Evaluating Weather Derivatives and Crop Insurance for Farm Production Risk Management in Southern Minnesota

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Abstract

Agriculture is one of the most weather sensitive industries and weather-related risks are a major source of crop production risk exposure. One method of hedging the risk exposure has been through the use of crop insurance. However, the crop insurance market suffers from several problems of asymmetric information and systemic weather risk. Without government subsidies or reinsurance crop insurers would have to pass the cost of bearing the risk exposures to farmers. The rising cost of the federal crop insurance program has been an incentive for the government to seek alternative ways to reduce the cost.

Weather derivatives have been suggested as a potential risk management tool to solve the problems. Previous studies have shown that weather derivatives are an effective means of hedging agricultural production risk. Yet, it is unclear what role weather derivatives will play as a risk management tool compared with the existing federal crop insurance program. This study compares the hedging cost and effectiveness of weather options with those of crop insurance for soybean and corn production in four counties of southern Minnesota. We calculate weather option premium by using daily simulation method and compare hedging effectiveness by several risk indicators: certainty equivalence, risk premium, Sharpe ratio, and value at risk.

Our results show that the hedging effectiveness of using weather options is limited at the farm level compared with crop insurance products. This is because weather options insure against adverse weather events causing damage at the county level, while crop insurance protects farmers against the loss of their crops directly at the farm level as well as at the county level. Thus, individual farmers will continue to use crop insurance with government subsidy for their production risk management.

However, we observe that the hedging effectiveness of using weather options increases as the level of spatial aggregation increases from farm level to county level to four-county aggregate level. This implies that the government as a reinsurer can reduce idiosyncratic yield risk by aggregating the individual risk exposures at the county or higher level, and hedge the remaining systemic weather risk by purchasing weather options in the financial market. As a result, weather derivatives could be used by the government as a hedging tool to reduce the social cost of the federal crop insurance program, since the government currently does not hedge their risk exposures in the program.

Against our expectation based on the conventional wisdom, geographic basis risk is not significant in hedging our local weather risk with non-local exchange market weather options based on Minneapolis. It is likely due to the fact that the Midwest area including Minnesota has relatively homogeneous (or less variable) weather conditions and crop yields across the counties compared to other U.S. regions. The result indicates that we can hedge local weather risk with non-local exchange market weather derivatives in southern Minnesota. However, it should be applied cautiously to other locations, crops, or other types of weather derivatives, considering spatial correlation of weather variables between a specific farm location and a weather index reference point.

Table of Contents

List of Tables

List of Figures

Chapter Ⅰ

Introduction

Research Problem

It is estimated that up to 70 percent of all businesses face some type of weather-related risk (Lettre, 2000) and nearly 30 percent of the U.S. economy is directly affected by the weather (www.cme.com). As a result, the earnings of businesses can be adversely impacted by summers that are hotter than normal or winters that are much colder than anticipated. Agriculture is one of the most weather-sensitive industries and weather-related risks, mostly arising from fluctuations in temperature and precipitation, are a major source of crop production risk exposure.

One method of hedging this risk exposure has been through the use of crop insurance. Farmers can choose from a variety of insurance plans; yield insurance plans, which protect farmers against the loss of their crops due to natural disasters, and revenue insurance plans, which protect them against the loss of revenue due to both natural disasters and crop price declines. Federal crop insurance markets have been able to achieve broader farmer participation through sharply higher federal costs in the form of crop insurance rate subsidies.

However, crop insurance indemnities are determined based on yield shortfall, which may or may not be actually caused by natural disasters. As a consequence, the crop insurance market suffers from several classic problems of asymmetric information: adverse selection, moral hazard, and verifiability (Chambers, 1989; Hyde and Vercammen, 1997; Skees and Reed, 1986). Adverse selection is a problem because individual farmers are better informed about their individual prospects for success than the insurer is, so that the low-risk farmers do not participate in the insurance program. This increases the insurer's loss. The moral hazard problem emanates from the fact that the insurer may be able to observe yield, but she does not observe all of the farmer's inputs into production (farmer effort, fertilizer expense, quality of equipment, etc.). Thus, once insured, the farmer has less incentive to expend as many costly resources for production as he would if he were uninsured. The third type of information problem is that of verifiability. Non-verifiability is when an insurer cannot observe the exact level of yield while the farmer observes yield with certainty. In order to induce the farmer to report his yield truthfully, the insurer must expend costly resources to monitor the farmer. As a result, the above three problems of asymmetric information increase the cost of the insurer. This is one of the economic arguments for a government to subsidize crop insurance.

More recently, it has been pointed out that the failure of crop insurance markets is closely related to the existence of systemic weather risk which stems from spatially correlated adverse weather events (Miranda and Glauber, 1997; Woodard and Garcia, 2008; Xu, Filler, Odening, and Okhrin, 2009). Miranda and Glauber (1997) argue that without reinsurance or government subsidies crop insurers would have to pass the cost of bearing the systemic risk through to farmers.

As a result, the government subsidizes a high proportion of the costs of crop insurance for participating farmers and private crop insurance companies. Farmers pay only 33-62% of the premium, depending on the coverage level (or none of the premium in the case of catastrophic coverage) and the federal government pays the rest of the premium (averaging nearly 60% of the total premiums). Insurance company losses are reinsured by the USDA and their administrative and operating (A&O) costs are reimbursed by the federal government. In fiscal year 2009, the cost of the government premium subsidy for farmers totaled $5.2 billion (or 71% of total cost). The next largest component was $1.6 billion (or 22% of total cost) in the form of reimbursement of A&O expenses to private insurance companies (Shields, 2010).

To solve these problems weather derivatives have been suggested as a potential risk management tool. In contrast to crop insurance, the problems of asymmetric information do not exist in the weather derivatives market because weather derivatives insure against the objective weather events causing damage, not the damage itself. Systemic weather risk is also effectively hedged using weather derivatives without the need for government subsidies because all weather risks are transferred to the derivatives market (Woodard and Garcia, 2008).

Just as professionals regularly use futures and options to hedge their risk in interest rates, equities and foreign exchange, now there are tools available for the management of risk from extreme movements of temperature and precipitation in an exchange market (Chicago Mercantile Exchange) or over-the-counter (OTC). For example, a put option is a common type of weather derivative which provides the buyer of the option (the farmer) with protection (the right to sell the weather event to the option seller in exchange for the indemnity payment which would reduce the loss of the option buyer) in the case of adverse weather events such as drought or excessively cold temperature. The weather derivatives market has been growing extremely fast in size as end users of weather derivatives and associated weather risk management tools increase in volume and diversity. According to the Chicago Mercantile Exchange (CME), in 2000, the first year with available records, there were just 87 trades, amounting to $1.2 million of notional value, climbing swiftly to 121,000 trades, worth $6.6 billion, by 2004. The peak volume was almost 930,000 trades in 2007, with a notional value of $17.9 billion. Even though standard vanilla weather derivatives volumes remain relatively lacklustre in recent years, more and more end-users are interested in tailor-made structured weather derivatives.

Previous empirical studies on weather derivatives have mostly focused on weather options pricing because there is no agreed pricing mechanism for the options underlying nonstorable and nontradable assets such as weather indices (Cao and Wei, 2004; Huang, Shiu, and Lin, 2008; Odening, Musshoff, and Xu, 2007; Richards, Manfredo, and Sanders, 2004; Yoo, 2003). Those studies also show that hedging effectiveness exists when using weather derivatives. Yet, it is still unclear what role weather derivatives will play in agriculture, even though the studies have shown the hedging effectiveness of weather derivatives. One reason for the uncertain role of weather derivatives is the popularity of crop insurance. In turn, that popularity is due significantly to the fact that the federal government subsidizes insurance premiums to keep farmers at lower rates and to maintain private crop insurance companies with adequate reserves in case of widespread crop disasters. The rising cost of the federal crop insurance program has been an incentive for the government to seek alternative ways to reduce that cost.

Research Objectives

The primary goal of this study is to analyze weather derivatives as a potential risk management tool compared with crop insurance in a more practical and comprehensive approach. Unlike previous studies, which compared hedging with weather derivatives to the no hedge alternative, we approach the hedging problem by comparing several risk indicators among alternative hedging tools. Based on the comparisons of hedging effectiveness between using weather options and crop insurance, we observe whether and how much weather options reduce the social cost that exists in the federal crop insurance program. In this study the social cost reduction is measured as an improvement of risk indicators such as value at risk, certainty equivalence or risk premium.

There are two sub-objectives under the above primary goal. First, this study plans to assess the literature on weather process models, weather derivative pricing and hedging effectiveness based on previous studies in different regions and different crops. This will facilitate an identification of the existing gaps in our knowledge based on the existing models and empirical results. Second, this study proposes to identify a composite modeling approach that integrates the temperature and precipitation processes. In comparing hedging effectiveness between weather options and crop insurance, all possible basis risks and spatial aggregation effects are considered. Various levels of crop yield data from individual farm level to county level to all county aggregate level are applied to observe the spatial aggregation effects on hedging effectiveness.

For the purposes we develop an empirical model for evaluating the hedging cost and effectiveness of weather options and multiple peril crop insurance (MPCI) for representative Midwest crops, soybean and corn, in four specific Minnesota counties (towns), Rock County (Luverne), Stevens County (Morris), Fillmore County (Preston), and Chisago County (Rush City). MPCI is a crop yield insurance plan that protects individual farmers against their farm level output losses caused by various adverse weather and/or natural disaster events. Because MPCI is the most widely used plan showing about 30% of total U.S. crop insurance usage and it covers yield risk, not revenue risk, MPCI is a good insurance plan to compare with weather derivatives which also protect against production risk caused by adverse weather. We also consider another crop yield insurance plan, group risk plan (GRP), which insures county yields to compare the hedging cost and effectiveness with weather options at the county level. The empirical analysis in this study is composed of the four steps:

- Estimating the yield response models to observe the relationship between crop yield and weather variables for optimal weather hedge
- Estimating the weather process models to generate a statistical distribution of weather variables for pricing weather options
- Pricing the weather options to compare the hedging cost with that of using crop insurance
- Evaluating the hedging effectiveness as measured by several risk indicators between using weather options and crop insurance.

The remainder of the dissertation is organized as follows. Chapter II contains a review of previous studies concerning crop insurance and weather derivatives. In Chapter III, we provide a conceptual framework of producer's maximization problem and three empirical models: yield response model, temperature process model, and precipitation process model. Weather options are priced based on the estimation of these three empirical models. Chapter IV contains the methodology for pricing weather options and comparing hedging effectiveness. In Chapter V, data and summary statistics are described. Empirical results are presented in Chapter VI. The last Chapter is a discussion of the conclusions.

Chapter Ⅱ

Literature Review

In this Chapter we review previous studies about crop insurance and weather derivatives. We start reviewing the papers which address the problems in existing crop insurance program and move to the papers estimating crop yield response models. Then we examine the papers pricing financial and weather derivatives which are followed by several recent papers measuring hedging effectiveness of using weather derivatives.

The Problems in Crop Insurance

Many papers have dealt with the problems of asymmetric information and limitation of crop insurance as a production risk management tool. Skees and Reed (1986) demonstrate the problem of adverse selection caused by insufficient information of individual farmers under Federal Crop Insurance (FCI). They derive the negative relationship between expected yields and theoretical insurance rates, and show that farmers with relatively high expected yields opt out crop insurance when the same premium is charged for all farmers. In 1985, FCI began to offer premium discounts as expected yields increases in order to address adverse selection. The results of their paper support the FCI's action. However, it would be difficult for the insurer to obtain sufficient information of each farmer and accurately determine an ideal premium based upon the individual risk-level of each insured.

Chambers (1989) examines the effect of moral hazard on all-risk agricultural insurance indemnity schedules with Pareto-Optimal and constrained Pareto-Optimal contracts model. He suggests three alternative ways to deal with moral hazard: (a) insurance companies provide farmers with the incentives to take appropriate actions, (b) collect a priori and contemporaneous information about the farmer's farming practices, and (c) write multiyear insurance contracts to detect consistent cheating statistically. However, any of these recipes has a limitation to mitigate the moral hazard problem completely if farmers try to cheat in various ways.

Hyde and Vercammen (1997) analyze both moral hazard and costly state verification in the hidden-action moral hazard model. The model illustrates that if both hidden action and costly state verification problems are present, optimal contracts require co-insurance which refers to the joint assumption of risk between the insurer and the farmer. Also, as the cost of verification increases, the level of insurance coverage decreases in the sense that smaller indemnity payments are made so that both the insurer and the farmer bear expenses from the hidden action.

These problems of asymmetric information combined with systemic weather risk increase the cost of the insurer. Miranda and Glauber (1997) indicate that private crop insurance markets are doomed to fail without affordable reinsurance or government subsidies, because systemic weather effects induce high correlation (covariance risk) among farm-level yields, defeating insurer efforts to pool risks across farms. Therefore, the extent to which asymmetric information and systemic risk each contribute to crop insurance market failure poses an important public policy question.

To mitigate the problems of asymmetric information and systemic risks, Group Risk Plan (GRP) was introduced within the Federal Crop Insurance Program. However, GRP are rarely used by farmers due to geographic basis risk and it does not remove the asymmetric information problems completely. Deng, Barnett, and Vedenov (2004) test the viability of GRP for cotton and soybean in Georgia and South

Carolina by comparing GRP with MPCI and find GRP performs poorly. They conclude that the potential demand for cotton and soybean GRP in the two states is low due to more heterogeneity in the production regions. Zhu, Ghosh, and Goodwin (2009) investigate spatial correlation of crop losses to determine the reasonable range and shape of the geographical area in the design of the optimal GRP.

Coble and Barnett (2008) also handle the question of how systemic risk should be addressed. They suggest that if the federal government absorbs a sufficient degree of the systemic risk by providing an area-based integrated crop insurance (named wrapping crop insurance) to producers, then only the remaining residual risk could be insured by the private insurance industry. However, it is still questionable whether the reduction of systemic risk is enough for private insurers to accommodate it and whether the government can remove the systemic risk completely without incurring any social cost by spending taxpayers' money.

Several current research efforts have been conducted to improve crop insurance premium rating procedures and the actuarial performance of the program. Premium rating procedures that more accurately reflect producer risks would reduce adverse selection and moral hazard problem. Babcock, Hart, and Hayes (2004) show that crop insurance premiums are overpriced for low-deductible (high-coverage) policies, which are inconsistent with actuarial fairness. This overpricing can be explained by increases in insurance losses from natural yield variations and information asymmetries such as fraud, moral hazard, and adverse selection. Thus, per-acre subsidies also increase as coverage levels increase. Adhikari, Knight, and Belasco (2010) show that sampling error under MPCI significantly increases expected indemnities and thus increases actuarially fair premiums and premium subsidies. The producer welfare loss due to sampling error is larger in high risk areas. Ramirez, Carpio, and Rejesus (2009) suggest that the additional time and effort spent trying to find more years of data and to model an appropriate yield distribution model can result in significant accuracy in premium rating.

Estimating Crop Yield Response Models

Everyone agrees that weather and technology are the main drivers of corn and soybean yields in the U.S. Corn Belt. However, despite nearly a century of research on the relationship between weather, technology, and yields, the exact relationship remains debatable. Thompson (1962, 1963, 1969, 1970, 1985, 1986, 1988) has investigated the relationship between weather, technology, and corn and soybean yields, and many multiple regression models have been developed based on his studies. Thompson's crop/weather model is used to determine the impact of changes in climate and weather variability on corn and soybean yields since 1930 for five U.S. Corn Belt states, Illinois, Indiana, Iowa, Missouri, and Ohio. His model (1986, 1988) is a simple quadratic equation to estimate the effects of departures from normal weather on corn yield as follows:

$$Y^L = a^L + \sum_{i=1}^{6} b_i^L X_i^L + \sum_{i=1}^{6} c_i^L (X_i^L)^2 + \sum_{j=1}^{3} d_j^L t_j + \varepsilon^L \,, \tag{2.1}$$

where Y^L is the corn yield for L location (Illinois, Indiana, Iowa, Missouri, and Ohio), X_1^L is the deviation from average preseason (September through June) precipitation, X_2^L is the deviation from average June temperature, X_3^L is the deviation from average July rainfall, X_4^L is the deviation from average July temperature, X_5^L is the deviation from average August rainfall, X_6^L is the deviation from average August temperature, t_1 is the first time trend (1930-1959), t_2 is the second time trend (1960-1972), and t_3 is the third time trend (1973-1983).

His primary results come from pooled regression with pooled data from the five states. First of all, he finds all six of the coefficients on the squared weather variables are estimated to be negative, implying that extreme of weather, in either direction, will depress yield. Next, he observes that highest yields of corn have been associated with normal preseason precipitation, normal June temperature, below normal temperature in July and August, and above normal rainfall in July and August.

Turvey's (2001) crop yield response model to estimate weather effects on crop yields shows two differences from Thompson's. First, he uses cumulative rainfall and cumulative crop heat units above 50^{o}F from June 1 to August 31 for independent variables on his Cobb-Douglas production function, instead of monthly rainfall and temperature on quadratic equation in Thompson's. Second, yields as dependent variable are detrended using a linear trend equation. He estimates these weather effects on three crops, corn, soybean, and hay, yields in Oxford County, Ontario with county data collected from 1935 to 1996. The R^2 for all three crops are around 0.30. Both coefficients of rainfall and heat for corn and soybean are positive but only heat is significant. Hay shows a positive and significant relationship with rainfall while it has negative and insignificant coefficient of heat. After estimating the yield response model, he calculates the premium of European-type option and specific/multiple-event insurance for rainfall and heat units using a simple "burn-rate" approach. The burn-rate approach calculates the premium of a particular contract by averaging the payoffs based on historical data, assuming that historical weather patterns provide the best measure of future weather patterns.

The most recent study on estimating crop yield response model is Tannura, Urwin, and Good (2008). To investigate the relationship between weather, technology, and corn and soybean yields, they develop multiple regression models based on Thompson's studies. Corn and soybean yields, monthly temperature, and monthly precipitation observations are collected from 1960 to 2006 for Illinois, Indiana, and Iowa. Analysis of the regression results shows that yields are reduced by unfavorable weather by a much larger amount than they are increased by favorable weather. Corn yields are particularly affected by technology, the magnitude of precipitation during June and July, and the magnitude of temperatures during July and August. The effect of temperatures during May and June appears to be minimal. Soybean yields are most affected by technology and the magnitude of precipitation during June through August (and especially during August). The magnitude of July and August temperatures are also important on soybean yields, but less so than precipitation.

Pricing Weather Derivatives

The fundamental framework for the pricing of stock options (and applying to most of options) was established by Black and Scholes (1973). The Black-Scholes model bases on a riskless portfolio consisting of a position in the option and a position in the underlying stock for a very short period of time. The Black-Scholes pricing equation can be derived by either solving its differential equation or by using risk-neutral valuation, assuming that the underlying stock price follows a lognormal diffusion process and that the continuously compounded return from the stock is lognormally distributed. The attractive feature of this Black-Scholes formula is that it does not depend on investor preferences or knowledge of the expected return on the underlying asset.

However, in the case of commodity derivatives, there is a problem that the log-normal spot price model does not work well for commodity prices. Black (1976) notes that commodity prices are characterized by the presence of seasonal patterns. These can be caused by planting/harvesting cycles, seasonal variations in weather, or even intra-day variations in demand (in the case of electricity) so that neither seasonal patterns nor the phenomenon of mean-reversion can be adequately captured with a log-normal spot price model.

Merton (1976) and Cox and Ross (1976) modify the classic Black-Scholes formula when underlying stock returns are discontinuous with several jumps, because the critical assumption of the classic Black-Scholes model is that the underlying stock return dynamics can be described by a stochastic process with a continuous sample path. They derive a more general option pricing formula with one of normal continuous stochastic processes and the other with a jump process. They assume the jump process follows the Poisson process with magnitude and frequency of jumps in the formula.

The methodology for calculating option values with various underlying assets has also been developed with the option pricing model. There exists a simple closed form solution in the case of a non-dividend paying stock (as in Black-Scholes model) and also in the case of a stock which pays a continuous dividend proportional to the stock price. For other dividend policies numerical methods must be used to solve the differential equation. If the distribution of the terminal stock value is known, the value of the option can be obtained by integration. In general the integrals involved will not have analytic solutions and they must be evaluated by numerical methods. As one of the important numerical methods, Boyle (1977) develops a Monte Carlo simulation to obtain numerical solutions to option valuation problems. The technique is simple and flexible in the sense that it can easily be modified to accommodate different stochastic processes governing the underlying stock returns. In particular, it has distinct advantages in some special situations involving jump process so that various option values, including weather derivatives, have been calculated using this Monte Carlo simulation method.

Weather derivatives, which were introduced in 1999 by Chicago Mercantile Exchange (CME), have been evaluated in various ways by economists. Dischel (1998) explains why it is hazardous to apply the Black-Scholes model to weather derivatives and asserts that stochastic Monte Carlo simulations may prove more effective models for the valuation. The primary reason not to use a Black-Scholes model to price weather options is that there is no underlying tradable commodity in weather options so that riskless portfolio with balanced long and short positions of option and underlying assets can not be constructed as in stock options. He suggests an equation incorporating meteorological mean reversion and separating long-term trends from short-term volatility as:

$$dT = [\alpha\theta(t) + \beta T(t)]dt + \gamma\tau(t)dz_1 + \delta\sigma(t)dz_2, \qquad (2.2)$$

where T is some weather variable (for example, temperature or rainfall) that varies over time t, the parameter θ is the average historical measure of that variable as it moves with the seasons and it is the gravitational core to which the simulated variable reverts in the absence of randomness. He separates the distribution of T from the change in T and designates them as τ and σ respectively. He samples the two distributions separately drawing from the Wiener processes dz_1 and dz_2. His model contributes to pricing weather derivatives by using stochastic Monte Carlo simulation, considering mean reversion processes in weather variables.

