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Three Essays on US Agricultural Insurance

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THREE ESSAYS ON US AGRICULTURAL INSURANCE

by

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ABSTRACT

Three Essays on US Agricultural Insurance

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Many economists and policy analysts have conducted studies on crop insurance. Three research gaps are identified: i) moral hazard in prevented planting (PP), ii) choice of PP and planting a second crop, and iii) selecting margin protection in the Dairy Margin Protection Program (MPP-Dairy).

The first essay analyzes the existence of moral hazard in PP. The PP provision is defined as the "failure to plant an insured crop by the final planting date due to adverse events". If the farmer decides not to plant a crop, the farmer receives a PP indemnity. Late planting (LP) is an option for the farmer to plant a crop while maintaining crop insurance after the final planting date. Crop insurance may alter farmers' behavior in selecting PP or LP and could increase the likelihood of PP claims even though farmers can choose LP. This study finds evidence that a farmer with higher insurance coverage tends to choose PP more often (moral hazard). Spatial panel models attest to the existence of moral hazard in PP empirically.

If a farmer chooses PP, s/he receives the PP indemnity and may either leave the acreage unplanted or plant a second crop, e.g., soybean for corn. If the farmer plants a second crop after the PP claim, the farmer receives a 35% of PP payment. The current PP provision fails to provide farmers with an incentive to plant a second crop; 99.9% of PP claiming farmers do not plant a second crop. Adjusting PP indemnity payment may encourage farmers to plant a second crop. The second essay explores this question using a stochastic simulation and suggests to increase the PP payment by 10%-15%.

The third essay investigates why Wisconsin dairy farmers purchase more supplementary protection than California farmers in a MPP-Dairy introduced in the 2014 Farm Bill. MPP-Dairy provides dairy producers with margin protection when the national dairy margin is below a farmer selected threshold. This study determines whether conditional probabilities regarding regional and national margins have a role in farmer's decision-making to purchase supplementary coverages using Copula models. Results indicate that Wisconsin farmers have higher conditional probabilities and purchase more buy-up coverages.

(110 pages)

PUBLIC ABSTRACT

Three Essays on US Agricultural Insurance

Taehoo Kim

Agricultural insurance programs such as crop insurance and Dairy Margin Protection program (MPP-Dairy) are managed by United State Department of Agriculture (USDA). The objective of these programs is to help farmers manage their financial risk. Agricultural insurance programs have played an important role for farmers in terms of maintaining farm profitability. There are several potential problems with insurance programs, such as moral hazard and adverse selection, which make them inefficient

With respect to these problems, three research gaps are identified: i) moral hazard in prevented planting (PP), ii) choice of PP and planting a second crop, and iii) selecting margin protection in the Dairy Margin Protection Program (MPP-Dairy). Theories and empirical results show that moral hazard exists in PP, meaning that a farmer who purchases a higher coverage level is likely to abandon cropping when the farmer experiences adverse events such as drought or excess moisture. Second, the farmer may not plant a second crop due to a low PP indemnity payment. Increasing the PP indemnity payment provides an incentive for the farmer to plant a second crop. Third, dairy farmers purchase more supplementary protection in MPP-Dairy when co-movement of dairy margins between US and regions is stronger.

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1.1. Federal Crop Insurance Program

The Federal Crop Insurance Program (FCIP) has grown over the past two decades (Figure 1-1) which is administered by the Risk Management Agency (RMA) within the United States Department of Agriculture (USDA) and delivered by private insurers. FCIP provides yield protection to farmers to help cover yield losses from various types of natural disasters including, but not limited to, drought, excessive moisture, freeze, and disease. Newer coverage options seek to combine yield protection and price protection to protect farmers against potential revenue loss, whether due to low yields (yield protection), decrease in market price (revenue protection) or a mixture of both.

The RMA sets the premium rates that can be charged to farmers and determines which crops can and cannot be insured. Private insurance companies are then obligated to sell insurance indiscriminately to eligible farmers. To reduce the cost to farmers, the federal government subsidizes the farmer-paid premiums which are highly dependent on the type of insurance coverage and policy. The federal government also provides reimbursement to the private insurance companies to offset operating and administrative costs that would otherwise be paid by farmers as part of their premium.

The 2014 Farm Bill eliminated direct payments and expanded crop insurance shifting the major means of agricultural supports to the crop insurance program. Hence, crop insurance became the central (federal) agricultural policy even though it might be expensive to taxpayers (Wright 2014). In 2014 alone, the program insured approximately $110 billion in liabilities (liability in Figure 1-1) on 294 million acres nationwide (net acre insured in Figure 1-1). Since 1996, insurance policies with a premium remained steady at about 1.2 million (policies with premium in Figure 1-1) but the net acre insured and liability has grown significantly (Figure 1-1). Steep increase in policies with a premium in 1995 was partly due to a substantial rise of premium subsidies in legislative actions in 1994 (Plastina and Hart 2014) and partly because of the new requirement of purchasing crop insurance to obtain other agricultural supports payments, which was eliminated in the 1996 Farm Bill (Plastina and Hart 2014).

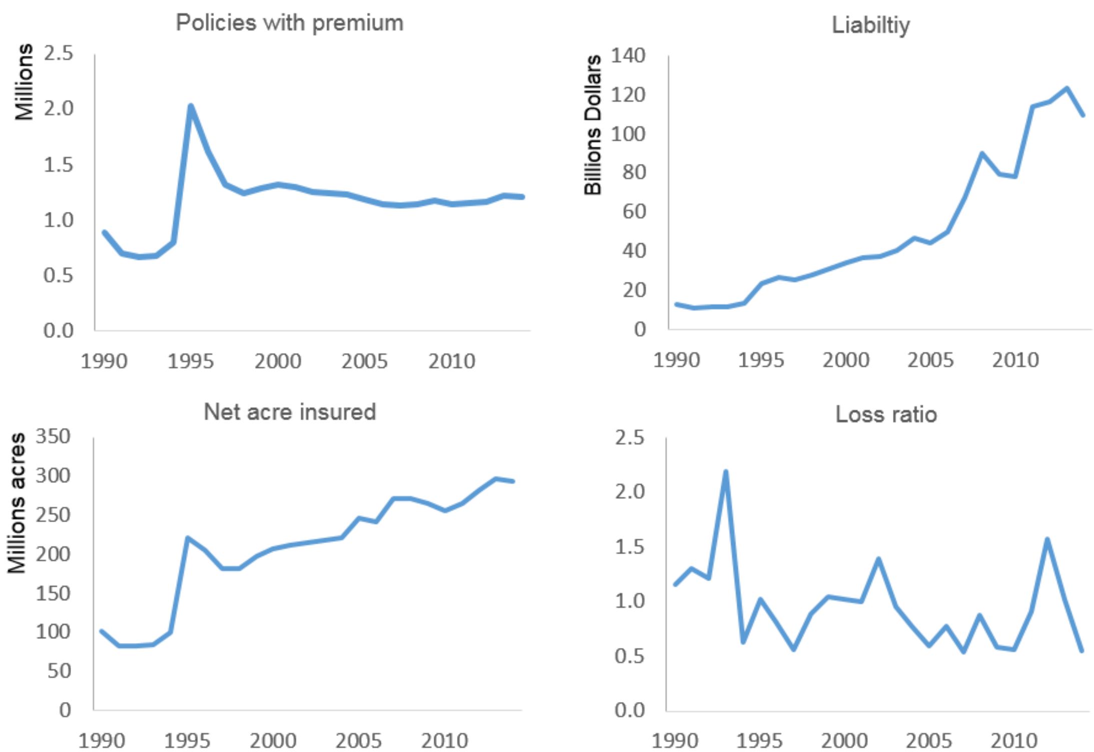

Figure 1-1. US Crop Insurance

Note: Steep increase in policies with premium in 1995 is the result of substantial rise of premium subsidies and subscription to receive the other supportive federal program in legislative actions in 1994.

1.1.1. Moral Hazard in Crop Insurance

It is by now well known that crop insurance may alter farmers' production practices to increase the likelihood of receiving an indemnity (moral hazard). Numerous studies, e.g., Chambers (1989), Horowitz and Lichtenberg (1993), Smith and Goodwin (1996), Babcock and Hennessy (1996), Wu (1999), and Chambers and Quiggin (2002), have examined whether crop insurance affects a farmers' production behavior. Each of these studies shows that there exist changes in input use, i.e., fertilizer and chemicals, validating the assumption that moral hazard exists. In other words, farmers who purchase crop insurance tend to reduce input applications (Smith and Goodwin 1996) or increase (risk-increasing) input use (Horowitz and Lichtenberg 1993) to increase the likelihood of receiving an indemnity.

1.1.2. Crop Yield Distribution

Proper calculation of the insurance premium is important. The RMA incorporates the distribution of crop yield in the calculation of the revenue insurance premium rate. Many studies, e.g., Nelson and Preckel (1989), Sherrick et al. (2004), and Woodard and Sherrick (2011), have attempted to find the best-fitting crop-yield distribution that would most accurately calculate this premium for farmers.

1.1.3. Subsidizing Crop Insurance

The role of insurance-premium subsidization has been highly debated in the literatures (Goodwin and Smith 2013; Coble and Barnett 2013; Wright 2014). Historical data suggests that a crop insurance subsidy encourages farmers to purchase crop insurance, e.g., the steep increase in policies with premium in 1995 in Figure 1-1. Further, the crop insurance subsidy reduces the problem of adverse selection, where otherwise only farmers with high production risk would participate in the program. Wright (2014) also points out that crop insurance subsidies have not been prohibited under current WTO regulations. However, crop insurance subsidies may have unintended impacts such as alteration of farming practice (moral hazard), expansion of crop lands, and related environmental concerns. In addition, subsidized crop insurance represents a budgetary transfer from taxpayers to farmers and private insurance companies, resulting in potential market distortions (Goodwin and Smith 2013).

1.1.4. Fairness of Premium Rate-making

The fairness of rate-making (loss ratio, total indemnity payments to total premium, must be one) is vital. Historically, loss ratio has been less than 1 or larger than 1 for a given crops year (loss ratio in Figure 1-1). Empirical studies by Babcock, Hart, and Hayes (2004), Woodard, Sherrick, and Schnitkey (2011), and Hu (2013) question whether current rate-making is fair. If rate-making is unfair, the crop insurance program will be lessened due to two reasons. First, farmers that incur a loss due to an unfair rate may choose not to participate in the crop insurance program in the future. Second, only farmers that make a gain from unfair rates would likely participate in the crop insurance program (Goodwin 1994). In other words, there exists a potential adverse selection problem.

1.1.5. Time Dependence of Yield Risk

The premium and indemnity depend on historical yield, which is known as the Actual Production History (APH). Both are biased downward over time due to technological advances that positively affect yield (Woodard et al. 2012). Since 2012, the RMA has implemented a trend-adjusted APH.

1.1.6. Research Gaps in the Crop Insurance Literature

Two research gaps in the crop insurance literature are identified: (i) the existence of moral hazard due to prevented planting (PP) program and (ii) understanding the farmer’s decision-making process with respect to planting a second crop.

The PP provision is defined as the “failure to plant an insured crop by the final planting date, or within any applicable late planting (LP) period,” due to adverse events such as excess moisture or drought (2013 Crop Insurance Handbook, USDA-RMA 2013). If a farmer decides not to plant a crop, s/he receives a PP indemnity. PP payments currently represent the large share of total indemnity in crop insurance programs. PP payments accounted for only 9% of total indemnity payments on average, from 1998 to 2008. From 2009 to 2013, however, PP payments accounted for roughly 17% of total indemnity payments. Farmers tend to choose PP in lieu of LP. This paper examines the existence of moral hazard in the choice of PP and LP. In particular, this paper tests the hypothesis that a farmer with a higher insurance coverage tend to choose PP more often.

If a farmer chooses PP, s/he receives the PP indemnity and may either leave the acreage unplanted or plant a second crop, e.g., soybean for corn. If the farmer plants a second crop, the farmer receives a reduced PP payment (currently, 35% of PP indemnity). The current reduced PP payment fails to provide farmers with an incentive to plant a second crop (99.9% of PP claiming farmers do not plant the second crop). Adjusting reduced PP indemnity payment may therefore encourage farmers to plant a second crop. The objective of the second study is to find and suggest the optimal percentage of reduced PP payment that may encourage farmers to plant a second crop.

1.2. Dairy Margin Protection Program

The Dairy Margin Protection Program (MPP-Dairy) administered by Farm Service Agency (FAS), USDA, is a financial risk management tool for dairy producers. The 2014 Farm Bill authorized the MPP-Dairy, which offers dairy producers protection of their milk production margin, income-over-feed-cost (IOFC) (Newton, Thraen, and Bozic 2015). The MPP-Dairy includes catastrophic coverage with an annual $100 administrative fee, and eight buy-up margin coverage levels with premium that varies with the level of protection (MPP dairy fact sheet 2014). The national dairy production margin is defined as the difference between the all-milk price and average feed costs (MPP dairy factsheet 2014). If the national average IOFC margin falls below $4/cwt (catastrophic coverage), MPP-Dairy provides indemnity payments to dairy farmers. Dairy farmers can purchase buy-up (supplementary) coverages with increase in $0.5/cwt up to $8.0/cwt (MPP dairy fact sheet 2014). The program's objective is that dairy producers, regardless of size, geographic location, or management practice, are offered self-selected protection levels against a drop in milk prices, rising feed costs, or a mixture of both (Newton and Thraen 2014).

2015 MPP-Dairy coverage data by states indicates that, for western states except Washington and Montana, less than 36% of those enrolled in the program purchased buy-up protection. As a reference, California (CA), which is the largest dairy producing state in the U.S., had only 29% of the enrolled dairy farms buying supplementary coverage, i.e., the majority-enrolled only purchased catastrophic coverage. In contrast, more than 50% of enrolled dairy producers in mid-western and eastern states bought buy-up coverages. For example, Wisconsin (WI), the second largest dairy producing state in the U.S., had 56% of enrolled producers buying supplementary coverages. Figure 1-2 shows the MPP-Dairy participation rates across margin protections in CA and WI. As shown, the distribution of MPP-Dairy participation rates differs in both regions. More than 70% of CA dairy producers solely purchased catastrophic protection, while 44% of WI producers enrolled solely in catastrophic protection. Instead, WI dairy farms bought buy-up coverage levels of $6/cwt and $6.5/cwt, and even the maximum protection level of $8/cwt.

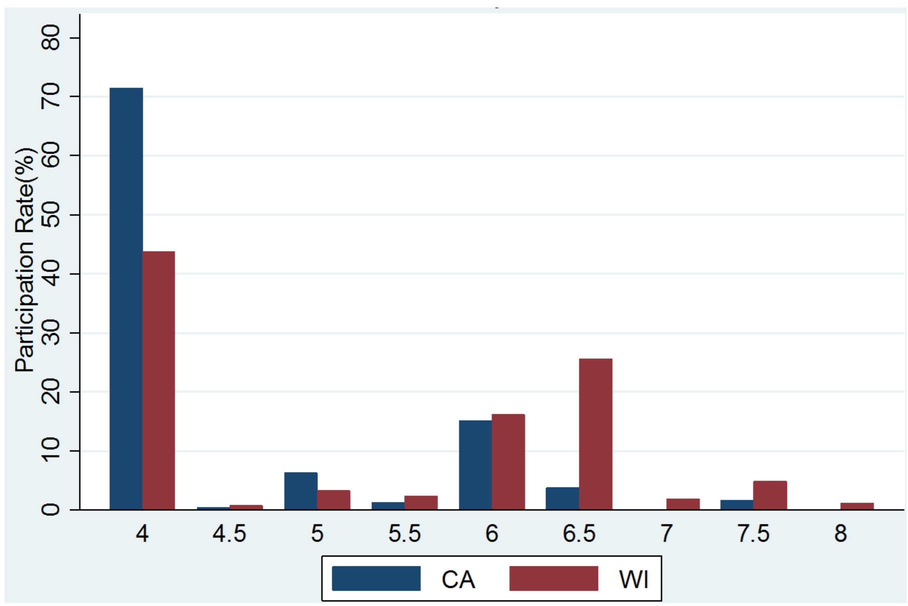

Figure 1-2. MPP-Dairy participation rate and margin protection in CA and WI in 2014
Note: Participation rate is the proportion of dairy producers who purchase dairy margin protection. $4/cwt is catastrophic coverage. Producers may purchase buy-up coverage that provides payments when margins are between $4.00 and $8.00/cwt.

The third essay explores this question, i.e., why western producers (CA producers) purchase less/lower buy-up levels than mid-western producers (WI producers). The study determines whether conditional probabilities regarding regional and national IOFC margins have a role in dairymens' decisions to purchase supplementary coverage at different levels.

1.3. Structure of Dissertation

In sum, three board research gaps are identified in this dissertation, namely 1) moral hazard in prevented planting and late planting, 2) the role of decision making with respect to prevented planting and planting a second crop, and 3) the role of conditional probability in determining dairy margin protection levels. This dissertation begins a discussion on these gaps in the crop insurance and MPP-Dairy literature.

Chapter two presents an overview of the literature regarding crop insurance and MPP-Dairy. The existence of moral hazard in prevented planting and late planting is examined in chapter three. Expected utility theory, stochastic simulation, and empirical analyses are presented. Chapter four investigates the relationship between the PP payment and planting a second crop and simulates how adjusting reduced PP indemnity payment can encourage farmers to plant a second crop. Chapter five investigates the role of conditional probability in influencing the dairy producers' decision-making on purchasing supplementary margin protections in MPP-Dairy. Finally, chapter six provides a summary of findings and concludes the dissertation.

2. LITERATURE REVIEW IN GENERAL

Chapter two reviews general literature regarding U.S. crop insurance and Margin Protection Program for Dairy Producers (MPP-Dairy).

2.1. Moral Hazard in Crop Insurance

Since the 1980s the US crop insurance program has been available to help farmers manage their yield and price risk. Researchers have investigated whether the crop insurance program gives farmers an incentive to change their production practices to receive more insurance indemnity (moral hazard) (Chambers 1989; Horowitz and Lichtenberg 1993; Smith and Goodwin 1996; Babcock and Hennessy 1996; Coble et al. 1997; Chambers and Quiggin 2002; Roberts, Key, and O'Dononghue 2006).

These studies have examined the existence of moral hazard in crop insurance, focusing primarily on the production input-use side. Horowitz and Lichtenberg (1993) study moral hazard by examining how corn farmers in the Corn Belt change fertilizer and pesticide use with crop insurance. They conclude that farmers who purchase crop insurance use more fertilizer and pesticides than those who do not purchase. However, both fertilizer and pesticides are risk-increasing inputs (Horowitz and Lichtenberg 1993), meaning that the more fertilizer and pesticide use could be considered to be a moral hazard.

Smith and Goodwin (1996) investigate the prevalence of moral hazard induced through crop insurance by examining the relationship between chemical use and crop insurance purchases for Kansas wheat farmers. Their main result conflicts with that of Horowitz and Lichtenberg (1993), as they find that farmers with crop insurance use less chemicals. Babcock and Hennessy (1996) also analyze the relationship between crop insurance and fertilizer application for the representative corn farmer in Iowa and show that farmers who purchase crop insurance are likely to decrease nitrogen fertilizer applications.

Coble et al. (1997) test for the existence of moral hazard in crop production using panel dataset of Kansas wheat farms. They show that moral hazard exists when the crop environment is unfavorable, e.g., drought, but does not exist under favorable environments, e.g., good weather. They argue that cross sectional studies, such as those of Horowitz and Lichtenberg (1993) and Smith and Goodwin (1996), do not allow for adequate measurement of moral hazard in crop insurance.

Wu (1999) studies the effect of crop insurance on crop mix and chemical use in the Central Nebraska Basin. He concludes that crop insurance affects crop mix and chemical use. Chambers and Quiggin (2002) investigate the effects of area-yield insurance [1] on producer's behavior in crop production. They claim that area-yield insurance is not different from other risk management tools available to farmers.

Roberts, Key, and O'Dononghue (2006) estimate the incidence of moral hazard using crop insurance administration data. They argue that previous studies did not control for endogeneity of the insurance decision since "insurance adoption is not randomly assigned", in an empirical analysis. To adjust for a non-random assignment of insurance adoption, the authors apply the difference-in-difference method and conclude that moral hazard exists among wheat and soybeans farms in Texas.

[1] Crop insurance for both premium rates and indemnities to be based not on the farmer's individual yield but rather on the aggregate yield of a surrounding area (Miranda 1991).

2.2. Crop Yield Distribution

It is crucial to identify which distribution best describes crop-yield variability since a crop-yield distribution must be pre-selected to estimate yield risk and ultimately determine the insurance premium rate. The RMA currently uses a censored normal distribution based on county level crop yield data provided by the National Agricultural Statistics Service (NASS) (Coble et al. 2010). However, researchers disagree on whether use of the censored normal distribution is appropriate (Coble et al. 2010).

Just and Weninger (1999) argue that the common assertion of non-normality of the yield distribution is not appropriate and suggest that normality of yield distribution is reasonable when researchers assess crop insurance programs. Atwood, Shaik, and Watts (2002) conduct a normality test using farm-level data of six crops: corn, soybean, wheat, cotton, sorghum and barley. They conclude that crop yield is distributed non-normal. They also examine the effect of crop insurance premiums under the normality assumption and data-based empirical distributions. They show that the premiums based on normal vs non-normal distribution are significantly different.

Sherrick et al. (2004) assess variety of crop yield distributions. They compare five distributions - normal, logistic, Weibull, beta, lognormal - according to mean percentage difference in expected payouts to corn and soybean. They show that choice of distribution can result in significantly large differences in indemnity payments.

2.3. Subsidizing Crop Insurance[2]

Recently, crop insurance subsidies have increased largely due to i) increases in the subsidy rate itself (2000: 37%, 2006: 58%, and 2012: 63%), ii) increases in crop price, iii) increases in enrolled acres, iv) increases in coverage level (2000: 56%, 2006: 71%, 2012: 72%, weighted average for corn and soybean), and v) radical shift from yield protection to revenue protection(revenue protection[3], 2000: 38%, 2006: 61%, 2012: 79% for corn and soybean).

