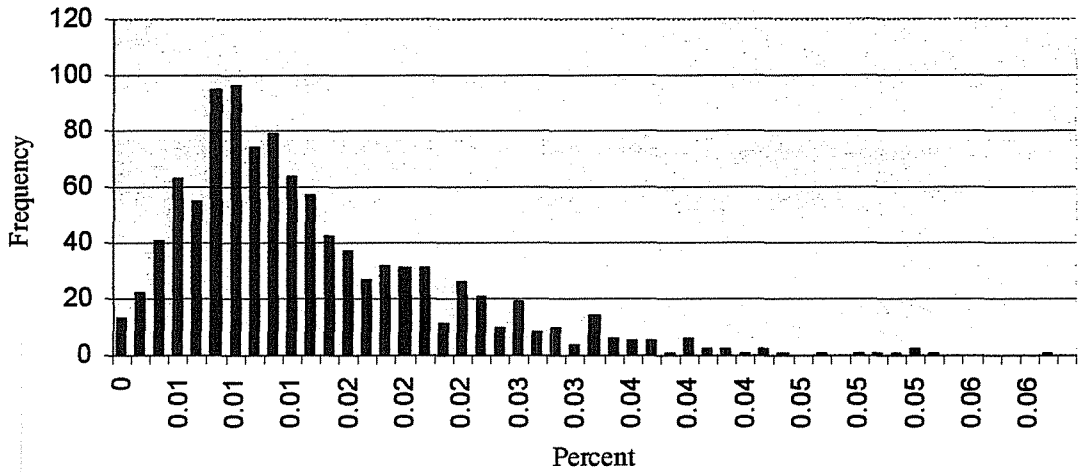

Figure 12: Average Farm Standard Deviation of Indexed Premium Rate

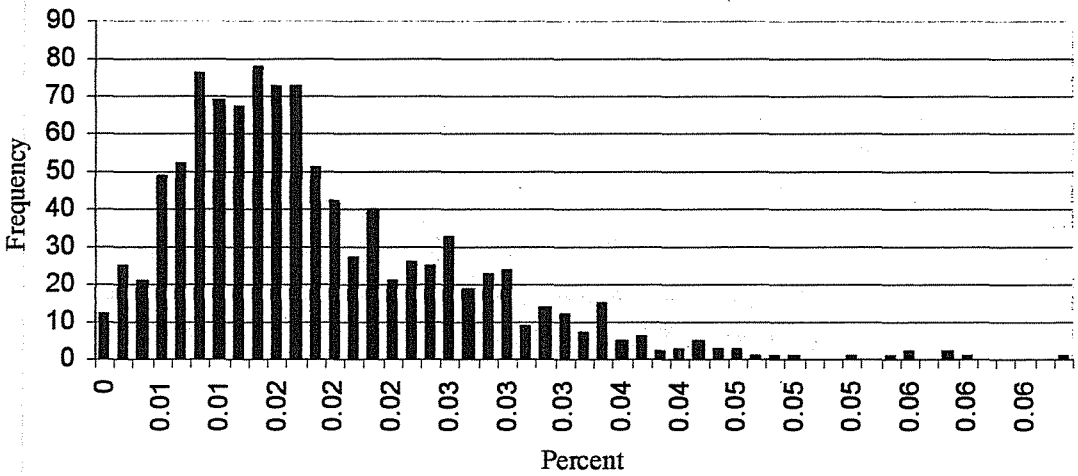

Table 3: Average Standard Deviation of Farm APH Yield and Premium Paid

	Non-indexed	Indexed
APH Yield	4.747 bushels/acre	3.987 bushels/acre
Premium Rate	1.86 %	1.52 %

Regression Results

Table 4 presents estimated coefficients for the independent variables included in the weighted OLS regressions employed to explain the dependent variable, participation (*part*).