Most of other studies after 2000 to price weather derivatives have used Monte Carlo simulation for various models. Cao and Wei (2004) and Richard, Manfredo, and Sanders (2004) extend Lucas' (1978) equilibrium asset-pricing model so that the fundamental uncertainties in the economy are generated by the aggregate dividend and a state variable representing the weather variable, i.e., the temperature. The model is calibrated with temperature and consumption data, and the market price of weather risk is then analyzed and quantified. Alaton, Djehiche, and Stillberger (2002) and Yoo (2003) derive the close form pricing formula for the temperature derivative using the Martingale method but the formula is not generalized in all cases.

Much of the conceptual framework for valuing temperature derivatives in our study is motivated by Richard, Manfredo, and Sanders (2004). They find that a temperature series for Fresno, CA follows a mean-reverting Brownian motion process with discrete jumps and autoregressive conditional heteroscedastic errors from conducting several specification tests. Based on the estimated parameters on this process by maximum likelihood estimation (Ball and Torous 1983, 1985), they calibrate the price of Cooling Degree Day (CDD) weather options through Monte Carlo simulation. Finally, they provide the comparison of option prices among three methods: a traditional burn-rate approach, a Black-Scholes approximation, and an equilibrium Monte Carlo simulation. These methods reveal significant differences.

Compared to temperature derivatives, there have been few papers which analyze the pricing of precipitation derivatives and the hedging effectiveness. In fact, rainfall is as important as temperature in agriculture and is even more important in some types of grain production than temperature. Odening, Musshoff, and Xu (2007) develop a daily precipitation model applying Woolhiser and Pegram (1978) and Stoppa and Hess (2003). They capture the following characteristics of daily rainfall in the Brandenburg region of Germany and depict the characteristics in their precipitation model: (a) The probability of rainfall occurrence follows a seasonal pattern. (b) The sequence of rainy and dry days obeys an autoregressive process. (c) The amount of precipitation on a rainy day varies with the season. (d) The volatility of the amount of precipitation also changes seasonally. Based on the estimated parameters in their precipitation model, they price a precipitation option using three different pricing methods; burn-rate analysis, index value simulation, and daily simulation. The precipitation model in our study is based on Odening, Musshoff, and Xu (2007), considering all other previous models for precipitation option pricing.

Weather Derivatives as an Effective Risk Management Tool

There have been many studies which provide methods to evaluate hedging effectiveness by various derivatives products including weather derivatives. The traditional approach to evaluating hedging effectiveness is through the ad hoc examination of R^2 values resulting from a minimum variance hedge regression. Minimum variance hedging effectiveness is most commonly evaluated through an ordinary least squares (OLS) regression of the change in cash price as a linear function of the change in the futures price (Leuthold, Junkus, and Cordier, 1989), where the resulting R^2 is the measure of hedging effectiveness (Hull, 5th edition, p.78-85).

Sanders and Manfredo (2004) and Manfredo and Richards (2005) present an empirical methodology, based on the encompassing principle, for evaluating alternative futures contracts in a hedging effectiveness framework. In doing this, they combine minimum variance hedging and forecast evaluation. Their model starts from the OLS regression to estimate minimum variance hedge ratio:

$$\Delta CP_t = \alpha + \beta \Delta FP_t + e_t, \qquad (2.3)$$

where ΔCP_t and ΔFP_t are the change in the cash price (CP) and futures price (FP), respectively, over interval t. The R^2 from estimating equation (2.3) is a measure of hedging effectiveness.

They assume there are two competing futures contracts available as:

$$\Delta CP_t = \alpha_0 + \beta_0 \Delta FP_t^0 + e_t^0 \tag{2.3a}$$

$$\text{and} \quad \Delta CP_t = \alpha_1 + \beta_1 \Delta FP_t^1 + e_t^1, \tag{2.3b}$$

where FP_t^0 is the preferred contract, FP_t^1 is the competing contract, β_0 is the hedge ratio for the preferred contract, β_1 is the hedge ratio for the competing contract, e_t^0 is the residual basis risk for the preferred contract, and e_t^1 is the residual basis risk for the competing contract.

For comparing the hedging performance of alternative futures contracts, Sanders and Manfredo (2004) derive an encompassing test as:

$$e_t^0 = \varphi + \lambda(e_t^0 - e_t^1) + v_t, \tag{2.4}$$

If the null hypothesis that λ is equal to zero is not rejected, then the competing contract provides no reduction in residual basis risk relative to the preferred contract. If the null hypothesis is rejected, then both the preferred and competing contracts are taken for effective hedging position. The new optimal hedge ratio for this composite hedging position is $\beta_0(1-\lambda)$ for the preferred contract and $\beta_1\lambda$ for the competing contract. This encompassing regression provides an easy and direct comparison of hedging effectiveness and encompassing test.

To measure the hedging effectiveness or change in risk exposure by purchasing weather derivatives, Vedenov and Barnett (2004) and Woodard and Garcia (2008) use the mean root square loss. The mean root square loss is a simple function of the semi-variance, which reflects downside risk, only measuring deviations below the mean. They determine the hedge ratio by minimizing the semi-variance of a portfolio consisting of yields and weather derivatives. In addition, Vedenov and Barnett (2004) measure two additional risk indicators, value-at-risk (VaR) and certainty equivalent, to support their result of hedging effectiveness.

One of the interesting recent studies to evaluate cost of derivatives and hedging effectiveness is Richards, Eaves, Fournier, Naranjo, Chu, and Henneberry (2006). They price bug options as a damage control tool and evaluate the hedging effectiveness by comparing four familiar risk indicators (certainty equivalent, risk premium, Sharpe ratio, and value-at-risk) between no hedge and a call option hedge to manage economic risk caused by insects. Bug options, which protect farmers from the economic damage caused by higher insect population, are comparable to weather options which protect against adverse weather events. Thus, their methodology of option pricing and evaluating hedging effectiveness can be well applied to the case of weather derivatives. Following Richards, et al. (2006), we measure the four risk indicators to compare hedging effectiveness between using crop insurance and weather options. More specific explanation of calculating these risk indicators is provided in Chapter IV.

One of the primary concerns of weather derivatives as a production risk hedging tool is basis risk. Basis risk is defined as the risk that the payoffs of a given hedging instrument do not correspond to shortfalls in the underlying exposure. Geographic basis risk, which comes from the distance between the weather station for weather derivatives and the exposure location, needs to be controlled to make weather derivatives a more effective hedging instrument. Odening, Musshoff, and Xu (2007) quantified the geographic basis risk by estimating the popular de-correlation function which represents the relationship between the correlation coefficient between the precipitation at different places and the distance between the places, as proposed by Rubel (1996).

Woodard and Garcia (2007) categorize basis risk into three types: local, geographic, and product. Local basis risk refers to the gap between shortfalls for a given exposure and the payoffs of the hedging derivative, where the underlying index on the weather derivative and the exposure being hedged correspond to the same geographic location. Geographic basis risk happens by different geographic locations for hedging as defined above. Product basis risk refers to the difference in hedging effectiveness between alternative hedging instruments. They suggest that while the degree of geographic basis risk may be significant, it should not preclude the use of geographic cross-hedging. They also find that the degree to which geographic basis risk impedes effective hedging diminishes as the level of spatial aggregation increases.

Chapter Ⅲ

Conceptual Framework

In this Chapter we provide a conceptual framework of the producer's profit maximization problem and three empirical models: yield response model, temperature process model, and precipitation process model. From the producer's maximization problem under production uncertainty we derive the three asymmetric information problems that exist in the crop insurance program and show why a numerical approach is ultimately required to compare the hedging cost and effectiveness between crop insurance and weather options. The three empirical models provide an important framework for pricing weather options. Specifically, we determine the optimal strike level and tick value of weather options based on the estimated yield response model. Based on the estimated temperature and precipitation process models, we generate a statistical distribution of weather indices to price weather options by using a daily simulation approach.

Producer's Maximization Problem under Production Uncertainty

Our problem statement can be constructed in the conceptual framework of producer's maximization problem. The production risk and alternative risk management tools faced by the farmer are incorporated into the producer's expected utility of profit maximization problem. From this conceptual framework, we observe the three asymmetric information problems; adverse selection, moral hazard, and non-verifiability of crop insurance as a risk management tool. In addition, we compare the expected utility of profit between a crop insurance hedge and a weather derivatives hedge mathematically to identify which theoretical characteristics might make the weather derivative product better for a farmer in terms of cost and hedging effectiveness. The conceptual framework presented here is based on the model of individual insurance decisions developed by McKenna (1986, p. 85-93) and modified to fit the farmer's problem under production risk with two alternative hedging tools.

If the farmer produces only one output, the profit function can be written as:

$$\pi = p_y y(r,t,x,a) - wx\,, \tag{3.1}$$

where p_y is the (scalar) price of output (y), r is the amount of precipitation, t is the temperature, x is the vector of inputs, a is the vector of all other external factors, and w is the vector of input prices.

In this simple model, we assume that production risk is only caused by the precipitation and temperature variables while prices and all other factors are assumed to be fixed, so that the profit function can be simplified as:

$$\pi = \Pi(y(r,t))\,. \tag{3.2}$$

We will assume that the farmer has an Actual Production History (APH) of $\bar{y}$ bushels and the profit from $\bar{y}$ bushels is \$ $\bar{\pi}$, that is, $\bar{\pi} = \Pi(\bar{y}(r,t))$. In addition, we assume that the farmer faces the risk of a loss \$ ℓ (compared with APH) with probability p ($0<p<1$). We assume that the farmer is risk-averse, implying that his utility function is concave. If no insurance is taken out, the farmer's expected utility is given by:

$$U_0 = pu(\bar{\pi} - \ell) + (1-p)u(\bar{\pi})\,. \tag{3.3}$$

Now assume that the farmer is provided with a multiple-peril crop insurance (MPCI) plan, where the coverage ratio is chosen by the farmer and the premium (h) is determined by the insurance firm. The insured farmer determines how much of the loss (ℓ) may be reclaimed from the insurer, say an amount c. We will refer to the difference between the loss (ℓ) and the claim (*c*) as the deductible (*D*):

$$D \equiv \ell - c. \tag{3.4}$$

The insurer sets the premium (*h*) equal to his total expected cost (*e*) of providing the coverage (or unit payout) *c*:

$$h = e = p(c + kc), \tag{3.5}$$

where *k* is an administrative cost per unit of payout *c*. By substituting (3.4) into (3.5), equation (3.5) can be restated as:

$$h = p(1 + k)(\ell - D), \tag{3.6}$$

which shows the negative relationship between the premium (*h*) and the insurance deductible (*D*).

Thus, the farmer's expected utility with the MPCI policy is:

$$U_1 = pu(\bar{\pi} - \ell + c - h) + (1 - p)u(\bar{\pi} - h) \tag{3.7}$$

or, again using (3.4) we get

$$U_1 = pu(\bar{\pi} - D - h) + (1 - p)u(\bar{\pi} - h). \tag{3.8}$$

From the first-derivative of (3.8) with respect to *h*, it is clear that the utility from taking out insurance falls as the premium rises:

$$\frac{dU_1}{dh} = -pu'(\bar{\pi} - D - h) - (1 - p)u'(\bar{\pi} - h) < 0, \tag{3.9}$$

since the marginal utility of profit, $u'(.)$, is assumed to be positive.

To see the optimal deductible level that the risk-averse farmer chooses, we take the first-derivative with respect to *D* in (3.8), bearing in mind the dependence of *h* on *D* in (3.6). We get

$$\frac{u'(\bar{\pi} - D^* - h)}{u'(\bar{\pi} - h)} = \frac{(1 - p)(1 + k)}{1 - p(1 + k)}. \tag{3.10}$$

The right-hand side of (3.10) is greater than unity. Therefore,

$$u'(\bar{\pi} - D^* - h) > u'(\bar{\pi} - h)\,, \tag{3.11}$$

which, by concavity of $u(.)$ for the risk-averter, implies that

$$\bar{\pi} - D^* - h < \bar{\pi} - h \tag{3.12}$$

or $D^*>0$. Thus, it is optimal for the risk-averter to choose a positive deductible and so the farmer has less than full insurance. The farmer pays the premium $h = p(1 + k)(\ell - D^*)$ and has the deductible written into the insurance contract. Thus, the insured farmer only makes a claim on the policy if the loss exceeds D^* and the claim is only the difference between the loss and the deductible. In actuality, MPCI provides a guaranteed level of yield from 50 to 85% of the farmer's APH and the remaining 15-50% is still exposed to production risk.

A slight modification of the preceding model will show the adverse selection and moral hazard problems under the crop insurance hedge. Let us suppose that the insurer in calculating the premium based on the expected cost in (3.5) is not able to identify the probability of loss (p) for a particular farmer. Rather, the insurer uses an average probability for the appropriate group of farmers, say $\bar{p}$. Thus, the premium determined by the insurer in equation (3.6) is

$$\bar{h} = \bar{p}\,(1 + k)(\ell - D). \tag{3.13}$$

Then by substitution from (3.13), equation (3.10) is modified slightly to

$$\frac{u'(\bar{\pi} - D^* - \bar{h})}{u'(\bar{\pi} - \bar{h})} = \frac{(1-p)(1+k)}{1-\bar{p}(1+k)}. \tag{3.14}$$

Now consider two types of farmers in the group who differ only in their personal loss probabilities, p_1 and p_2, with $p_1 > p_2$ and $(p_1 + p_2)/2 = \bar{p}$. Differentiation of (3.8) gives us

$$\frac{dD^*}{dp} = \frac{u(\bar{\pi} - \bar{h}) - u(\bar{\pi} - D^* - \bar{h})}{-pu'(\bar{\pi} - D^* - \bar{h})} < 0, \tag{3.15}$$

for a given $\bar{p}$, where the numerator is positive and the denominator is negative by the farmer's concave utility function. This implies that the farmer with the higher probability of loss chooses a lower deductible (higher insurance coverage level), while the farmer with lower probability of loss chooses a higher deductible (lower coverage) or opts out of the insurance program. The insurer cannot identify each farmer's probability of loss and uses an average probability to determine the premium level. Hence, high-risk and low-risk types all pay the same premium but the former (high risk) group receives more from claims on their insurance contracts with higher insurance coverage as observed in (3.15) than does the latter (low risk) group. If these claims are large, the average premium may have to rise and some low risk producers may leave the insurance scheme. This is referred to as the adverse selection problem.

Moral hazard arises when farmers have some control over either the probability or magnitude of the loss but changes in these controls are not observed by the insurer and do not affect the premium. Suppose that the farmer is able to affect the possibility of loss by making an expenditure *z*, such that a higher expenditure achieves a lower probability of loss. Thus, *p* is a function of *z*, and the profit is correspondingly reduced by the amount *z*. Instead of (3.7) the expected utility is

$$U_m = p(z)u(\bar{\pi} - \ell + c - h - z) + (1 - p(z))u(\bar{\pi} - h - z), \tag{3.16}$$

where $p'(z) < 0$ is assumed. The expected utility maximizing agent chooses the level of expenditure (*z*) from the first-order condition

$$p'(z)[u(\bar{\pi} - \ell + c - h - z) - u(\bar{\pi} - h - z)] = p(z)u'(\bar{\pi} - \ell + c - h - z) + (1 - p(z))u'(\bar{\pi} - h - z) \tag{3.17}$$

where the right-hand side is greater than zero by the assumption of $u'(.) > 0$. Since $p'(z) < 0$, it follows that

$$u(\bar{\pi} - h - z) > u(\bar{\pi} - \ell + c - h - z). \tag{3.18}$$

This implies that

$$\bar{\pi} - h - z > \bar{\pi} - \ell + c - h - z \tag{3.19}$$

or $c < \ell$. This means that the insured farmer expending some amount of z on self-protection chooses a positive deductible.

Moral hazard in this model is represented by the assumption that the premium is unaffected by the level of expenditure on self-protection. Since the level of z is unobservable to the insurer, it follows that the premium cannot be made to depend on it. That is

$$\frac{dh}{dz} = 0. \tag{3.20}$$

This implies that the farmer does not find any benefits from expending additional cost and may succumb to the moral hazard temptation.

The verifiability problem is captured from the calculation of the premium in equation (3.6). When the farmer reports his loss as $\ell + \alpha$ where $\alpha > 0$, instead of the true loss ℓ, the premium will be increased by $p(1 + k)\alpha$. Even though the insurer expends additional administrative cost β to induce the farmer to report his true yields, assuming the additional cost detects all dishonest reports completely, the premium will be still increased by $p\beta(\ell - D)$. Thus, the honest and low risk farmer will leave the crop insurance scheme due to the increased premium caused by the verifiability problem.

Next we return to equation (3.7) for a comparison between the choices of no hedge and a hedge by using crop insurance. For the expected utility maximizing farmer choosing to take out insurance, the expected utility U_1 in (3.7) should be certainly no less than U_0 in (3.3). That is

$$U_1 - U_0 = p[u(\bar{\pi} - \ell + c - h) - u(\bar{\pi} - \ell)] + (1-p)[u(\bar{\pi} - h) - u(\bar{\pi})] \geq 0\,. \qquad (3.21)$$

The second part of (3.21), $(1-p)[u(\bar{\pi} - h) - u(\bar{\pi})]$, is always negative, but the first part, $p[u(\bar{\pi} - \ell + c - h) - u(\bar{\pi} - \ell)]$, can be either positive or negative, depending on the sign of ($c - h$). Even in the case of positive (c - h) where the first part is positive, total value of $U_1 - U_0$ depends on the probability of loss (p), since the second part is always negative. Thus, this inequality condition depends on the claim or coverage (c), the premium (h), and the probability of loss (p). This implies that an analytical comparison of expected utility between no hedge and insurance hedge is not available and a numerical approach needs to be applied.

If the farmer uses weather put options rather than crop insurance, his expected utility is:

$$U_2 = pu(\bar{\pi} - \ell + Max(0, T(K-w)) - o) + (1-p)u(\bar{\pi} + Max(0, T(K-w)) - o)\,, \quad (3.22)$$

where Max(0, $T(K\text{-}w)$) is the vector of temperature and precipitation put options payoffs and o is the vector of their premiums. For the options payoffs, w is the vector of values for the weather indices at maturity, K is the vector of their strike levels which are the predetermined index levels at which the option buyers can exercise, and T is the vector of their tick values which are the indemnity payments per unit of adverse weather event. The weather option payoffs, Max(0, $T(K\text{-}w)$), will be paid to the farmer in both cases of probability of loss, p and (1-p), because the payoffs depend on the weather events not the yield levels, even though there is a relationship between weather events and yield levels.

Conceptually, to compare the expected utility between weather derivatives and crop insurance, we subtract (3.22) from (3.7):

$$U_1 - U_2 =$$

$$p[u(\bar{\pi} - \ell + c - h) - u(\bar{\pi} - \ell + Max(0, T(K - w)) - o)] + (1 - p)[u(\bar{\pi} - h) - u(\bar{\pi} + Max(0, T(K - w)) - o)] \quad (3.23)$$

Again, it is not possible to compare the expected utilities U_1 and U_2 analytically in this model, because the crop insurance payoff and premium, c = Max(0, ℓ - D) and h, are determined by crop yield and various conditions in the contract such as the deductible level (D) chosen, selected crops, loss history of the county, and the farmer's APH, while the weather derivative payoff and premium, Max(0, T(K-w)) and o, are determined by the weather index. In addition, crop insurance covers the production risk by only 50-85%, while the hedge by weather derivatives induces local or geographic basis risk. The basis risks are caused by a hedging gap due to the imperfect relationship between crop yield and weather variables or distance between weather station for weather derivatives and the risk exposure location. Therefore, simulation methods based on historical processes of weather indices and crop yields will be applied to the comparison among no-hedge, hedge by crop insurance, and hedge by weather derivatives in our empirical study.

For the simulation process, three empirical models are introduced. First, alternative yield response models are examined to estimate the relationship between crop yield and weather variables for optimal weather hedge. The yield response model is also applied to the stochastic profit simulation model to compare the hedging effectiveness in various simulated situations. Next, the temperature and precipitation process models are considered to price the weather options. Weather derivatives are evaluated mostly based on daily simulation of underlying weather processes, so an appropriate weather process model needs to be determined.

Yield Response Model

Yield response model shows the relationship between crop yield and weather variables. The estimated parameters of the yield response model determine the optimal tick value and strike level of weather options as an effective hedging instrument. The estimated yield response model is also used to generate stochastic yield and profit simulations on which the expected profits and various risk indicators are measured and compared under alternative hedging strategies.

Alternative yield response models are considered to estimate crop yields on weather variables by Ordinary Least Squares (OLS) and to choose the model which fits the weather relationship best. The three models are (3.24) linear, (3.25) quadratic, and (3.26) Cobb-Douglas:

$$Yt = \beta_0 + \beta_1 Rt + \beta_2 Gt \tag{3.24}$$

$$Yt = \beta_0 + \beta_1 Rt + \beta_2 Gt + \beta_3 Rt^2 + \beta_4 Gt^2 \tag{3.25}$$

$$Yt = \mathrm{A} Rt^{\beta 1} Gt^{\beta 2} \tag{3.26}$$

where Yt is the detrended crop yield (bushels per planted acre), Rt is the deviation of the cumulative daily rainfall for growing season (between June and August), and Gt is the deviation of the cumulative daily temperature for growing season. Although there are many other factors that potentially influence yields, if they are uncorrelated with weather variables, then relatively simple models will provide reliable estimates of the weather-yield relationship (Richards, Manfredo, and Sanders, 2004).