Coble and Barnett (2013) discuss implications associated with these increases; i) higher crop insurance subsidies induce higher participation in crop insurance programs, ii) there is a correlation between the increase in crop insurance purchases and reduced ex-post disaster assistance even if there seem not to be sufficient evidence to show a causal relationship between them, iii) there are regional differences in received subsidies due to the difference in degree of the risk, iv) higher crop insurance subsidies mask the adverse selection and moral hazard effects, and v) induced rent-seeking; the most farmer organization are opt to prefer crop insurance program to other farm policy programs, such as direct payment or counter-cyclical, or Average Crop Revenue Election (ACRE) programs.

As Goodwin and Smith (2013) point out, the crop insurance subsidy can also alter farming practices and lead to expansion of crop lands and related environmental concerns. In addition, subsidized crop insurance represents a budgetary transfer from

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[2] The numbers in section 2.3. are from author's calculation using summary of business data provided by the RMA.

[3] Crop Revenue Coverage (CRC), Revenue Assurance (RA), Income Protection (IP), Revenue Protection (RP) and Revenue Protection Harvest Price Exclusion (RP-HPE) are included to calculate the percentage.

taxpayers to farmers and private insurance companies which can lead to market distortions.

2.4. Fairness of Rate-Making and Time Dependence of Yield Risk

The major technique used to determine the crop insurance premium rate is known as Multiple Peril Crop Insurance (MPCI) rate-making. MPCI rate-making depends on the loss cost ratio (LCR) approach. MPCI rate-making has been widely criticized because of potential biasedness and inefficiencies in determination of coverage guarantees (Skees and Reed 1986), state excess loads (Josephson, Lord, and Mitchell 2000), and intra-county yield risk heterogeneity (Goodwin 1994). Recently, researchers have focused on the time dependence of yield risk (Umarov 2009; Woodard et al. 2012; Adhikari, Knight, and Belasco 2013). That is, since measurement of Actual Production History (APH) is based on a simple moving average yield over four to ten years, the premium and indemnity based on APH is downward biased due to advances in crop-yield technology. Moreover, farmers have complained that the current APH calculation does not reflect technical advances. In response to these criticisms, the RMA introduced the Trend Adjusted Actual Production History (TA-APH) pilot program in the 2012 crop year primarily in the Corn-Belt regions and has expanded to other regions.

2.5. Dairy Margin Protection Program

Few studies are available regarding the MPP-Dairy. A handful of Farmdoc publications, such as Newton and Thraen (2014), Newton and Bozic (2014), and Newton and Balagtas (2015) address the MPP-Dairy. This is partly because the MPP-Dairy is a relatively new policy option included in the 2014 Farm Bill. Historically, dairy policy has been designed to increase dairy farmers' income (Newton, Thraen, and Bozic 2015).

Among others, Milk Income Loss Contract (MILC) in 2002 Farm Bill had provided income support based on a target milk price. In MILC, a dairy producer receives direct payment that is equal to 45% of the difference between the fluid milk price and a reference price, 16.94/cwt, when the fluid milk price is lower than the reference price. Program participants can receive payments on only maximum 2.4 million pounds (Price 2004). Since MILC is premised on the assumption of stable, MILC program has failed to provide a safety net for dairy farms in the face of the recent rise in feed prices. The 2008 Farm Bill adopted variable reference pricing whenever weighted feed cost is above $7.35/cwt (Schnepf 2012).

The 2014 Farm Bill replaced income and commodity price support programs with Margin Protection Program for Dairy Producers (MPP-Dairy) to protect farmers' income-over-feed-cost (IOFC) margins rather than the milk price per se (Farm Service Agency 2011). The MPP-Dairy includes catastrophic coverage, at no cost to the producer other than an annual $100 administrative fee. Various levels of buy-up coverage are offered with premiums that vary with the level of protection (Newton, Thraen, and Bozic 2015). Catastrophic coverage provides payments to participating producers when the national dairy production margin is below $4/cwt. Producers may purchase buy-up coverage for national margins that range from $4.50/cwt to $8.00/cwt, rising by increments of $0.50. The program's objective is to ensure that dairy producers, regardless of their size, geographic location or management practices, are offered self-selected protection levels against declines in milk prices, rising feed costs, or a mixture of both (Newton and Thraen 2014; Newton, Thraen, and Bozic 2015).

Perhaps the first MPP-Dairy study is Newton and Thraen (2014) which classifies the MPP-Dairy as a dairy safety net. Newton and Bozic (2014) also explain how the MPP-

Dairy works and evaluate milk price levels required to trigger the MPP-Dairy. Newton and Balagtas (2015) explore the MPP-Dairy participation pattern particularly the relationship between the farm size (in terms of annual average milk production) and participation rate. They find that the MPP-Dairy participation rate is positively related to dairy farm operation size across states. They also find that purchase of the buy-up option is negatively related to farm operation size across states. They point out that states with larger average dairy farm size tend to exhibit higher participation rates since the $100 administration fee is relatively small for larger dairy farms (Newton and Balagtas 2015). Novakovic et al. (2015) summarize the enrollment data for the MPP-Dairy program. They find that there is low negative correlation between enrollment rate and the number of farms in a state, and positive correlation between enrollment rate and average farm size across states, too. Also, they find that participation rate for supplementary coverage level of eastern states is higher than that of western states.

Newton, Thraen, and Bozic (2015) argue that MPP-Dairy has led to higher taxpayer costs compared with prior dairy farm support programs. Two reasons are suggested. First, dairy farmers may be able to predict the national dairy margins quite accurately using publicly available information from futures markets, which in turn allows them to maximize program returns. Second, the lack of production constraints shifts benefits toward larger dairy farms and causes more burden to the US budget.

Regarding the dairy production margin, which is defined as the difference between all-milk price and feed costs, Bozic et al. (2012) shows that the dairy margin exhibits a slow mean-reverting path over time when the margins are very high or very low. Their findings can be used to design strategies for managing margins, especially in a futures market.

Bozic et al. (2014) explore the method to determine Livestock Gross Margin Insurance for Dairy Cattle (LGM-Dairy) which is the previous dairy support program. They point out that the current rate-making method using a Gaussian copula fails to capture crucial features of milk and feed markets. They find that, since 2005, the dependence between milk price and corn price has become stronger compared to 1990~2005. This is because the number of larger dairy farms (> 1000 dairy cattle) has increased over time, and most of large farms purchase their feed from the grain markets. It ties milk price and corn price strongly which causes stronger tail dependence which is not captured in the Gaussian copula.

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3. MORAL HAZARD IN PREVENTED PLANTING

Abstract

This study examines the existence of moral hazard associated with the choices of prevented planting (PP) and late planting (LP). The PP provision is defined as the "failure to plant an insured crop by the final planting date due to adverse events" such as excess moisture or drought. If the farmer decides not to plant the crop, (after appraised by an agency) the farmer receives a PP indemnity. LP is an option for the farmer to plant the crop and still maintain the crop insurance when the farmer fails to plant crop by the final planting date. However, by choosing the LP option the farmer receive a lower the insurance coverage level depending upon the LP date due to potential yield loss. Crop insurance may alter farmers' decision choices in the selection of PP or LP. In other words, crop insurance can increase the likelihood of PP claims even though farmers can choose LP. In particular, this paper seeks to explain why a farmer with higher insurance coverage would tend to choose PP statistically more often, i.e., exhibit moral hazard. A stochastic simulation driven by expected utility theory demonstrates the existence of moral hazard in PP numerically. Spatial panel econometrics models attest to the existence of moral hazard in PP empirically.

Key Words: Crop Insurance, Moral hazard, Prevented Planting, Late Planting

JEL Codes: D81, G22, Q12, Q14

3.1. Introduction

The Risk Management Agency (RMA) has included prevented planting (PP) in crop insurance programs since 1998. The PP provision is defined as the “failure to plant an insured crop by the final planting date, or within any applicable late planting (LP) period,” due to adverse events such as excess moisture or drought (2013 Crop Insurance Handbook, USDA-RMA 2013). If a farmer with a base PP coverage level (base PP) claims PP payments, 60% (varies from 25% to 60% depending upon the specific crop insured) of the original liability is paid as an indemnity[4] on approval of the insurer. The farmer also can choose buy-up PP coverage level of 5% and 10%. In this case, PP payments are given at 65% and 70% of the original liability, respectively.

PP payments account for a growing large share of total indemnity from crop insurance programs. For example, PP payments accounted for roughly 9% of total indemnity on average from 1998 to 2008. From 2009 to 2013, however, PP payments accounted for 17% of total indemnity. In 2010 the share of PP payments increased to approximately 29% of total indemnity (author’s calculation using Cause of Loss Historical Data Files from RMA).

Late planting (LP) is another option that a farmer may choose when s/he fails to plant a crop in the normal planting period. Choosing LP maintains his/her crop insurance, but the farmer does not receive PP indemnity and has to lower the insurance coverage level depending upon the LP date due to potential yield loss (1% per day after final plating

[4] PP indemnity payments depend on insurance coverage level, buy-up PP, and choice of a second crop after late planting date. For example, if a farmer buys 75% coverage level with base PP, s/he receives indemnity, PP indemnity = 0.75*0.60*APH*price election*claimed acre, where APH is the actual production history. When s/he chooses to plant a second crop, s/he receives 35% of the PP indemnity.

date).[5] Figure 3-1 presents the timeline for the choice between PP and LP as well as PP options for a second crop after claiming PP.

As evidenced by the recent increase in PP payments, farmers tend to choose PP in lieu of LP. Rejesus et al. (2003) and Rejesus, Escalante, and Lovell (2005) show that crop insurance provides farmers with an incentive to choose PP. In other words, crop insurance may increase the likelihood of PP claims even though farmers have the option of choosing LP. In this case moral hazard is observed. If moral hazard exists in PP, farmers are inefficiently abandoning cropland. Abandoning cropland in a given year leads to two problems. First, insurance premium subsidies paid to farmers has a negative effect on production because no crop is produced. Second, it is a contradiction of the goal of USDA that promotes agricultural production to improve food security (USDA's strategic Plan FY 2010-2015, Goal 3) (OIG 2013).

This paper examines the existence of moral hazard associated with the choice of PP and LP and, in particular, seeks to explain why a farmer with higher insurance coverage tends to choose PP. Specifically, this paper investigates the prevalence of moral hazard by examining the effects of crop insurance, its type, and coverage level on the farmer's PP decision. An Intra-seasonal expected utility maximization model for the representative farmer is developed in the context of a stochastic simulation. Further, spatial panel econometrics models are developed to uncover the relationship between the PP ratio and coverage level.

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[5] For example, the coverage level is lowered to 0.75*0.95=0.7125, if the insured purchases an insurance plan with a 75% coverage level and plants the crop after 5 days of the final planting date.

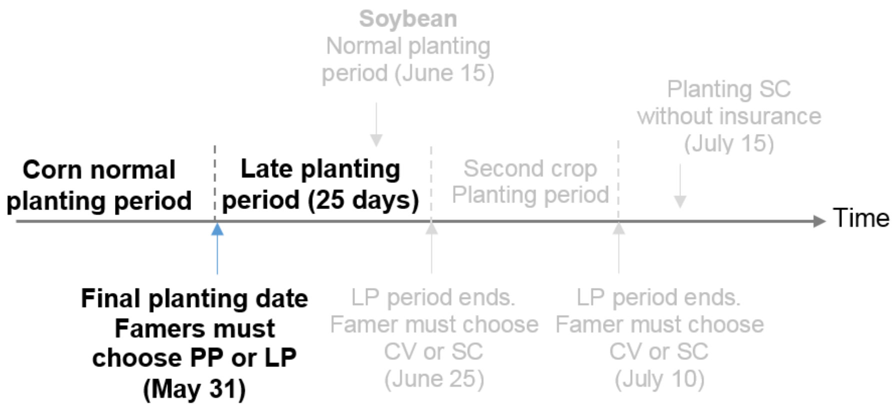

Figure 3-1. Timeline for choice between prevented planting and late planting
Note: PP = prevented planting, LP = late planting, CV = cover crop, SC = second crop
Dates are for the typical farm in Iowa. Some texts which are not discussed in this paper are greyed out

3.2. Literature Review

Several studies have examined moral hazard in crop insurance, focusing primarily on production inputs. Horowitz and Lichtenberg (1993) study moral hazard by examining how corn farmers in the Corn Belt change fertilizer and pesticide use with crop insurance. They conclude that farmers who purchase crop insurance use more fertilizer and pesticides than those who do not.

Smith and Goodwin (1996) test for the existence of moral hazard in crop insurance by examining the relationship between chemical use and crop insurance purchases by Kansas wheat farms. Contrary to Horowitz and Lichtenberg (1993), they conclude that farmers with crop insurance use fewer chemicals. Babcock and Hennessy (1996) also analyze the relationship between crop insurance and fertilizer application for a representative corn farmer in Iowa, and show that farmers who purchase crop insurance are more likely to decrease nitrogen fertilizer applications.

Coble et al. (1997) test for moral hazard in crop production using a panel dataset of Kansas wheat farms. They find that moral hazard exists solely when the cropping environment is unfavorable, e.g., drought, and does not exists under favorable environments. They argue that single-year cross-sectional data, approach used in previous studies by Horowitz and Lichtenberg (1993) and Smith and Goodwin (1996), are inadequate for testing for the existence of moral hazard.

Wu (1999) studies the effect of crop insurance on crop mix and chemical use in the Central Nebraska Basin. He concludes that crop insurance affects crop mix and chemical use. Chambers and Quiggin (2002) investigate the effects of area-yield insurance [6] on producer's behavior in crop production. They claim that area-yield insurance is not different from other risk management tools available to farmers.

Roberts, Key, and O'Dononghue (2006) estimate the incidence of moral hazard using crop insurance administration data. They argue that previous studies did not control for endogeneity of the insurance decision since "insurance adoption is not randomly assigned", in an empirical analysis. To adjust for a non-random assignment of insurance adoption, the authors apply the difference-in-difference method and conclude that moral hazard exists among wheat and soybeans farms in Texas.

There exist few studies focused on PP. Rejesus et al. (2003) empirically analyze potential fraudulence in PP claims. They show that higher insurance coverage level induces more fraudulent PP claims. Moreover, they find that revenue protection leads to more fraudulent PP claims than that associated with yield protection. Rejesus Escalante and Lovell (2005) also analyze the relationship between PP claims, land ownership, and

[6] Crop insurance for both premium rates and indemnities to be based not on the farmer's individual yield but rather on the aggregate yield of a surrounding area (Miranda 1991).

farm business structure. They find that a tenant under a leasing contract has an increased the likelihood of claiming more PP. They also find that sole ownership and partnership farms claim more PP than cooperative farms.

This study differs from Rejesus et al. (2003) in two respects. First, this study investigates the evidence of moral hazard in choosing PP, not committing PP fraud. Second, Rejesus et al. (2003) argue that revenue protection insurance leads to more PP claims (PP fraud) than yield protection insurance. This argument is questionable since revenue protection schemes such as Crop Revenue Coverage (CRC) and Revenue Assurance Harvest Price Option (RA-HPO)[7] have an option to choose a higher price between an elected price and harvest price. Thus, if a farmer expects the crop price to be higher than the elected price at time of harvest, s/he would not file a PP claim, or at least the probability of filing a claim would be lower.

3.3. Moral Hazard in Insurance Economics

Moral hazard describes a change of the insured’s unobserved behavior caused by purchase of insurance contract providing protection against risk. Moral hazard has two different definitions in insurance economics, i.e., ex-ante and ex-post moral hazard.

[7] CRC and RA-HPO have been eliminated since 2011. Currently, revenue protection (RP) and revenue protection harvest price exclusion (RP-HPE) are in operation as crop revenue protection program. A farmer can choose the higher between elected (guaranteed) price and harvest price in RP, while s/he cannot choose the higher price in RP-HPE. Close to 99% of corn farmers currently purchase RP policy not RP-HPE in 2013 (author’s calculation using data from State/County/Crop/Coverage Level 1989-2015 Data Files and Record Layout, RMA summary of business Reports and Data).

3.3.1. Ex-Ante Moral Hazard

Ex-ante moral hazard means the change of insured's unobserved behavior before losses occur. For example, a farmer with crop insurance may decrease (or increase) an input uses compared with farmers without crop insurance, as discussed in Horowitz and Lichtenberg (1993), Smith and Goodwin (1996), and Coble et al. (1997). This behavior affects the probability or size of loss. Deductible and co-insurance are well known as insurance design schemes to mitigate ex-ante moral hazard.

3.3.2. Ex-Post Moral Hazard

Ex-post moral hazard describes the changes of insured's behavior after losses occur. If insured has a more comprehensive insurance contract, s/he is more likely to claim indemnity payments than an insured who has less comprehensive insurance contract. Economists are more interested in ex-ante moral hazard than ex-post moral hazard in that ex-ante moral hazard describes the change for insured's behavior more directly. However, insurance suppliers are more interested in ex-post moral hazard than ex-ante moral hazard because ex-post moral hazard is directly related to their profit.

3.3.3. Prevented Planting and Ex-Post Moral Hazard

A farmer claims prevented planting after losses occur. This research examines the existence of ex-post moral hazard in PP.

3.4. PP and LP Decision Making

Assume that a farmer is risk averse and maximizes expected utility from uncertain profit at harvesting time. Suppose that, due to adverse events such as drought or excess moisture, the farmer should choose PP or LP. The farmer is at final planting time (see

Figure 3-1 PP timeline), i.e., time period 1 $(t = 1)$, and should make the insurance decision. If the farmer claims PP at $t = 1$, s/he obtains the profit from the PP indemnity, π_{PP}, with certainty, which can be written as

(3-1) $\pi_{PP} = p_g \theta_{pp} \theta q_{APH} - c_1 - m - c_{cv}$,

where p_g is the elected (guaranteed) price by the RMA (Commodity Exchange Price Provisions (CEPP) based on data from the futures market), θ_{pp} is the PP coverage level (60%, 65% or 70% depending upon buy-up), and θ is the insurance coverage rate $\theta \in [50\%, x]$, x varying from 75% to 85% in 5% increments. The term q_{APH} is the farmer's actual product history (APH) per acre for the past 4-10 years, c_1 is the input cost per acre for normal planting, m is the crop insurance premium, and c_{cv} is the cost for planting a cover crop, which is a requirement of any PP claim.

If the farmer chooses LP, s/he obtains profit level,

(3-2) $\tilde{\pi}_{LP} = \left[(\tilde{p}\tilde{q} - c_1 - m - c_2) + ind_j\right], \;\; j = yp, rp,$

where tilde above the variable indicates that it is a stochastic variable at $t = 1$. $\tilde{\pi}_{LP}$ is the profit for LP at the harvesting time, $t = 2$, $\tilde{p}$ is the crop price at $t = 2$ which is stochastic at $t = 1$, $\tilde{q}$ is the yield at $t = 2$ which is also stochastic at $t = 1$, c_1 is, again, the input cost per acre for the normal planting of the first crop, and c_2 is the cost of LP until the harvesting time. The term $\max\{0, ind_j\}$ is the amount of indemnity that the farmer expects at $t = 1$. Depending on types of crop insurance, the indemnity can be rewritten as follows. In the case of yield protection, yp, the indemnity is given by

(3-3) $ind_{yp} = p_g \cdot \max\{0, \rho\theta q_{APH} - \tilde{q}\}$,

where, p_g is the elected price if a farmer choose 100% of price election, ρ is the coverage reduction factor depending on late planting date (1% per day after normal planting date),

θ is the coverage level, q_{APH} is the APH, and $\tilde{q}$ is the stochastic yield. If the crop yield is higher than the coverage level, $\rho\theta q_{APH}$, the farmer is not eligible for the yield protection indemnity regardless of the price level at harvest time.

In the case of revenue protection, rp, the indemnity becomes

(3-4) $\quad ind_{rp} = \max\{0, \min(2p_g, \max(p_g, \tilde{p})) \cdot \rho\theta q_{APH} - \tilde{p}\tilde{q}\}.$

If the revenue at the harvesting period, $\tilde{p}\tilde{q}$, is greater than the covered revenue, $\min(2p_g, \max(p_g, \tilde{p})) \cdot \rho\theta q_{APH}$, the farmer does not qualify for the receive revenue protection indemnity.

To make the decision process simple, suppose the farmer has either yield protection with either 100% price election or revenue protection. The farmer will claim PP if

(3-5) $\quad u(\pi_{pp}) > EU(\tilde{\pi}_{LP}),$

where $u(\cdot)$ is a strictly increasing twice-continuously differentiable farmer's utility function and $EU(\cdot)$ is the expected utility function. Conditional on the information known to the farmer at $t = 1$, expected utility can be rewritten as

(3-6) $\quad EU(\tilde{\pi}_{LP}) = u(E(\tilde{\pi}_{LP}) - RPM),$

where $E(\tilde{\pi}_{LP})$ is the farmer's expected value of $\tilde{\pi}_{LP}$, and RPM is the risk premium assuming s/he is a risk averter (Chavas 2004, p.36). In other words, the farmer chooses PP when $\pi_{pp} > E(\tilde{\pi}_{LP}) - RPM$ and indifferent when

(3-7) $\quad \pi_{pp} = E(\tilde{\pi}_{LP}) - RPM.$

Equation (3-7) can be interpreted as a PP-LP indifference curve (PP-LP curve). The PP-LP curve depicts the combinations of $E(\tilde{p})$ and $E(\tilde{q})$ that satisfy equation (3-7) or

(3-8) $\pi_{pp} = E\left[(\tilde{p}\tilde{q} - c_1 - m - c_2) + \max\{0, ind_j\}\right] - RPM$

$$= E(\tilde{p})E(\tilde{q}) + cov(\tilde{p}, \tilde{q}) - c_1 - m - c_2 + \max\{0, ind_j\} - RPM,\ \ j = yp, rp.$$

In the case of yield protection, equation (3-8) can be rewritten as

(3-9) $\pi_{pp} = E(\tilde{p})E(\tilde{q}) + cov(\tilde{p}, \tilde{q}) - c_1 - m - c_2 + p_g \cdot \max\{0, \rho\theta q_{APH} - E(\tilde{q})\}) - RPM.$

If $\rho\theta q_{APH} < E(\tilde{q})$, or guaranteed yield < expected yield, then the expected indemnity = 0. Equation (3-9) then becomes

(3-10) $E(\tilde{p})E(\tilde{q}) = \pi_{pp} - cov(\tilde{p}, \tilde{q}) + c_1 + m + c_2 + RPM$

$$\Rightarrow\ E(\tilde{q}) = \frac{1}{E(\tilde{p})}\left(\pi_{pp} - cov(\tilde{p}, \tilde{q}) + c_1 + m + c_2 + RPM\right).$$

If $\rho\theta q_{APH} > E(\tilde{q})$, or guaranteed yield > expected yield, then the expected indemnity = $p_g(\rho\theta q_{APH} - E(\tilde{q}))$. Equation (3-9) then becomes

(3-11) $\left(E(\tilde{p}) - p_g\right)E(\tilde{q}) = \pi_{pp} - cov(\tilde{p}, \tilde{q}) + c_1 + m + c_2 - p_g\rho\theta q_{APH} + RPM$

$$\Rightarrow E(\tilde{q}) = \frac{1}{E(\tilde{p}) - p_g}\left(\pi_{pp} - cov(\tilde{p}, \tilde{q}) + c_1 + m + c_2 - p_g\rho\theta q_{APH} + RPM\right).$$

In either case, the PP-LP curve is convex toward origin in the q-p plane (hyperbola) as shown in Figure 3-2. Above $\rho\theta q_{APH}$, i.e., guaranteed yield, the PP-LP curve follows equation (3-10) and below $\rho\theta q_{APH}$, the PP-LP curve follows equation (3-11) which is flatter than the curve equation (3-10).