Table 4: Estimated Regression Coefficients

Coefficients with respect to independent variables (t-statistics) * = significant at $\alpha = 0.10$ ** = significant at $\alpha = 0.05$				
Regression Number	Expected Payout	Effective Coverage	MPCI Rate	R^2
1	0.43813 (5.0294)**	-1.5607 (-1.3470)*	-0.51857 (-0.24734)	0.6345
2	0.43861 (5.1197)**	-1.6316 (-1.4774)*	-	0.6337
3	0.52018 (6.4588)**	-	-	0.6071

Regressions one and two yielded some surprising results with respect to effective coverage. The sign of the effective coverage (*ec*) coefficient was negative. The estimated parameters were significant at the 90 percent confidence level but not significant at a confidence level of 95 percent. The negative coefficient would suggest that as a region's

average coverage level decreased, the amount of insurance purchased would increase, which is very counterintuitive.

There may be several possible explanations for the sign of the effective coverage coefficient. The crop insurance mechanism is inherently dynamic because of the moving averages contained within. These dynamics make it difficult to clearly define the effects of effective coverage levels upon participation rates. The effective coverage variable may be confounded with other variables such as farm debt structure and farmer expectations. If the model is mis-specified, the estimated coefficient for effective coverage will be biased and inconsistent.

With regard to debt structure, farmers who have low effective coverage levels may also have experienced recent problems with their lenders. Years in which effective coverage is eroded by poor yields are also likely produce adverse effects upon the producer's income and thus their ability to pay back operating and/or capital loans. As a producer's debt to asset ratio increases, the lender will be more likely to require the borrower's participation in crop insurance. The crop insurance program may pay off farm debts in years when farmers aren't able to. Many articles in the crop insurance literature have pointed to farm's debt structure as a variable in the crop insurance participation decision (Bray 1963; Jones and Larson 1965; Calvin 1990; Atwood et al. 1996).

The negative correlation between effective coverage levels and participation may also be a sign that the variable reflects expectations as to whether an indemnity will be collected. Low effective coverage levels indicate poor recent yields. In the years that below-average yields were experienced, producers would likely receive an indemnity, possibly increasing

their likelihood of purchasing insurance in the future. Gardner and Kramer (1986) reported that producers weighted recent history more heavily in their participation decision. Other variables, such as loss ratio, were used in an attempt to account for producer expectations but yielded no different results. If the process by which producers make their participation decision is indeed a dynamic one, time series data would be required to more accurately assess the situation.

Not surprisingly, the expected indemnity payout (*pay*) coefficient was positive and strongly significant at both the 90 and 95 percent confidence levels. The sign of the estimated parameter suggests that as expected indemnity payments increase, participation rates increase. Expected indemnity payment increases are a reflection of subsidized MPCI rates being lowered relative to the premium rates implied by producers' true underlying risks. When this happens, producers who did not previously participate in the crop insurance program may purchase contracts because their individual expected rate of return increased enough. This may not necessarily mean that the expected rate of return is positive.

The elasticity of participation with respect to expected indemnity payments computed is 1.29 at the means. This suggests that when *part*= 0.22602 and *pay*=0.6697, a one percent increase in *pay* will result in a 1.298 percent increase in *part*. An explicit price elasticity of demand was not calculated.

The rates variable (*mpci*) had the expected negative sign but was not significant. The regression line including all variables had an R^2 of 0.6345.

A second regression was ran in which the MPCI rates variable was omitted. This omission had no noticeable effects on the results. The coefficients for effective coverage and

for expected indemnity payouts did not change significantly and the t-values were also relatively unaffected. The R^2 for this regression was 0.6337. Using a common F-test, the regression including MPCI rates failed to explain participation more efficiently than the regression excluding MPCI rates.

A final regression was ran using expected payout as the only explanatory variable. The results continued to exhibit the importance of expected indemnity payouts in explaining crop insurance participation rates. With an R^2 of 0.6071, there was no significant difference in explaining participation between this specification and the regression including effective coverage levels and premium rates.