As we will see in Chapter V, the raw yield data used in this study is both non-stationary and highly variable. Thus, in analyzing the impact of weather on yield, our data must be corrected for the impact of a general upward trend in yields by using a detrending method.

Following Turvey's (2001) yield response model, we use the cumulative daily rainfall and temperature for growing season from June to August instead of monthly or shorter time intervals. There are two reasons for this. First, month-to-month U.S. weather conditions are typically autocorrelated (Jewson and Brix, 2005), so this may induce a multicollinearity problem. Second, using multiple derivative contracts based on monthly weather indices increases the probability of over fitting the hedging parameters and may diminish the accuracy of the hedging estimates (Woodard and Garcia, 2007).

Temperature Model

Pricing of weather options is carried out by a burn-rate analysis and a daily simulation in our study. In a non-parametric burn-rate analysis, we price weather options based on the empirical distribution of the weather index derived from the historical weather data. In a daily simulation approach, on the other hand, weather options are evaluated based on daily simulation of underlying weather processes, so an appropriate weather process model needs to be determined.

Temperature variables tend to generate abnormal variations or irregular jumps due to unexpected weather events, and then they revert back to some long-run average level. In addition, the daily temperature process shows a significant seasonal behavior in southern Minnesota. More detailed data description will be provided in Chapter V. Based on our daily temperature process in southern Minnesota and previous studies (Cao and Wei, 2004; Richards, Manfredo, and Sanders, 2004; Richars, et al., 2006; Yoo, 2003) we construct our temperature process model using mean-reverting Brownian motion with log-normal jumps and seasonal volatility. Richards, Manfredo, and Sanders (2004) show the mean-reverting Brownian motion with log-normal jumps and ARCH is preferred based on their likelihood-ratio test results.

The change of average daily temperature (*Wt*) is not entirely deterministic and it is assumed to follow a Brownian motion process:

$$dWt = \mu \, dt + \sigma \, dz, \tag{3.27}$$

where μ is the drift rate per unit of time (*dt*), σ is the standard deviation of the process, and *dz* is an increment of a standard Weiner process with zero mean and variance of *dt*. We approximate the change of *Wt* (*dWt*) with a discrete change ($W_t - W_{t-1}$).

The daily temperature process would be volatile in the short run, but any irregular trend away from the mean would not be sustained over the long run. Therefore, the process (3.27) is rewritten by including a mean-reversion term as:

$$dWt = \kappa \, (W_t^m - Wt) \, dt + \sigma \, dz, \tag{3.28}$$

where κ is the rate of mean reversion, and W_t^m is the instantaneous mean of the process. If the rate of mean reversion (κ) of a process is equal to 1, then it forces daily temperature (*Wt*) back to exactly its instantaneous mean (W_t^m) in the next day (neglecting noise). On the other hand, if κ of a process is equal to 0, then any irregular trend never reverts back to its long-term mean and turns into a Wiener process.

To estimate the instantaneous mean of the process (W_t^m), we set up another equation accommodating seasonality, time trend, and autoregression in a manner similar to Alaton, Djehiche, and Stillberger (2001), Campbell and Diebold (2005), Richards, Manfredo, and Sanders (2004), and Yoo (2003). Seasonal cycle is observed clearly in our historical temperature data (in Chapter V). Time trend may be relevant but is likely minor in the short 68-year span (from 1941 to 2008) of our data. Autoregressive lags are included to capture any sort of persistent covariance stationary dynamics in the daily temperature process. Assembling the three pieces, we estimate the following instantaneous mean of weather process model:

$$W_t^m(W_t, t) = \gamma_0 + \gamma_1 \sin(2\pi t/365) + \gamma_2 \cos(2\pi t/365) + \gamma_3 t + \sum_{j=1}^{p} \rho_j W_{t-j} , \quad (3.29)$$

where t is the time variable, measured in days. We let t = 1, 2, … denote January 1, January 2, and so on. Since we know that the period of the oscillations is one year (neglecting leap years) we have ($2\pi t / 365$). In addition, the optimal lag is found to be p=3 by the Akaike Information Criterion (AIC), AIC = ln(residual sum of squares/sample size) + 2 (number of independent variables/sample size), which is a statistical criterion for model selection.[1] The optimal number of lags is the one which minimizes AIC.

Next, the unexpected discrete jumps in temperature which happen to occur need to be considered. We assume that discrete jumps occur according to a Poisson process q with average arrival rate (or mean number of jumps occurring per unit time) λ and a random percentage shock (or jump size) φ. The random shock is assumed to be distributed as $\ln(\varphi) \sim N(\theta, \delta^2)$, where θ is the mean jump size and δ^2 is the variance of the jump (Jorion, 1988). The Poisson process (q) is distributed as:

$$dq = 0 \text{ with probability } 1 - \lambda\, dt \text{ and} \quad (3.30)$$
$$1 \text{ with probability } \lambda\, dt.$$

Combining (3.28)~(3.30), the stochastic differential equation for the temperature process accommodating mean reversion and jump diffusion is as:

$$dWt = (\kappa\,(W_t^m - Wt) - \lambda\theta)\, dt + \sigma\, dz + \varphi\, dq, \quad (3.31)$$

where $W_t^m(W_t, t) = \gamma_0 + \gamma_1 \sin(2\pi t/365) + \gamma_2 \cos(2\pi t/365) + \gamma_3 t + \sum_{j=1}^{p} \rho_j W_{t-j}$.

The parameters (κ, σ, λ, θ, δ) of the weather process model (3.31) are estimated by maximum likelihood estimation (MLE). The log-likelihood function is derived by solving the stochastic differential equation (3.31) as:

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[1] The AIC statistics for optimal lag are reported in Chapter VI.

$$\log L(W) = -T\lambda - \frac{T}{2}\ln(2\pi) + \sum_{t=1}^{T}\ln\left[\sum_{n=0}^{N}\frac{\lambda^n}{n!}\frac{1}{\sqrt{\sigma^2+\delta^2 n}} \times \exp\left(\frac{-(dW_t - (\kappa(W_t^m - W_t) - n\theta))^2}{2(\sigma^2+\delta^2 n)}\right)\right], \qquad (3.32)$$

where T is the total number of time-series observation and N is the number of jumps sufficiently large to include all potential jumps in the observed data (See Appendix I for the derivation of likelihood function (3.32) from the stochastic differential equation (3.31)).

Precipitation Model

To describe a daily precipitation model, we need to observe the process carefully and compare with the temperature process to see if the same model can be applied. The precipitation process in Midwest area has the following characteristics:

- The probability of rainfall obeys a seasonal pattern. Rainfall is much more in summer than in winter.
- The sequence of precipitation follows an autoregressive process, implying that the probability of rainfall is higher if the previous day was rainy.
- The amount of precipitation varies with the season. Rainfall is more intensive in summer than in winter.
- The volatility of the amount of precipitation is higher in summer than in winter.

The third and fourth characteristics, which are caused by the truncated data at 0 inch most of days in winter season, do not allow the same process model as in temperature which shows continuously smooth trend (without truncation) with unexpected jumps.

A combination of a Markov chain and a gamma distribution function (a two-part model) has been recognized as a simple and effective approach in generating daily precipitation data for many environments (Geng, Penning de Vries, and Supit, 1986; Richardson and Wright, 1984). Odening, Musshoff, and Xu (2007) and Wilks

(1999) use a mixed exponential distribution, which is a weighted combination of two simple exponential distributions, instead of a gamma distribution for the two-part model.

The stochastic process of daily precipitation can be decomposed into the binary event (X_t) "rainfall" and "dryness" respectively, and a gamma distribution for the amount of precipitation (Y_t) for rainy days. Thus, the amount of precipitation falling on a date t is assumed to be a random variable $R_t = X_t \cdot Y_t$.

The first part of the process is described as:

$$X_t = \begin{cases} 0, \text{ if day } t \text{ is dry} \\ 1, \text{ if day } t \text{ is rainy} \end{cases}. \tag{3.33}$$

Assume that X_t follows a first-order Markov process. Then, the probability of rainfall occurrence at day t (p_t) is calculated as:

$$p_t = p_{t-1} q_t^{11} + (1 - p_{t-1}) q_t^{01}, \quad \text{for } t = 1,2,\ldots,\mathrm{T}, \tag{3.34}$$

where q_t^{11} is the transition probability from rainfall at day t-1 to rainfall at day t, and q_t^{01} is the transition probability from dryness at day t-1 to rainfall at day t.

The second part of the process is a non-negative distribution for the amount of precipitation (Y_t) for rainy days. Y_t is assumed to be a stochastically independent sequence of random variables having a gamma distribution whose probability density is given by

$$\mathrm{f}(Y_t \mid X_t = 1) = \frac{Y_t^{\alpha-1} \exp(-Y_t / \beta)}{\beta^{\alpha} \Gamma(\alpha)}, \quad Y_t, \alpha, \beta > 0 \tag{3.35}$$

where α and β are distribution parameters, and Γ(α) is the gamma function of α.

Since it is known that the rainfall pattern depends on the seasonality in a year, the Markov chain can best be applied for each month separately (Geng, Penning de Vries, and Supit, 1986). The estimation of the transitional probabilities q_t^{11} and q_t^{01} are obtained directly from the historical daily rainfall under the assumption that we have at least twenty years of data (Richardson and Wright, 1984). Thus, we estimate the transitional probabilities based on our 68 years of rainfall data.

To estimate the gamma distribution parameters α and β by maximum likelihood estimation (MLE) we derive the log-likelihood function for N observations (Y_1, …, Y_N) from its probability density function (3.35):

$$\ln L(\alpha,\beta) = (\alpha - 1)\sum_{t=1}^{N} \ln(Y_t) - \sum_{t=1}^{N} Y_t / \beta - N\alpha \ln(\beta) - N \ln(\Gamma(\alpha)), \qquad (3.36)$$

where N is the number of rainy days. Finding the maximum with respect to β by taking the derivative and setting it equal to zero yields the maximum likelihood estimator of the β parameters:

$$\hat{\beta} = \frac{1}{\alpha N}\sum_{t=1}^{N} Y_t . \qquad (3.37)$$

Substituting (3.37) into (3.36) gives:

$$\ln L(\alpha) = (\alpha - 1)\sum_{t=1}^{N} \ln(Y_t) - N\alpha - N\alpha \ln(\frac{\sum Y_t}{\alpha N}) - N \ln(\Gamma(\alpha)). \qquad (3.38)$$

Finding the maximum with respect to α by taking the derivative and setting it equal to zero yields:

$$\ln(\alpha) - \psi(\alpha) = \ln(\frac{1}{N}\sum_{t=1}^{N} Y_t) - \frac{1}{N}\sum_{t=1}^{N} \ln(Y_t), \qquad (3.39)$$

where $\psi(\alpha) = \frac{\Gamma'(\alpha)}{\Gamma(\alpha)}$ is the digamma function. There is no closed-form solution for α. Following Greenwood and Durand (1960) and Richardson and Wright (1984), α is estimated using the approximation as:

$$\hat{\alpha} = (0.5000876 + 0.164885520\Theta - 0.0544274\Theta^2) / \Theta, \qquad (3.40)$$

where $\Theta = \ln(Y_A/Y_G)$, Y_A is the arithmetic mean, and Y_G is the geometric mean. We rewrite (3.37) as:

$$\hat{\beta} = Y_A / \hat{\alpha}. \qquad (3.37)'$$

Chapter Ⅳ

Methodology

In this Chapter we describe methodology to analyze weather options compared with crop insurance. Three different methods are used to calculate the weather option premium, and four alternative risk indicators are used to compare hedging effectiveness. Finally, we address geographic basis risk, which has been pointed out as a primary concern for implementing weather hedges, and spatial aggregation approach.

Valuation of Weather Options

Valuation of the weather option premium is carried out by three different analyses in the study: a burn-rate (BR) analysis, a Black-Scholes (BS)-based pricing model, and a daily (Monte Carlo) simulation. Originally, practitioners used simple BR models while most recent studies use simulation methods. BS prices, which are calculated applying the arbitrage-free approach, are inappropriate for the weather problem due to non-tradable weather indices and are computed only for comparison purpose.

The BR option value is calculated as the mean of the discounted payoffs of the option for each historical year, assuming that historical weather patterns provide the best measure of future patterns. For example, in the case of (European) rainfall call option which is contracted in year t, the option buyer receives the payoff in maturity year T, C_T, by exercising his option if the level of rainfall in T, R_T, is greater than strike level, K, which is predetermined by contract. If R_T is less than or equal to K, the option buyer will not exercise his option and the payoff is zero. Thus, the payoff in maturity year T from a long (or buying) position in a rainfall call option is given by:

$$C_T(R_T,K) = \text{Max}\ (0, D(R_T - K)), \tag{4.1}$$

where D is the tick value, as measured in \$ per inch of rainfall, which is the indemnity per unit of adverse weather event. The option price or premium (C_t) that the option buyer has to pay in year t is calculated by discounting C_T up to year t at the risk-free rate of interest (r):

$$C_t = e^{-r\,(T-t)}\, C_T. \tag{4.2}$$

A BR method evaluates the call option price by simply averaging all calculated C_T from equation (4.1) using all historical rainfall data in year T = 1, …, 68 (R_T) from 1941 to 2008 and discounting the average payoffs at the risk free rate (r).

In the case of a put option, the payoff in year T, P_T, from a long put option is given by:

$$P_T(R_T,K) = \text{Max}\ (0, D(K - R_T)). \tag{4.3}$$

A BR analysis is the simplest approach and does not require strong assumptions about the distribution of the underlying index. However, the BR analysis has been criticized because the derivative prices measured by this method are rather sensitive to the number of observations (Cao, Li, and Wei, 2003) and the method cannot accommodate the probabilities of adverse weather events (Richards, Manfredo, and Sanders, 2004). The option prices calculated using the BR method in the study are provided only for comparison with the prices using Monte Carlo simulation.

Black-Scholes (BS) is the most widely used pricing model for most derivative products in both exchange markets and over-the-counter markets. The BS pricing formula is presented in Hull (2002, p.246-247). However, no-arbitrage models such as a BS type of model are inappropriate for weather derivatives because weather is not a traded asset, but rather a state variable, so traders cannot form the riskless hedge on which such models are based. Thus, the option prices calculated using the BS pricing formula are inaccurate and not reported in the study.

A daily (Monte Carlo) simulation follows steps similar to the BR analysis, but the empirical distribution is replaced by a statistical model for the stochastic process of the underlying weather indices. The option value is calculated by averaging the implied derivative prices over 10,000 weather values that are generated by Monte Carlo simulation based on the estimated parameters in the weather process models. This simulation approach has been commonly used in recent studies. The advantage of daily simulation is to produce more accurate results than the BR analysis, because it evaluates a considerably larger number of simulated values and it incorporates possible weather forecasts such as mean reversion or extreme events into the pricing model.

We use a risk-neutral valuation method, which discounts the payoffs of the options at expiry by the risk-free rate, under the assumption that the market price of weather risk is zero. If there is no correlation between the weather index and an aggregate market index, then the market price of weather risk must be zero (Hull, 2002). To observe the correlation we use the annual personal income data (to represent the aggregate market index) and annualized temperature and precipitation residuals for each of our four counties. Historical personal income data at the county level are obtained from the Bureau of Economic Analysis (BEA). We find a statistically significant correlation between personal income and weather series residuals for only Chisago county (Rush City). Odening, Musshoff, and Xu (2007) also show that there is no (or negligible) correlation between rainfall indexes and stock market returns for the precipitation option. Turvey (2005) argues that the market price of risk should be zero in equilibrium because of spatial arbitrage.

Comparison of Hedging Cost and Effectiveness

Using a stochastic expected utility framework, we evaluate the hedging effectiveness of weather options by comparing several simulated risk indicators: certainty equivalence (CE), risk premium (RP), Sharpe ratio (SR), and value at risk (VaR). These are the alternative hedging strategy performance measures evaluated by Richards, *et al*. (2006).

To calculate the risk indicators, we specify a utility function representing economic value of profit (or net income) of farmers. Richards, *et al*. (2006) use a well known power utility as:

$$U(\pi) = \frac{\pi^{1-\gamma}}{1-\gamma}, \tag{4.4}$$

where π is profit and γ is the degree of risk aversion ($0 < \gamma < 1$ for concavity). This function is attractive for observing risk indicators because it represents all risk characteristics by γ: if $0 < \gamma < 1$, the farmer is risk averse, if $\gamma = 0$, he is risk neutral, and if $\gamma > 1$, he is a risk lover. However, this utility function has a shortcoming in our application because the degree of concavity of the utility function varies with profit. We can observe that the degree of concavity, as measured by $-U''(\pi)/U'(\pi) = \gamma/\pi$, depends on both γ and π, showing decreasing absolute risk aversion as profit increases for $0 < \gamma < 1$. If some of our simulated profits are negative, the utility will not even be determined for this risk averter ($0 < \gamma < 1$).

To overcome the shortcoming of power utility function, we consider an alternative negative exponential utility function with expectation written as:

$$\mathrm{E}[U(\pi)] = \mathrm{E}[-\exp(-\gamma\pi)], \tag{4.5}$$

where $\exp(\cdot)$ is an exponential function. The degree of concavity of this utility function is γ which does not depend on profit (π). This implies that the utility function shows constant absolute risk aversion for $\gamma > 0$, regardless of any profit or loss level. Hence, the certainty equivalence (CE) and risk premium (RP) in our study are measured based on the negative exponential utility function.

Profit is defined by the difference between crop revenue and total production cost per planted acre, where crop revenue is the product of uncertain yields and price. Uncertain crop yields are simulated based on the estimated yield response model under the assumption of a normally distributed error term in the yield response model. Crop price is taken from maximum price elections set by the Risk Management Agency (RMA) every year (Prices Inquiry System, RMA Information Browser). Total production costs are estimated on the county-level yields using FINBIN farm financial database (Center for Farm Financial Management). Payoffs and costs of hedging instruments are included in crop revenues and production costs, respectively.

The certainty equivalent (CE) value is defined as a minimum amount of payoff with certainty in lieu of a uncertain amount of net income with expectation $E(\pi)$. The CE value is obtained by solving (4.5) for π, which becomes:

$$CE(\pi) = (1 / \gamma) \ln E[U(\pi)]. \tag{4.6}$$

We interpret the social cost of crop insurance to be the $CE(\pi)$ using weather options less the $CE(\pi)$ using unsubsidized crop insurance. In this measurement we assume that there is no social cost from using weather derivatives alone because all weather risks are transferred to the derivatives market.

The risk premium (RP), which is the minimum amount to compensate the farmer for taking a risk, equals:

$$RP(\pi) = E(\pi) - CE(\pi) = E(\pi) - (1 / \gamma) \ln E[U(\pi)]. \tag{4.7}$$

The CE and RP have been used in the traditional expected utility model by assuming the decision maker is an expected utility maximizer with a Bernoulli utility function.

A shortcoming of this approach is that the value is subject to the choice of utility function and the assumption of risk attitude of the agent. However, this does not pose a particular problem for our comparison, as we assume the same utility function with the same degree of risk aversion for both crop insurance and the weather option hedge.

The Sharpe ratio (SR) is a measure of the excess return (or risk premium) per unit of production risk in our farm production. It is defined as:

$$\mathrm{SR} = \frac{\mathrm{E}(R) - R_f}{\sigma(R)}, \tag{4.8}$$

where E(R) is the expected rate of return from the crop production, R_f is the risk-free rate of return (0.05 in our study), and $\sigma(R)$ is the standard deviation of the crop production returns. The SR is used to characterize how well the return from the crop production compensates the farmer for the risk taken. The SR does not need the assumption of utility function or risk attitude of the farmer, but it is limited to the underlying distribution with only mean and variance in the calculation.

The value at risk (VaR) measures the maximum amount of loss expected at some specified confidence level. There are three common VaR calculation models: historical simulation, Monte Carlo simulation, and variance-covariance model. Historical simulation assumes that profit (or loss) from the crop production in the future will have the same distribution as they had in the past. The VaR for the 95% confidence interval using historical simulation method is evaluated as:

$$\mathrm{VaR} = H \times \sigma_p \times 1.65, \tag{4.9}$$

where H is the average of historical profit (or loss) and σ_p is the historical volatility of profit (or loss).

Monte Carlo simulation is conceptually simple and goes as follows: (a) Compute the profit (or loss) for each of N iterations. (b) Sort the resulting profit (or loss) for the simulated profit (or loss) distribution. (c) Calculate VaR at a particular confidence level using the percentile function. For example, if we computed 5000 simulations, our estimate of the 95% percentile corresponds to the 250th largest loss; i.e., (1 - 0.95) * 5000.

The third method, a variance-covariance model, was popularized by J.P. Morgan in the early 1990s. The model assumes that risk factor returns are normally distributed and that the change in portfolio value is linearly dependent on all risk factor returns. VaR for the 95% confidence interval using this method is calculated as:

$$\text{VaR} = -V_p\,(\mu_p - 1.645\sigma_p), \tag{4.10}$$

where V_p is the initial value of the return on the portfolio, μ_p and σ_p are the mean and standard deviation of the portfolio, respectively.

The VaR has been preferred by financial institutes to calculate maximum losses on their portfolio of investment frequently. The VaR has an advantage of being easy to calculate based on various risk periods. The shortcoming is that the choice of confidence interval is arbitrary and subjective. The VaR is measured using Monte Carlo simulation at the 90% confidence level in our study.