Note that the expectation operator in equations (3-7) to (3-11) is not necessarily the expected value of a random variable (price and yield). It is more or less like **anticipated values** from the farmer with information at $t = 1$. For example, suppose that the farmer's expectation (anticipation) of price and yield based on information known to her/him at $t = 1$ is $\left(E(\tilde{p}_1), E(\tilde{q}_1)\right)$. If the combination of the expected price and yield lies above the PP-LP curve, the farmer would choose LP, otherwise s/he would choose PP. In Figure 3-2 $\left(E(\tilde{p}_1), E(\tilde{q}_1)\right)$ lies on the curve and the farmer is indifferent.

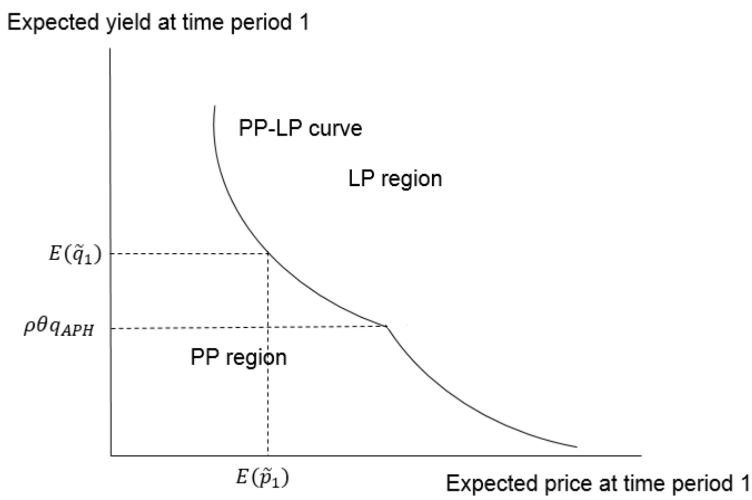

Figure 3-2. PP-LP curve for yield protection

In the case of revenue protection, the farmer is indifferent between PP and LP when

(3-12) $\pi_{pp} = E(\tilde{p})E(\tilde{q}) + \mathrm{cov}(\tilde{p}, \tilde{q}) - c_1 - m - c_2$

$$+ \max\left\{0, \min\left(2p_g, \max\left(p_g, E(\tilde{p})\right)\right) \cdot \rho\theta q_{APH} - E(\tilde{p})E(\tilde{q})\right\} - RPM.$$

If $\min\left(2p_g, \max\left(p_g, E(\tilde{p})\right)\right) \cdot \rho\theta q_{APH} < E(\tilde{p})E(\tilde{q})$, i.e., guaranteed revenue < expected revenue, the expected revenue protection indemnity is zero then the PP-LP curve in equation (3-8) becomes

(3-13) $E(\tilde{q}) = \frac{1}{E(\tilde{p})}\left(\pi_{pp} - \mathrm{cov}(\tilde{p}, \tilde{q}) + c_1 + m + c_2 + RPM\right).$

Equation (3-13) is similar to equation (3-10), the PP-LP curve for yield protection.

If instead $\min(2p_g, \max\left(p_g, E(\tilde{p})\right)) \cdot \rho\theta q_{APH} > E(\tilde{p})E(\tilde{q})$, i.e., guaranteed revenue > expected revenue, the farmer expects to receive the RP indemnity. When $p_g < E(\tilde{p}) < 2p_g$, i.e. the price at $t = 2$ is anticipated to be higher than the elected price but less than $2p_g$, the farmer's expected indemnity would be $E(\tilde{p})\rho\theta q_{APH} - E(\tilde{p})E(\tilde{q})$. Note that the condition to receive the revenue indemnity, i.e., $\rho\theta q_{APH} > E(\tilde{q})$, must hold. In other words, farmer's expected yield must be lower than guaranteed yield, otherwise there is no revenue protection indemnity. In this case, the PP-LP curve becomes

(3-14) $\pi_{pp} = E(\tilde{p})E(\tilde{q}) + cov(\tilde{p},\tilde{q}) - c_1 - m - c_2 + E(\tilde{p})\rho\theta q_{APH} - E(\tilde{p})E(\tilde{q}) - RPM$

$$\Rightarrow \quad E(\tilde{p}) = \frac{1}{\rho\theta q_{APH}}(\pi_{pp} - cov(\tilde{p},\tilde{q}) + c_1 + m + c_2 + RPM)$$

Equation (3-14) tells us that $E(\tilde{p})$ is now a fixed value because all of parameters in the right hand side are known to the farmer at $t = 1$ (vertical line from $E(\tilde{p})$ axis in Figure 3-3).

The expected indemnity is $2p_g\rho\theta q_{APH} - E(\tilde{p})E(\tilde{q})$ when $E(\tilde{p}) > 2p_g$, i.e. the anticipated price at $t = 2$ is higher than twice of the elected price. In this case, $2p_g\rho\theta q_{APH} > E(\tilde{p})E(\tilde{q})$ to receive the RP indemnity. Both terms $E(\tilde{p})$ and $E(\tilde{q})$ disappear from equation (3-12) and the PP-LP line is not defined. However, the farmer will most likely choose LP because the anticipated price is very high. The combination $\left(E(\tilde{p}), E(\tilde{q})\right)$ will be then located on the right hand side of the vertical line in Figure 3-3.

When $E(\tilde{p}) < p_g$, i.e. the price at $t = 2$ is expected to falls below the elected price, the expected indemnity is $p_g\rho\theta q_{APH} - E(\tilde{p})E(\tilde{q})$. Again, $p_g\rho\theta q_{APH} > E(\tilde{p})E(\tilde{q})$ to satisfy the condition of receiving RP indemnity. Note that $p_g\rho\theta q_{APH}$ is represented by a grey rectangular in Figure 3-3 and the expected revenue should be smaller than the size of the rectangular. It implies that the farmer would choose PP in this case even though the PP-LP line is not defined because both terms $\mathrm{E}(\tilde{\mathrm{p}})$ and $\mathrm{E}(\tilde{\mathrm{q}})$ disappear from equation (3-12).

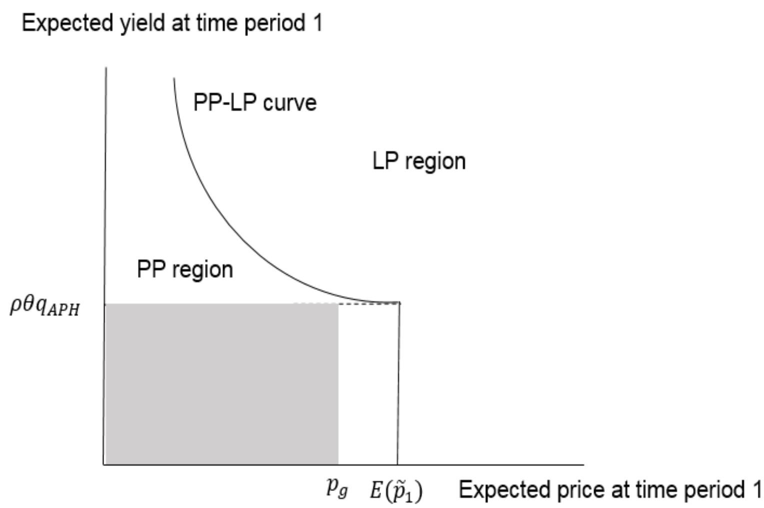

Figure 3-3. PP-LP curve for revenue protection

Once the PP-LP curve is constructed, the change in the probability of choosing PP given different insurance coverage rates can be computed as

(3-15) $\Delta\,\mathrm{Pr(PP)} = \mathrm{Pr(PP|\theta^1)} - \mathrm{Pr(PP|\theta^0)},$

where, $\mathrm{Pr(PP)}$ is the probability of choosing PP and θ^0 and θ^1 represent any two coverage levels, θ^0, $\theta^1 \epsilon [50\%, \mathrm{x}]$. If $\Delta\,\mathrm{Pr(PP)} > 0$, when $\theta^1 > \theta^0$, then, the probability of (ex-post) moral hazard increases. Or, simply, the PP-LP curve with higher coverage lies above the PP-LP curve with lower insurance coverage.

3.5. Representative Farmer and Stochastic Simulation

In this section, stochastic simulation of a representative farmer is developed in order to derive numerical PP-LP curves that will show how moral hazard is affected by changes in θ in PP decision making. Our simulation of a representative farmer's behavior on crop insurance is not original to this paper. Babcock and Hennessy (1996) and Coble, Heifner, and Zuniga (2000) have previously created a representative farmer.

3.5.1. Representative Farmer

A representative farmer is modeled based on corn budget data from Hamilton County, Iowa to generate the PP-LP curves. For this simulation, historical corn price and yield, insurance premium including subsidy over insurance plans, and farm cost data are compiled from Iowa extension, the RMA quick cost estimator, and USDA NASS (Table 3-1). There are be 48 different crop insurance plans from two different insurance types, RP and YP, three different PP coverages, θ_{pp}, (60%, 65%, and 70%), and eight different insurance coverages, θ, (50%, 55%, 60%, 65%, 70%, 75%, 80%, and 85%). To make the comparisons simple, a subset of six crop insurance plans is presented (Simulation have been done for all of the possible crop insurance plans). Table 3-1 presents information for the representative farmer.

3.5.2. Risk Premium

Risk premium is defined as a certain amount of money that farmer is willing to pay to avoid the risk. Thus, risk premium is intuitively interpreted as the shadow cost of private risk bearing (Chavas 2004). Certainty equivalent means the difference between the expected monetary value of the alternative (here, LP profit) and risk premium.

Table 3-1. Representative Corn Farmer in Hamilton County, Iowa

	Yield Protection			Revenue Protection		
	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3
PP coverage level (θ_{pp})	60%	65%	70%	60%	65%	70%
Coverage level (θ)	65%	75%	85%	65%	75%	85%
LP reduction factor (ρ)	0.95					
Elected price[1] (p_g)	$4.62/bushel					
Volatility of corn price[2]	0.19					
APH[3] (q_{APH})	189 bushels/acre					
Avg. yield	179.52 bushels/acre					
St. Dev. of yield	35.42 bushels/acre					
Insurance premium ($/acre) ($m$)	7	11	17	10	19	37
Coverage subsidy rate[4]	0.59	0.55	0.38	0.59	0.55	0.38
Additional premium for buy-up PP ($/acre)[5]	0	0.22	0.85	0	0.22	0.85
Cost at t=1 ($/acre), ($c_1$)	$327.8/acre					
Cost of planting cover crop (c_{cv})	$38/acre					
Cost of LP at time period 2 (c_2)	$424.08/acre					
Correlation between price and yield[6]	-0.30					
Covariance between price and yield[7]	-$9.05					
Utility function[8]	$u(\pi) = -\exp(-r\pi)$					
Risk aversion parameter[9] (r)	0.002					
Risk Premium, RPM[10]	$32.83	$30.47	$27.35	$31.09	$26.71	$21.20

[1] The elected corn price is $4.62/bushel in 2014 and is considered an average price.

[2] Historical corn futures price data from the RMA.

[3] Trend-adjusted APH.

[4] The farmer is responsible for (1 – coverage subsidy rate)×insurance premium. Federal government pays subsidy rate × insurance premium.

[5] For example, a farmer in Hamilton County should pay $17+$0.85 to purchase buy-up 10% PP (70% coverage) with 85% coverage level (case 3). Buy-up PP premiums differ by county.

[6] For numerical simulation, corn price and yield are generated randomly in consideration of correlation between price and yield. The correlation is calculated using historical data from 1990 to 2005.

[7] Covariance between historical corn price and yield.

[8] Negative exponential utility function exhibits constant absolute risk aversion (CARA), which is given by r. This function has been used extensively in decision analysis (Hardaker et al. 2004, p.103).

[9] When r = 0, the decision maker is risk neutral and higher values of r imply risk averse decision makers. We select r = 0.002 based on Table 2 in Babcock, Choi, and Feinerman (1993). The risk aversion coefficient of 0.002 is relatively risk averse farmer.

[10] RPM is calculated using given the utility function and risk aversion coefficient.

The risk premium, RPM, in Table 3-1 is derived assuming a negative exponential utility function, as follows

1. Generate random corn price and yield, $\tilde{p}$ and $\tilde{q}$, at the harvesting time, $t = 2$.
2. Calculate profit from late planting, $\tilde{\pi}_{LP}$.
3. Repeat steps 1 and 2 for 1000 times.
4. Calculate the certainty equivalent (CE) using simulated profit from step 3 using the formula, $\mathrm{CE}(r) = \ln[\left(\frac{1}{1000}\sum \exp(-r \cdot \pi_i)\right)^{-\frac{1}{r}}]$, where i represents each iteration and r stands for the absolute risk aversion coefficient (Hardarker et al. 2004, p. 257).
5. Derive the risk premium following the definition, $\mathrm{RPM} = \mathrm{E}(\tilde{\pi}_{LP}) - u^{-1}(\mathrm{EU}(\tilde{\pi}_{LP}))$ (Chavas 2004, p. 34) which is equivalent to $\mathrm{RPM} = \mathrm{E}(\tilde{\pi}_{LP}) - \mathrm{CE}(r)$.

3.5.3. PP-LP Curve

The PP-LP curves are then derived as follows

1. Generate random corn price and yield, $\mathrm{E}(\tilde{p})$ and $\mathrm{E}(\tilde{q})$, at the harvesting time $t = 2$.
2. Calculate profit in equation (3-2) with insurance indemnity if any using equations (3-3) and (3-4).
3. Using equation (3-5), the farmer decides what to do, i.e., PP or LP.
4. Repeat steps 1 to 3 for 50,000 times.
5. Plot the combination of $\mathrm{E}(\tilde{p})$ and $\mathrm{E}(\tilde{q})$ in red if the farmer chooses PP, otherwise in blue.

Figure 3-4 presents the PP-LP curves from the simulation for the farmer who is relatively risk averse, r = 0.002. As expected from Figures 3-2 and 3-3, the PP-LP curves are negatively sloped and convex towards the origin.

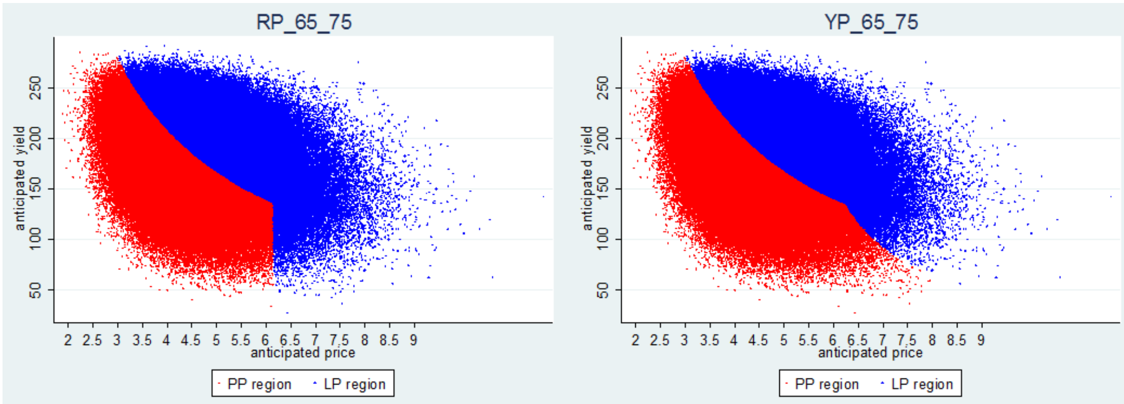

Figure 3-4. PP-LP curve from stochastic simulation

Note: Legend example: RP_65_75 = revenue protection with 65% buy-up PP and 75% insurance coverage and YP_65_75 = yield protection with 65% PP and 75% insurance coverage.

Red area = PP region and blue area = LP region.

Figures 3-5 presents the PP-LP curves for cases of yield protection (cases 1, 2, and 3 in Table 3-1) and revenue protection (cases 4, 5 and 6 in Table 3-1) to compare the effects of different crop insurance coverage levels on the and PP-LP decision. The PP-LP curves for revenue protection are truncated where the expected yield is relatively low and the expected price is relatively high. This is because a farmer can be protected when yield declines as well as price declines. For higher coverage levels, the likelihood of claiming PP becomes larger which represents an increase in moral hazard, i.e., $\Delta\,\mathrm{Pr(PP)} = \Delta(\mathrm{PP|high}\ \theta) - \Delta(\mathrm{PP|low}\ \theta) > 0$. Differing with Rejesus et al. (2003), revenue protection has a smaller probability of claiming PP than yield protection (Figure 3-6). To identify how sensitive to the level of risk aversion coefficient, PP_LP curves for different risk aversion coefficients are compared (Figure 3-7). The Figure 3-7 indicates PP_LP curves with higher risk aversion coefficient shift proportionally to the right. It means that farmer with more risk averse preference is likely to claim PP more.

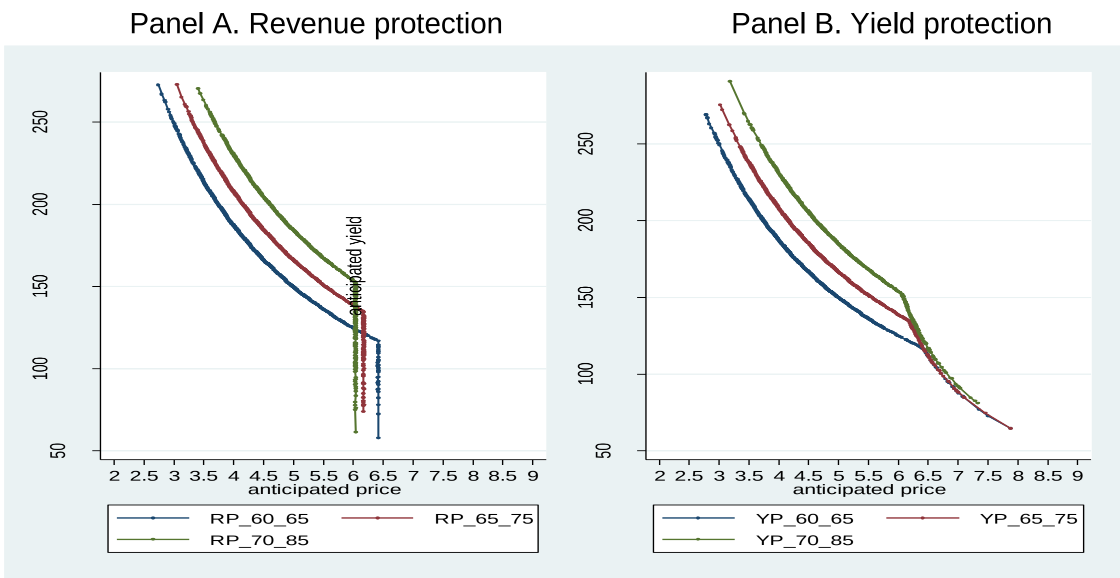

Figure 3-5. PP-LP curves over different types and coverages of crop insurance

Note: Legend example: RP_60_65 = revenue protection with 60% PP and 65% insurance coverage and YP_70_85 = yield protection with 70 buy-up PP and 85% insurance coverage.

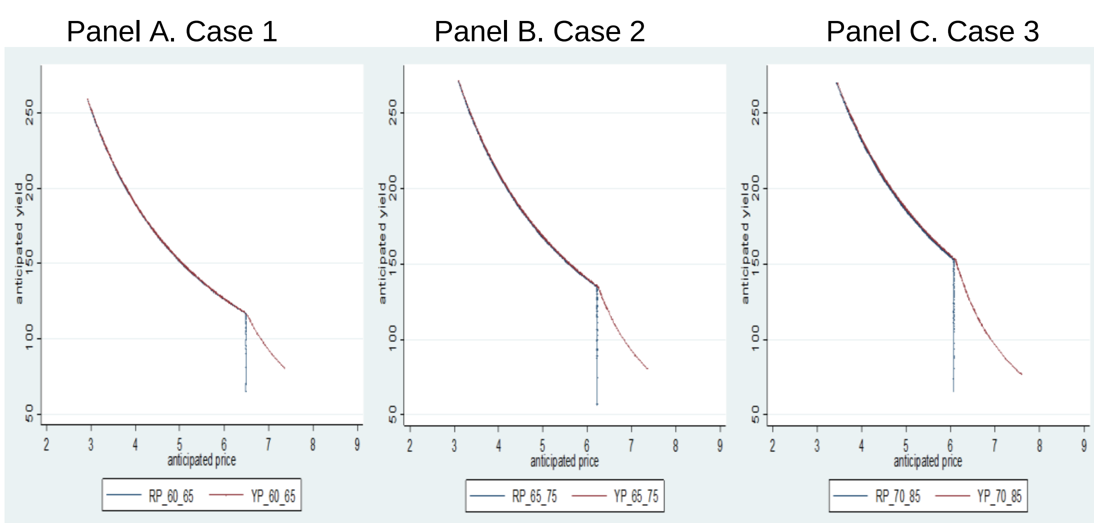

Figure 3-6. Comparison of PP-LP curves for revenue protection and yield protection

Note: Legend example: RP_60_65 = revenue protection with 60% PP and 65% insurance coverage and YP_70_85 = yield protection with 70 buy-up PP and 85% insurance coverage.