Potential problems in this analysis do exist. Particularly, there may be collinearity among the variables. This analysis does not correct for any potential bias, but does point out that collinearity problems are negligible because of the different time periods that each variable encompasses. Effective coverage spans six years, expected indemnity payouts, which includes IIP rates, span fifty years, and MPCI rates span twenty years.

Conclusions

This thesis has demonstrated the effects of adverse selection and effective coverage on participation rates. While effective coverage appears to be positively related to participation in the simulation, the converse appears in the statistical section of the analysis. The estimated coefficient for effective coverage is negative, but is not significant at the 95 percent confidence level. Once again, it is important to note the difficulty in modeling the effects of effective coverage and adverse selection separately.

The simulation shows that indexing APH rates stabilizes participation ratios. This suggests that RMA may want to examine its current procedure for setting producer APH rates.

The statistical analysis concludes that a producer's expected indemnity payment is significant in explaining participation rates while effective coverage and premium rates are not. At this point, the conflicting results of the simulation and the statistical procedures are bothersome. Future research, however, may be able to reconcile the current differences by examining more comprehensive data sets.

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APPENDICES

APPENDIX A

Estimation of Relationship Between Average Yield and Premium Rate

The initial rate equation was arrived at by calculating actuarially neutral rates using data from Chouteau County, Montana. The data used included the Chouteau county CAR yields consisting of 51 observations. Also, farm level errors were used from the pool of insured Chouteau county producers.

A base 65 percent rate for each insurable yield from 1 to 100 bushels per acre was computed in one bushel increments. This was done in much the same manner of the neutral rate calculation for each farmer in the main simulation. For every insurable yield, which would be exactly equal to the farm's true expected yield, the difference between the yield and the average county yield was computed:

(A1) $$d=Y-\bar{C}.$$

After this was computed, a realized farm yield was constructed by randomly drawing a farm error and combining it with the insurable yield and difference term:

(A2) $$\hat{f}_i=y+d+e_i.$$

This farm realization was computed 10,000 times by randomly drawing from the farm error pool with replacement.

An indemnity was computed for each estimated farm yield by taking the minimum of $I_i = 0.65 * y - \hat{f}_i$ and zero. The 10,000 indemnities were averaged and this was the base 65 percent rate for each insurable yield generating 100 base rate observations.

The manner in which FCIC administers its crop insurance rates is by using an equation which estimates the relationship between an insurable yield and its corresponding rate. This relationship is adjusted up or down from year to year according to whether the average rate increases or decreases by changing the intercept term of the equation.

With this in mind, the relationship between insurable yield and rate was estimated. The form chosen was the gamma function:

(A3) $$rate = A * yield^{\alpha} * e^{-\beta * yield}$$

which was empirically estimated as:

(A4) $$\ln(rate) = \alpha_0 + \alpha_1 \ln(yield) - \beta yield.$$

The coefficients were estimated as:

(A5) $$\ln(rate) = -0.683 - 0.038 * \ln(yield) - 0.059 * yield.$$

This estimation yielded an $R^2 = 0.999$ with all coefficients being significant. By plugging in the producer's insurable yield, the appropriate 65 percent coverage rate can be recovered through use of this equation.

APPENDIX B[21]

Yield Trend Estimation

Over time technological developments have increased crop yields. In order to estimate expected crop yields from historical data, yields trends must be estimated. There are several functional forms that are chosen between. The forms estimated are:

(B1) $$R_t = a_1^R$$

(B2) $$R_t = a_1^R + a_2^R * t$$

(B3) $$R_t = a_1^R + a_2^R * t^{a_3^R}$$

(B4) $$R_t = a_1^R + \frac{a_2^R * t^2}{a_4^R + t^2}$$

(B5) $$R_t = a_1^R + \frac{a_2^R * t^{a_3^R}}{a_4^R + t^2}$$

[21] This description summarizes and expands on a portion of Income Protection,, by Atwood, Baquet, and Watts, Montana State University Staff Paper, August 1997.