To compare the hedging cost and effectiveness of weather derivatives with multiple peril crop insurance (MPCI), we calculate the indemnity payments and premium cost of MPCI. The MPCI premium is directly obtained from the 2007 crop insurance calculator (www.farmdoc.uiuc.edu) based on farm location (county), actual production history (APH), and coverage levels. We calculate the average of 24 insurance premiums of farmers who reported their yield histories for at least 17 years during 1984-2006 in each of our four counties.

The MPCI participating farmer has to decide the level of yield coverage and the level of price coverage in order to determine the amount of protection obtained from MPCI. For the level of yield coverage he can choose from 50 to 85 percent of his actual production history (APH) which is an estimate of his average yield on the insured unit for four to ten consecutive years. He can also select an indemnity price level between 55 and 100 percent of the maximum price elections set by the Risk Management Agency (RMA) for each crop every year.

In practice indemnity payments are calculated based on the guaranteed yield and price the farmer chooses. If his actual yield per planted acre is not less than his yield guarantee, no indemnity is paid. If his yield per planted acre is less than his yield guarantee, the indemnity paid is equal to: the yield difference × the guaranteed price × the number of acres insured.

Premium cost per acre is calculated as: APH yield × level of yield coverage × the guaranteed price × premium rate × subsidy factor. Premium rates are based on the coverage level chosen, the loss history of the farmer's county, and his APH yield. APH yield is a simple average of from four to ten consecutive years of the farmer's actual yields. Subsidy factor is the percentage of total premium paid by the farmer, with the remaining subsidized by the government.

For example, assume the farmer's APH corn yield is 130 bu. per acre and he chooses 75% level of yield coverage and 100% level of price coverage. The corn price election based on 2007 maximum price elections set by the RMA is $3.50/bu. Assume that his number of acres insured is 300 acres and actual yield is 81 bu. per acre. Then, the guaranteed yield equals 97.5 bu. (= 130 bu. × 75%) and the indemnity payment is $19,057.50 (= (97.5 – 81 bu.) × $3.50 × 330 acres). The premium per acre is $6.76/acre, which is calculated as: 130 bu./acre × 75% × $3.50/bu. × 4.4% × 0.45, assuming that the premium rate is 4.4% and the subsidy factor is 0.45. Subsidy factor 0.45 means that the farmer pays only 45% of total premium and government covers the remaining 55%.

Neither MPCI nor weather options provide 100 percent coverage on the farmer's crop yield loss. MPCI insures each farmer's crop from 50 to 85 percent of his or her APH yield. Weather derivatives induce a hedging gap, caused by the imperfect relationship between crop yield and weather variables. We call the hedging gap as local basis risk in weather hedge. The hedging gap is unavoidable in using weather derivatives, even though it can be minimized by using a better fitted yield response model to determine the optimal weather hedge. Therefore, we calculate the weighted hedging costs for MPCI and for weather options by adjusting each cost by the corresponding coverage ratio in order to compare the hedging cost at the same coverage level.

Geographic Basis Risk and Spatial Aggregation

In this study weather options are priced based on the weather process at each of the four locations, assuming the existence of an over-the-counter (OTC) weather option contract for the weather index at each location. However, OTC weather options based on each specific location are not traded now due to liquidity and fair pricing problems. The liquidity problem is caused by very low demands for the weather derivatives based on the remote agricultural regions. Each remote region may not have sufficient historical weather data, which induces the fair pricing problem, and speculators may require considerable risk premiums (Woodard and Garcia, 2007).

The Chicago Mercantile Exchange (CME) offers weather options and futures only for 24 major cities in the United States. Thus, geographic basis risk, a hedging gap caused by distance between the CME weather station and the agricultural field, may arise when we use the CME options instead of OTC options. For example, a farmer who produces corn and soybean in Rock county, one of our four agricultural regions in southern Minnesota, will hedge the weather risk by purchasing the CME weather derivatives based on Minneapolis which is the closest CME reference city to Rock county. To measure the geographic basis risk for each county, we compare the hedging effectiveness between CME options based on the Minneapolis weather index and OTC options based on each local weather index, because there is no geographic basis risk in using the OTC options for each county.

Woodard and Garcia (2007) show that the use of spatial aggregation diminishes the degree to which geographic basis risk impedes effective hedging. We compare the hedging effectiveness between crop insurance and CME weather options for the spatially aggregated four counties in order to verify that the weather option is a more efficient hedging instrument with less significant geographic basis risk as we increase the level of spatial aggregation.

Chapter Ⅴ

Data and Summary Statistics

Raw weather (temperature and precipitation) and crop yield (soybean and corn) data for our four locations are presented in this Chapter. Summary statistics and graphical representation help us to get some intuition for estimating yield response functions and weather process models.

Raw Weather Data

The period of analysis begins in 1941. The primary reason for choosing to begin the analysis in the 1941 growing season is that genetic engineering and fertilization practices did not begin to substantially improve crop yields until the 1930's.

Weather data is obtained from the Minnesota Climatology Working Group, which is a collaboration between the State Climatology Office (Minnesota Department of Natural Resources - Division of Waters), Extension Climatology Office (University of Minnesota - Minnesota Extension Service), and Academic Climatology (University of Minnesota). In order to analyze a cross-section of the Southern Minnesota region, we use weather data from four dispersed measurement stations in the region. The southwest and southeast points in the region under consideration lie at approximately 43.6° latitude. The northwest and northeast locations lie approximately 2° to the north at 45.6° latitude. The southwest and northwest locations lie approximately 96° longitude. The southeast and northeast locations lie approximately 92° longitude. The nearest measurement locations near these points of intersection are in the Minnesota communities of Luverne, Morris, Preston, and Rush City, mapping into the southwest, northwest, southeast, and northeast points of intersection, respectively. For each location (L), daily high temperature ($\text{Max}T_t^L$), daily low temperature ($\text{Min}T_t^L$), and daily precipitation ($prec_t^L$), were obtained for the period from September 1, 1940 to August 31, 2008 (t = 1 to 24,837).

Table 5.1 and Table 5.2 show descriptive statistics for monthly average temperature and cumulative precipitation for each region, respectively. Table 5.1 shows that Luverne which is located in southwest is the warmest of the four regions throughout the growing season from May through August, while Rush City located in northeast is always the coolest, implying that south and west is warmer than north and east, respectively. The values of average temperature in May are relatively lower and wider spread around the mean compared with other months based on the negative kurtosis, and are right skewed for all four regions. On the other hand, July shows the highest average temperature for all regions and the values are left skewed except Preston.

Table 5.2 reveals that Preston which is located in southeast is the wettest while Morris located in northwest is the driest for most of the growing season, implying that south and east tend to be wetter than north and west, respectively. It is evident that the amounts of precipitation are right skewed throughout the growing season for all regions, implying that the frequency of excessively large amounts of rainfall is rare in southern Minnesota.

Table 5.1 Temperature (degree Fahrenheit) Statistics for Luverne, Morris, Preston, and Rush City, 1941-2008

Period/Region	Mean	Maximum	Minimum	Stand. Dev.	Kurtosis	Skewness
May						
Luverne	57.9	66.6	50.5	3.76	-0.71	0.09
Morris	56.3	66.0	50.2	3.60	-0.46	0.35
Preston	56.9	65.2	50.8	3.40	-0.79	0.16
Rush City	55.7	64.7	49.6	3.49	-0.66	0.24
June						
Luverne	67.5	75.3	59.8	3.10	0.22	-0.38
Morris	65.9	73.9	58.8	2.87	0.21	-0.12
Preston	66.5	71.9	58.7	2.67	0.72	-0.28
Rush City	64.8	69.2	58.7	2.64	-0.55	-0.33
July						
Luverne	72.4	77.9	64.8	2.68	-0.05	-0.37
Morris	70.6	75.3	63.0	2.33	0.57	-0.29
Preston	70.9	77.3	64.3	2.45	-0.02	0.04
Rush City	69.7	74.6	62.7	2.44	0.04	-0.22
August						
Luverne	70.2	77.9	64.5	2.73	0.32	0.26
Morris	68.6	75.5	62.1	2.71	0.01	-0.04
Preston	68.7	77.0	61.6	2.77	0.70	0.04
Rush City	67.6	74.0	60.9	2.71	-0.03	-0.10

Source: Minnesota Climatology Working Group (http://www.climate.umn.edu).

Table 5.2 Precipitation (inches) Statistics for Luverne, Morris, Preston, and Rush City, 1941-2008

Period/Region	Mean	Maximum	Minimum	Stand. Dev.	Kurtosis	Skewness
May						
Luverne	3.42	10.85	0.00	2.09	2.41	1.34
Morris	2.97	8.89	0.28	1.61	1.94	1.17
Preston	3.90	8.72	0.74	1.69	0.42	0.61
Rush City	3.57	8.12	0.57	1.79	-0.56	0.47
June						
Luverne	4.24	9.13	0.00	2.20	-0.16	0.44
Morris	4.02	7.62	0.49	1.84	-0.98	0.12
Preston	5.06	12.12	0.80	2.49	0.19	0.75
Rush City	4.51	10.93	0.75	2.27	1.07	1.01
July						
Luverne	3.36	10.49	0.00	2.15	0.79	0.73
Morris	3.65	9.77	0.74	2.02	0.47	0.91
Preston	4.22	12.42	0.68	2.44	2.09	1.35
Rush City	3.87	9.21	1.07	1.79	0.63	0.75
August						
Luverne	3.15	7.66	0.35	2.00	-0.61	0.64
Morris	3.04	7.43	0.14	1.62	-0.28	0.48
Preston	4.26	14.88	0.31	2.62	3.42	1.43
Rush City	4.21	14.11	0.61	2.14	5.92	1.75

Source: Minnesota Climatology Working Group (http://www.climate.umn.edu).

Figure 5.1A and 5.1B depict the daily high and low temperature for 68 years in Luverne, one of our four regions, respectively. We do not provide the graphs for the other three regions, since they have similar trends to those for Luverne. The graphs show that the temperature oscillates through summer and winter. Some irregular jumps occur but return to the long-run seasonal trend. These characteristics justify the inclusion of seasonality, autoregression, and mean reversion with discrete jumps of temperature in our temperature process model. Increasing trend of temperature due to global warming is not noticeable due to a relatively short period of 68 years.

Figure 5.2 shows the historical daily precipitation for 68 years in Luverne. The probability and the amount of rainfall vary with the season. Rainfall is much more intensive in summer than in winter. In particular most of the winter days have no precipitation. It can also be seen that the volatility of the daily precipitation is higher in summer than in winter.

For our empirical analysis using temperature-based weather call/put option, the standard measure of Growing-Degree-Day (GDD), rather than outright temperature, for a particular day is calculated as:

$$GDD_t = \frac{\text{Max}[\text{Min}[\text{Min}T_t, 86], 50] + \text{Max}[\text{Min}[\text{Max}T_t, 86], 50]}{2} - 50. \qquad (5.1)$$

In essence, the growing degree day restricts the low temperature (floor) at 50 degrees Fahrenheit (temperature below which no growth occurs) and the high temperature (cap) at 86 degrees (temperature above which benefits of an additional degree are minimal). Precipitation is measured in inches.

Both temperature (GDD) and precipitation data used in our estimation are the cumulative daily measures during the sensitive period (between June and August) for corn and soybean yield in the form of deviation from the observed mean values.

Figure 5.1A Daily High Temperature – Luverne (September 1940 – August 2008)

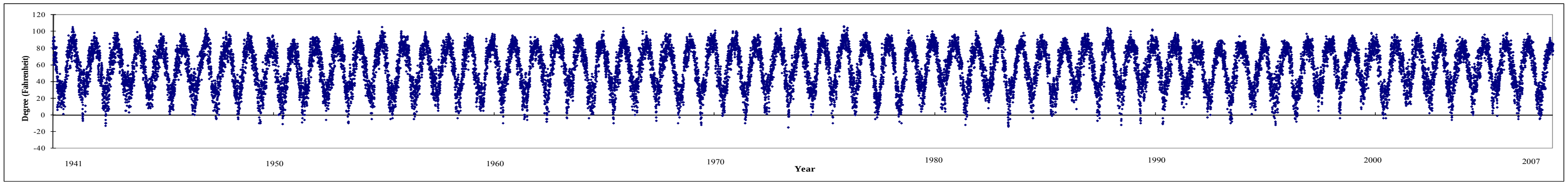


Figure 5.1B Daily Low Temperature – Luverne (September 1940 – August 2008)

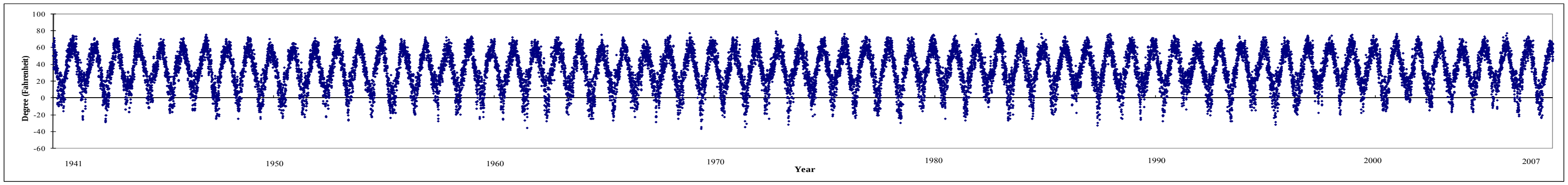
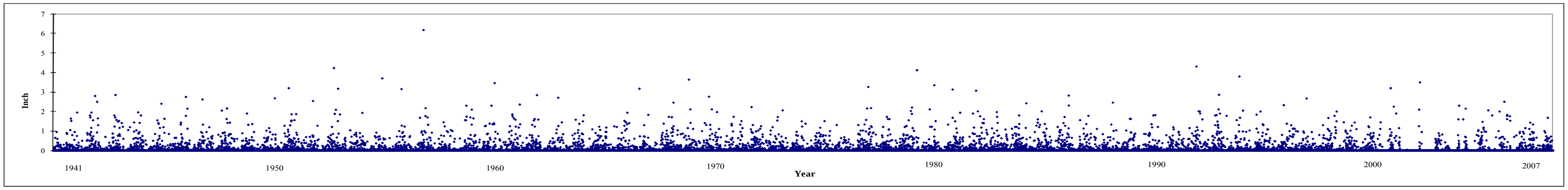


Figure 5.2 Daily Precipitation – Luverne (September 1940 – August 2008)



Raw Yield Data

Both county-level and farm-level crop yield data are used to observe the effects of spatial aggregation on hedging effectiveness. County-level and farm-level soybean and corn yields (per planted acre) data are obtained from the National Agricultural Statistics Service (NASS) and Risk Management Agency (RMA), respectively, for four Minnesota counties (towns): Rock County (Luverne), Stevens County (Morris), Fillmore County (Preston), and Chisago County (Rush City). For location *L*, growing season *t* (from 1941 to 2008), crop yield per planted acre is calculated as:

$$Y_t^L = \frac{prod_t^L}{acre_t^L}, \tag{5.2}$$

where $prod_t^L$ is the crop production and $acre_t^L$ is the acres planted.

The NASS provides the county-level yields per planted acre only from 1972 while they provide the county-level yields per harvested acre from 1941. Since yields per planted acre and per harvested acre are correlated, we create a county-level yield per planted acre distribution before 1972 by calibrating the yields per harvested acre. For the calibration we follow the calibration method suggested by Fulton, King, and Fackler (1988). First, we generate detrended yields per harvested acre and per planted acre for our four counties from an ordinary least squares regression of yield on time (from 1972 to 2008) to remove the effects of technological change over time (see Appendix II-1 and II-2). Then, each element of the calibrated yields per harvested acre (Y_{ht}) from 1941 to 1971 is obtained from:

$$Y_{ht} = (m + (\sigma_p / \sigma_h)\,(Y_t - m)) + d, \tag{5.3}$$

where *m* is the mean of the 68-year (from 1941 to 2008) uncalibrated yields per harvested acre, σ_p and σ_h are the standard deviation for the yields per planted acre and per harvested acre (from 1972 to 2008), respectively, Y_t is the year *t* observation of the

68-year uncalibrated yields per harvested acre data, d is the difference between the mean of the yields per planted acre and the mean of the yields per harvested acre (from 1972 to 2008). Calibrated soybean and corn yield per harvested acre are reported in Appendix II-3 and II-4, respectively.

The farm-level yields per planted acre are provided by RMA for 23 growing seasons from 1984-2006. We select 24 farms reporting at least 17 years of yield out of 23 years to evaluate the crop insurance and weather derivatives at the farm level. Sets of 10,000 simulated farm-level yields for each of the 24 farms are based on the fitted yield distribution function from its reported farm-level data. We find each individual farm's fitted yield distribution function using @Risk statistical software (Palisade Corporation, 2009).

In Table 5.3 we report the summary of statistics for the county-level soybean and corn yields (bushels per planted acre) in the four counties during 1941-2008. We can observe that Preston, which is the wettest and second warmest area, shows the highest average yield in corn and the almost highest in soybean. This implies that there is enough moisture and higher than average temperature (not too hot) during growing season to increase the yield of corn and soybean.

Table 5.3 County-Level Soybean and Corn Yields (Bushels per Planted Acre) in the Four Counties, MN, 1941-2008

Crop/Region	Mean	Maximum	Minimum	Stand. Dev.	Kurtosis	Skewness
Soybean						
Luverne	29.1	52.4	10.1	11.7	-1.13	0.21
Morris	23.9	42.7	6.8	10.5	-1.39	0.29
Preston	28.6	56.4	10.9	11.5	-0.71	0.47
Rush City	19.6	41.6	4.5	8.3	-0.37	0.48
Corn						
Luverne	87.0	189.9	32.2	42.9	-0.84	0.55
Morris	80.5	168.0	27.2	43.9	-1.09	0.54
Preston	97.0	190.8	40.6	40.7	-0.92	0.42
Rush City	73.1	136.3	23.7	28.7	-0.81	0.28

Source: National Agricultural Statistics Service (http://www.nass.usda.gov).

* Luverne, Morris, Preston, and Rush City represent Rock County, Stevens County, Fillmore County, and Chisago County, respectively.

A graphical representation of soybean and corn yields is provided for each of our four measurement locations over 68 growing seasons in Figure 5.3 and Figure 5.4, respectively. We notice that yields have been increasing in all locations over time with the notable exception of the early years in the study.

The primary driver behind the positive slope is the fact that agricultural (mechanical, biological, and chemical) technology has experienced many advances since 1940, allowing farmers to achieve higher yields. Additional reasons for the observed increase in productivity could involve economies of size (the number of farmers has drastically decreased over time, while acreage farmed has not), and selection bias due to differences in management ability ("low-ability" farmers may have been "weeded-out" of the farming profession as the industry has become more competitive, leaving behind a more talented pool of farmers).

To correct a general upward trend in our non-stationary yield data, we use a quasi-linear detrending method following Thompson (1986). Rather than using a linear detrending method over the entire period, Thompson divides his time series data into three periods: pre-1960, 1960-1972, and post-1972 periods. He points out that the relatively steeper trend between 1960 and 1972 is caused by remarkable improvements in both fertilization practices and crop genetics.

For each location L, county-level yield per planted acre (Y_t^L) is estimated on three time trends (t_1, t_2, *and* t_3) as follows:

$$Y_t^L = \beta_0 + \beta_1 t_1 + \beta_2 t_2 + \beta_3 t_3 + \varepsilon_t^L, \tag{5.4}$$

where the time variables for each year (t_1, t_2, *and* t_3) are provided in Appendix III.