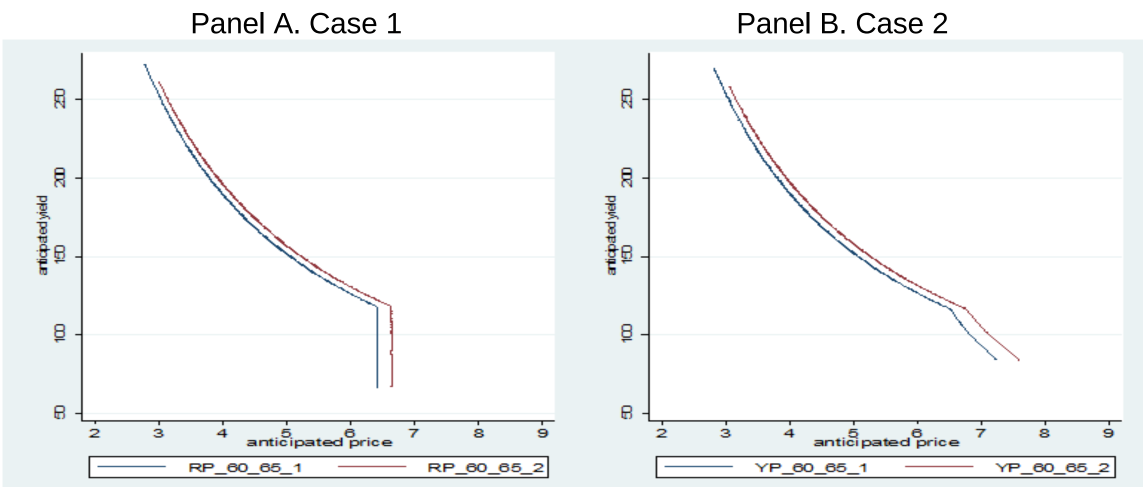

Figure 3-7. Comparison of PP-LP curves for different risk aversion parameters

Note: Legend example: RP_60_65_1=revenue protection with 60% PP an 65% insurance coverage with risk aversion coefficient 0.002, RP_60_65_2= revenue protection with 60% PP an 65% insurance coverage with risk aversion coefficient 0.004 and YP_60_65_1=revenue protection with 60% PP an 65% insurance coverage with risk aversion coefficient 0.002, YP_60_65_2=revenue protection with 60% PP an 65% insurance coverage with risk aversion coefficient 0.004.

3.6. Spatial Econometric Model

3.6.1. Basic Model

As shown in Figures 3-4, 3-5, and 3-6 the PP-LP curves are a function of crop insurance coverage level, types of coverage, expected price, and expected yield. To estimate the statistical relationship between the PP ratio and crop insurance coverage level, the following regression model is expressed

(3-16) $$y_{it} = \beta_0 + \sum_{k=1}^{K} x_{itk}\beta_k + \varepsilon_{it},$$

where y_{it} is the ratio of PP claims to number of earning premium policies in county i at time t, x_{itk} is the kth explanatory variable including the insurance coverage level, expected price and expected yield in county i at time t, and other control variables as explained in the following section.

3.6.2. Spatial Model

Equation (3-16) might be spatially correlated since data are collected at the county level. It is plausible that the PP claims in county i may affect the PP claims in a neighboring county and vice versa. Omitting a spatial lag of PP claims in the regression model may cause omitted variable bias (LeSage and Pace 2009). To control for the spatial correlation, equation (3-16) is therefore converted to

(3-17) $$y_{it} = \beta_0 + \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \sum_{k=1}^{K} x_{itk} \beta_k + \varepsilon_{it} \rightarrow \mathbf{y} = \rho \mathbf{W} \mathbf{y} + \mathbf{X} \boldsymbol{\beta} + \boldsymbol{\varepsilon},$$

where y_{it} is the PP ratio in county i, y_{jt} is the PP ratio of a neighboring county j, and w_{ij} is the spatial weight between county i and j. The coefficient ρ is the spatial correlation coefficient, x_{ikt} is the kth explanatory variable, such as insurance coverage level, lagged corn yield and price, and the (absolute value of) PDSIs. The error term, ε_{it}, also spatially correlated such that $\varepsilon_{it} = \mu_i + \lambda \sum_{j=1}^{N} w_{ij} \varepsilon_{jt} + u_{it}$, where λ is the spatial (error) correlation, and u_{it} is a white noise error term. Parameters $\boldsymbol{\beta}'s, \rho,$ and λ are estimated. In addition, equation (3-17) can be rewritten such that

(3-18) $$\mathbf{y} = (\mathbf{I} - \rho \mathbf{W})^{-1} \mathbf{X} \boldsymbol{\beta} + (\mathbf{I} - \rho \mathbf{W})^{-1} \boldsymbol{\varepsilon},$$

where $\mathbf{W}$ is a spatial weighting matrix, $\mathbf{W} = [w_{ij}]$. Naturally, it is important to construct the weighting matrix $\mathbf{W}$ in spatial econometrics since the spatial econometrics renders direct impact and indirect impact through spatial weighting matrix (LeSage and Pace 2009).

3.6.3. Estimation

Maximum likelihood estimation (MLE) is used to estimate the parameters in equation (3-17). Fixed effects models are estimated in order to control for an unobserved time invariant effect. Random effects model assume the unobserved time invariant components are uncorrelated with the explanatory variables (Wooldridge 2010, p. 286), otherwise parameter estimates are inconsistent. In this research, random effects models are not considered because unobserved time invariant components, for example, soil quality are clearly correlated with explanatory variables, for example, insurance coverage level and PP ratio, in equation (3-17).

Fixed effect models, however, suffer from the "incidental parameter problem" when MLE is used, i.e., estimates are inconsistent (Neyman and Scott 1948; Lancaster 2000). Inconsistency of parameters occurs because the number of parameters increases when the cross-sectional units, N, becomes large relative to the time dimension, T. To overcome this problem, Lee and Yu (2010) propose using the Helmert transformation procedure. The Helmert transformation (Arellano and Bover 1995) transforms data as follows. First define

(3-19) $$\tilde{y}_{it} = \frac{1}{T-t}\sum_{m=t+1}^{T} y_{im},$$

where $\tilde{y}_{it}$ represents the mean obtained from the future values of y_{it}, where T denotes the last time period of data. Then the Helmert transformed data are

(3-20) $$\hat{y}_{it} = \sqrt{\frac{T-t}{T-t+1}}(y_{it} - \tilde{y}_{it}).$$

All explanatory variables and error terms are transformed in the same fashion. Thus equation (3-17) becomes

(3-21) $$\hat{y}_{it} = \beta_0 + \rho\sum_{j=1}^{N} w_{ij}\hat{y}_{jt} + \sum_{k=1}^{K}\hat{x}_{itk}\beta_k + \hat{\varepsilon}_{it}.$$

3.6.4. Data

Data are collected from various sources. Crop insurance data, such as number of policies and number of PP claims, are compiled from the Summary of Business Reports and Data (http://www.rma.usda.gov/data/sob.html) and the Summary of Business with

Month of Loss (http://www.rma.usda.gov/data/cause.html) both provided by the RMA. County-level corn yield and corn price data are collected from the USDA NASS database. The Palmer Drought Severity Index (PDSI) from the National Oceanic and Atmospheric Administration (NOAA) (http://www1.ncdc.noaa.gov/pub/data/cirs/climdiv/climdiv-pdsidv-v1.0.0-20160204) is also used to control for potentially unexpected yield change.

A total of 594 counties located in the Corn-Belt[8] states are included in the analysis. Table 3-2 contains the summary statistics of these variables from 2000-2013. Note that data for the year 2010 are dropped from the analysis due to their unreliability. Note that reported PP ratios are greater than 1 even 10 in many counties in year 2010. By definition of the PP ratio, this is impossible. In addition, some counties are dropped from the dataset since they do not have crop insurance data and/or no corn was planted during some years.

Table 3-2. Summary Statistics (2000 – 2013)[a]

Variables	Mean	St.Dev	Min	Max
PP ratio (y_{it})	4.97%	14.59%	0%	100%
Insurance coverage ($Covg_{it}$)	67.85%	6.31%	50%	83.89%
(Lagged) Corn Yield (bushel/acre)	142.86	29.71	19	211.5
(Lagged) Corn Price ($/bushel)	3.47	1.60	1.65	7.34
Absolute PDSI in April	1.95	1.31	0	7.42
Absolute PDSI in May	1.99	1.28	0	7.62
Absolute PDSI in June	1.96	1.37	0	7.9

[a] 2010 data are dropped because data for 2010 from the Summary of Business with Month of Loss is unreliable. Many counties reported the PP ratio being greater than 1 even 10. By definition of the PP ratio, it is impossible.

[b] PDSI = Palmer Drought Severity Index. A higher PDSI value implies severe adverse events, such as drought or excess moisture, which prevent the planting of corn during planting season. PDSI is close to zero for a normal season.

[8] IL, IN, IA, KY, MI, MN, MO, OH, and WI.

The average PP ratio is 4.97% from 2000-2013. The standard deviation of the PP ratio is computed to be 14.59%, which shows that the PP ratio has varied substantially across counties and over time. This is possibly because of the adverse events occurring at planting time over a wide range of regions simultaneously. The variable $\mathrm{Covg}_{\mathrm{it}}$ is a weighted average of insurance coverage levels using insured acres, i.e., $\mathrm{Covg}_{\mathrm{it}} = \frac{\sum_{\mathrm{k}} \mathrm{c}_{\mathrm{k}} \mathrm{A}_{\mathrm{k}}}{\sum_{\mathrm{k}} \mathrm{A}_{\mathrm{k}}}$, where $\mathrm{k} =$ type of insurance coverage, c_{k} = coverage from 50% to 85%, and A_{k}= insured acres under kth type of crop insurance. The average of insurance coverage rate is estimated to be 69.85% with a standard deviation 6.31%. Minimum coverage level is 50%, while the maximum coverage level is 84%.

As in equation (3-16), the anticipated corn yield and price in planting season may affect the level of PP claims. As shown in Figures 3-4 and 3-5, a farmer may not claim the PP when s/he anticipates the high corn yield and price at the harvesting time. Unfortunately, these two variables are not observed directly. Lagged corn yield and prices are used as proxy variables for the anticipated corn yield and price. The average of lagged corn yield is 142.86 bushels/acre with an average price of $3.47/bushel (Table 3-2).

A PP claim depends heavily on the weather at planting time. The PDSI[9] for April, May, and June are included in the analysis to control weather variations especially drought or excess soil moisture. A negative PDSI represents the (severity of) drought and positive PDSI indicates (severe) excess soil moisture. Both drought and excess soil moisture adversely impact corn growth. Following Chen and Miranda (2007), the absolute value of

[9] The PDSI is a measurement of dryness based on recent precipitation and temperature. The PDSI is an effective measure determining long-term drought. A PDSI of 0 is normal, and the negative PDSI indicates drought. For example, -2 considered moderate drought, -3 indicates severe drought, and -4 of extreme drought. A positive PDSI indicates the excess moisture. For example, +2 indicates moderate wetness, +3 severe wetness, and +4 is extreme wetness (Alley 1984).

the PDSI is used as our explanatory variable. A higher PDSI value indicates the severity of adverse events faced by farmers. The average of absolute values of PDSI is given by 1.82 ~ 1.97 in the planting season. The average of *actual* PDSI is estimated to be 0.58 ~ 0.81 which is close to normal.

3.6.5. <u>Weighting Matrix</u>

There are various ways to build a weighting matrix, $\mathbf{W} = [w_{ij}]$, such as queen contiguity, rook contiguity, and inverse-distance (Drukker, Peng, and Pruncha 2013). The queen contiguity method assigns a non-zero spatial weight when a county shares borders with neighboring counties as defined in equation (3-22):

$$w_{ij} = \begin{cases} 1 \text{ if boundary i} \cap \text{boundary j} \neq \emptyset \\ 0 \text{ if boundary i} \cap \text{boundary j} = \emptyset \end{cases} \text{for } \forall i \neq j \text{ and } w_{ii} = 0 \text{ for } \forall \text{ i.} \tag{3-22}$$

If county i and j share at least one boundary (common border), the element of the weighting matrix, w_{ij}, takes 1, otherwise 0. County i is given a 0 weight for itself. In other words, counties are not considered neighbors to themselves. The rook contiguity is similar to queen contiguity but is more restrictive contiguity than queen. The rook contiguity assigns a non-zero weight when a county shares a certain portion of boundary with neighboring counties.

An inverse distance spatial weighting matrix is constructed by weights inversely related to the distances among counties. The inverse distance method assigns a non-zero spatial weight as follows

$$w_{ij} = \begin{cases} \frac{1}{d_{ij}} \text{ if } d_{ij} < \bar{d} \\ 0 \text{ if } d_{ij} > \bar{d} \end{cases} \text{ for } \forall i \neq j \text{ and } w_{ii} = 0 \text{ for } \forall \text{ i,} \tag{3-23}$$

where d_{ij} is the distance between county i and j and $\bar{d}$ indicates a predetermined threshold (66.4 miles in this study), which makes all the counties in the dataset have at least one neighbor. By dropping some observations (explained in data section) there exists five counties isolated.

For the purpose of forming a spatial lag, the matrix $\mathbf{W}$ can be normalized to avoid a singularity of un-normalized spatial weighting matrix (LeSage and Pace 2009; Kelejian and Prucha 2010). There are various ways to normalize $\mathbf{W}$ such as row-sum, minimax, and spectral normalization (Drukker, Peng, and Prucha 2013). The row-sum method divides each element in $\mathbf{W}$ by its corresponding row-sum, i.e., $\tilde{w}_{ij} = w_{ij}/r_i$, where r_i is the sum of the ith row of $\mathbf{W}$. However, the normalized weighting matrix under this method is asymmetric and this property needs a justification of asymmetry (Kelejian and Prucha 2010). To make $\mathbf{W}$ symmetric, the minimax or spectral method can be used. The (i, j)th element of normalized minimax weighting matrix, $\widetilde{\mathbf{W}}$ is defined such that $\tilde{w}_{ij} = w_{ij}/m$ and $m = \min\{\max(r_i), \max(c_i)\}$, where r_i is the sum of the ith row and c_i is the sum of ith column (Drukker, Peng, and Prucha 2013). The (i, j)th element of normalized spectral weighting matrix, $\widetilde{\mathbf{W}}$ is defined such that $\tilde{w}_{ij} = w_{ij}/v$, where v is the largest of the moduli of the eigenvalues of un-normalized weighting matrix $\mathbf{W}$ (Drukker, Peng and Prucha 2013). In this research, the spectral normalization method is used since there is no reason to impose different weights across counties. The user-written command *spmat* in Stata (Drukker, Peng, and Prucha 2013) is used to build and normalize the weighting matrix. A total of 594 counties for 13 years are included in the dataset, and the size of the corresponding $\mathbf{W}$ matrix is (594 counties x 13 years) x (594 counties x 13 years), which is a block diagonal.

3.6.6. Results and Discussion

Table 3-3 contains the estimation results of equation (3-17) with four different specifications, i) fixed effect model ($\rho = 0$ and $\lambda = 0$), ii) spatial error model (SEM) ($\rho = 0$ and $\lambda \neq 0$), iii) spatial autoregressive model (SAR) ($\rho \neq 0$ and $\lambda = 0$, and iv) spatial autocorrelation model (SAC) ($\rho \neq 0$ and $\lambda \neq 0$).

Table 3-3. Estimation Results with Four Spatial Specifications[a]

PP ratio (%)	(1) OLS	(2) SEM	(3) SAR	(4) SAC
Covg	0.304***	0.195***	0.160***	0.189***
	(0.055)	(0.073)	(0.045)	(0.063)
Yield(-1)	-0.039***	-0.012	-0.016***	-0.016**
	(0.006)	(0.009)	(0.005)	(0.008)
Price(-1)	-0.942***	-1.100***	-0.583***	-0.806***
	(0.160)	(0.368)	(0.133)	(0.236)
Apr PDSI	-0.661***	0.230	-0.127	-0.053
	(0.186)	(0.308)	(0.148)	(0.232)
May PDSI	2.288***	1.740***	0.908***	1.405***
	(0.195)	(0.348)	(0.166)	(0.256)
Jun PDSI	0.854***	0.869***	0.570***	0.759***
	(0.145)	(0.306)	(0.113)	(0.204)
Constant[b]	-12.543***			
	(3.500)			
Lambda		1.165***		0.701***
		(0.005)		(0.030)
Rho			0.932***	0.634***
			(0.018)	(0.034)
N[c]	7722	7128	7128	7128
BIC	58597.1	52319.9	52487.0	52160.1

Note: Numbers in parentheses are cluster robust standard errors; Significance levels are 1% (***), 5% (**), and 10% (*).

[a] All the models are fixed effect models, i.e., $y_{it} - \bar{y}_{i\cdot} = \beta_0 + \beta(x_{it} - \bar{x}_{i\cdot}) + (\varepsilon_{it} - \bar{\varepsilon}_{i\cdot})$, to control for the unobserved time invariant effect.

[b] Spatial models do not have constant terms because of Helmert transformation

[c] Spatial models have less observations because of Helmert transformation

The relationship between the PP ratio and insurance coverage level is positive and statistically significant in all four models, with magnitudes between 0.160 ~ 0.304, which is consistent with the theory and simulation results presented in the previous sections. If a farmer purchases the higher coverage, s/he would claim PP more when experiencing adverse events such as drought or excessive moisture. However, when controlling for spatial lag, the magnitude of coverage level of OLS is higher than other spatial models. Thus, OLS result implies there may exist for upward biasedness for coverage level due to omission of spatial lag of PP ratio. Lagged price (our proxy for the expected price) has a negative effect on the PP ratio as expected. If the farmer anticipates a higher price at a harvest, s/he would be more likely to plant corn (late planting) instead of claiming PP. In spatial models, the values of ρ and λ are positive and statistically significant, which implies that PP ratios and error terms are spatially correlated across counties.

3.7. Summary and Concluding Remarks

This study examines the existence of moral hazard in the choices of prevented planting (PP) and late planting (LP). The PP provision is defined as the “failure to plant an insured crop by the final planting date due to adverse events”, such as excess soil moisture or drought. If a farmer decides not to plant a crop, the farmer receives a PP indemnity. LP is an option for the farmer to plant the crop and still maintain the crop insurance when s/he fails to plant a crop by the final planting date. However, by choosing LP option the farmer has to lower the insurance coverage level depending on the LP date due to potential yield loss.

Crop insurance may alter a farmer's production choice between PP and LP. In other words, crop insurance can increase the likelihood of PP claims even though farmers can still choose LP. This paper seeks to find evidence that the farmer with higher insurance coverage tends to choose PP more often, which suggests an increase in moral hazard.

Assuming a relatively risk averse farmer, we derive a PP-LP curve representing the farmer's indifference between PP and LP. As shown in Figures 3-4, 3-5, and 3-6, the PP-LP curve is convex to the origin in the expected yield and price plane. These figures demonstrate that a farmer chooses LP when s/he expects a higher crop price and yield at harvest time. Two important findings from the stochastic simulation are i) farmers with higher insurance coverage are more likely to choose PP more, and ii) all else equal, farmers with revenue protection, as opposed to yield protection, are less likely to claim PP which differs from the findings of Rejesus et al. (2003).

Empirical research is conducted to estimate the statistical relationship between the PP ratio, on the one hand, and insurance coverage level and anticipated price on the other. Spatial fixed effect models are estimated to control for unobserved time invariant effects and spatial correlation among neighboring counties. Estimation results indicate that the PP ratio has a positive relationship with insurance coverage levels and a negative relationship with anticipated price. These empirical results correspond to a stochastic simulation results.

Results presented in this study carry important implications for crop insurance. Existing (ex-post) moral hazard in PP claim should be mitigated so as not to discourage farmers from planting a crop. Abandoning cropland (in a given year) leads to a contradiction with USDA's goal of promoting agricultural production to improve food security (USDA's strategic Plan FY 2010-2015, Goal 3) (OIG 2013). Exploring how best to mitigate moral hazard in the PP provision is an area for future study.

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4. PREVENTED PLANTING AND PLANTING SECOND CROP

Abstract

If a farmer chooses prevented planting (PP), s/he receives the PP indemnity and may either leave the acreage unplanted or plant a second crop, e.g., soybean for corn. If the farmer chooses to plant a second crop after prevented from planting a first crop, s/he receives a reduced PP payment (35% of PP indemnity) and s/he is assigned to 60% of the approved yield of the first crop in the APH for the next crop year. The current PP provision fails to provide farmers with an incentive to plant a second crop (99.9% of PP claiming farmers do not plant the second crop). Adjusting reduced PP indemnity payment may encourage farmers to plant a second crop, which is currently fixed at 35% of the total PP indemnity. The objective in this second study is to estimate the optimal PP payment percentage that may better encourage farmers to plant a second crop, which would help achieve a goal of USDA to better promote agricultural production. Using corn-soybean budget data from Hamilton County, Iowa, a representative farmer is depicted. We show through stochastic simulation, that under the current PP reduction factor, the farmer is unlikely to plant a second crop. However, if a reduction factor increases, the farmer becomes more likely to do so. This study finds that the optimal reduced PP payment percentage is greater than the existing 35%.

Key Words: Crop Insurance Prevented Planting, Second Crop, Expected Utility Theory

JEL Codes: D81, G22, Q18

4.1. Introduction

The Risk Management Agency (RMA) has included prevented planting (PP) in its crop insurance program since 1998. PP is defined as the "failure to plant an insured crop by the final planting date, or within any applicable late planting (LP) period due to adverse events", such as excess soil moisture or drought (2013 Crop Insurance Handbook, USDA-RMA 2013). If a farmer with a base PP coverage level (base PP) claims PP payments, 60% (varies from 25% to 60% depending on crops insured) of the original liability is paid as an indemnity on approval of the insurer. The farmer also can choose to buy-up his or her PP coverage level by 5% or 10%. In this case, PP payments are given at 65% and 70% of the original liability, respectively.