Using county yield data from NASS aggregated to the regional level, the functional forms are estimated and the proper form is chosen by using standard F-tests.[22] Once this has been done, the errors are checked for heteroskedasticity and are corrected if need be.

After this procedure has been performed, the correct errors are added back to the most recent predicted yield. This generates the set of detrended yields:

(B6) $$R_t^d = \hat{R}_T + e_t$$

where R_t^d is the detrended regional yield in year t, $\hat{R}_T$ is the predicted regional yield of most recent observation in the data set (T), and e_t is the correct error for year t.

To derive the county observations used, the average difference between the regional yield and the county yield was computed. This average was added to each data point to generate the county-adjusted regional yield series:

(B7) $$CAR_t = R_t^d + \bar{d}$$

Furthermore, the estimated functional form may be used to generate a prediction beyond the range of data acquired. This is done by simply substituting the desired year for the prediction into the estimated regression equation.

[22] Each region is a group of counties with similar yield variability as concluded by FCIC.

APPENDIX C

Variance of Indexed APH Yields Versus Non-Indexed APH Yields

In a given year, t, a producer's actual yield, y_t, will be equal to the county yield, c_t, plus the difference between the farm yield and the county yield, d_t:

(C1) $$y_t = c_t + d_t.$$

Assuming the county yield and the difference term are uncorrelated, the variance of a producer's actual yield will be equal to the sum of the variance of the county yield and the variance of the difference term:

(C2) $$var(y_t) = var(c_t) + var(d_t).$$

Dividing equation (C2) by the number of observations, n, will yield the result that the variance of the sample mean of farm yields is equal to the variance of the sample mean of county yields plus the variance of the sample mean of the difference term:

(C3) $$var(\bar{y}) = var(\bar{c}) + var(\bar{d}).$$

In this equation, $\bar{y}$ is equal to the average realized farm yield.

Current RMA practices assign insurable yields by simply averaging a producer's previous four to ten years of yields, depending on availability of data. Thus, the variance of a producer's APH yield will be the variance computed in equation (C3).

Alternatively, by using the indexing procedure, a producer's APH yield, $\tilde{y}$, will be equal to the long-term county average (currently averaged over 50 years), $\bar{c}_{50}$, plus his average difference from the county yield over the previous four to ten years, $\bar{d}$:

(C4) $$\tilde{y}=\bar{c}_{50}+\bar{d}.$$

By construction, the variance of the indexed APH yield, $\tilde{y}$, will equal the variance of the long-term county average plus the variance of the average difference between farm and county:

(C5) $$var(\tilde{y})=var(\bar{c}_{50})+var(\bar{d}).$$

In this equation the variance of the county average is equal to the variance the county yield divided by the number of observations used in computing the average, 50.

By comparing equations (C3) and (C5), we can compare the variability of non-indexed APH yields to the variability of indexed APH yields. For a given producer, the variance of the average difference, $var(\bar{d})$, will be identical under either procedure. The difference in variability between non-indexed APH yields and indexed APH yields will be equal to the difference in variability between the short-term county average (10 years for purposes of illustration) used in computing non-indexed APH yields and the long-term county average used in computing indexed APH yields:

(C6) $$var(\bar{y})-var(\tilde{y})=var(\bar{c})-var(\bar{c}_{50}).$$

which is equivalent to:

(C7) $$var(\bar{y})-var(\tilde{y})=\frac{var(c_t)}{10}-\frac{var(c_t)}{50}.$$

This can be simplified into:

(8) $$var(\tilde{y})=var(\bar{y})-\frac{4}{5}var(c_t).$$

If the variance of c_t is positive, then it follows that the variance of the indexed APH yield, $\tilde{y}$, must be less than the variance of the non-indexed APH yield, $\bar{y}$:

(C9) $$var(\tilde{y})<var(\bar{y}).$$