Figure 5.3 Soybean Yields (Bushels per Planted Acre) in Four Counties, MN, 1941-2008

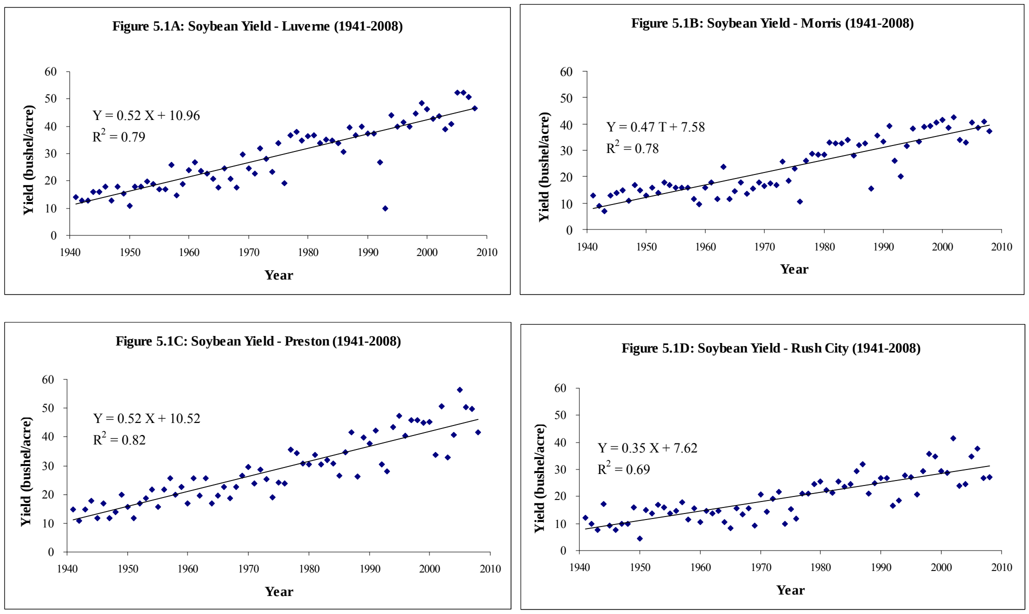
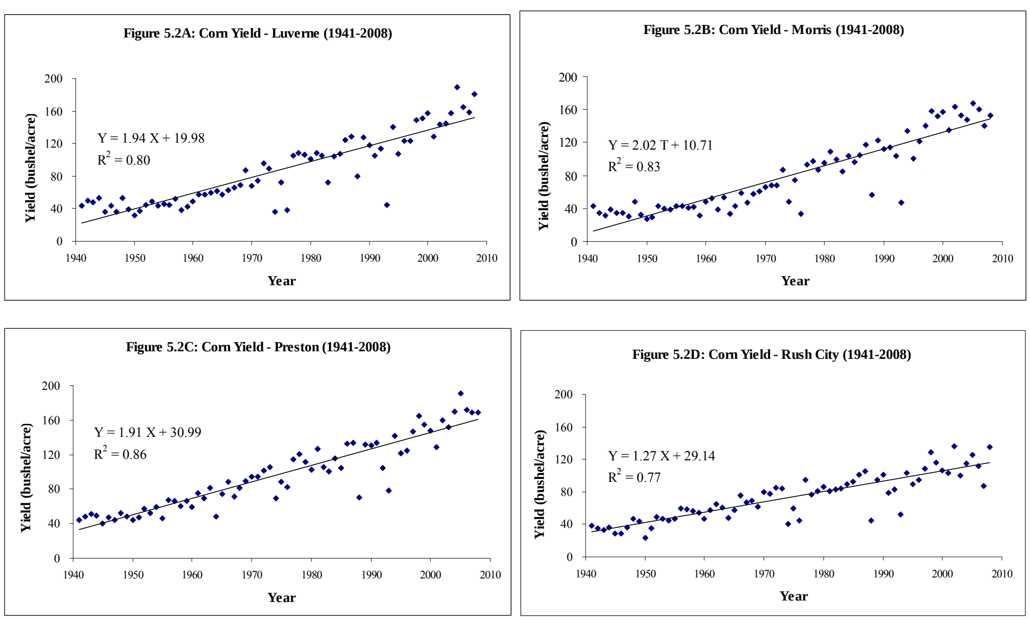


Figure 5.4 Corn Yields (Bushels per Planted Acre) in Four Counties, MN, 1941-2008



Tables 5.4 and 5.5 contain the time-trend regression results for soybean and corn, respectively. We notice that all quasi-linear regressions are characterized by high R^2 and significant *p*-values on most of the coefficients. A graphical representation of detrended soybean and corn yields is provided for each of the four locations in Figure 5.5 and Figure 5.6, respectively.

Table 5.4 Time-Trend Regression Results for Soybean

Location	β_0 (S.E.)	β_1 (S.E.) (1941-59)	β_2 (S.E.) (1960-72)	B_3 (S.E.) (1973-2008)	F	R^2	S.E.	Obs.
Luverne	13.21**(2.25)	0.38**(0.18)	0.55**(0.20)	0.56**(0.08)	81.10**	0.79	5.46	68
Morris	12.43**(1.95)	0.11 (0.15)	0.54**(0.17)	0.57**(0.07)	90.16**	0.81	4.72	68
Preston	12.85**(1.99)	0.43**(0.16)	0.36**(0.18)	0.64**(0.07)	105.17**	0.83	4.82	68
RushCity	10.78**(1.87)	0.13 (0.15)	0.32*(0.17)	0.44**(0.07)	52.81**	0.71	4.54	68

** Significant at 5% level * Significant at 10% level

Table 5.5 Time-Trend Regression Results for Corn

Location	β_0 (S.E.)	β_1 (S.E.) (1941-59)	β_2 (S.E.) (1960-72)	B_3 (S.E.) (1973-2008)	F	R^2	S.E.	Obs.
Luverne	41.58**(7.28)	0.40 (0.58)	1.93**(0.68)	2.52**(0.25)	110.83**	0.84	17.64	68
Morris	34.60**(6.66)	0.30 (0.53)	2.03**(0.59)	2.66**(0.23)	144.08**	0.87	16.15	68
Preston	42.20**(6.13)	1.17**(0.49)	1.97**(0.55)	2.17**(0.21)	146.31**	0.87	14.86	68
RushCity	29.56**(5.80)	1.42**(0.46)	1.00*(0.52)	1.36**(0.20)	71.83**	0.77	14.06	68

** Significant at 5% level * Significant at 10% level

Figure 5.5 Detrended Soybean Yields (Bushels per Planted Acre) in Four Counties, MN, 1941-2008

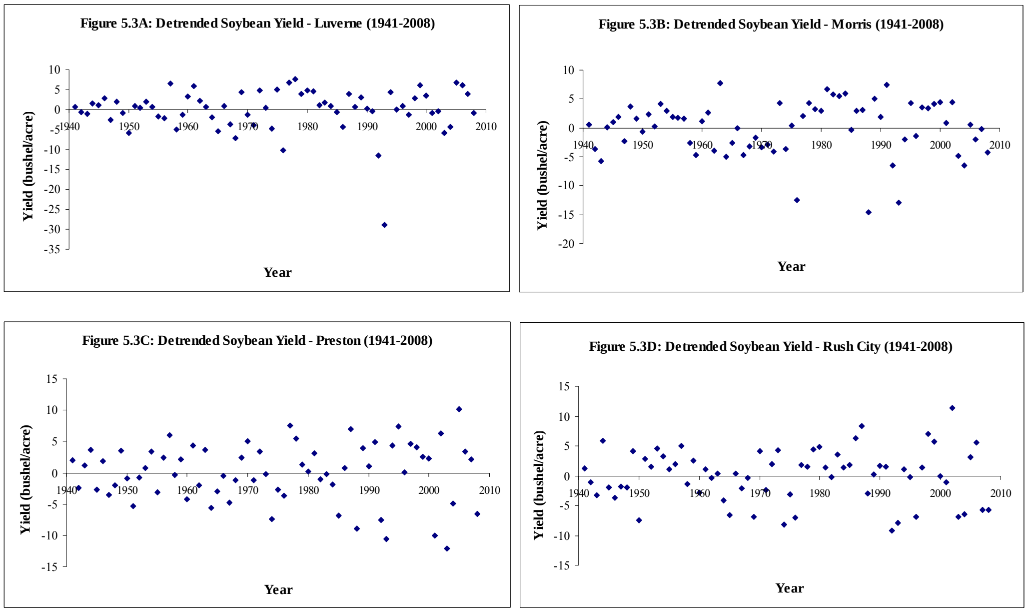


Figure 5.6 Detrended Corn Yields (Bushels per Planted Acre) in Four Counties, MN, 1941-2008

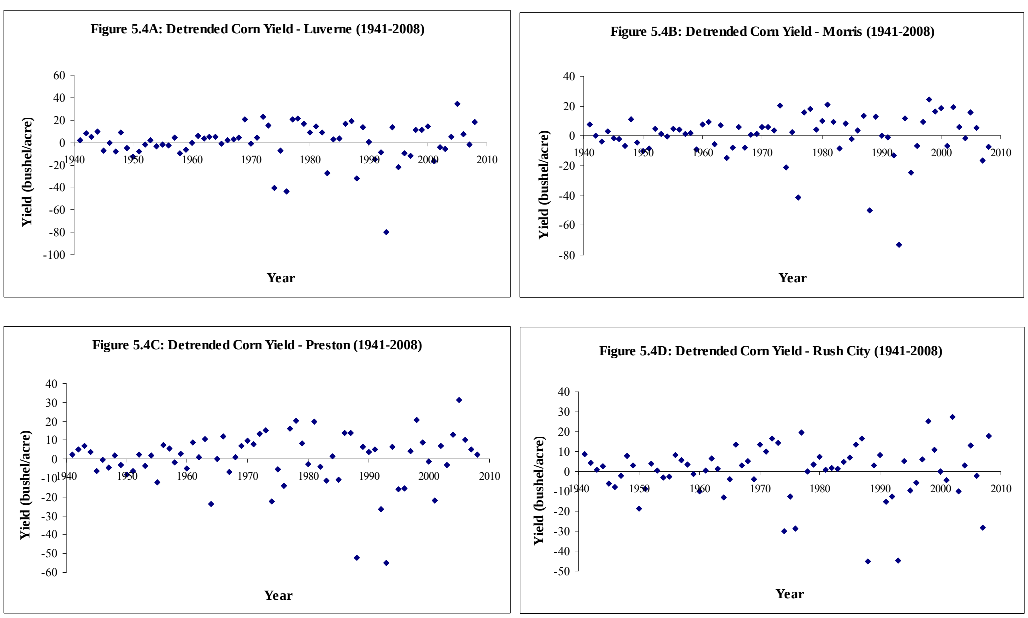


Table 5.6 shows the correlation between annual crop yields and growing season (from June to August) weather variables for the four measurement stations. GDD representing temperature is negatively related with rainfall in most of stations for every month. The relationships between crop yields and monthly weather variables (GDD6 to Rain8) are not strong across stations. However, there appears to be a relatively strong positive correlation between June temperature (GDD6) and yields, while August temperature (GDD8) appears to be negatively correlated with yields. We can also observe that July and August precipitation has a relatively strong positive relationship with yields in Rush City and Preston, and June and July precipitation is positively correlated with yields in Morris. When we consider the relationship between crop yields and growing season weather variables (GDD3m and Rain3m), the correlation coefficients (except Luverne) are between 0.10 and 0.30 which are similar to previous studies including Turvey (2001).

Table 5.6 Correlation between Crop Yields and Growing Season Weather Variables in the Four Counties, MN

Region	Variable	Soybean	Corn	GDD3m	Rain3m	GDD6	GDD7	GDD8	Rain6	Rain7	Rain8
Morris	Soybean	1.00									
	Corn	0.95	1.00								
	GDD3m	0.13	0.08	1.00							
	Rain3m	0.17	0.08	-0.01	1.00						
	GDD6	0.20	0.17	0.71	-0.00	1.00					
	GDD7	0.14	0.10	0.68	0.06	0.25	1.00				
	GDD8	-0.07	-0.12	0.68	-0.07	0.15	0.23	1.00			
	Rain6	0.14	0.13	-0.16	0.57	-0.21	-0.04	-0.07	1.00		
	Rain7	0.12	0.05	0.01	0.55	0.07	-0.13	0.07	-0.11	1.00	
	Rain8	0.01	-0.06	0.15	0.51	0.15	0.32	-0.13	0.06	-0.11	1.00
Luverne	Soybean	1.00									
	Corn	0.94	1.00								
	GDD3m	0.28	0.14	1.00							
	Rain3m	-0.21	-0.17	-0.19	1.00						
	GDD6	0.30	0.22	0.70	-0.16	1.00					
	GDD7	0.27	0.14	0.76	-0.17	0.30	1.00				
	GDD8	0.02	-0.10	0.65	-0.08	0.08	0.35	1.00			
	Rain6	-0.22	-0.19	-0.19	0.60	-0.24	-0.22	0.07	1.00		
	Rain7	-0.24	-0.14	-0.16	0.73	-0.11	-0.11	-0.10	0.23	1.00	
	Rain8	0.10	0.04	0.02	0.43	0.09	0.05	-0.11	-0.21	0.04	1.00
Rush City	Soybean	1.00									
	Corn	0.90	1.00								
	GDD3m	0.26	0.10	1.00							
	Rain3m	0.14	-0.03	-0.09	1.00						
	GDD6	0.23	0.10	0.65	-0.04	1.00					
	GDD7	0.26	0.11	0.73	-0.08	0.25	1.00				
	GDD8	0.07	0.01	0.72	-0.08	0.16	0.31	1.00			
	Rain6	-0.05	-0.15	-0.13	0.59	-0.16	-0.04	-0.08	1.00		
	Rain7	0.09	0.04	-0.21	0.54	-0.02	-0.22	-0.20	-0.03	1.00	
	Rain8	0.20	0.08	0.16	0.63	0.12	0.10	0.12	-0.02	0.13	1.00
Preston	Soybean	1.00									
	Corn	0.95	1.00								
	GDD3m	0.03	-0.09	1.00							
	Rain3m	0.27	0.27	-0.10	1.00						
	GDD6	0.15	0.04	0.68	-0.01	1.00					
	GDD7	0.04	-0.02	0.73	-0.10	0.27	1.00				
	GDD8	-0.12	-0.20	0.70	-0.10	0.15	0.32	1.00			
	Rain6	0.03	0.08	-0.10	0.58	-0.11	-0.07	-0.03	1.00		
	Rain7	0.18	0.15	-0.17	0.50	0.01	-0.13	-0.23	-0.12	1.00	
	Rain8	0.27	0.24	0.09	0.68	0.08	0.01	0.08	0.15	0.03	1.00

Chapter Ⅵ

Empirical Results

In this Chapter we provide empirical results, and report the results following the empirical process presented in Chapter I:

- Estimating the yield response models to determine the optimal strike level and tick vale of weather options
- Estimating the weather process models to generate a statistical distribution of weather variables
- Pricing the weather options to compare the hedging cost with that of using crop insurance
- Evaluating the hedging effectiveness as measured by several risk indicators between using weather options and crop insurance.

Estimation of Soybean Yield Response Models

Three alternative yield response models are estimated: linear, quadratic, and Cobb-Douglas. Table 6.1 reports the regression results of the three models for soybean yield at the county level. Remember that the response variable (Y_t) is the detrended crop yield and two explanatory variables (R_t and G_t) are the deviations from the mean of the cumulative daily rainfall and Growing-Degree-Day (GDD), respectively, for growing season (June to August). We notice that the quadratic yield response model fits the relationship between soybean yield and the two weather variables best. This is consistent with the previous literature (Thompson, 1986; Tannura, Irwin, and Good, 2008). Thus, we choose the quadratic yield response model for determining the optimal strike level and tick value of weather options and simulating soybean yields to measure expected profits and risk indicators.

Considering the four location-specific and pooled quadratic models in Table 6.1B, the R-square measures are lower than 0.50 for all equations. This result is expected since we restrict the nature of specific event risks to the rainfall and GDD between June 1 and August 31, and we assume that direct physical inputs are held constant. Rather than interpreting R-square in terms of low predictive ability, it should be interpreted as the percent of total variability explained by the specific weather events (the June 1 to August 31 rainfall and temperature).

To see if pooling data rather than four location specific data is appropriate to our estimation, we apply Chow's F-test at the 95% confidence interval:

$$\frac{(ESS_R - ESS_{UR})/K}{ESS_{UR}/(4N-4K)} = 5.12 > F(5,252) = 2.21$$

where ESS_R : Error Sum of Squares(ESS) of restricted (pooled) model = 4,640

ESS_{UR} : ESS of unrestricted (four location specific) model = 4,213

K : number of parameters in restricted model = 5

N : number of observations in unrestricted model = 68.

Therefore, we reject the null hypothesis which is that $\beta_0 = \beta_0^i$, $\beta_1 = \beta_1^i$, $\beta_2 = \beta_2^i$, $\beta_3 = \beta_3^i$, $\beta_4 = \beta_4^i$ (for location i = 1, 2, 3, 4) implying that we reject pooled model and use each location specific model to hedge the production risk.

Table 6.1 Soybean Regression Results of Alternative Yield Response Models

In the yield response model, Y_t is the detrended crop yield (bushels per planted acre), R_t is the deviation from the mean of the cumulative daily rainfall for growing season (June to August), and G_t is the deviation from the mean of the cumulative daily Growing-Degree-Day (GDD) for growing season.

6.1A Linear Yield Response Model: $Y_t = \beta_0 + \beta_1 R_t + \beta_2 G_t + \varepsilon_t$

Location	β_0 (S.E.)	β_1 (S.E.)	β_2 (S.E.)	F	R^2	S.E.	Obs.
Luverne	0.00 (0.63)	0.01 (0.17)	0.01* (0.00)	2.34	0.07	5.23	68
Morris	0.00 (0.55)	0.38**(0.18)	0.00 (0.00)	2.68*	0.08	4.50	68
Preston	0.00 (0.53)	0.28**(0.12)	0.01**(0.00)	5.73**	0.15	4.41	68
RushCity	0.00 (0.46)	0.51**(0.13)	0.01**(0.00)	13.41**	0.29	3.79	68

6.1B Quadratic Yield Response Model: $Y_t = \beta_0 + \beta_1 R_t + \beta_2 G_t + \beta_3 R_t^2 + \beta_4 G_t^2 + \varepsilon_t$

Location	β_0 (S.E.)	β_1 (S.E.)	β_2 (S.E.)	β_3 (S.E.)	β_4 (S.E.)	F	R^2	S.E.	Obs.
Luverne	1.99**(0.67)	0.33**(0.15)	0.01 (0.00)	-0.15**(0.02)	0.00 (0.00)	12.26**	0.44	4.12	68
Morris	1.85**(0.80)	0.27 (0.18)	0.00 (0.00)	-0.10* (0.06)	-0.00**(0.00)	4.23**	0.21	4.23	68
Preston	1.39* (0.80)	0.32**(0.12)	0.01**(0.00)	-0.05**(0.02)	-0.00 (0.00)	4.49**	0.22	4.28	68
RushCity	0.72 (0.66)	0.58**(0.13)	0.01**(0.00)	-0.05**(0.02)	-0.00 (0.00)	8.34**	0.35	3.70	68
Pooled	1.52**(0.36)	0.36**(0.07)	0.01**(0.00)	-0.08**(0.01)	-0.00**(0.00)	21.49**	0.24	4.17	272

6.1C Cobb-Douglas Yield Response Model: $\ln Yt = \beta_0 + \beta_1 \ln Rt + \beta_2 \ln Gt + \varepsilon_t$

Location	β_0 (S.E.)	β_1 (S.E.)	β_2 (S.E.)	F	R^2	S.E.	Obs.
Luverne	0.00 (0.03)	0.06 (0.07)	0.64* (0.34)	2.03	0.06	0.22	68
Morris	-0.00 (0.03)	0.18**(0.09)	0.19 (0.33)	2.27	0.07	0.23	68
Preston	-0.00 (0.02)	0.12**(0.05)	0.71**(0.25)	6.12**	0.16	0.16	68
RushCity	0.00 (0.02)	0.48**(0.08)	0.99**(0.28)	24.10**	0.43	0.20	68

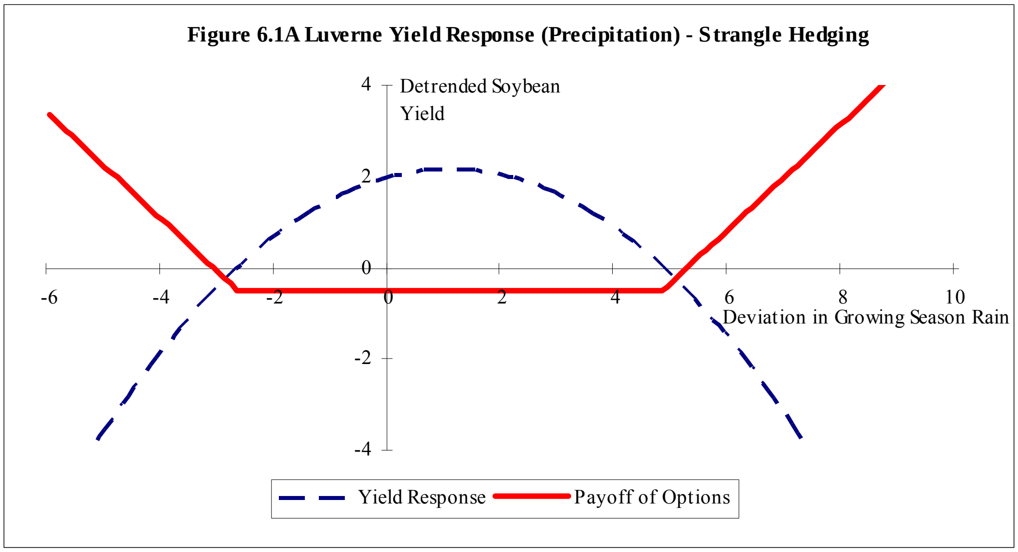
** Significant at 5% level * Significant at 10% level

We find two distinguishing characteristics from the estimated coefficients of the quadratic yield response models in Table 6.1B. First, negative coefficients on the squared weather variables (β_3 and β_4) say that large deviations (in either direction) from the historical mean precipitation and temperature (GDD) tend to depress yields. Second, the right-hand vertices on the x-axis of our negative quadratic functions imply that a slightly higher than average temperature and precipitation level is predicted to optimize the yield response function. For example at Luverne (in Table 6.1B), to optimize the quadratic yield response function for rainfall, we rewrite the function $Y_t = -0.15R_t^2 + 0.33R_t + 1.99$ in the form $Y_t = -0.15\ (R_t - 1.1)^2 + 2.1715$. Then the vertex ($R_t$, Y_t) is (1.1, 2.1715). This implies that the amount of precipitation which is 1.1 inches higher than average precipitation maximizes soybean yield.

Based on the estimated negative quadratic function, we select the strangle hedging strategy which involves buying a put option and a call option with different strike levels on the underlying precipitation and GDD variables in order to provide the buyer of the option (the farmer) with protection from extreme weather events in either direction. Figures 6.1A- 6.1D display the estimated soybean yield response functions and the payoffs of strangle hedging strategies in our four locations. We observe the loss in the two extreme weather events is covered by the payoff of strangle options. Two exceptions of yield response functions are observed in Figure 6.1A (GDD for Luverne) and Figure 6.1D (GDD for Rush City). The two particular graphs show that soybean yield increases as growing season temperature (represented by GDD) increases. We do not hedge against GDD for Luverne, since a global minimum yield exists at slightly above the historic mean across the deviations in GDD. Rush City needs to hedge against GDD by purchasing a put option rather than a strangle purchase to protect only against downside GDD risk which occurs in the GDD level whose deviation is lower by 65 degree days (or more) than the mean.