PP payments currently accounted for the large shares of total indemnity in crop insurance programs. PP payments accounted for roughly 9% of total indemnity payments from 1998 to 2008. From 2009 to 2013, PP payments accounted for roughly 17% of total indemnity, on average. In 2010 alone, the share of PP payments increased to approximately 29% of total indemnity (author's calculation from Indemnities with Month of Loss in the RMA Cause of Loss, http://www.rma.usda.gov/data/cause.html).

Late planting (LP) is another option that a farmer may take when s/he fails to plant a (first) crop during the normal planting period. However, by choosing LP, the farmer does not receive a full PP indemnity. The coverage level is lowered based on LP date due to estimated yield loss (1% per day after final planting date). As evidenced by the recent increase in PP payments, farmers tend to choose PP in lieu of LP. Rejesus et al. (2003) and Rejesus, Escalante, and Lovell (2005) show that crop insurance provides farmers with an incentive to choose PP. Kim and Kim (2015) also find that farmers with higher insurance coverage are more likely to claim PP than LP.

Second crop (SC) is the choice of planting a second crop, e.g., soybeans for corn after the LP period and having declared PP. When a farmer chooses to plant a second crop s/he receives 35% of the PP indemnity (2013 Crop Insurance Handbook, USDA-RMA 2013) and is assigned to 60% of the approved yield of the first crop in the Actual Production History (APH) for the next crop year. Figure 1 briefly explains the timeline of PP, LP, and SC options.

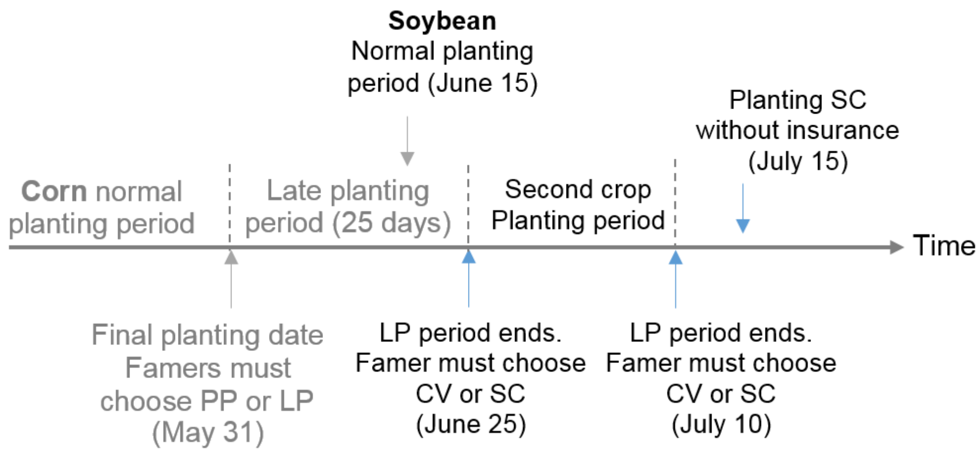

Figure 4-1. Timeline for choice between prevented planting and late planting
Note: PP = prevented planting, LP = late planting, CV = cover crop, SC = second crop.
Dates are for a typical farm in Iowa. Text which is not the subject of this section is greyed out.

In 2013, the Office of Inspector General (OIG) audited the RMA's PP provisions. The OIG found that "producer's currently plant only 0.1 percent of prevented planting acres to a second crop." (OIG 2013, p. 8). This implies the current PP provision discourages farmers from planting a second crop. Abandoning this cropland in a given year leads to two problems. First, insurance premium subsidies paid to farmers are, in effect, wasted because no crop is produced. Second, it is a contradiction of the USDA's goal of promoting agricultural production to improve food security (USDA's strategic Plan FY 2010-2015, Goal 3) (OIG 2013).

The OIG (2013) points out that the incentive not to plant a second crop is caused by the design of the PP provision, which assigns 60% of the approved yield of the first crop in the APH calculation for the next crop year. Compared to 1995-1997, when the APH adjustment was not included in the PP provision, the ratio between acres planted to a second crop and the total PP claim acres was about 36%. In 2008-2011, when the RMA included the APH adjustment in the PP provision, this ratio was only 0.1%. The OIG (2013) recommended to the RMA "to determine whether an assignment of yield to all PP acres is not prohibited…" (OIG 2013, p. 10). Following the OGC's recommendation, the RMA agreed to assess whether the APH adjustment is appropriate. However, "the RMA doesn't anticipate this to be the likely outcome." (OIG 2013, p.11)

In addition to modifying the APH calculation, adjusting the PP indemnity payment which is currently fixed at 35% of the total PP indemnity may also encourage farmers to plant a second crop. The main objective of this study is to estimate the appropriate percentage reduction in PP payments for farmers who choose to plant a second crop. A conceptual model to characterize the farmer's choice is developed. An analytical solution of the percentage of PP payment may not be easily derived due to the complexity of decision making process on PP and SC. Instead, a stochastic simulation is conducted to estimate the proper percentage reduction. Specifically, the objective in this paper is to discover what percentage reduction in PP payment induces farmers to plant a second crop when they fail to plant the first crop and claim PP.

4.2. Literature Review

Few academic studies exist concerning PP. Rejesus et al. (2003) analyze potential fraudulence of PP claims. They show empirically that a higher insurance coverage level induces more fraudulent PP claims. Also, they find that revenue protection leads to more fraudulent PP claims than yield protection. Rejesus, Escalante, and Lovell (2005) also analyze the relationship between PP claims and land ownership and farm business structure. They find that tenant status under a leasing contract increases the likelihood of claiming PP. They also show that sole ownership and partnership farms claim more PP than cooperate farms. Kim and Kim (2015) examine the existence of moral hazard inherent in the choices of PP and late planting and show that a farmer with higher insurance coverage may tend to choose PP more often.

To the best of author's knowledge, regarding a choice of second crop, there are no academic studies except some University extension reports to introduce and explain second crop provision, e.g., Schnitkey (2013) and Edwards (2014).

4.3. Conceptual Model

Assume that a farmer is risk averse and maximizes expected utility from uncertain profit at harvest time. Suppose that, due to adverse events such as drought or excess soil moisture at planting time, the farmer must choose PP or SC. The farmer is at the final "late" planting time (See Figure 4-1), time period 1 ($\mathrm{t} = 1$), and must make a decision. If the farmer decides to claim PP, s/he obtains the profit from the PP indemnity, π_{PP}, with certainty, where

(4-1) $$\pi_{\mathrm{PP}} = \mathrm{p}_{\mathrm{g}}^{\mathrm{fc}}\theta_{\mathrm{pp}}\theta\mathrm{q}_{\mathrm{APH}}^{\mathrm{fc}} - \mathrm{c}_{1}^{\mathrm{fc}} - \mathrm{m}^{\mathrm{fc}} - \mathrm{c}_{\mathrm{cv}},$$

where the superscript fc indicates a first crop, e.g., corn, $\mathrm{p}_{\mathrm{g}}^{\mathrm{fc}}$ is the elected (guaranteed) price of the first crop, θ_{pp} is the PP coverage level (60%, 65% or 70% depending on buy-up), and θ is the insurance coverage level and $\theta \in [50\%, \mathrm{x}]$ with an increase in 5% and x varies from 75% to 85% over crops and regions. $\mathrm{q}_{\mathrm{APH}}^{\mathrm{fc}}$ is the APH for the first crop. $\mathrm{c}_1^{\mathrm{fc}}$ is input cost per acre for the normal planting, m^{fc} is the crop insurance premium for the first crop, and c_{cv} is the cost for planting the cover crop which is a requirement of PP claim.

Suppose that a farmer ultimately chooses to plant a second crop, e.g., soybean, after declaring PP, then the farmer receives:

(4-2) $\tilde{\pi}_{\mathrm{sc}} = \alpha \cdot \mathrm{ind}_{\mathrm{pp}}^{\mathrm{fc}} + \widetilde{\mathrm{nr}}^{\mathrm{sc}}$,

where $\mathrm{ind}_{\mathrm{pp}}^{\mathrm{fc}}$ represents the PP indemnity for the first crop, and $\alpha = 0.35$, i.e., the farmer receives 35% of the total PP indemnity when s/he chooses to plant a second crop. The term $\widetilde{\mathrm{nr}}^{\mathrm{sc}}$ is the net return from the second crop at the harvest time. The net return from the second crop in equation (4-2) is defined in equation (4-3), which depends on whether crop insurance is purchased for the second crop:

(4-3) $\widetilde{\mathrm{nr}}^{\mathrm{sc}} = \tilde{\mathrm{p}}^{\mathrm{sc}}\tilde{\mathrm{q}}^{\mathrm{sc}} - \mathrm{c}_1^{\mathrm{fc}} - \mathrm{m}^{\mathrm{fc}} - \mathrm{c}_2^{\mathrm{sc}} - \mathrm{m}^{\mathrm{sc}} + \max\left(0, \mathrm{ind}_{\mathrm{j}}^{\mathrm{sc}}\right)$ crop insurance purchased,

$\widetilde{\mathrm{nr}}^{\mathrm{sc}} = \tilde{\mathrm{p}}^{\mathrm{sc}}\tilde{\mathrm{q}}^{\mathrm{sc}} - \mathrm{c}_1^{\mathrm{fc}} - \mathrm{m}^{\mathrm{fc}} - \mathrm{c}_2^{\mathrm{sc}}$ crop insurance not purchased,

where $\tilde{\mathrm{p}}^{\mathrm{sc}}$ is the market price of the second crop at harvest time, which is stochastic at $\mathrm{t} = 1$, $\tilde{\mathrm{q}}^{\mathrm{sc}}$ is the yield of the second crop at the end of the season, which is also stochastic, $\mathrm{c}_1^{\mathrm{fc}}$ indicates the cost of planting the first crop, m^{fc} is the insurance premium for the first crop, $\mathrm{c}_2^{\mathrm{sc}}$ represents the cost of planting, cultivating and harvesting the second crop at $\mathrm{t} = 2$, m^{sc} is the insurance premium for the second crop, and $\mathrm{ind}_{\mathrm{j}}^{\mathrm{sc}}$ $(\mathrm{j} = \mathrm{yp}, \mathrm{rp})$ is the insurance indemnity for the second crop, where yp represents the yield protection and rp represents the revenue protection. Note that tilde above the variable indicates that the corresponding variable is stochastic to farmers at $t = 1$.

The insurance indemnity ind_j^{sc} depends on the type of crop insurance chosen. In the case of yield protection, ind_{yp}^{sc}, is given by

(4-4) $\mathrm{ind}_{yp}^{sc} = p_g^{sc} \max\{0, \rho\theta q_{APH}^{sc} - \tilde{q}^{sc}\}$,

where, p_g^{sc} is the elected (guaranteed) price of a second crop, ρ is the coverage reduction factor depending on the second crop's planting date[10] (roughly 0.89), θ is the coverage level for the second crop, q_{APH}^{sc} is a second crop APH, and $\tilde{q}^{sc}$ is the anticipated yield of the second crop at $t = 2$. If the anticipated yield is higher than the production associated with coverage level $\rho\theta q_{APH}^{sc}$, the farmer does not receive the yield protection indemnity, regardless of the actual price level at harvest time.

In the case of revenue protection, the anticipated indemnity, ind_{rp}^{sc}, becomes

(4-5) $\mathrm{ind}_{rp}^{sc} = \max\left\{0, \min\left(2p_g^{sc}, \max\left(p_g^{sc}, \tilde{p}^{sc}\right)\right) \cdot \rho\theta q_{APH}^{sc}) - \tilde{p}^{sc}\tilde{q}^{sc}\right\}$.

If the anticipated revenue at the harvest time from planting the second crop, $\tilde{p}^{sc}\tilde{q}^{sc}$, is greater than covered revenue, $\min\left(2p_g^{sc}, \max\left(p_g^{sc}, \tilde{p}^{sc}\right)\right) \cdot \rho\theta q_{APH}^{sc})$, the farmer does not receive the revenue protection indemnity.

Assuming that the farmer is risk averse, s/he will choose not to plant a second crop when $u\left(\pi_{pp}\right) > EU(\tilde{\pi}_{sc})$, and s/he will plant a second crop when $u\left(\pi_{pp}\right) < EU(\tilde{\pi}_{sc})$, where $u(\cdot)$ is a strictly increasing twice-continuously differentiable utility function and $EU(\cdot)$ is the

[10] A second crop is planted after the late planting date. In the case of corn in Iowa, the normal planting date is May 31, and the late planting date is June 25. The second crop, usually soybeans, is planted after June 25, which is a second crop's late planting period (See Figure 4-1).

expectation of the utility function. Data (OIG 2013) reveals that 99.9% acres associated with a PP claim are planted to a cover crop, not a second crop, which implies

(4-6) $\mathrm{u}(\pi_{pp}) > \mathrm{EU}(\tilde{\pi}_{sc})$.

Meanwhile, conditional on the information known to the farmer at $t = 1$, the expected utility is rewritten as $\mathrm{EU}(\tilde{\pi}_{sc}) = \mathrm{u}(\mathrm{E}(\tilde{\pi}_{sc}) - \mathrm{RPM})$, where $\mathrm{E}(\tilde{\pi}_{sc})$ is the farmer's expected value of $\tilde{\pi}_{sc}$, and RPM is the risk premium assuming s/he is a risk averter (Chavas, 2004, p.36). Since $\mathrm{u}(\cdot)$ is strictly increasing in π_{pp} and $\tilde{\pi}_{sc}$, equation (4-6) can be written as

(4-7) $\pi_{pp} > \mathrm{E}(\tilde{\pi}_{sc}) - \mathrm{RPM}$.

We can simulate the farmer's decision-making process using stochastic simulation, i.e., generating random price, $\tilde{p}^{sc}$ and yield, $\tilde{q}^{sc}$, for $\alpha = 0.35$. We expect equation (4-7) holds for most cases of our simulation, which is consistent with OIG (2013). The expression in equation (4-7) cannot be solved analytically for α due to the complexity of the decision making problem. The stochastic simulation is undertaken with various values of α and the probability of choosing PP determined such that

(4-8) $\Pr(\mathrm{PP}|\alpha) = \Pr(\pi_{pp} > \mathrm{E}(\tilde{\pi}_{sc}) - \mathrm{RPM}|\alpha)$.

Specifically, the stochastic simulation enables us to find the value of α such that $\pi_{pp} = \mathrm{E}(\tilde{\pi}_{sc}) - \mathrm{RPM}$, i.e., farmers are indifferent between choosing PP and SC.

4.4. Representative Farmer and Stochastic Simulation

A stochastic simulation of representative farmer is used in this study. Simulation of the representative farmer's behavior on crop insurance is not original to this paper. Babcock and Hennessy (1996) and Coble, Heifner, and Zuniga (2000) have previously created a representative farmer.

4.4.1. Representative Farmer

The representative farmer is created based on corn and soybean budget data from Hamilton County, Iowa. For the simulation, historical corn and soybean price and yield, insurance premium including subsidies associated with different insurance plans, and farming cost data are compiled from Iowa extension, RMA quick cost estimator, and USDA NASS (Table 4-1). There are a total of 48 different crop insurance plans pertaining to two different insurance types (revenue protection and yield protection), three different PP coverages, θ_{pp}, (60%, 65%, and 70%), and eight different insurance coverages, θ, (50%, 55%, 60%, 65%, 70%, 75%, 80%, and 85%). To simplify the comparisons, the representative farmer is assumed to choose a single crop insurance plan for a second crop, and thus results for a total of six crop insurance plans are presented (simulations were done for all of possible crop insurance plans).

4.4.2. Risk Premium

The risk premium, RPM, in Table 4-1 is derived assuming a negative exponential utility function as follows,

1. Generate random soybean price and yield, $\tilde{p}^{sc}$ and $\tilde{q}^{sc}$, at harvest time considering correlation, $\mathrm{corr}(\tilde{p}^{sc}, \tilde{q}^{sc})$ (Richardson et al. 2000).
2. Calculate profit from a second crop, $\tilde{\pi}_{sc}$, including possible insurance indemnity associated with this second crop.
3. Repeat steps 1 and 2 for 1000 times.
4. Calculate the certainty equivalent (CE) using simulated profit from step 3 using the formula, $\mathrm{CE}(r) = \ln[\left(\frac{1}{1000}\sum \exp(-r \cdot \pi_i)\right)^{-\frac{1}{r}}]$, where i represents each iteration and r is the absolute risk aversion coefficient (Hardarker et al. 2004, p. 257).
5. Derive the risk premium following the definition, $\mathrm{RPM} = \mathrm{E}(\tilde{\pi}_{sc}) - u^{-1}(\mathrm{EU}(\tilde{\pi}_{sc}))$ (Chavas 2004, p. 34) which is equivalent to $\mathrm{RPM} = \mathrm{E}(\tilde{\pi}_{sc}) - \mathrm{CE}(r)$.

Table 4-1. Representative Corn-Soybeans Farmer in Hamilton County, Iowa

	Symbols	Choice of Insurance for Second Crop						
		No Insurance	Yield Protection			Revenue Protection		
			Case 1	Case 2	Case 3	Case 1	Case 2	Case 3
PP coverage level	θ_{pp}	-	60%	65%	70%	60%	65%	70%
Coverage level	θ	-	65%	75%	85%	65%	75%	85%
LP reduction factor	ρ	-	0.89					
PP indemnity reduction factor	α	0.35						
Corn elected price[1]	p_g^{fc}	$4.62/bushel						
Corn APH[2]	q_{APH}^{fc}	189 bushels/acre						
Soybeans elected price[3]	p_g^{sc}	$11.36/bushel						
Volatility of soybean price[4]		0.13						
Soybeans APH[2]	q_{APH}^{sc}	-	50 bushels/acre					
Soybeans late planting yield[5]		20 bu [6]	26.5 bushels/acre					
St. dev. of soybean yield		4.46 bushels/acre						
Corn insurance premium	m^{fc}	-	7	11	17	10	19	37
Corn insurance subsidy[7]		-	0.59	0.55	0.38	0.59	0.55	0.38
Additional premium for buy-up PP[8]		-	0	0.22	0.85	0	0.22	0.85
Soybeans insurance premium	m^{sc}	-	5	9	16	7	13	25
Soybeans subsidy rate[7]		-	0.59	0.55	0.38	0.59	0.55	0.38
Cost at time period 1($/acre)	c_1^{fc}	$327.8/acre						
Cost at time period 2($/acre)	c_2^{sc}	$186.65/acre						
Corr. Bet/ soybeans price and yield[9]		-0.24						
Utility function[10]		$u(\pi) = -\exp(-r\pi)$						
Risk aversion parameter[11]	r	0.005						
Risk Premium	RPM	6.88	3.85	3.65	3.72	2.14	2.13	2.64

[1] The elected corn price is $4.62/bushel in 2014 and is considered as the average price. It is given by the RMA based on historical corn futures price data. [2] Trend adjusted APH. [3] The elected soybean price is $11.36/bushel in 2014 and is considered as average price. It is calculated by the RMA based on historical soybean futures price data. [5] 53% (Pedersen, 2008, Iowa Extension) of average soybean yield from normal planting due to potential yield loss from late planting. [6] If a farmer doesn't purchase crop insurance for a second crop, the farmer must plant a second crop after the late planting date of the second crop, usually July 10 in Iowa (Edwards, 2012, Iowa Extension). In this case, the potential yield loss would be 40% of the normal yield. [7] The insured is responsible for (1 – coverage subsidy rate)×insurance premium. Federal government pays coverage subsidy rate×insurace premium. [8] For example, a farmer in Hamilton County, Iowa should pay $11.37+$0.57 to purchase buy-up of 10% PP (70% coverage) with 85% coverage level. Additional insurance premiums for buy-up PP differs by counties. If a farmer chooses to plant a second crop, s/he will get 65% of the insurance premium back. [9] For numerical simulation, soybean price and yield are generated randomly based on the correlation between price and yield. The correlation is calculated using historical data from 1990 to 2005. [10] Negative exponential utility function exhibits constant absolute risk aversion (CARA), which is given by r. This function has been used extensively in decision analysis (Hardaker et al. 2004, p.103). [11] When r = 0, the decision maker is risk neutral and higher values of r imply risk averse decision makers. We select r = 0.005 as the risk aversion coefficient based on Table 2 in Babcock, Choi, and Feinerman (1993). The risk aversion coefficient of 0.005 denotes a relatively risk averse farmer (risk premium 20% Table 2).

4.5. Stochastic Simulation

Once RPM is calculated for the second crop with different insurance types and coverages including no crop insurance for the second crop, π_{pp} and $E(\tilde{\pi}_{sc}) - RPM$ are compared assuming $\alpha = 0.35$ and given various combinations of random prices ($\tilde{p}^{sc}$) and yields ($\tilde{q}^{sc}$) for the second crop. Random prices and yields are generated based on the correlation between $\tilde{p}^{sc}$ and $\tilde{q}^{sc}$ to maintain a simultaneous price-quantity relationship (Richardson et al. 2000).

Table 4-2 presents our simulation results. As expected, in most cases PP is chosen over SC. The probability of choosing PP varies between 81% and 96%. However, the probability of choosing PP is not 99.9% when the farmer purchases crop insurance for a second crop. This is because assigning 60% of the approved yield of the first crop in the APH calculation is not considered explicitly. Assignment of 60% of the approved yield to APH calculation may increase the insurance premium and may reduce the expected indemnity for the next crop year for the first crop. The probability of choosing PP in this case would be higher because the corresponding RPM would be larger than before.

Table 4-2. $\Pr(\pi_{pp} > E(\tilde{\pi}_{sc}) - RPM \mid \alpha = 0.35)$ from Stochastic Simulation

	Choice of Insurance for Second Crop						
	No Insurance	Yield Protection			Revenue Protection		
		Case 1	Case 2	Case 3	Case 1	Case 2	Case 3
PP coverage level, θ_{pp}		60%	65%	70%	60%	65%	70%
Insurance coverage level, θ		65%	75%	85%	65%	75%	85%
$\Pr(\pi_{pp} > E(\tilde{\pi}_{sc}) - RP \mid \alpha = 0.35)$[1]	**100%**	**85%**	**93%**	**96%**	**81%**	**86%**	**91%**

[1] Probability of choosing PP and not to plant a second crop. The higher coverage, the higher probability of choosing PP because the higher coverage (of the first crop) provides the more PP payment.

Note: choice of insurance plan for the second crop is assumed to be the same for the first crop or not purchase insurance for the second crop.

Another set of stochastic simulations is conducted to determine appropriate values of α that might encourage farmers to plant a second crop. As shown in Figure 4-2, the probability of choosing PP decreases when the farmer faces higher values of α. From Figure 4-2, the probability of choosing PP depends on type of crop insurance and insurance coverage level. In the case of revenue protection, there exists a tipping point where the probability of choosing PP would reach zero at roughly when $\alpha = 0.6$. Beyond this point most of farmers choose to plant a second crop. This is because revenue protection insurance now guarantees the minimum revenue. At some points, i.e., $\alpha \geq 0.6$, the profit from a second crop is greater than π_{pp} all the time, i.e., truncated over various levels of crop insurance coverages. In the case of yield protection, however, the insurance guarantees only yield, not the revenue from a second crop, and thus the farmer is not guaranteed minimum revenue.

Results presented in Figure 4-2 demonstrate some policy implications associated with PP provision. First, the current PP reduction factor is too low to induce farmers to plant a second crop, which impedes reaching USDA's goal of promoting agricultural production. Second, the optimal reduction factor depends upon the type of insurance and insurance coverage. Crop insurance coverage data for 2014 (based on the number of policies with premium from Pregenerated SOB Reports in RMA Summary of Business Reports and Data, http://www.rma.usda.gov/data/sob.html) show that close to 90% of farmers purchase revenue protection. Farmers who purchase revenue protection choose coverage levels of 70%(15%), 75%(25%), 80%(24%), and 85%(18%).

		YP			RP		
	θ	θ_{pp}			θ_{pp}		
		60	65	70	60	65	70
$\alpha = 0.35$	50	0.69	0.77	0.84	0.68	0.76	0.83
	55	0.77	0.85	0.90	0.76	0.84	0.90
	60	0.83	0.90	0.94	0.81	0.88	0.93
	65	0.85	0.93	0.96	0.81	0.90	0.95
	70	0.84	0.93	0.97	0.80	0.89	0.94
	75	0.82	0.92	0.97	0.76	0.86	0.93
	80	0.78	0.91	0.97	0.73	0.85	0.92
	85	0.74	0.89	0.96	0.71	0.83	0.91
$\alpha = 0.40$	50	0.61	0.69	0.76	0.60	0.68	0.76
	55	0.69	0.77	0.85	0.67	0.76	0.84
	60	0.73	0.83	0.90	0.70	0.81	0.88
	65	0.74	0.85	0.92	0.70	0.81	0.89
	70	0.71	0.84	0.93	0.67	0.80	0.88
	75	0.65	0.82	0.92	0.63	0.76	0.86
	80	0.59	0.78	0.90	0.59	0.73	0.84
	85	0.53	0.74	0.89	0.56	0.71	0.82
$\alpha = 0.45$	50	0.51	0.60	0.67	0.50	0.59	0.67
	55	0.58	0.68	0.76	0.56	0.66	0.75
	60	0.61	0.72	0.82	0.58	0.69	0.79
	65	0.59	0.73	0.84	0.57	0.69	0.80
	70	0.53	0.70	0.83	0.52	0.66	0.78
	75	0.45	0.64	0.79	0.00	0.62	0.74
	80	0.37	0.57	0.75	0.00	0.58	0.71
	85	0.30	0.51	0.71	0.00	0.55	0.69
$\alpha = 0.50$	50	0.42	0.50	0.57	0.40	0.48	0.57
	55	0.46	0.57	0.65	0.44	0.54	0.63
	60	0.46	0.58	0.70	0.44	0.55	0.67
	65	0.41	0.56	0.70	0.00	0.54	0.66
	70	0.34	0.50	0.65	0.00	0.00	0.62
	75	0.25	0.42	0.59	0.00	0.00	0.58
	80	0.18	0.33	0.52	0.00	0.00	0.54
	85	0.13	0.26	0.45	0.00	0.00	0.00
$\alpha = 0.55$	50	0.31	0.39	0.46	0.30	0.37	0.45
	55	0.33	0.43	0.52	0.31	0.41	0.50
	60	0.30	0.42	0.53	0.00	0.40	0.51
	65	0.24	0.37	0.51	0.00	0.00	0.49
	70	0.17	0.29	0.43	0.00	0.00	0.00
	75	0.11	0.21	0.35	0.00	0.00	0.00
	80	0.07	0.15	0.26	0.00	0.00	0.00
	85	0.04	0.10	0.20	0.00	0.00	0.00
$\alpha = 0.60$	50	0.21	0.28	0.34	0.20	0.26	0.33
	55	0.20	0.29	0.37	0.00	0.27	0.36
	60	0.17	0.25	0.36	0.00	0.00	0.00
	65	0.12	0.20	0.30	0.00	0.00	0.00
	70	0.07	0.13	0.22	0.00	0.00	0.00
	75	0.04	0.08	0.15	0.00	0.00	0.00
	80	0.02	0.05	0.10	0.00	0.00	0.00
	85	0.01	0.03	0.06	0.00	0.00	0.00
$\alpha = 0.65$	50	0.13	0.17	0.22	0.00	0.16	0.21
	55	0.10	0.16	0.23	0.00	0.00	0.00
	60	0.07	0.12	0.19	0.00	0.00	0.00
	65	0.04	0.08	0.13	0.00	0.00	0.00
	70	0.02	0.05	0.08	0.00	0.00	0.00
	75	0.01	0.02	0.05	0.00	0.00	0.00
	80	0.00	0.01	0.03	0.00	0.00	0.00
	85	0.00	0.01	0.01	0.00	0.00	0.00

Figure 4-2. Probability of PP under various PP reduction factor (α)

Note: Green color = farmer tends to choose second crop, red color = farmer tends to choose more PP. Numbers in colored cells represent the probability of choosing PP.

In addition, according to PP indemnity data (from Indemnities with Month of Loss in RMA Cause of Loss, http://www.rma.usda.gov/data/cause.html), most farmers choose either base PP or 10% buy-up PP. Base PP accounted for 61% of total PP indemnity, and 10% buy-up PP 38% in 2013.

In sum, the most popular choice of crop insurance type and coverage in recent years has been 75-80% covered revenue protection with base PP. This study estimates an optimal reduction factor of 0.45-0.50, which induces most farmers to plant a second crop. In cases where a farmer does not purchase crop insurance for a second crop, the farmer most often chooses to claim PP, not to plant a second crop. This is because the risk of planting a second crop is much higher without insurance. In turn, the farmer faces a much higher risk premium, which discourages him/her from planting the second crop. The probability of claiming PP is simulated to be close to one until the value of α becomes very high like 0.6.

4.6. Summary and Concluding Remarks

If a farmer chooses prevented planting (PP), s/he receives a PP indemnity and may either leave the acreage unplanted or plant a second crop. e.g., soybean for corn. If the farmer plants a second crop after having chosen not to plant a first crop, s/he receives a reduced PP payment (35% of PP indemnity) and is assigned to 60% of the approved yield of the first crop in the APH for the next crop year. The current PP provision fails to provide farmers with an incentive to plant a second crop (99.9% of PP claiming farmers do not plant a second crop). Adjusting the PP indemnity payment may encourage farmers to plant a second crop, which is currently fixed at 35% of the total PP indemnity.

The objective in this study is to estimate the optimal percentage reduction in PP payment that may encourage farmers to plant a second crop. Assuming a relatively risk averse farmer, we derive the probability of choosing PP using corn-soybean budget data in Hamilton County, Iowa. Using stochastic simulation based upon a negative exponential utility function, and the current reduction factor, most farmers choose not to plant a second crop (Table 4-2). However, if the reduction factor increases, the farmer begins planting a second crop (Figure 4-2).

Policy implications regarding PP provision in crop insurance are twofold. First, the current PP reduction factor is not inducing farmers to plant a second crop, which conflicts with USDA's goal of promoting agricultural production. Second, the optimal reduction factor depends upon insurance coverage and type. The most popular choice of crop insurance type and coverage in recent years has been 75-80% coverage revenue protection with base PP. This study suggests an optimal reduction factor of 0.45-0.50 (from Figure 4-2), which may induce most of farmers to plant a second crop.

An obvious extension of this study would be a statistical test of our simulation results using historical data for insurance type and coverage, and the planting of a second crop. However, statistical analysis is precluded because of 99.9% of farmers chose not to plant a second crop. In addition, the suggest of PP payment rate of 0.45-0.50 is based upon parameterization for a single crop in a single place (Hamilton County, Iowa) where the corn yields tend to be high. Thus, related numerical analysis with parameterization for multiple locations should be conducted.

Additionally, in this study, the representative farmer is assumed to be relatively risk averse with a negative exponential utility function. In reality, however, a farmer's attitude toward risk and the type of utility function are unknown to researchers. If farmers are more risk averse than the representative farmer, the risk premium (RPM), would be higher and the value of α may also be higher than that of suggested here.

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5. MARGIN PROTECTION PROGRAM FOR DAIRY: CONDITIONAL PROBABILITY AND CHOICE OF MARGIN PROTECTION

Summary

The Margin Protection Program for dairymen (MPP-Dairy) provides dairy producers with insurance coverage (indemnity) when the national dairy margin (all milk price minus feed costs) falls beneath a producer-selected threshold level beginning at the catastrophic level of $4/cwt, requiring a $100 administration fee. Buy-up or supplementary coverage levels incurring additional premium costs are also offered in increments of $0.50/cwt, beginning at $4.5/cwt up to $8.0/cwt. MPP-Dairy enrollment data (http://www.fsa.usda.gov/programs-and-services/Dairy-MPP/index) indicates that California, the nation's largest dairy producing state, has only 29% of enrolled dairy farms purchasing supplementary coverage. In contrast, Wisconsin, the second largest dairy producing state, has 56% of enrolled producers purchasing buy-up coverage. This paper determines whether conditional probabilities regarding regional and national margins play a role in dairymen's decisions to purchase supplementary coverage. Results indicate that Wisconsin producers exhibit larger probabilities of purchasing supplementary coverage conditional on regional and national margins than do California producers.

Key Words: MPP-Dairy, Expected utility, Copula, conditional probability

JEL Codes: D81, Q14, Q18

5.1. Introduction

The Dairy Margin Protection Program (MPP-Dairy), administered by the Farm Service Agency (FSA USDA), is a risk management tool for dairy producers that addresses the income-over-feed-costs (IOFC) margin risk. The 2014 Farm Bill authorized the MPP-Dairy (FSA 2014), which offers dairy farms protection of their production margins. The MPP-Dairy includes catastrophic coverage, at no cost to the producer other than an annual $100 administrative fee. Various levels of buy-up coverage are offered with premiums that vary with the level of protection (Newton, Thraen, and Bozic 2015). Catastrophic coverage provides payments to participating dairy producers when the national dairy production margin is below $4/cwt. The national production margin is the difference between the monthly average all-milk price and monthly average feed costs (which includes the costs of corn, soybean, meal and alfalfa) (Newton, Thraen, and Bozic 2015). Producers may purchase buy-up coverage for national margins that range from $4.50/cwt to $8.00/cwt, rising by increments of $0.50. Producers receive indemnity payments when the actual margins (between $4.50 and $8.00/cwt) are below their selected margin level (Newton, Thraen, and Bozic 2015). The program's objective is to offer dairy producers (regardless of their size, geographic location, or management practices) self-selected protection levels against declines in milk prices, rising feed costs, or a mixture of both (Newton and Thraen 2014; Newton, Thraen, and Bozic 2015).

2015 MPP-Dairy coverage data by states indicate that, for western states other than Washington and Montana, less than 36% of those enrolled in the program purchase buy-up protection. California (CA), which is the largest dairy producing state in the U.S., has only 29% of enrolled dairy farms purchasing supplementary coverage (i.e. the majority enrolled solely purchase catastrophic coverage). In contrast, more than 50% of dairy producers in mid-western and eastern states typically purchase buy-up coverage. For example, Wisconsin (WI), the second largest dairy producing state in the U.S., has 56% of enrolled producers purchasing supplementary coverage. Figure 5-1 shows the MPP-Dairy participation rates across different margin protection in CA and WI. As shown, the distribution of MPP-Dairy participation rates differs in both regions. More than 70% of CA dairy producers typically purchase catastrophic protection, while 44% of WI producers do so. To the contrary, a larger percentage of WI dairy farms purchase buy-up coverage levels of $6/cwt and $6.5/cwt, as well as the maximum protection level of $8/cwt.

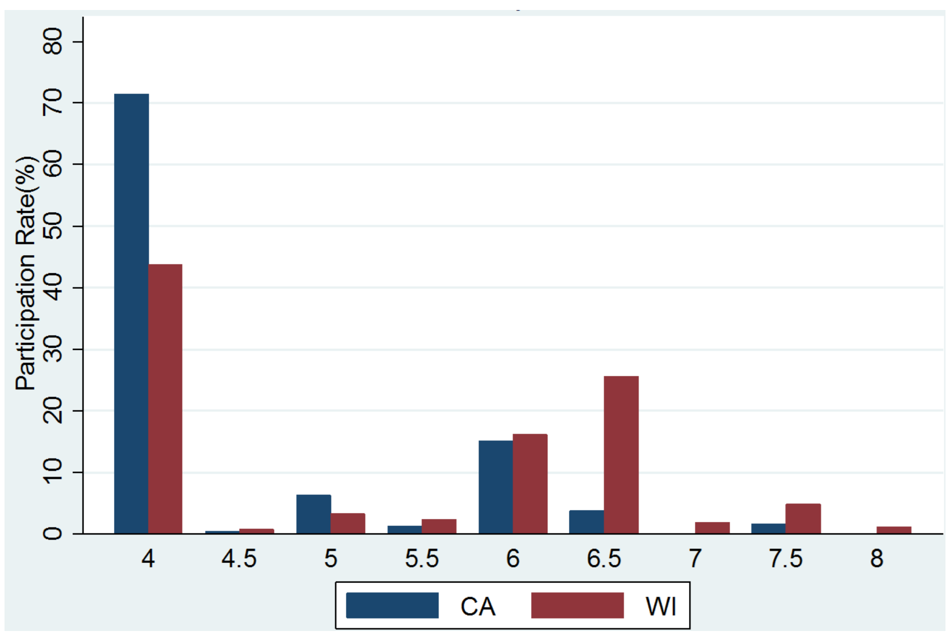

Figure 5-1. MPP-Dairy participation rate and margin protection in CA and WI in 2015
Note: Participation rate is the proportion of dairy producers who purchase dairy margin protection. $4/cwt is catastrophic coverage. Producers may purchase buy-up coverage that provides additional payments when margins are between $4.00 and $8.00/cwt.

The objective of this study is to investigate why WI dairy producers may have purchased more supplementary coverages than CA dairy producers. There are several potential factors explaining this difference, such as farm size (average size of dairy operation in CA is much larger than that in WI), regional milk price, regional feed costs, technology, and producers' attitude toward risk. Newton and Balagtas (2015) explore the MPP participation pattern focusing on farm size. They find that the enrollment rate is positively associated with farm size across state. They also find that supplementary coverage is negatively associated with farm size across state. This is because the $100 administration fee is relatively smaller for larger dairy producers. Thus, states with larger farms tend to exhibit higher participation rates (Newton and Balagtas 2015).

This study attempts to answer this question from a different perspective by demonstrating that the dairy production margins in particular the conditional probabilities among the national and each local market, may play a key role in determining which farms are more likely to purchase supplementary coverage. This is due to the fact that the dairy farms receive payments when the national (average) dairy production margin is below their selected margin protection level. If a dairy farm can accurately estimate the extent of the relationship between the US margin and her/his own margin, i.e., if the farmer can estimate how closely the US margin 'tracks' the changes in her/his margin, then the farm has an incentive to increase its selected protection rate and purchase a buy-up option.

Expected utility theory, which is used extensively in the insurance literature, is used to characterize the role of the conditional probability in the decision to purchase buy-up coverage. The level of margin protection is modeled as a function of the conditional probability between the margins of US and CA, or between the margins of US and WI, whichever the case may be. Comparative statics reveal that there exists a positive relationship between margin protection buy-up and the conditional probability defined over the national and local margins. The empirical conditional probability is derived using different copula models to see whether WI farms have larger conditional probabilities than CA farms.

Section 5-2 reviews the literature regarding the MPP-Dairy. The conceptual model for choice of margin protection and the role of conditional probability is described in section 5-3. Section 5-4 explores the various copula models used to calculate conditional probabilities of dairy production margins between US-CA and US-WI. Section 5-5 describes the data used. Section 5-6 presents the empirical methods to derive conditional probabilities between US-CA and US-WI. Results are discussed in Section 5-7. Section 5-8 provides a summary.

5.2. Literature Review

Few studies have investigated the MPP-Dairy. A handful of Farmdoc publications, such as those by Newton and Thraen (2014), Newton and Bozic (2014), and Newton and Balagtas (2015) address the MPP-Dairy. This is partly because the MPP-Dairy is a relatively new policy option included in the 2014 Farm Bill.

Newton and Thraen (2014) describe the MPP-Dairy as a “dairy safety net”. Newton and Bozic (2014) evaluate milk prices needed to trigger the MPP-Dairy. Newton and Balagtas (2015) explore the MPP-Dairy participation pattern focusing on farm size. They find that the enrollment rate is positively related with farm size across states. They also find that supplementary coverage is negatively associated with farm size across state. This is because the $100 administration fee is relatively small for larger dairy producers.

Thus, states with larger farms tend to exhibit higher participation rates (Newton and Balagtas 2015).

Newton, Thraen, and Bozic (2015) argue that MPP-Dairy leads to higher taxpayer cost compared with prior dairy support programs. Two reasons are suggested. First, dairy farmers may accurately predict the national dairy margins using publicly available information from futures markets, which allows them to maximize program returns. Second, a general lack of production constraints shifts benefits toward larger dairy farms and causes a larger taxpayer burden.

Regarding the dairy production margin, which is defined as the difference between all-milk price and feed costs, Bozic et al. (2012) finds that the dairy margin exhibits a slow mean-reverting property when margins are very high or very low. Their findings can be used to design risk management strategies for managing margins, especially in a futures market.

Bozic et al. (2014) explore the method used to determine the Livestock Gross Margin Insurance for Dairy Cattle (LGM-Dairy), which is the nation's prior dairy support program. They point out that the current rate-making method using a Gaussian copula fails to capture crucial features of milk and feed markets. They find that, since 2005, the dependence between milk and corn prices became stronger compared to 1990~2005. This is because the number of larger dairy farms (> 1000 dairy cattle) has increased over time, and most of large farms purchase their feed from grain markets. This causes stronger tail dependence, which is not accounted for by the Gaussian copula.

5.3. Conceptual Model

Suppose a dairy farm located in region j chooses a level of margin protection, $\overline{\mathrm{m}}_{\mathrm{j}}$. To make the problem simple, suppose there are four *discrete* states of nature (SON) governing the US and region jth margins, i.e., $S = \{S_1, S_2, S_3, S_4\}$. In SON S_1 the US margin exceeds the producer's chosen margin of protection ($\overline{\mathrm{m}}_{\mathrm{j}} < \mathrm{m}_{\mathrm{us}}^{\mathrm{H}}$) denoted by $\mathrm{m}_{\mathrm{us}}^{\mathrm{H}}$, and region jth's margin is also high ($\mathrm{m}_{\mathrm{j}} = \mathrm{m}_{\mathrm{j}}^{\mathrm{H}}$) as well.[11] Under S_1 no MPP-Dairy payment is made. In SON S_2, the US margin is lower than producer's protection margin ($\overline{\mathrm{m}}_{\mathrm{j}} > \mathrm{m}_{\mathrm{us}}^{\mathrm{L}}$) , and region jth's margin is again high ($\mathrm{m}_{\mathrm{j}} = \mathrm{m}_{\mathrm{j}}^{\mathrm{H}}$). In this case, the producer receives an MPP-Dairy payment (per-unit of production) of $\alpha_{\mathrm{j}}(\overline{\mathrm{m}}_{\mathrm{j}} - \mathrm{m}_{\mathrm{us}}^{\mathrm{L}})$, where α is the coverage level (from 25% to 90%). In SON S_3, the US margin is again high ($\mathrm{m}_{\mathrm{us}} = \mathrm{m}_{\mathrm{us}}^{\mathrm{H}}$) but region jth's margin is low ($\mathrm{m}_{\mathrm{j}} = \mathrm{m}_{\mathrm{j}}^{\mathrm{L}}$). In SON S_4, both the US and regional jth's margins are low. The dairy farm is paid $\alpha_{\mathrm{j}}(\overline{\mathrm{m}}_{\mathrm{j}} - \mathrm{m}_{\mathrm{us}}^{\mathrm{L}})$. Figure 5-2 presents these four SONs.

		US Margins (m_{us})	
		Higher than $\overline{\mathrm{m}}$	Lower than $\overline{\mathrm{m}}$
Regional Margins (m_{j})	High	S_1	S_2
	Low	S_3	S_4

Figure 5-2. State of nature

Note: US margin is high when $\overline{\mathrm{m}} < \mathrm{m}_{\mathrm{us}}$ and the dairy farm doesn't receive MPP-Dairy payments. US margin is low when $\overline{\mathrm{m}} > \mathrm{m}_{\mathrm{us}}$ and the dairy farm receives MPP-Dairy payments.

[11] Discretizing margins as high vs. low helps to make the model tractable. A high regional margin is defined as a margin exceeding the (historical) average, while a low regional margin is defined as a margin below the (historical) average. A high US margin occurs when the US margin exceeds a farmer selected threshold. A low US margin occurs when the US margin is lower than the farmer selected threshold.

The corresponding MPP-Dairy premium (per unit of production) is calculated as $P_j = \alpha_j \pi_{us}(\overline{m}_j - m_{us}^L)$, where P is the premium per unit of production for dairy farm to participate in the MPP-Dairy program 'buy-up' program, α_j is chosen coverage level, and $\pi_{us} = \Pr(m_{us} = m_{us}^L)$. [12] The corresponding wealth for the dairy farm (per unit of production) located in region j for the SONs is provided in the second column of Table 5-1. Here w_0 represents the producer's initial wealth level. In S_1, for instance, the dairy farm receives no MPP-Dairy payment but s\he has a high dairy margin, so the wealth is $w_0 - P_j + m_j^H$. In S_2, the producer receives a MPP-Dairy payments with a high dairy margin, so the wealth is $w_0 - P_j + m_j^H + \alpha_j(\overline{m}_j - m_{us}^L)$. In S_3, the dairy farm doesn't receive payments and s\he has a low dairy margin as well, so the wealth is $w_0 - P_j + m_j^L$. Lastly, in S_4, the dairy farm receives the payment with a low dairy margin, so the wealth is $w_0 - P_j + m_j^L + \alpha_j(\overline{m}_j - m_{us}^L)$.