The optimal strike and tick values of the options are determined based on the estimated parameters. For example, the optimal strike level (R_t^*) for the precipitation option in the quadratic function is obtained by solving $\hat{\beta}_0 + \hat{\beta}_1 R_t^* + \hat{\beta}_3 (R_t^*)^2 = 0$. By setting $\frac{d}{dR_t^*}(\hat{\beta}_0 + \hat{\beta}_1 R_t^* + \hat{\beta}_3 (R_t^*)^2) = 0$, we determine the resulting optimal tick value as: $Tick^* = \hat{\beta}_1 + 2\hat{\beta}_3 (R_t^*)$.

Figure 6.1A Estimated Soybean Yield Response Functions and Hedging Strategies in Rock County (Luverne)



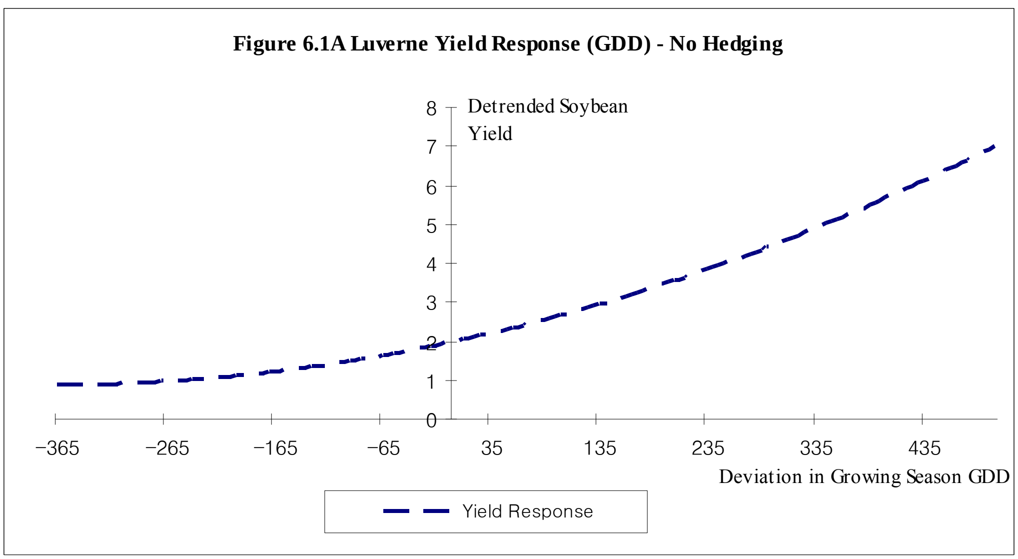
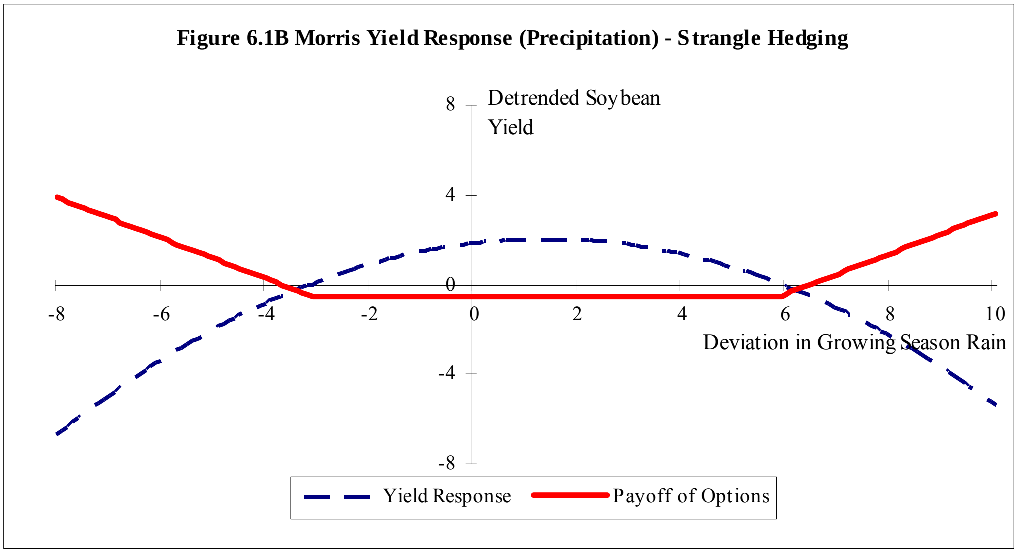


Figure 6.1B Estimated Soybean Yield Response Functions and Hedging Strategies in Stevens County (Morris)



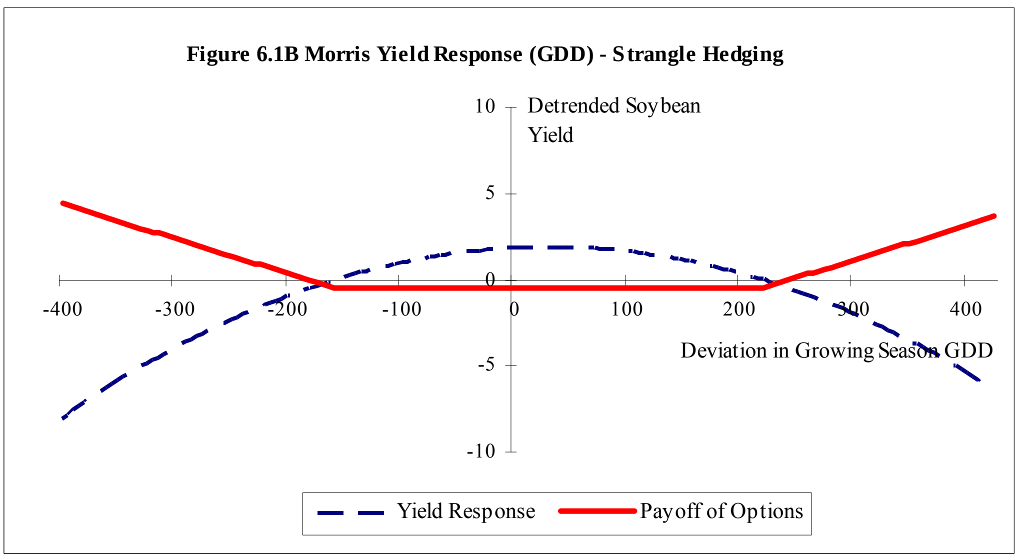
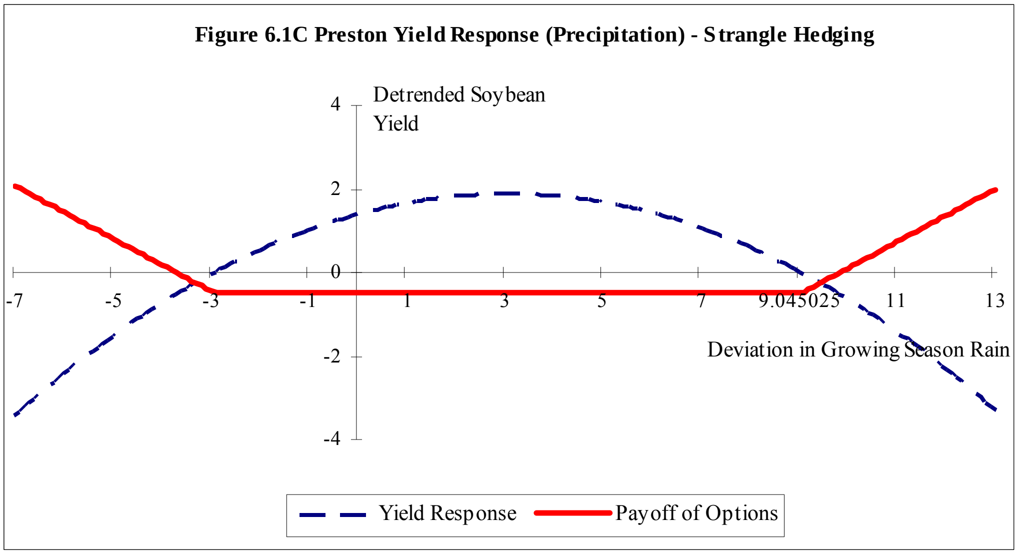


Figure 6.1C Estimated Soybean Yield Response Functions and Hedging Strategies in Fillmore County (Preston)



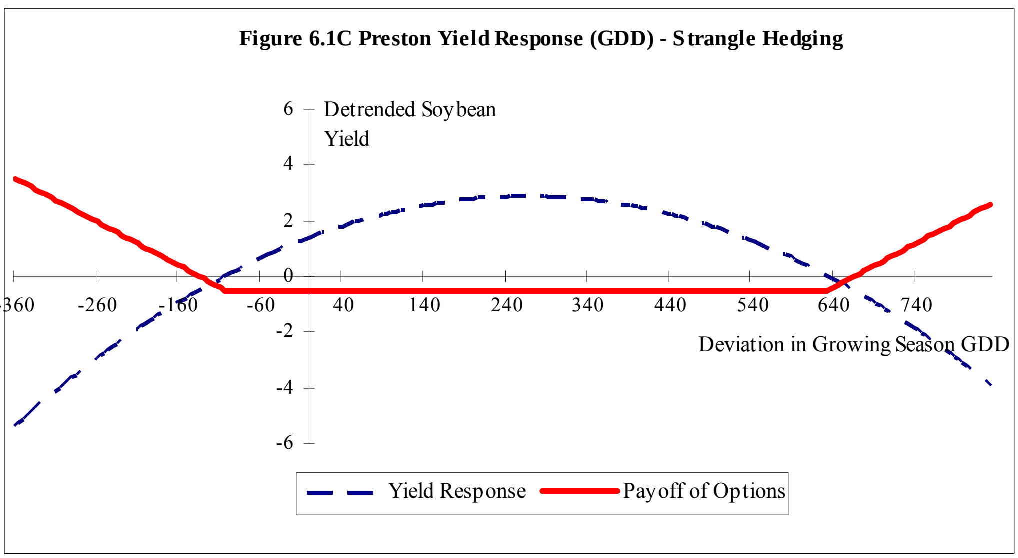
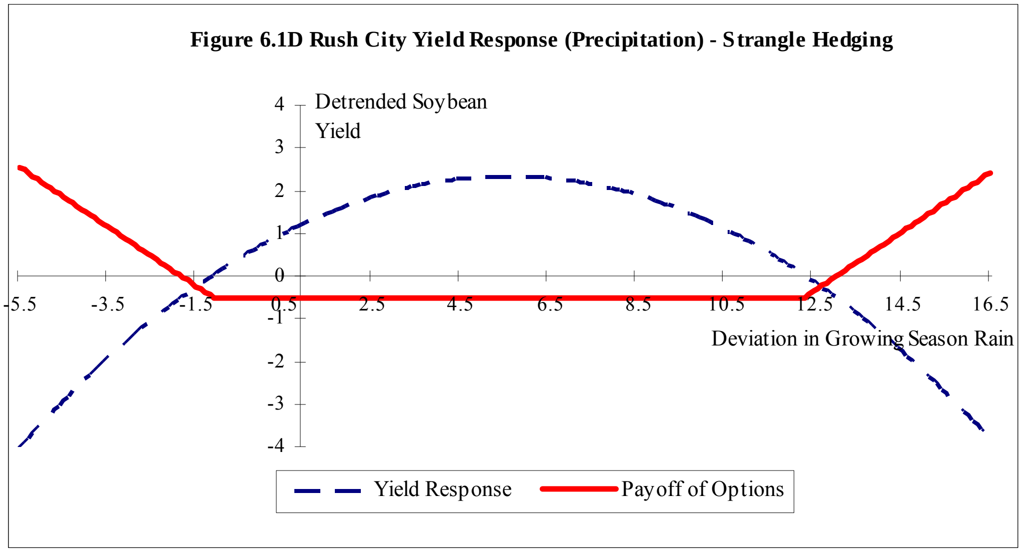
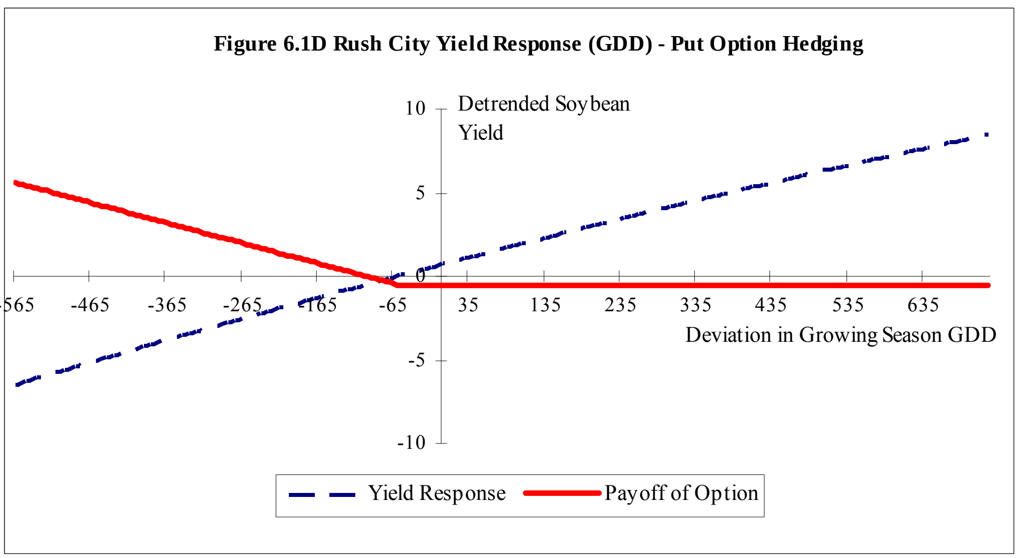


Figure 6.1D Estimated Soybean Yield Response Functions and Hedging Strategies in Chisago County (Rush City)





Estimation of Corn Yield Response Models

Regression results of the three yield response models for corn yield at the county level are reported in Table 6.2. As in the soybean yield response model, the quadratic model fits the relationship between corn yield and the two weather variables best.

We apply Chow's F-test at the 95% confidence interval to test if each of the four location specific models can be used rather than a pooling model.

$$\frac{(ESS_R - ESS_{UR})/K}{ESS_{UR}/(4N-4K)} = 3.70 > F(5{,}252) = 2.21$$

where ESS_R : Error Sum of Squares(ESS) of restricted (pooled) model = 52,608

ESS_{UR} : ESS of unrestricted (four location specific) model = 49,009

K : number of parameters in restricted model = 5

N : number of observations in unrestricted model = 68.

We reject the null hypothesis that $\beta_0 = \beta_0^i$, $\beta_1 = \beta_1^i$, $\beta_2 = \beta_2^i$, $\beta_3 = \beta_3^i$, $\beta_4 = \beta_4^i$ (for location i = 1, 2, 3, 4) implying that we use each location specific model to hedge the production risk.

Figures 6.2A-6.2D depict the estimated quadratic corn yield response models and strangle hedging strategies for our four locations. We determine the optimal strike level and tick values of the put and call options for hedging based on the estimation of quadratic yield response model.

Table 6.2 Corn Regression Results of Alternative Yield Response Models

In the yield response model, Y_t is the detrended crop yield (bushels per planted acre), R_t is the deviation from the mean of the cumulative daily rainfall for growing season (June to August), and G_t is the deviation from the mean of the cumulative daily Growing-Degree-Day (GDD) for growing season.

6.2A Linear Yield Response Model: $Y_t = \beta_0 + \beta_1 R_t + \beta_2 G_t + \varepsilon_t$

Location	β_0 (S.E.)	β_1 (S.E.)	β_2 (S.E.)	F	R^2	S.E.	Obs.
Luverne	0.00 (2.11)	0.41 (0.58)	0.00 (0.02)	0.25	0.01	17.44	68
Morris	0.00 (1.94)	0.18 (0.66)	-0.00 (0.01)	0.04	0.00	16.01	68
Preston	-0.00 (1.73)	0.82** (0.39)	0.00 (0.01)	2.15	0.06	14.28	68
RushCity	-0.00 (1.68)	0.42 (0.46)	0.01 (0.01)	0.56	0.02	13.83	68

6.2B Quadratic Yield Response Model: $Y_t = \beta_0 + \beta_1 R_t + \beta_2 G_t + \beta_3 R_t^2 + \beta_4 G_t^2 + \varepsilon_t$

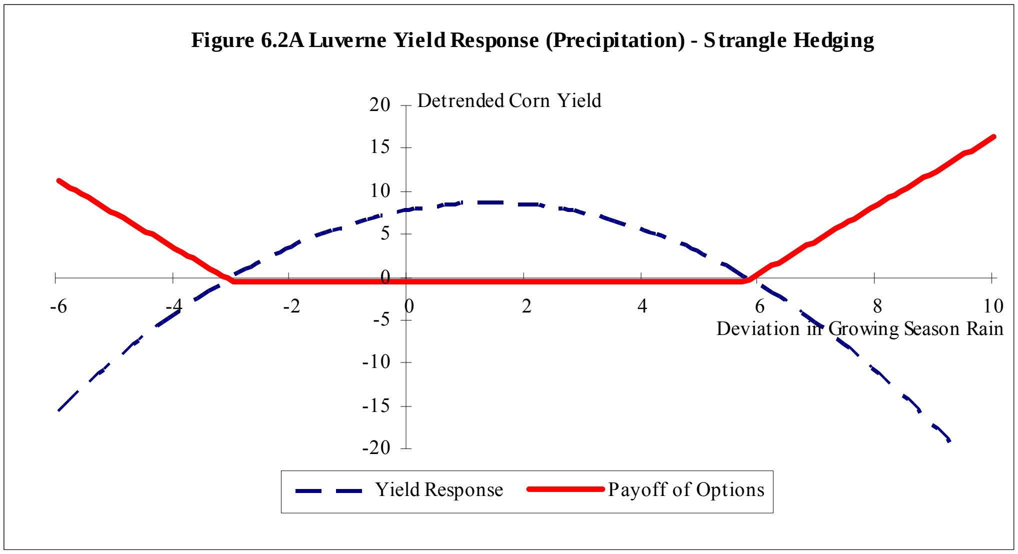
Location	β_0 (S.E.)	β_1 (S.E.)	β_2 (S.E.)	β_3 (S.E.)	B_4 (S.E.)	F	R^2	S.E.	Obs.
Luverne	7.83** (2.27)	1.23** (0.51)	-0.02 (0.01)	-0.45** (0.08)	-0.00 (0.00)	9.39**	0.37	14.1	68
Morris	7.88** (2.74)	-0.27 (0.61)	-0.00 (0.01)	-0.46** (0.21)	-0.00** (0.00)	3.92**	0.20	14.6	68
Preston	5.97** (2.51)	0.83** (0.39)	-0.00 (0.01)	-0.15** (0.07)	-0.00** (0.00)	3.76**	0.19	13.5	68
RushCity	2.88 (2.43)	0.60 (0.47)	0.01 (0.01)	-0.15* (0.08)	-0.00 (0.00)	1.20	0.07	13.7	68
Pooled	5.87** (1.20)	0.67** (0.24)	-0.01 (0.01)	-0.23** (0.04)	-0.00** (0.00)	13.69**	0.17	14.0	272

6.2C Cobb-Douglas Yield Response Model: $\ln Yt = \beta_0 + \beta_1 \ln Rt + \beta_2 \ln Gt + \varepsilon_t$

Location	β_0 (S.E.)	β_1 (S.E.)	β_2 (S.E.)	F	R^2	S.E.	Obs.
Luverne	0.00 (0.03)	0.16** (0.07)	0.20 (0.34)	2.64*	0.08	0.22	68
Morris	0.00 (0.03)	0.07 (0.09)	-0.01 (0.32)	0.38	0.01	0.22	68
Preston	0.00 (0.02)	0.12** (0.05)	0.08 (0.23)	3.02*	0.08	0.14	68
RushCity	-0.00 (0.02)	0.18** (0.07)	0.24 (0.27)	3.30**	0.09	0.20	68

** Significant at 5% level * Significant at 10% level

Figure 6.2A Estimated Corn Yield Response Functions and Hedging Strategies in Rock County (Luverne)