Table 5-1. Wealth and Probability for Four States of Nature

SON	Wealth	Probability
S_1	$w_0 - P_j + m_j^H$	$\pi_1 = 1 - \pi_{us} - \pi_j + \pi_j\pi_{us\|j}$
S_2	$w_0 - P_j + m_j^H + \alpha_j(\overline{m}_j - m_{us}^L)$	$\pi_2 = \pi_{us} - \pi_j\pi_{us\|j}$
S_3	$w_0 - P_j + m_j^L$	$\pi_3 = \pi_j - \pi_j\pi_{us\|j}$
S_4	$w_0 - P_j + m_j^L + \alpha_j(\overline{m}_j - m_{us}^L)$	$\pi_4 = \pi_j\pi_{us\|j}$

Note: SON = state of nature.
$\pi_1 = \Pr(S_1)$, $\pi_2 = \Pr(S_2) = \Pr(m_{us} = m_{us}^L, m_j = m_j^H)$, $\pi_3 = \Pr(S_3) = \Pr(m_{us} = m_{us}^H, m_j = m_j^L)$, and $\pi_4 = \Pr(S_4) = \Pr(m_{us} = m_{us}^L, m_j = m_j^L)$, where $\pi_{us} = \Pr(m_{us} = m_{us}^L)$, $\pi_j = \Pr(m_j = m_j^L)$, and $\pi_{us|j} = \Pr(m_{us} = m_{us}^L | m_j = m_j^L)$.

[12] MPP-Dairy premium rates are fixed at predetermined levels for the duration of the farm bill (Newton, Thraen and Bozic 2015). This research assumes that these fixed premium rates are calculated as $P_j = \alpha_j \pi_{us}(\overline{m} - m_{us}^L)$, which satisfies the equivalence principle, i.e., expected MPP-Dairy payment = premium.

The third column of Table 5-1 presents the associated probabilities for each of SON, where $\pi_{us} = \Pr(m_{us} = m_{us}^{L})$, $\pi_j = \Pr(m_j = m_j^{L})$, and $\pi_{us|j} = \Pr(m_{us} = m_{us}^{L} | m_j = m_j^{L})$. The probability of S_4 can be therefore written as $\pi_4 = \Pr(S_4) = \Pr(m_{us} = m_{us}^{L}, m_j = m_j^{L}) = \pi_j \pi_{us|j}$ using Bayes' Theorem $\Pr(m_{us} = m_{us}^{L} | m_j = m_j^{L}) = \frac{\Pr(m_{us}=m_{us}^{L}, m_j=m_j^{L})}{\Pr(m_j=m_j^{L})} \leftrightarrow \pi_{us|j} = \frac{\Pr(S_4)}{\pi_j}$. Likewise, the probability of S_3 is given by $\pi_3 = \Pr(S_3) = \Pr(m_{us} = m_{us}^{H}, m_j = m_j^{L}) = \pi_j - \pi_j \pi_{us|j}$, and the probability of S_2 is given by $\pi_2 = \Pr(S_2) = \Pr(m_{us} = m_{us}^{L}, m_j = m_j^{H}) = \pi_{us} - \pi_j \pi_{us|j}$. The probability of S_1, in turn, can be written as $\pi_1 = \Pr(S_1) = 1 - \Pr(S_2) - \Pr(S_3) - \Pr(S_4) = 1 - \pi_{us} - \pi_j + \pi_j \pi_{us|j}$.

Assuming a risk averse dairy producer with a strictly twice-continuously differentiable utility function, the maximization of the producer's expected utility function is given by

$$(5\text{-}1) \quad \max_{\bar{m}_j} \ EU_j = \pi_1 u\left(w_0 - P_j + m_j^{H}\right) + \pi_2 u\left(w_0 - P_j + m_j^{H} + \alpha_j\left(\bar{m}_j - m_{us}^{L}\right)\right) + \pi_3 u\left(w_0 - P_j + m_j^{L}\right) + \pi_4 u\left(w_0 - P_j + m_j^{L} + \alpha_j\left(\bar{m}_j - m_{us}^{L}\right)\right)$$

$$\text{subject to } P_j = \alpha_j \pi_{us}\left(\bar{m}_j - m_{us}^{L}\right).$$

Given α_j, the producer's first order condition (j subscript is omitted for expository convenience) is given by,

$$(5\text{-}2) \quad \frac{\partial EU}{\partial \bar{m}} = -\alpha\pi_{us}\pi_1 u'(1) + \alpha(1-\pi_{us})\pi_2 u'(2) - \alpha\pi_{us}\pi_3 u'(3) + \alpha(1-\pi_{us})\pi_4 u'(4) = 0.$$ [13]

[13] "1" $= w_0 - P_j + m_j^{H}$, "2" $= w_0 - P_j + m_j^{H} + \alpha_j\left(\bar{m}_j - m_{us}\right)$, "3" $= w_0 - P_j + m_j^{L}$, and "4" $= w_0 - P_j + m_j^{L} + \alpha_j\left(\bar{m}_j - m_{us}\right)$.

The optimal solution is denoted $\bar{m}^* = \bar{m}\left(\pi_{us}, \pi_j, \pi_{us|j}, w_0, \alpha_j, m_{us}, m_j^H, m_j^L\right)$ if an interior solution exists[14]. The second order condition for a local maximum satisfies,

(5-3) $$\frac{\partial^2 EU}{\partial \bar{m}^2} = \alpha^2 \pi_{us}^2 \pi_1 u''(1) + \alpha^2 (1-\pi_{us})^2 \pi_2 u''(2) + \alpha^2 \pi_{us}^2 \pi_3 u''(3) + \alpha^2 (1-\pi_{us})^2 \pi_4 u''(4) < 0,$$

which holds automatically by our underlying assumption of risk aversion.

By implicit function theorem, $\frac{\partial \bar{m}^*(\cdot)}{\partial \pi_{us|j}} = -\frac{\frac{\partial^2 EU}{\partial \bar{m}\, \partial \pi_{us|j}}}{\frac{\partial^2 EU}{\partial \bar{m}^2}}$, where the numerator satisfies

(5-4) $$\frac{\partial^2 EU}{\partial \bar{m}\, \partial \pi_{us|j}} = -\alpha \pi_j \pi_{us} u'(1) - \alpha \pi_j (1-\pi_{us}) u'(2) + \alpha \pi_j \pi_{us} u'(3) + \alpha \pi_j (1-\pi_{us}) u'(4)$$

$$\rightarrow\ \alpha \pi_j \pi_{us}\left(u'(3) - u'(1)\right) + \alpha \pi_i (1-\pi_{us})\left(u'(4) - u'(2)\right) > 0,$$

which again holds automatically by our underlying assumption of risk aversion. Thus,

(5-5) $$\frac{\partial \bar{m}^*(\cdot)}{\partial \pi_{us|j}} = -\frac{\frac{\partial^2 EU}{\partial \bar{m}\, \partial \pi_{us|j}}}{\frac{\partial^2 EU}{\partial \bar{m}^2}} > 0.$$

In words, when the conditional probability, $\pi_{us|j} = \Pr(m_{us} = m_{us}^L | m_j = m_j^L)$, increases, the dairy producer chooses a higher margin protection level.

Now the question becomes how to identify empirically the conditional probabilities, $\pi_{us|j}$. We use the Copula method. Copula models are flexible forms that can be used to estimate dependence structures among (stochastic) variables, here, dairy production margins.

5.4. Copula Theory

Copulas are functions that “join or couple multivariate distribution functions to their marginal distribution functions” (Nelson 2006). According to Nelson (2006), Copula

[14] All the dairy producers are assumed to purchase margin protection. This is not unrealistic since dairy producers can purchase catastrophic level with no premium other than $100 administration fee.

functions provide a flexible dependence structure among N-dimensional multivariate joint distribution that can take any distributional form. Consider a continuous N-dimensional multivariate joint distribution function $F(x_1, x_2, \dots, x_N)$ with univariate marginal distributions $F_1(x_1), \cdots, F_N(x_N)$ and inverse probability transforms (quantile functions), $F_1^{-1}, \cdots, F_N^{-1}$. Then $x_i = F_i^{-1}(u_i) \sim F_i$, $i = 1, \cdots, N$, where u_i is a uniformly distributed variable. Hence,

(5-6) $$F(x_1, x_2, \dots, x_N) = F\left(F_1^{-1}(u_1), F_2^{-1}(u_2), \dots, F_N^{-1}(u_N)\right) = C(u_1, u_2, \dots, u_N).$$

By Sklar's Theorem (Sklar 1973), copula function $C(\cdot)$ allows a dependence structure among marginal distributions by introducing dependence parameter, θ, in the copula function:

(5-7) $$F(x_1, x_2, \dots, x_N) = C(u_1, u_2, \dots, u_N |\, \theta),$$

where θ is a scalar-valued dependence parameter.

5.4.1. Classes of Copula Functions

Most copula research to date focuses on bivariate copulas, because extensions to higher dimensions introduce nontrivial restrictions on dependence (Zimmer 2012). Following Zimmer (2012), the bivariate copula is applied in this study. Generally, there are two types of copulas, i) Elliptical and ii) Archimedean. Elliptical copulas are symmetrical in shape (Meyer 2009), which include Gaussian (normal) copula and student's t copulas.

The Bivariate Gaussian copula, C_g, with a dependence parameter θ, is written as

(5-8) $$C_g(u_1, u_2|\theta) = \Phi(\Phi^{-1}(u_1), \Phi^{-1}(u_2)|\theta)$$

$$= \int_{-\infty}^{\Phi^{-1}(u_1)} \int_{-\infty}^{\Phi^{-1}(u_2)} \frac{1}{2\pi\sqrt{(1-\theta^2)}} \exp\left\{\frac{-s^2 + 2\theta st - t^2}{2(1-\theta^2)}\right\} dsdt,$$

where Φ is a cumulative standard normal distribution, $\theta \in (-1,1)$, and u_1 and u_2 are uniformly distributed variables (Zimmer 2012). The Gaussian copula exhibits asymptotic independence, i.e., dependence approaches zero in upper and lower tail areas (Embrechts, Frey, and McNeil 2005). The Gaussian copula has been used widely in finance due to its simplicity and familiarity (Zimmer 2012).

The Bivariate student's t copula, C_t, with $\theta \in (-1,1)$ and degrees of freedom υ, is written as

(5-9) $C_t(u_1, u_2|\theta, \upsilon) = t_{\theta,\upsilon}\,(t_\upsilon^{-1}(u_1), t_\upsilon^{-1}(u_2)|\theta, \upsilon)$

$$= \int_{-\infty}^{t_\upsilon^{-1}(u_1)} \int_{-\infty}^{t_\upsilon^{-1}(u_2)} \frac{1}{2\pi\sqrt{(1-\theta^2)}} \left\{1 + \frac{-s^2 + 2\theta st - t^2}{\upsilon(1-\theta^2)}\right\}^{\frac{-(\upsilon+2)}{2}} dsdt,$$

where $t_{\theta,\upsilon}$ is the cumulative student's distribution function with degrees of freedom υ and dependence parameter θ. u_1 and u_2 are again uniformly distributed variables. The student's t copula has a symmetric pattern in the upper and lower tail areas and has tail dependence in upper and lower tail areas. Both the Gaussian and student's t copulas make use of Pearson linear correlation coefficient as a dependence parameter. There exists a strong negative dependence between two random variables when θ approaches -1, and a strong positive dependence when θ approaches 1.

Archimedean copulas such as Gumbel and Clayton can identify asymmetric dependence in lower (Clayton) or upper tails (Gumbel). A bivariate Gumbel copula, C_{gum} with a dependence parameter θ, is

(5-10) $$C_{gum}(u_1, u_2|\theta) = \exp\left(-\left((-\log u_1)^\theta + (-\log u_2)^\theta\right)\right)^{\frac{1}{\theta}},$$

where the dependence parameter is restricted to $\theta \in [1, \infty)$. If two random variables are independent, θ approaches 1. When two random variables are strongly dependent, θ approaches infinity. The Gumbel copula exhibits asymmetric upper tail dependence.

The bivariate Clayton copula, C_c with a dependence parameter θ is written as

(5-11) $$C_c(u_1, u_2|\theta) = \left(u_1^{-\theta} + u_2^{-\theta} - 1\right)^{-\frac{1}{\theta}},$$

where the dependence parameter is restricted to $\theta \in (0, \infty)$. If two random variables are independent, θ approaches 0. Conversely, if two random variables are strongly dependent, θ approaches to infinity. The Clayton copula exhibits a lower tail dependence.

Copulas can be derived from combinations of individual copulas to better fit the data. A mixture copula with two different copulas can be written as

(5-12) $$C_m(u_1, u_2|p, \theta_1, \theta_2) = pC_1(u_1, u_2|\theta_1) + (1 - p)C_2(u_1, u_2|\theta_2),$$

where, p is the proportional contribution of the first copula to the mixture copula, and C_1 and C_2 are different two copulas (Zimmer 2012). This type of mixture copula can capture lower and upper tail dependence if Gumbel and Clayton copulas are used (Zimmer 2012).

5.4.2. Dependence Parameter

The dependence parameter, θ, in Elliptical copulas is simply a (Pearson) correlation coefficient. Dependence parameters of Archimedean copulas, however, are somewhat ambiguous in measuring how two random variables are dependent, and not directly comparable to dependence parameters from Elliptical copulas. The dependence parameter,θ, may be converted to a Kendal's rank correlation, τ, for direct comparison with an Elliptical copula. Kendall's rank correlation (τ) is restricted to values between $(-1,1)$ like the Pearson linear correlation, though it is not the same type of correlation (i.e. rank vs. linear). Table 5-2 shows the relationship between Kendall's τ and θ for various copula functions.

Table 5-2. Relationship between θ and τ

Copula function	Dependence parameter θ-domain	Kendall's rank correlation τ
Gaussian and Student's *t*	$-1 < \theta < 1$	$\frac{2}{\pi}\arcsin(\theta)$
Gumbel	$1 \leq \theta < \infty$	$1 - \theta^{-1}$
Clayton	$0 < \theta < \infty$	$1 - \frac{2}{\theta + 2}$

Source: Trivedi and Zimmer (2007) Table 2.1 revised.

5.5. Data

Monthly US average prices for all milk, corn, and alfalfa hay are obtained from the National Agricultural Statistics Service (NASS), USDA; and soybean meals prices are compiled from Agricultural Marketing Services (AMS), USDA. All data ranges from January 2000 to September 2015. Monthly CA and WI average prices for all milk and alfalfa hay are obtained from NASS USDA, and monthly CA and WI average prices for corn and soybean meals are obtained from AMS USDA. (NOTE: WI soybean meal prices used are same as for the US national average, which are from Decatur, Illinois)

The dairy production margin, $\mathrm{m_i}$, is the difference between all milk price (in $/cwt) and 'converted feed' cost (i.e. in $/cwt) of corn, soybean meal and alfalfa hay for region i

(5-13) $\mathrm{m_i = P_{milk,i} - (1.078P_{corn,i} + 0.0137P_{alfalfa,i} + 0.00735P_{SBM,i})}$, $\mathrm{i = US, CA, WI}$,

where, $\mathrm{P_{milk}}$ is all milk price, $\mathrm{P_{corn}}$ is corn price (per bushel), $\mathrm{P_{alfalfa}}$ is alfalfa hay price (per ton), and $\mathrm{P_{SBM}}$ is soybean meal price (per ton).

Figure 5-3 shows the US, CA and WI margins from January 2000 to September 2015. As shown, US and WI margins move very closely together through time. The CA margin is lower than that of US and WI in each period. Note that all three margins experienced steep drops to (below 4 $/cwt) in 2009 and 2012 Moreover, CA dairy producers experienced negative margins in 2009 and 2012.

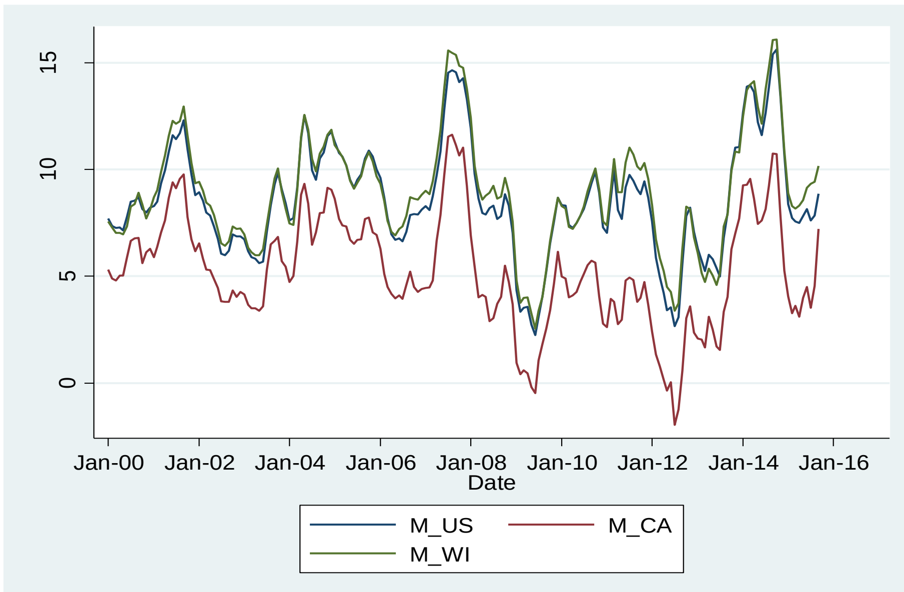

Figure 5-3. Margin co-movement among US, CA, and WI

Note: Region i's margin is calculated as $\mathrm{m_i} = \mathrm{P_{milk}} - (1.078\mathrm{P_{corn}} + 0.0137\mathrm{P_{alfalfa}} + 0.00735\mathrm{P_{SBM}})$, $\mathrm{i} = \mathrm{US}, \mathrm{CA}$, and WI; Phillips-Perron test indicates that margins are stationary.

Table 5-3 presents basic statistics for milk price, feed cost and IOFC margins. Average US and WI milk prices are aligned around $16.35/cwt. The average CA milk price is roughly $1 less than those of US and WI. In contrast, CA (converted) average feed cost is higher than that of US and WI by roughly $2 per cwt. The high feed cost in CA is likely driven by the fact that large (commercial size) CA dairy farms purchase feed from directly crop markets. CA dairy producers may be more sensitive to variation of crop prices. Since CA has relatively low milk price and high feed cost, its IOFC margin is less than the margins for US and WI. The average US IOFC margin was $8.57/cwt, WI $8.93/cwt, and CA $5.21/cwt for 2000~2015.

Table 5-3. Basic Statistics for Milk Price, Feed Cost and Margin for 2000-2015

		Mean	St. Dev	Min	Max
Milk Price ($/cwt)	US	16.37	3.67	11.00	25.70
	WI	16.34	3.72	11.00	25.70
	CA	15.01	3.49	9.92	23.62
Converted Feed Cost ($/cwt)	US	7.81	3.03	3.95	15.12
	WI	7.41	3.01	3.42	14.90
	CA	9.80	3.53	5.14	17.76
Margin ($/cwt)	US	8.57	2.63	2.25	15.62
	WI	8.93	2.70	2.55	16.09
	CA	5.21	2.64	-1.97	11.63

Note: Margin is calculated as $m_i = P_{milk} - (1.078P_{corn} + 0.0137P_{alfalfa} + 0.00735P_{SBM})$, $i = US, CA$, and WI.

5.6. Empirical Methods

5.6.1. Specification of Marginal Distributions

The first step in copula modeling is to specify the marginal distribution functions, $F_1(m_1)$ and $F_2(m_2)$, where m_1 is the US IOFC margin and m_2 is a regional (CA or WI) dairy margin. An AR(p)-GARCH(1,1) model is used to eliminate the deterministic components from the margin variables and to find the dependence structure between margins (Zimmer 2012). The AR(p)-GARCH(1,1) model eliminates serial correlation and autoregressive conditional heteroscedasticity in margin variables as well. The AR(p)-GARCH(1,1) model is given by

(5-14) $$m_{i,t} = \beta_{i,0} + \beta_{i,1}m_{i,t-1} + \cdots + \beta_{i,p}m_{i,t-p} + \varepsilon_{i,t},$$

for $i =$ US, CA, and WI. $\varepsilon_{i,t}$ is an error term with zero mean and conditional variance,

(5-15) $$\sigma_{i,t}^2 = \alpha_{i,0} + \alpha_{i,1}\varepsilon_{i,t-1}^2 + \delta_i\sigma_{i,t-1}^2.$$

After estimation, a new series $\tilde{m}_i$ is calculated as

(5-16) $$\tilde{m}_{i,t} = \frac{\hat{\varepsilon}_{i,t}}{\sqrt{\hat{\alpha}_{i,0}+\hat{\alpha}_{i,1}\hat{\varepsilon}^2{}_{i,t-1}+\hat{\delta}_i\hat{\sigma}^2{}_{i,t-1}}}.$$

The series $\tilde{m}_{i,t}$ is referred to as a filtered margin.

5.6.2. Copula Estimation

Maximum likelihood estimation (MLE) is used to estimate the dependence parameter θ. The probability density function (pdf) is rewritten as

(5-17) $$f(\tilde{m}_{us}, \tilde{m}_j) = c(F_{us}(\tilde{m}_{us}), F_j(\tilde{m}_j)|\theta) = \frac{d^2C(F_{us}(\tilde{m}_{us}), F_j(\tilde{m}_j)|\theta)}{d\tilde{m}_{us}d\tilde{m}_j} f_{us}(\tilde{m}_{us})f_j(\tilde{m}_j), j = CA, WI$$

MLE maximizes the natural logarithm of equation (5-17), summing all observations with respect to θ. The Bayes Information Criterion (BIC) and Vuong test (Vuong 1989) are used for the goodness of fit measures of different choice of copula functions following Zimmer (2012).

5.6.3. Conditional Probability

The estimation of conditional probabilities for the US margin given the CA (or WI) margin is the next estimation step. A conditional probability can be derived from copula estimation. The conditional probability is given by

(5-18) $$\hat{P}(\tilde{m}_{us,t} < k|\tilde{m}_{j,t} < k) = \frac{\hat{P}(\tilde{m}_{us,t}<k,\tilde{m}_{j,t}<k)}{\hat{P}(\tilde{m}_{j,t}<k)} = \frac{\hat{C}(\hat{F}_{us}(k),\hat{F}_j(k)|\theta)}{\hat{F}_j(k)}, j = CA, WI.$$

Equation (5-18) gives the probability that the US margin is less than k given that the CA (or WI) margin is less than k. Similarly, for the case where the US margin exceeds k given that CA (or WI) margin also exceeds k, the conditional probability is written as

(5-19) $$\hat{P}(\tilde{m}_{us,t} > k|\tilde{m}_{j,t} > k) = \frac{\hat{P}(\tilde{m}_{us,t}>k,\tilde{m}_{j,t}>k)}{\hat{P}(\tilde{m}_{j,t}>k)} = \frac{1-\hat{F}_{us}(k)-\hat{F}_j(k)+\hat{C}(\hat{F}_{us}(k),\hat{F}_j(k)|\theta)}{1-\hat{F}_j(k)}.$$

If the probability of (filtered) US margin conditional on (filtered) WI margin is larger than the probability of (filtered) US margin conditional on (filtered) CA margin (for a certain margin level k), WI dairy farmers tend to purchase (more) buy-up margin protection as shown in equation (5-5), i.e., $\frac{\partial \bar{m}^{*}(\cdot)}{\partial \pi_{us|j}} > 0$.

5.7. Results

5.7.1. Filtered Margins

Table 5-4 presents the estimation results for the AR(p)-GARCH(1,1) model in equation (5-14). The 3 autoregressive terms for the US and WI margins, and the 2 autoregressive terms for the CA margin remove autocorrelation, which is confirmed using a Breusch-Godfrey test (Breusch 1978; Godfrey 1978). A GARCH(1,1) eliminates autoregressive conditional heteroscedasticity in the margin variables, which is confirmed using LM tests (Bollerslev 1986). Filtered margins $\tilde{m}_{i,t}$ $(i = US, CA, WI)$ in equation (5-16) appear to be approximately standard normal. Skewness and kurtosis (S-K) tests fail to reject the null hypotheses that the distribution of the filtered margins are normal. In addition, Chi square tests of variance fail to reject the null hypothesis that the respective variances of the filtered margins are equal to 1.

Figure 5-4 presents scatterplots of filtered margins between US-CA and US-WI. Both plots indicate that US-CA and US-WI exhibit strong positive relationships. US-WI seems to have stronger correlation. Figure 5-5 reports comparisons between filtered margin kernel density (blue lines) and normal density (red lines) functions. Figure 5-5 shows that each filtered margin, $\tilde{m}_{it}$, is approximately distributed standard normal.

Table 5-4. AR(P)-GARCH(1,1) Estimation Results

	(1) US filtered margin	(2) CA filtered margin	(3) WI filtered margin
Constant (β_0)	8.068***	5.462***	7.954***
	(0.509)	(0.728)	(0.600)
ARMA			
L1.AR (β_1)	1.660***	1.387***	1.692***
	(0.090)	(0.074)	(0.094)
L2.AR (β_2)	-0.960***	-0.480***	-1.006***
	(0.149)	(0.0717)	(0.148)
L3.AR (β_3)	0.218**		0.241**
	(0.082)		(0.079)
ARCH			
L.ARCH (α_1)	0.218*	0.0198	0.251*
	(0.102)	(0.022)	(0.180)
L.GARCH (δ)	0.693***	0.994***	0.653***
	(0.131)	(0.045)	(0.131)
Constant (α_0)	0.0522	-0.00565	0.0595
	(0.036)	(0.020)	(0.039)
N	189	189	189
Log likelihood	-191.22	-230.67	-193.68

Note: Numbers in parentheses are standard errors. Significance levels are 1% (***), 5% (**), and 10% (*).

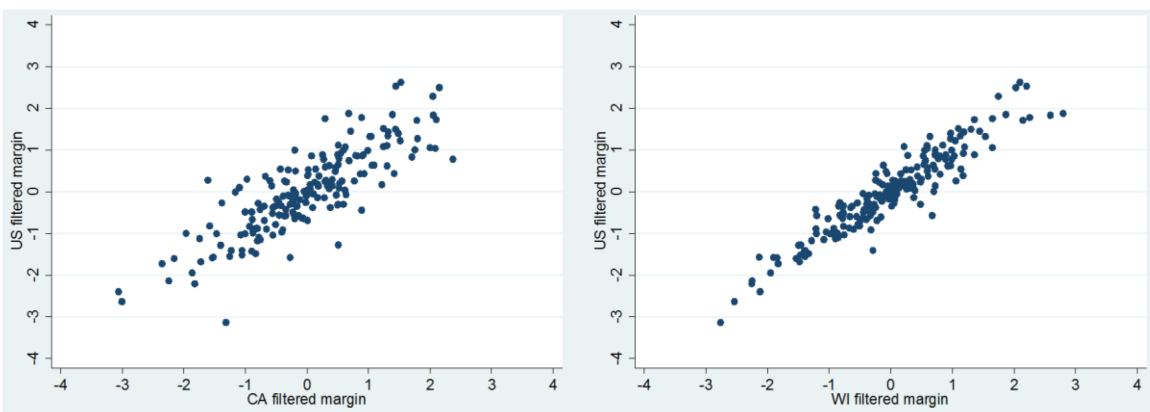

Figure 5-4. Scatter plot of filtered margins (US-CA and US-WI)

Note: Filtered margin ($\tilde{m}_{it}$) is the series with filtered out AR(p) and GARCH(1,1) components of the margins, m_{it}.

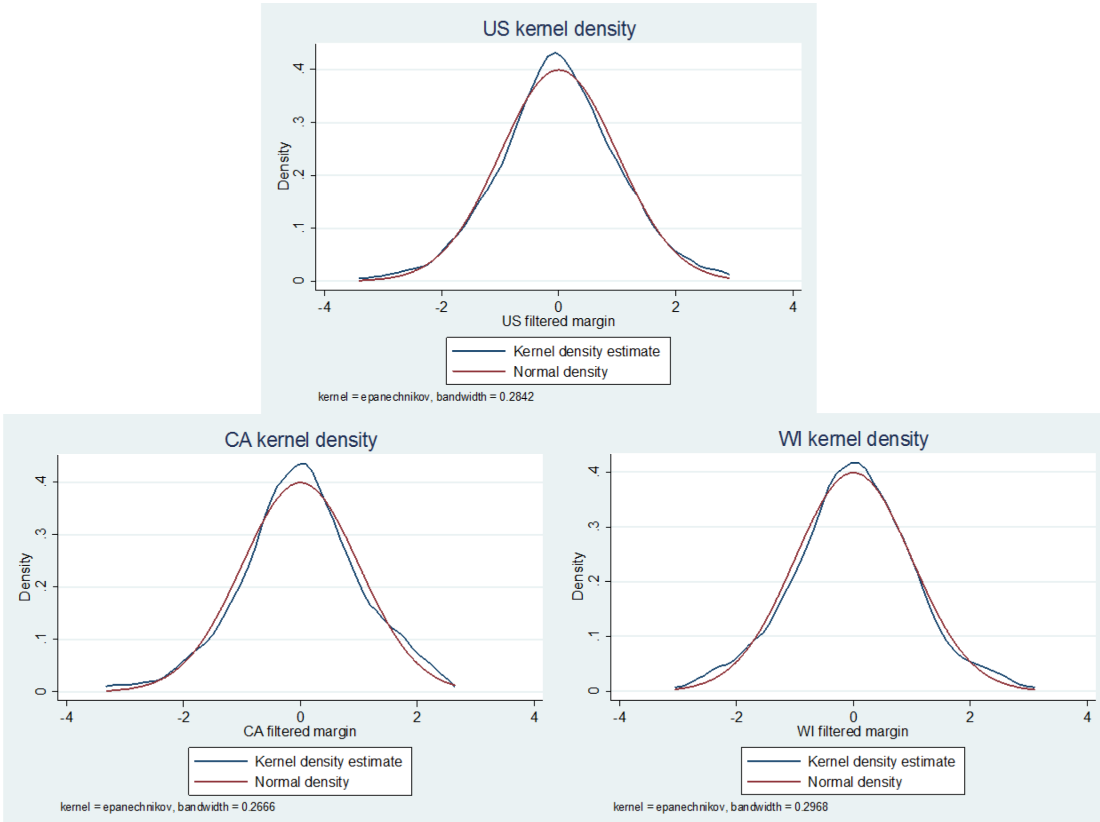

Figure 5-5. Filtered margin kernel density functions

Note: Filtered margin ($\tilde{m}_{it}$) is the series with filtered out AR(p) and GARCH(1,1) components of the margins, m_{it}.

5.7.2. Estimates of Dependence[15]

Table 5-5 reports estimates of the dependence parameter θ. Parameter θ is converted to Kendall's τ for comparison across different copulas. As shown in Table 5-5, the correlation between US and WI filtered margins is generally larger than that between US and CA filtered margins across (single) copulas. For the Gumbel/Clayton mixture, estimates of τ are reported for each part of the mixture, with the proportion (p) accounted

[15] Vector autoregressive (VAR) model is also used to estimates of dependence parameter. The VAR model gives a similar result as AR(p)-GARCH(1,1).

for by each component - in accordance with equation (5-12). The estimated proportion pertaining to Clayton is estimated to be 0.46 for US-CA and 0.84 for US-WI, indicating lower-tail dependence is stronger among US-WI filtered margins.

All standard errors reported in Table 5-4 are computed using a block bootstrapping (Kreiss and Lahiri 2012). Eight overlapping blocks of 24 consecutive observations (which provide two years of monthly margin data) are drawn from the original filtered margins. The 8 times 24 observations provide a bootstrap sample of similar length to the original data. The AR-GARCH and filtered margins are re-estimated using the bootstrap sample. This process is repeated 500 times and standard errors are calculated.

Table 5-5. Estimates of Dependence (Kendall's τ)

Copula	US-CA	US-WI
Gaussian		
$\hat{\tau}$	0.63***	0.78***
	(0.05)	(0.04)
Student's t		
$\hat{\tau}$	0.64***	0.78***
	(0.06)	(0.31)
Degrees of freedom	9.03	10.83
	(40.37)	(18.15)
Gumbel		
$\hat{\tau}$	0.61***	0.75***
	(0.14)	(0.09)
Clayton		
$\hat{\tau}$	0.53***	0.72***
	(0.07)	(0.06)
Gumbel-Clayton Mixture		
Gumbel $\hat{\tau}$	0.49***	0.50***
	(0.11)	(0.03)
Clayton $\hat{\tau}$	0.74***	0.77***
	(0.20)	(0.08)
Proportion due to	0.46*	0.84***
Clayton $\hat{p}$	(0.24)	(0.22)

Note: Numbers in parentheses are standard errors. Significance levels are 1% (***), 5% (**), and 10% (*).

5.7.3. Selection of Copula

Table 5-6 provides the values for the Bayes Information Criterion (BIC) and Vuong test statistics (Vuong 1989) to choose the best copula. Gaussian copula is selected for both US-CA and US-WI filtered margins, based on having the smallest BIC. Student's t and Gaussian copulas are associated with relatively close BIC values. The Clayton copula for US-CA, and Gumbel copula for US-WI produce the worst BIC results. Vuong test results are also reported in Table 5-6 comparing each copula to the Gaussian copula. As the test statistic follows a normal distribution, significant positive values indicate inferior fit compared with the Gaussian copula. Taken together Vuong and BIC values indicate that the Gaussian copula is superior to other copulas.

5.7.4. Conditional Probabilities

The conditional probabilities in equations (5-18) and (5-19) are calculated across different values of $\mathrm{k} \in [-3,3]$ using the Gaussian copula. The k values can be interpreted as the standard deviations of the filtered margins since $\tilde{\mathrm{m}}_{\mathrm{it}}$ are essentially the standardized residuals from the AR-GARCH model. Figure 5-6 presents the conditional probabilities associated with different values of the filtered margins. If filtered margin for CA falls more than one standard deviation below its mean ($\mathrm{k} = -1$), then the probability that the US filtered margin drops more than one standard deviation below its mean is approximately 0.65. In contrast, the conditional probability of the US margin subject to the WI margin - for this same scenario - is approximately 0.80; which is roughly 23% points larger than CA. The conditional probabilities decrease over the values of k, but the differences between the conditional probabilities of CA and WI become larger as k increases in magnitude.

Table 5-6. Goodness of Fit Measures and Vuong Test Statistics

Copula model	US/CA	US/WI
Bayes information criteria		
Gaussian	850.56	667.89
Student's t	852.87	670.31
Gumbel	869.08	715.76
Clayton	899.89	707.75
Gumbel/Clayton mixture	859.35	704.56
Vuong test statistics		
Gaussian	-	-
Student's t	0.68	0.64
Gumbel	1.60	3.64***
Clayton	2.95***	2.28**
Gumbel/Clayton mixture	0.36	1.85*

Note: The smallest BIC value represents the best fit.

Vuong test statistics is $z = \frac{LR(\theta_g,\theta_a)}{\sqrt{N}\omega} \sim N(0,1)$, where $LR(\theta_g, \theta_a) = L_g - L_a - \frac{k_g - k_a}{2} \ln N$, L_g= maximum log likelihood of Gaussian copula, L_a = maximum log likelihood of alternative copula, k = number of parameters to estimate in models, and N = number of observations. ω is the standard deviation of $\ln \frac{f_g(x_{it}|\theta_g)}{f_a(x_{it}|\theta_a)}$. Gaussian copula is preferred with significance level α if the z statistics exceeds the positive $(1-\alpha)$-quantile of the $N(0,1)$. A copula's fit is inferior to the Gaussian copula's at * 0.1, ** 0.05, and *** 0.01 significance levels.

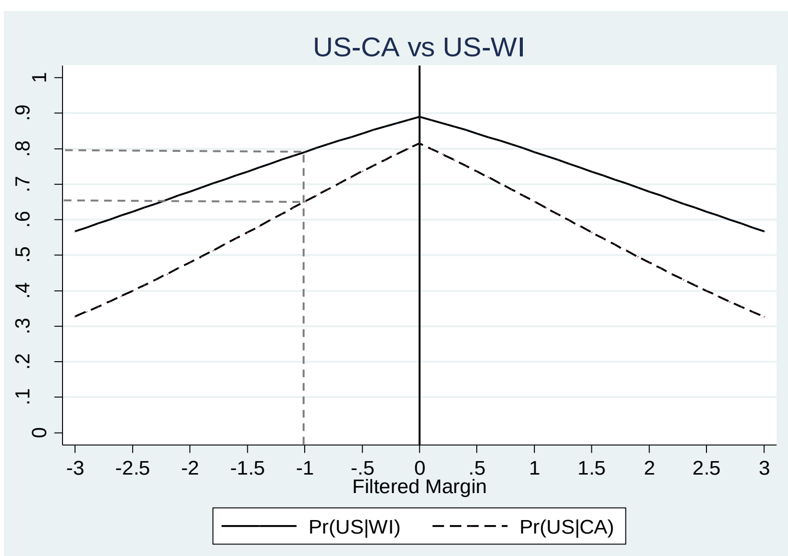

Figure 5-6. Conditional probabilities from Gaussian copula

Note: Filtered margin ($\tilde{m}_{it}$) is the series filtered out AR(p) and GARCH(1,1) components of margins, m_{it}.

5.8. Summary and Concluding Remarks

The MPP-Dairy program contained in the 2014 Farm Bill is a risk management tool for dairy producers, offering protection of income-over-feed-cost (IOFC) margin, which is defined as the difference between the all-milk price and average feed costs. The MPP-Dairy includes catastrophic and eight buy-up coverage levels with premiums that vary with the level of protection. The program's objective is to provide dairy producers (regardless of size, geographic locations or management practices) self-selected protection levels against drops in milk prices, rising feed costs, or a mixture of both.

2015 MPP-Dairy coverage data by states indicates that California (CA), which is the largest dairy producing state in the U.S., has only 29% of the enrolled dairy producers purchasing supplementary coverage (i.e. the majority enrolled purchase only catastrophic coverage). In contrast, Wisconsin (WI), the second largest dairy producing state in the U.S., has 56% of enrolled producers buying supplementary coverages (Figure 5-1). More than 70% of CA dairy producers purchased solely catastrophic protection, while 44% of WI producers enrolled only in catastrophic protection. Instead, WI dairy farms purchased buy-up coverage levels of $6/cwt and $6.5/cwt, and even the maximum protection level of $8/cwt (Figure 5-1).

The objective of the third essay has been to investigate why WI dairy producers have purchased more supplementary coverage than CA producers. There are several likely factors explaining this difference, such as farm size (average size of dairy operation in CA is much larger than that of WI), regional milk price, regional feed costs, technology, and producers' attitudes toward risk. This study demonstrates that the relationships between dairy production margins among US and CA and among US and WI, specifically the conditional probabilities for the national and each local market, may play a key role in determining which producers purchase supplementary coverage. This is because farms receive payments when the national (average) dairy production margin (not their state margin) falls below their selected level of margin protection. If a dairy producer knows the extent of the relationship between the US margin and her/his margin, i.e., if the producers knows how closely the US margin ‘tracks’ the changes in her/his margin, then the producer may have an incentive to increase his/her protection and purchase buy-up options.

Several different copula models are used to estimate the conditional probability of US-CA and US-WI margins, such as Gaussian, Student’s t, Gumbel, Clayton and mixture of Clayton-Gumbel. A AR(p)-GARCH(1,1) model is used to eliminate spurious finding due to serial correlation and conditional heteroscedasticity from the series data. Filtered margins are then obtained from the AR(p)-GARCH models. The filtered margins are shown to be distributed normally. The Gaussian copula model is determined to fit the data best via BIC and Vuong tests and the corresponding conditional probabilities are calculated. Results indicate that the conditional probability of the US margin on the WI margin is statistically stronger than that of the US margin conditional on the CA margin. Expected utility theory developed in Section 5-3 tell us that WI dairy producers would therefore tend to have higher self-selected margin protection.

One caveat emerges. Self-selected margin protection may depend heavily on farm size (production size) and MPP-Dairy premiums. For example, CA producers are currently paying higher premiums because their farm size is, on average, larger than that of WI. It is possible for dairy producers in WI to select a higher level of MPP-Dairy.

5.9. References

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6. SUMMARY AND CONCLUSION

Agricultural insurance programs such as crop insurance and Dairy Margin Protection program (MPP-Dairy) are managed by United State Department of Agriculture (USDA). The objective of these programs is to help farmers to manage their financial risk. Agricultural insurance programs have played important role for farmers in continuing their farming stably. There are several issues in insurance programs such as moral hazard and adverse selection which make insurance programs inefficient. Many economists and policy analysts have conducted various studies on crop insurance. Among others three board research gaps are identified in this research, namely 1) moral hazard in prevented planting (PP) and late planting (LP), 2) decision making on PP and planting a second crop (SC), and 3) role of conditional probability for selecting dairy margin protection level in MPP-Dairy.

First study analyzes the existence of moral hazard within the choice of PP and LP. The PP provision is defined as the “failure to plant an insured crop by the final planting date due to adverse events” such as excess moisture or drought. If the farmer decides not to plant the crop, (after appraised by an agency) the farmer receives a PP indemnity. LP is an option for the farmer to plant the crop and still maintain the crop insurance when the farmer fails to plant crop by the final planting date. However, by choosing LP option, the farmer has to lower the insurance coverage level depending on the LP date due to potential yield loss. Crop insurance may alter farmers’ decision choices in production in making the selection of PP or LP. In other words, crop insurance can increase the likelihood of PP claims even though farmers can choose LP. Under the assumption that the farmer behaves to maximize expected utility, the simulation results show that the higher coverage level induces the claim of PP more. Also, revenue protection is likely to claim more PP than yield protection when the farmers expect that anticipated price at the harvest time is higher. Spatial panel models attest to the existence of moral hazard in PP empirically.

Second study examines the incentives to choose second crop when the farmers claim PP due to adverse events such as drought and excess moisture. If a farmer chooses PP, s/he receives the PP indemnity and may either leave the acreage unplanted or plant a second crop, e.g., soybean for corn. If the farmer plants a second crop after prevented from planting a first crop, the farmer receives a reduced PP payment (35% of PP indemnity) and s/he is assigned to the 60% of the approved yield of the first crop in the APH for the next crop year. The current PP provision fails to provide farmers with an incentive to plant a second crop (99.9% of PP claiming farmers do not plant the second crop). It is a contradiction of the goal of USDA that promotes agricultural production to improve food security. Adjusting PP indemnity payment may encourage farmers to plant a second crop, which is currently fixed at 35% of the total PP indemnity.

The objective in the second study is to find and suggest the optimal percentage of PP payment that may encourage farmers to plant a second crop. In doing so, the goal of USDA to promote agricultural production is achieved. Using corn-soybean budget data in Hamilton County, Iowa, the representative farmer is created. Using the stochastic simulation, under the current reduction factor, most of farmers do not choose to plant a second crop. However, if the reduction factor increases, the farmer begins planting the second crop. This study suggests the optimal reduction factor would be around 45-50%.

Third study investigates the role of conditional probability of income-over-feed-cost (IOFC) margin when the dairy producers choose the level of supplementary margin protection. MPP-Dairy administered by Farm Service Agency (FAS), USDA, is a risk management tool for dairy producers. The 2014 Farm Bill authorized the MPP-Dairy which offers dairy producers protection of their milk production margin. 2015 MPP coverage data by state indicates that California (CA), the largest dairy producing state, had only 29% of enrolled producers buying supplementary coverage. In contrast, Wisconsin (WI), the second largest dairy producing state, had 56% of enrolled producers buying supplementary coverage. More than 70% of CA dairy producers purchased catastrophic protection, \$4/cwt, while only 44% of WI producers enrolled in catastrophic protection.

The role of conditional probability between US IOFC margin and regional margin is examined to explain regional differences in the choice of the buy-up levels. Copula model reveals that the conditional probability of US IOFC margin subject to the margin in WI is much stronger than that of US margin given in CA margin. Expected utility theory reveals that WI dairy producers tend to have higher self-selected margin protection.

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Publications

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