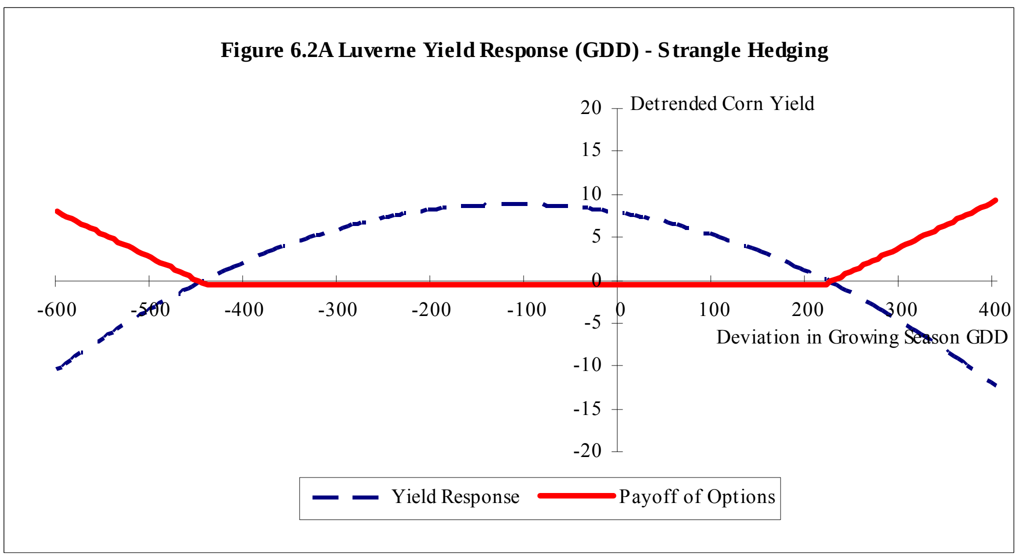
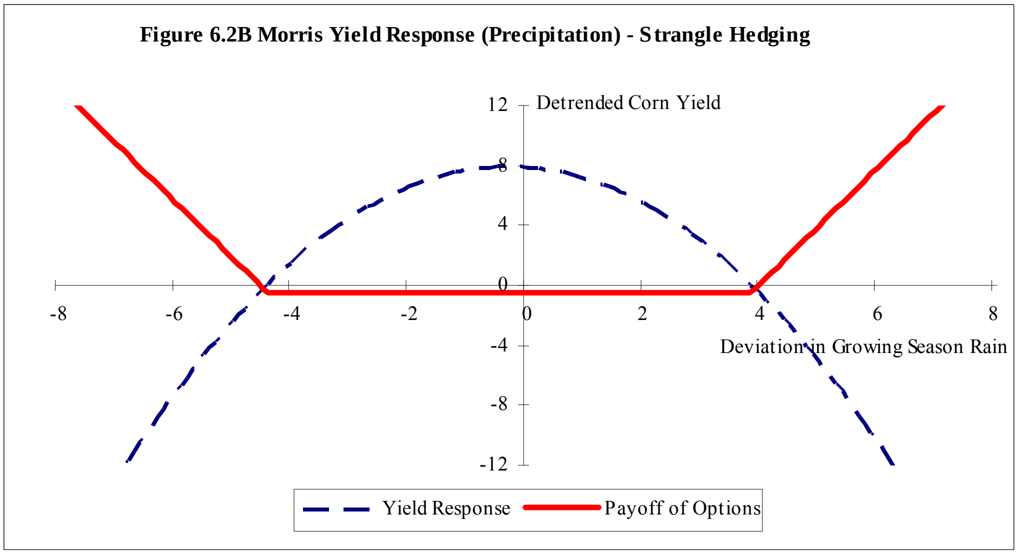


Figure 6.2B Estimated Corn Yield Response Functions and Hedging Strategies in Stevens County (Morris)



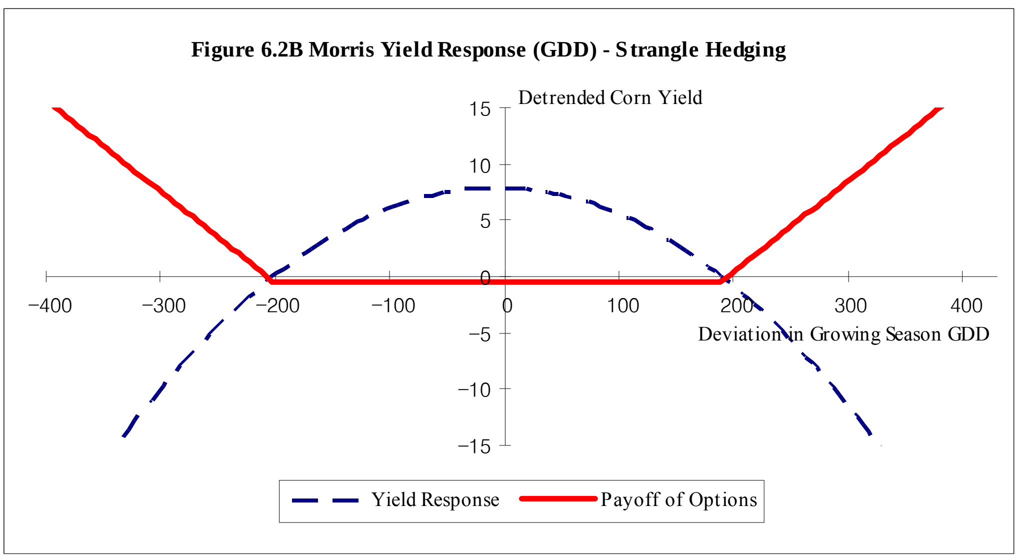
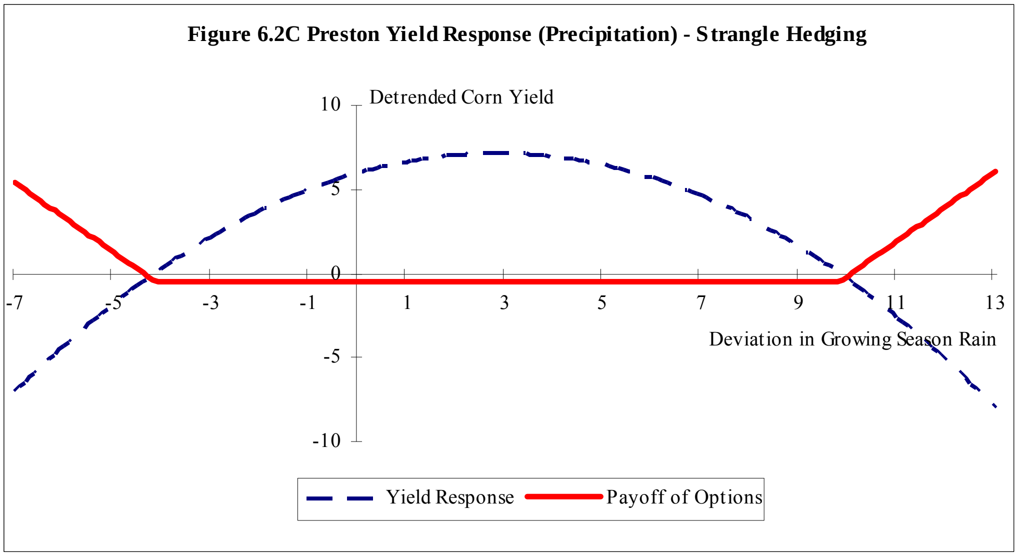


Figure 6.2C Estimated Corn Yield Response Functions and Hedging Strategies in Fillmore County (Preston)



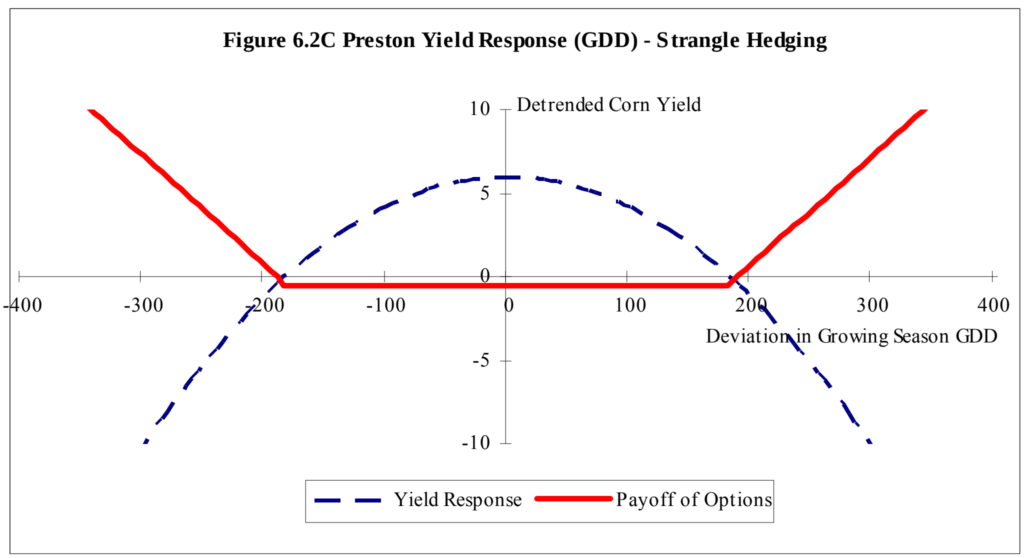
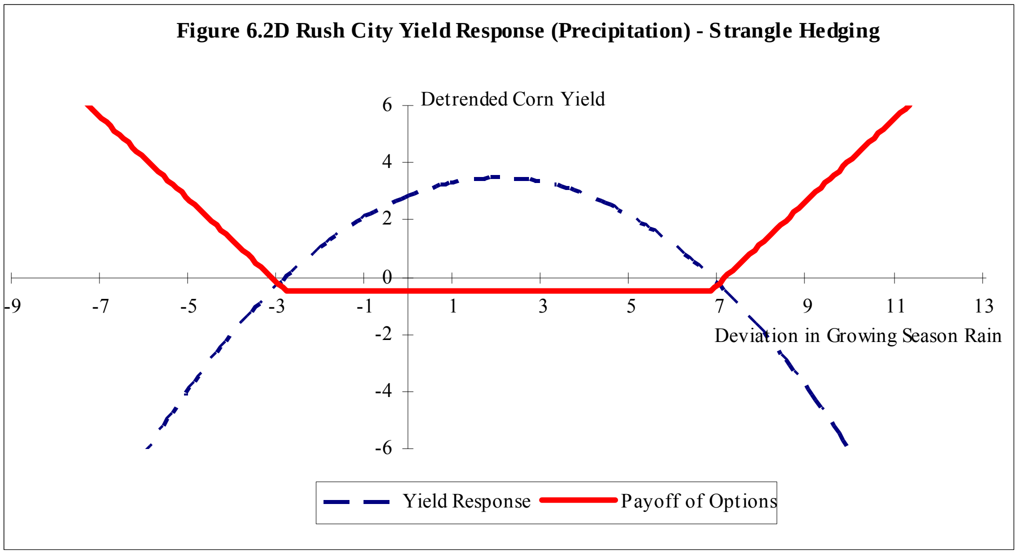
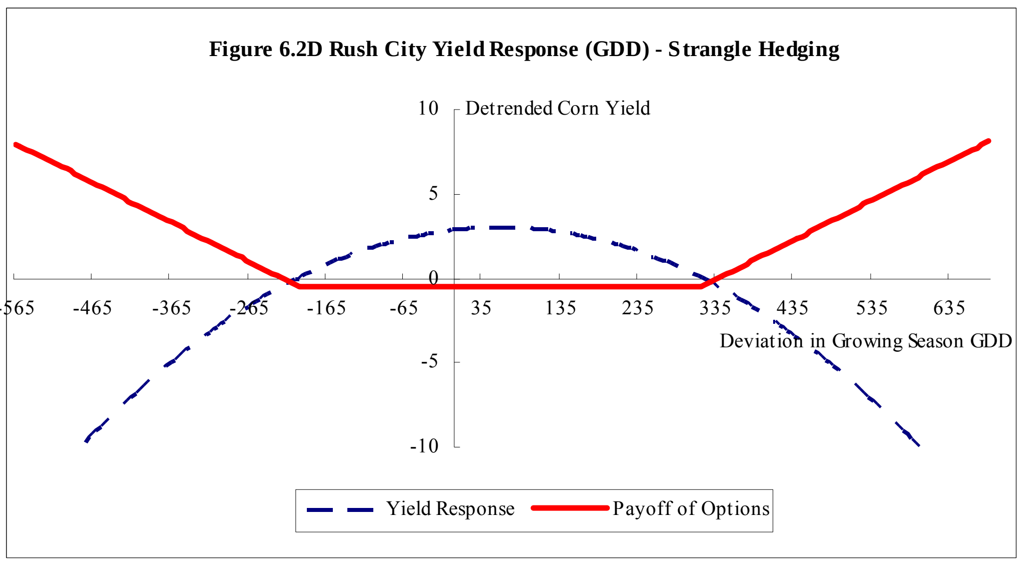


Figure 6.2D Estimated Corn Yield Response Functions and Hedging Strategies in Chisago County (Rush City)





Estimation of Weather Process Models

In Tables 6.3, 6.4A, and 6.4B we report the estimation results of the daily low and high temperature process models, respectively. Growing-Degree-Day (GDD) option prices using the daily simulation method are calculated over 10,000 simulated GDD processes which are generated based on the estimated daily low and high temperature process models.

Table 6.3 presents the estimated parameters for the instantaneous mean of the daily low and high temperature for our four locations. We also report the Akaike Information Criterion (AIC) statistics to determine the optimal number of lags. The optimal number of lags is the one which minimizes AIC. We see the AIC statistic at p=3 is much lower than that at p=2, but is slightly higher than that at p=4 (or higher number of lags ($p \geq 5$), though we do not report them). Thus, we determine p=3 as the optimal lag for a more parsimonious model, which is consistent to the optimal lag of the model by Richards, Manfredo, and Sanders (2004).

All parameters for both daily low and high temperature are statistically significant at the 5% level in all four locations. The R-square measures are very high for all equations. As expected from the strong seasonality in daily temperature in Figures 5.1A and 5.1B, seasonality factor coefficients (γ_1 and γ_2) are statistically significant. The coefficient of time trend (γ_3) is a very small positive number but statistically significant at 5% level, implying a warming trend. All three lag variables (ρ_1, ρ_2, and ρ_3) are also statistically significant. The estimated instantaneous mean of the daily low and high temperature processes (W_t^m) in Table 6.3 are used to estimate the parameters of the daily low and high temperature process models in Table 6.4A and Table 6.4B, respectively.

Table 6.3 Instantaneous Mean of the Temperature Process Model

The instantaneous mean of the daily temperature process model uses the following equation:

$$W_t^m(W_t, t) = \gamma_0 + \gamma_1 \sin(2\pi t/365) + \gamma_2 \cos(2\pi t/365) + \gamma_3 t + \sum_{j=1}^{p} \rho_j W_{t-j}$$

The estimated instantaneous mean of the daily low and high temperature processes (W_t^m) are used to estimate the parameters of the daily low and high temperature process models in Table 6.4A and Table 6.4B, respectively.

Parameter	Luverne		Morris		Preston		Rush City	
	Low	High	Low	High	Low	High	Low	High
γ_1	-1.73**	-1.11**	-1.75**	-1.31**	-1.81**	-1.00**	-1.79**	-1.15**
γ_2	1.01**	0.26**	1.05**	0.40**	1.20**	0.16**	1.22**	0.24**
γ_3	0.0001**	0.0001**	0.0001**	0.0001**	0.0002**	0.0001**	0.0001**	0.0001**
ρ_1	0.79**	0.89**	0.87**	0.80**	0.76**	0.88**	0.88**	0.84**
ρ_2	-0.03**	-0.11**	-0.13**	-0.03**	-0.02**	-0.11**	-0.13**	-0.06**
ρ_3	0.18**	0.19**	0.19**	0.19**	0.18**	0.20**	0.18**	0.19**
N	23,722	23,722	23,722	23,722	23,722	23,722	23,722	23,722
F-statistic	99,302**	99,999**	99,999**	99,999**	75,985**	99,999**	94,529**	99,999**
R-square	0.9617	0.9821	0.9642	0.9767	0.9506	0.9839	0.9599	0.9811
AIC (p=1)	4.1637	4.2490	4.0557	4.4272	4.4070	4.1236	4.1315	4.2016
AIC (p=2)	4.1513	4.2452	4.0543	4.4109	4.3922	4.1189	4.1307	4.1906
AIC (p=3)	4.1196	4.2092	4.0163	4.3738	4.3594	4.0780	4.0986	4.1544
AIC (p=4)	4.1058	4.1918	4.0051	4.3557	4.3419	4.0614	4.0845	4.1380

** Significant at 5% level * Significant at 10% level

Table 6.4A shows the estimation result of the daily low temperature process model. Most of the parameters of the model are significant at the 5% level for all locations. For example at Luverne, if the daily temperature departs from the instantaneous mean of the process, it returns to the mean at the rate of $\kappa = 0.12$. Subscripts "s" and "w" stand for summer and winter, respectively. The estimated average arrival rate or mean number of jumps occurring per unit time (λ) is 0.08. The estimated mean (θ) and variance (δ^2) of the random shock are -0.33 and 3.72, respectively. The variance of the Brownian motion process (σ^2) is estimated to be 3.88. These estimated parameters explain reasonably well the seasonal temperature process in southern Minnesota where the standard deviation of winter temperature from December to February is about twice as large as that of summer temperature from June to August. The variance of the jump (δ^2) and the variance of the process (σ^2) are much larger in winter than in summer for all locations. The rate of mean reversion (κ) is higher in summer compared to winter, which implies that irregular jumps in summer tend to more quickly revert to the mean. This also supports a smaller standard deviation for the summer temperature. The daily high temperature process model in Table 6.4B has a similar result to the daily low temperature model. The GDD processes are simulated based on the estimated parameters of the daily low and high temperature process models.

Table 6.4A Daily Low Temperature Process Model

The daily low temperature process model uses the following equation:

$dW_t = (\kappa(W_t^m - W_t) - \lambda\theta)dt + \sigma dz + \varphi dq$

$$where \quad W_t^m(W_t,t) = \gamma_0 + \gamma_1 \sin(2\pi t/365) + \gamma_2 \cos(2\pi t/365) + \gamma_3 t + \sum_{j=1}^{p} \rho_j W_{t-j}$$

Parameters κ, λ, θ, δ^2, σ^2 represent the rate of mean reversion, average arrival rate, mean jump size, variance of the jump, and variance of the Brownian motion process, respectively. Subscript "s" and "w" stand for "summer" and "winter" respectively. The Growing-Degree-Day (GDD) processes are simulated based on the estimated parameters of the daily low and high temperature process models.

Parameter	Luverne		Morris		Preston		Rush City	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
κ	0.12**	0.00	0.12**	0.00	0.10**	0.00	0.11**	0.00
κ_s	0.16**	0.00	0.17**	0.00	0.14**	0.00	0.16**	0.00
κ_w	0.10**	0.00	0.10**	0.00	0.09**	0.00	0.09**	0.00
λ	0.08**	0.01	0.20**	0.02	0.46**	0.03	0.14**	0.01
λ_s	0.01	0.01	0.28**	0.03	0.19**	0.03	0.00	0.00
λ_w	0.33**	0.06	0.04**	0.02	0.44**	0.08	0.42**	0.07
θ	-0.33**	0.07	0.62**	0.07	-0.80**	0.08	-0.47**	0.08
θ_s	-0.19*	0.10	0.47**	0.10	-0.57**	0.12	-0.08	0.10
θ_w	-0.55**	0.16	0.30*	0.16	-0.63**	0.19	-0.61**	0.18
δ^2	3.72**	0.06	3.69**	0.06	4.00**	0.07	3.82**	0.06
δ_s^2	2.68**	0.08	2.28**	0.08	2.88**	0.09	2.37**	0.08
δ_w^2	4.38**	0.13	4.64**	0.14	4.82**	0.15	4.84**	0.15
σ^2	3.88**	0.03	3.73**	0.03	4.73**	0.04	3.98**	0.03
σ_s^2	3.04**	0.05	3.07**	0.05	3.70**	0.06	3.17**	0.05
σ_w^2	4.70**	0.08	4.39**	0.08	5.79**	0.10	4.93**	0.09

** Significant at 5% level   * Significant at 10% level

Table 6.4B Daily High Temperature Process Model

Parameter	Luverne		Morris		Preston		Rush City	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
κ	0.11**	0.00	0.10**	0.00	0.11**	0.00	0.11**	0.00
κ_s	0.15**	0.00	0.13**	0.00	0.16**	0.00	0.14**	0.00
κ_w	0.10**	0.00	0.09**	0.00	0.10**	0.00	0.10**	0.00
λ	0.01*	0.00	0.31**	0.03	0.04**	0.01	0.21**	0.02
λ_s	0.00	0.00	0.45**	0.05	0.06**	0.01	0.22**	0.03
λ_w	0.05**	0.02	0.22**	0.05	0.02	0.01	0.28**	0.05
θ	-0.23**	0.08	0.61**	0.09	0.15**	0.07	0.47**	0.08
θ_s	-0.13	0.11	0.69**	0.13	0.17	0.11	0.45**	0.12
θ_w	-0.45**	0.17	0.42**	0.19	-0.01	0.17	0.49**	0.17
δ^2	3.95**	0.06	4.23**	0.07	3.78**	0.06	3.73**	0.06
δ_s^2	2.84**	0.09	2.96**	0.10	2.68**	0.09	2.90**	0.09
δ_w^2	4.47**	0.14	5.02**	0.16	4.31**	0.14	4.26**	0.14
σ^2	4.01**	0.03	4.59**	0.04	3.77**	0.03	4.07**	0.03
σ_s^2	2.99**	0.05	3.71**	0.06	2.89**	0.05	3.25**	0.06
σ_w^2	4.65**	0.08	4.97**	0.08	4.23**	0.07	4.53**	0.07

** Significant at 5% level * Significant at 10% level

Note: Subscripts “s” and “w” stand for summer and winter, respectively.

In Table 6.5 we report the estimation result of the precipitation process model. The estimated parameters of the model explain the historical precipitation process well in the four counties. Preston and Rush City are located in the east, and they have relatively larger amounts of precipitation compared to Luverne and Morris in the west. The estimated transition probability from dryness to rainfall (q^{01}) and from rainfall to rainfall (q^{11}) are higher, and the β parameter of the gamma distribution (which determines to what extent extremely heavy rainfall occurs) are larger for Preston and Rush City compared to Luverne and Morris, respectively. Precipitation option prices using the daily simulation method are calculated over 10,000 simulated precipitation processes based on the estimated parameters of this precipitation process model.

Table 6.5 Precipitation Process Model

The precipitation process model uses a two-part model:

$P_t = P_{t-1} \cdot q_t^{11} + (1 - P_{t-1}) \cdot q_t^{01}$, for $t = 1,2,\ldots,T$

$$f(Y_t \mid X_t = 1) = \frac{Y_t^{\alpha-1} \exp(-Y_t / \beta)}{\beta^{\alpha}\Gamma(\alpha)}, \quad Y_t, \alpha, \beta > 0$$

In the first equation, P_t, q_t^{11}, and q_t^{01} represent the probability of rainfall occurrence at day t, the transition probability from rainfall at day t-1 to rainfall at day t, and the transition probability from dryness at day t-1 to rainfall at day t, respectively. In the second equation, gamma distribution function, Y_t is the amount of precipitation, given X_t=1 when day t is rainy. The α and β are shape and scale parameters of the gamma distribution function, respectively. Subscript "6", "7", and "8" stand for "June", "July", and "August" respectively.

Parameter	Luverne	Morris	Preston	Rush City
q^{01}_6	0.27	0.33	0.31	0.33
q^{01}_7	0.23	0.30	0.28	0.29
q^{01}_8	0.21	0.26	0.27	0.28
q^{11}_6	0.44	0.48	0.48	0.50
q^{11}_7	0.34	0.40	0.37	0.38
q^{11}_8	0.37	0.40	0.42	0.38
α_6	0.61	0.63	0.61	0.62
α_7	0.61	0.63	0.61	0.62
α_8	0.62	0.64	0.62	0.61
β_6	17.95	13.81	18.43	15.74
β_7	17.84	14.60	18.57	16.50
β_8	16.23	13.16	17.21	17.99

Valuation of Weather Options and Crop Insurance

The weather option prices (or premiums) for soybean obtained by applying the burn-rate analysis and the daily simulation method are reported in Table 6.6. The tick values and option prices are measured in 2007 dollars, using the 2007 maximum price election of $7.00/bu. for soybean in order to compare with the 2007 MPCI premiums. To observe the relative option price level, we also report the prices as the percent of the 2007 soybean revenue per acre in parenthesis. The "w/Basis Risk" variable is the option price calculated under the local basis risk of $(1 – R^2)$ in the yield response model. Local basis risk is interpreted as the hedging gap caused by an imperfect weather yield relationship in the same geographic location. The "w/o Basis Risk" variable reflects weighted option prices by adjusting each price by the corresponding R^2 measure, assuming 100% of R^2 provides perfect coverage. For example at Luverne, the total price as calculated by daily simulation (DS) for both the precipitation call and put options is $4.24 per acre under the local basis risk of 0.56 ($R^2 = 0.44$). The weighted option price assuming no local basis risk ($R^2 = 1.00$) is $9.64 per acre, which is calculated by dividing $4.24 by 0.44. This adjustment is an approximate measure to compare the weighted hedging cost for weather options and MPCI (which has no basis risk but insures up to 85 percent of the farmer's APH yield) at the same coverage level.

The option prices calculated by daily simulation (DS) are slightly lower than the prices derived from burn-rate analysis (BA). At Luverne total option price (w/Basis Risk) calculated by daily simulation is $4.24 which is lower than $5.57 calculated by BA. The other three locations also show slightly lower option prices calculated by daily simulation than those by burn-rate analysis. This result is consistent with previous studies (Odening, Musshoff, and Xu, 2007; Richards,

Table 6.6 Weather Option Prices for Soybean

Location	Precipitation Options		GDD Options		Both Options	
	Put (%)[a]	Call (%)	Put (%)	Call (%)	w/Basis Risk	w/o Basis Risk
Luverne						
Strike[b]	8.09	15.58	- [e]	-		
Tick[c]	$8.11	$8.11	-	-		
Price:BA[d]	$3.51 (0.99%)	$2.06 (0.58%)	-	-	$5.57 (1.57%)	$12.66 (3.57%)
Price: DS[d]	$2.79 (0.78%)	$1.45 (0.41%)	-	-	$4.24 (1.19%)	$9.64 (2.72%)
Morris						
Strike	7.56	16.62	1,521	1,898		
Tick	$6.30	$6.30	$0.14	$0.14		
Price: BA	$1.39 (0.49%)	$0.00 (0.00%)	$1.46 (0.51%)	$0.16 (0.06%)	$3.01 (1.05%)	$14.33 (5.02%)
Price: DS	$1.00 (0.35%)	$0.33 (0.12%)	$1.14 (0.40%)	$0.04 (0.01%)	$2.51 (0.88%)	$11.95 (4.18%)
Preston						
Strike	10.61	22.59	1,622	2,358		
Tick	$4.41	$4.41	$0.11	$0.11		
Price: BA	$2.62 (0.75%)	$0.08 (0.02%)	$1.91 (0.55%)	$0.00 (0.00%)	$4.61 (1.33%)	$20.95 (6.02%)
Price: DS	$1.67 (0.48%)	$0.13 (0.04%)	$1.65 (0.47%)	$0.00 (0.00%)	$3.45 (0.99%)	$15.68 (4.51%)
Rush City						
Strike	11.46	24.89	1,551	- [e]		
Tick	$4.88	$4.88	$0.08	-		
Price: BA	$3.90 (2.08%)	$0.00 (0.00%)	$2.60 (1.38%)	-	$6.50 (3.46%)	$18.57 (9.90%)
Price: DS	$4.10 (2.18%)	$0.02 (0.01%)	$2.19 (1.17%)	-	$6.31 (3.36%)	$18.03 (9.61%)

Note: a) Option price represented as a percent (in the parenthesis) is calculated as a percent of the soybean revenue per acre (county average based on the price election $7.00/bu. per acre) in 2007. b) Strike is the predetermined level by contract at which the put (call) option buyer can sell (buy) the weather event to the option seller. The unit of strike for precipitation options is inch and the unit of strike for GDD options is degree days. c) Tick value is the indemnity payments per unit of adverse weather event (per inch for precipitation options and per degree for temperature options). The tick values and option prices are measured per acre. d) BA and DS represent the burn-rate and the daily simulation, respectively. e) Not available because we do not purchase the options based on the estimated yield response functions (See Figure 6.1A (GDD) and Figure 6.1D (GDD).)

Manfredo, and Sanders, 2004). To explain the relatively lower prices calculated by daily simulation, Richards, Manfredo, and Sanders (2004) point out that weighting the occurrence of irregular discrete jumps by their probability significantly reduces their ultimate impact on the daily simulated option values. On the other hand, Odening, Musshoff, and Xu (2007) note that daily precipitation models should be used with some caution in the context of derivative pricing, because they tend to underestimate rainfall variability. To show the less variable rainfall index by daily simulation, they present the mean and the standard deviation of their rainfall index distribution obtained by applying burn-rate and daily simulation. Nevertheless, we use the option prices calculated by daily simulation because a daily temperature model is widely used in the literature to construct temperature-based weather indexes and a daily precipitation model is often used by meteorologists and agricultural scientists. Simulated total prices (w/Basis Risk) for both precipitation and GDD put and call options range from \$2.51 to \$6.31 per acre (or 0.88% to 3.36% of revenue from soybean) across locations.

In Table 6.7 we report the weather options for corn which are calculated by the two methods: burn rate and daily simulation. Total prices with basis risk for both options by applying the daily simulation method range from \$2.42 to \$5.51 per acre (or 0.50% to 1.00% of revenue from corn) across locations. The option prices for corn as a percent of revenue with basis risk (0.50% to 1.00%) are lower than those for soybean (0.88% to 3.36% in Table 6.6). However, the adjusted option prices for corn without basis risk range from 2.63% to 11.22% of revenue across locations, and they are similar to those for soybean (2.72% to 9.61% of revenue across locations).

Table 6.7 Weather Option Prices for Corn

Location	Precipitation Options		GDD Options		Both Options	
	Put (%)[a)]	Call (%)	Put (%)	Call (%)	w/Basis Risk	w/o Basis Risk
Luverne						
Strike[b)]	7.73	16.50	1,362	2,023		
Tick[c)]	$13.84	$13.84	$0.19	$0.19		
Price:BA[d)]	$4.84 (0.87%)	$2.39 (0.43%)	$0.00 (0.00%)	$0.26 (0.05%)	$7.49 (1.35%)	$20.24 (3.65%)
Price: DS[d)]	$3.76 (0.68%)	$1.55 (0.28%)	$0.00 (0.00%)	$0.20 (0.04%)	$5.51 (1.00%)	$14.89 (2.68%)
Morris						
Strike	6.30	14.55	1,476	1,865		
Tick	$13.43	$13.43	$0.28	$0.28		
Price: BA	$0.82 (0.17%)	$0.74 (0.15%)	$1.81 (0.37%)	$0.83 (0.17%)	$4.20 (0.85%)	$21.00 (4.27%)
Price: DS	$0.62 (0.13%)	$2.42 (0.49%)	$1.34 (0.27%)	$0.35 (0.07%)	$4.73 (0.96%)	$23.65 (4.81%)
Preston						
Strike	9.40	23.36	1,543	1,907		
Tick	$7.18	$7.18	$0.23	$0.23		
Price: BA	$2.39 (0.40%)	$0.04 (0.01%)	$1.26 (0.21%)	$0.88 (0.15%)	$4.57 (0.77%)	$24.05 (4.07%)
Price: DS	$1.27 (0.21%)	$0.14 (0.02%)	$0.97 (0.16%)	$0.58 (0.10%)	$2.96 (0.50%)	$15.58 (2.63%)
Rush City						
Strike	9.78	19.38	1,409	1,927		
Tick	$5.07	$5.07	$0.08	$0.08		
Price: BA	$1.70 (0.55%)	$0.37 (0.12%)	$0.45 (0.14%)	$0.00 (0.00%)	$2.52 (0.82%)	$36.00 (11.69%)
Price: DS	$1.74 (0.56%)	$0.38 (0.12%)	$0.30 (0.10%)	$0.00 (0.00%)	$2.42 (0.79%)	$34.57 (11.22%)

Note: a) Option price represented as a percent (in the parenthesis) is calculated as a percent of the corn revenue per acre (county average based on the price election $3.50/bu. per acre) in 2007.
b) Strike is the predetermined level by contract at which the put (call) option buyer can sell (buy) the weather event to the option seller. The unit of strike for precipitation options is inch and the unit of strike for GDD options is degree days. c) Tick value is the indemnity payments per unit of adverse weather event (per inch for precipitation options and per degree for temperature options). The tick values and option prices are measured per acre. d) BA and DS represent the burn-rate and the daily simulation, respectively.

Comparison of Hedging Cost and Effectiveness

In Table 6.8 and 6.9 we compare the prices of weather options to those of the two crop insurance products, multi-peril crop insurance (MPCI) and group risk plan (GRP), for soybean and corn, respectively. The prices of weather options and GRP are calculated at the county level, while MPCI premiums are computed at the farm level. The prices of weather options for soybean and corn come from the Table 6.6 and 6.7, respectively (See the prices using daily simulation for both precipitation and GDD options in the tables). For crop insurance prices, the "85%" coverage variable means that the premium is calculated at the 85% coverage level, the highest level in the MPCI plan and the second highest level in the GRP, and "100%" coverage variable is the adjusted premium recalculated at the 100% coverage level (even though full coverage insurance is not provided in the market). The first two rows of MPCI prices in each location, 85% (38%) and 100% (38%) coverage prices, are the premium amounts paid by the farmer under 38% government subsidy. Under the government subsidy the farmer pays only 62% of the total premium and the remaining 38% is subsidized by the government. The GRP at the 85% coverage level is provided with 59% subsidy rate so that farmers pay only 41% of the total premium. Subsidy rates, which are set by the Agricultural Risk Protection Act of 2000, vary by coverage level and type of insurance. The last row of each location, 100% (0%) coverage price, is the total premium at the 100% coverage level, assuming no subsidy is provided. The price coverage election is assumed to be 100% of the maximum price, $7.00 per bushel for soybean and $3.50 per bushel for corn in 2007. The average Actual Production History (APH) 10Y for each county is calculated as a simple average of the county-level yields for ten consecutive years from 1997 to 2006.

Table 6.8 Comparison of Prices between Weather Options and Crop Insurance for Soybean

Location	Weather Option		MPCI (Price Election: $7.00/bu. in 2007)		GRP (Price Election: $7.00/bu. in 2007)	
	Coverage	Price (%)[a)]	Coverage (Gov. Subsidy)	Price (%)[a)]	Coverage (Gov. Subsidy)	Price (%)[a)]
Luverne	44%	$ 4.24 (1.19%)	85% (38%)[b)]	$12.15 (3.42%)	85% (59%)[b)]	$ 5.44 (1.53%)
(Avg. APH 10Y =	100%	$ 9.64 (2.72%)	100% (38%)	$14.29 (4.03%)	100% (59%)	$ 6.40 (1.80%)
45.0 bu./acre)[c)]			100% (0%)	$23.06 (6.50%)	100% (0%)	$15.61 (4.40%)
Morris	21%	$ 2.51 (0.88%)	85% (38%)	$14.30 (5.01%)	85% (59%)	$ 5.20 (1.82%)
(Avg. APH 10Y =	100%	$11.95 (4.19%)	100% (38%)	$16.82 (5.89%)	100% (59%)	$ 6.12 (2.14%)
38.7 bu./acre)			100% (0%)	$27.13 (9.51%)	100% (0%)	$14.93 (5.23%)
Preston	22%	$ 3.45 (0.99%)	85% (38%)	$17.17 (4.93%)	85% (59%)	$ 3.17 (0.91%)
(Avg. APH 10Y =	100%	$15.68 (4.50%)	100% (38%)	$20.20 (5.80%)	100% (59%)	$ 3.73 (1.07%)
44.6 bu./acre)			100% (0%)	$32.58 (9.36%)	100% (0%)	$ 9.10 (2.61%)
Rush City	35%	$ 6.31 (3.37%)	85% (38%)	$14.95 (7.98%)	85% (59%)	$ 3.96 (2.11%)
(Avg. APH 10Y =	100%	$18.03 (9.63%)	100% (38%)	$17.59 (9.39%)	100% (59%)	$ 4.66 (2.49%)
32.0 bu./acre)			100% (0%)	$28.37 (15.15%)	100% (0%)	$11.37 (6.07%)

Note: a) Prices represented as a percent (in the parenthesis) are calculated as a percent of the soybean revenue per acre (county average based on the price election $7.00/bu. per acre) in 2007. b) The "85%" coverage variable means that the crop insurance premium is calculated at the 85% coverage level, and "100%" coverage variable is the adjusted premium recalculated at the 100% coverage level. The "38%" in the parenthesis for MPCI ("59%" in the parenthesis for GRP) represent the government subsidy rate. c) The average Actual Production History (APH) 10Y is a simple average of the county-level soybean yields for ten consecutive years from 1997 to 2006.

Table 6.9 Comparison of Prices between Weather Options and Crop Insurance for Corn

Location	Weather Option		MPCI (Price Election: $3.50/bu. in 2007)		GRP (Price Election: $3.50/bu. in 2007)	
	Coverage	Price (%)[a)]	Coverage (Gov. Subsidy)	Price (%)[a)]	Coverage (Gov. Subsidy)	Price (%)[a)]
Luverne	37%	$ 5.51 (0.99%)	85% (38%)[b)]	$20.79 (3.75%)	85% (59%)[b)]	$11.98 (2.16%)
(Avg. APH 10Y =	100%	$14.89 (2.68%)	100% (38%)	$24.46 (4.41%)	100% (59%)	$14.09 (2.54%)
151.0 bu./acre)[c)]			100% (0%)	$39.45 (7.11%)	100% (0%)	$34.38 (6.20%)
Morris	20%	$ 4.73 (0.96%)	85% (38%)	$24.77 (5.03%)	85% (59%)	$10.41 (2.12%)
(Avg. APH 10Y =	100%	$23.65 (4.81%)	100% (38%)	$29.14 (5.92%)	100% (59%)	$12.25 (2.49%)
153.3 bu./acre)			100% (0%)	$47.00 (9.55%)	100% (0%)	$29.87 (6.07%)
Preston	19%	$ 2.96 (0.50%)	85% (38%)	$23.24 (3.93%)	85% (59%)	$ 6.86 (1.16%)
(Avg. APH 10Y =	100%	$15.58 (2.64%)	100% (38%)	$27.34 (4.63%)	100% (59%)	$ 8.07 (1.37%)
158.6 bu./acre)			100% (0%)	$44.10 (7.46%)	100% (0%)	$19.68 (3.33%)
Rush City	7%	$ 2.42 (0.79%)	85% (38%)	$24.91 (8.13%)	85% (59%)	$ 8.13 (2.65%)
(Avg. APH 10Y =	100%	$34.57 (11.29%)	100% (38%)	$29.31 (9.57%)	100% (59%)	$ 9.56 (3.12%)
115.1 bu./acre)			100% (0%)	$47.27 (15.43%)	100% (0%)	$23.33 (7.62%)

Note: a) Prices represented as a percent (in the parenthesis) are calculated as a percent of the soybean revenue per acre (county average based on the price election $3.50/bu. per acre) in 2007. b) The "85%" coverage variable means that the crop insurance premium is calculated at the 85% coverage level, and "100%" coverage variable is the adjusted premium recalculated at the 100% coverage level. The "38%" in the parenthesis for MPCI ("59%" in the parenthesis for GRP) represent the government subsidy rate. c) The average Actual Production History (APH) 10Y is a simple average of the county-level soybean yields for ten consecutive years from 1997 to 2006.

The approximate MPCI premiums for soybean at the 100% coverage level with no government subsidy range from $23.06/acre at Luverne to $32.58/acre at Preston (Table 6.8). They are much higher than the corresponding weather option premiums, which range from $9.64/acre at Luverne to $18.03/acre at Rush City at the 100% coverage level. Main reason of the higher MPCI premiums compared with weather options is that MPCI premium is calculated at the individual farm level which reflects larger yield variability, while the weather option premium is calculated at the county level which removes the individual farmer's yield variability.

When we compare the weather option premiums with GRP premiums at the 100% coverage level with no subsidy, the gaps between the two premiums are much smaller. This is because both weather options and GRP premiums are measured at the same county level. However, the gaps between the two premiums are mixed across locations. The GRP premiums at the 100% coverage without subsidy for Luverne and Morris, $15.61/acre and $14.93/acre, are higher than the corresponding weather option premiums, $9.64/acre and $11.95/acre, respectively. On the other hand, The GRP premiums for Preston and Rush City, $9.10/acre and $11.37/acre, are lower than the corresponding weather option premiums, $15.68/acre and $18.03/acre, respectively. Table 6.9, which presents the comparison of prices between weather options and crop insurance for corn, shows the similar result to Table 6.8 for soybean.

In Table 6.10 we compare hedging effectiveness indicators for soybean in our four locations, when using alternative hedging strategies at the farm level to analyze weather options as a more effective risk management tool for individual farmers in various scenarios. The comparison of hedging effectiveness for corn among alternative hedging strategies is similar to that for soybean and is reported in Appendix IV. The seven alternative hedging strategies include: "no hedge," "MPCI with no subsidy," "MPCI with subsidy," "GRP with no subsidy," "GRP with subsidy," "Local station-based weather options," and "Minneapolis-based weather options." For the farm-level risk indicators we take the average of the individual 24 farm risk indicators in each location, based on the 10,000 simulated yields and corresponding cost estimates for each individual farm.

We find that the hedging effectiveness of weather options compared with no hedge at the farm level is limited. Higher Sharpe ratio, VaR, certainty equivalent, and lower risk premium imply higher hedging effectiveness. Most of our risk indicators by using weather options at the farm level are not significantly improved compared with no hedge and are even worse when compared with both MPCI and GRP hedges. For example at Luverne, the Sharpe ratio, VaR, certainty equivalent at γ=0.005, and risk premium at γ=0.005 by using local weather options are 1.240, \$35.03, \$147.86, and \$34.39, respectively, and they are slightly improved from 1.226, \$32.69, \$146.73, and \$35.55 with no hedge. They are even worse than 1.322, \$61.07, \$151.47, and \$24.22 by using MPCI with no government subsidy. Vedenov and Barnett (2004) also suggest there is only limited efficacy of weather derivatives in hedging disaggregated production exposures due to large yield variability at the farm level. MPCI insures the highly variable individual farm-level yields relatively better than weather derivatives do, because MPCI covers individual farm-level losses directly. Even GRP based on the county-level yield provides better hedging effectiveness to individual farmers compared with weather options. This shows the limitation of weather options as an effective hedging tool for individual farmers at the farm level mainly due to hedging gap caused by imperfect relationship between weather and crop yield.

Table 6.10 Comparison of Hedging Effectiveness of Crop Insurance and Weather Options for Soybean

This table compares the risk indicators (Sharpe Ratio, Value at Risk, Certainty Equivalent, Risk Premium) when using alternative hedging strategies (No Hedge, MPCI with No Subsidy, MPCI with Subsidy, GRP with No Subsidy, GRP with Subsidy, Local Station-based Weather Options, and Minneapolis-based Weather Options) at the farm level. Sharpe Ratio is calculated under the assumption of risk free rate of 0.05. Value at Risk (VaR) is measured at the 10% confidence interval. Certainty Equivalent (CE) and Risk Premium (RP) are measured at the three different levels of risk aversion (γ=0.001, 0.005, 0.009).

		Farm Level (Average of Farms)						
Location	Indicator	No Hedge	MPCI (No Sub.)	MPCI (Subsidy)	GRP (No Sub.)	GRP (Subsidy)	Option (Local)	Option (Mpls.)
Luverne	Net Income	$182.28	$175.69	$183.29	$183.52	$191.35	$182.25	$183.28
	Sharpe Ratio	1.226	1.322	1.381	1.387	1.449	1.240	1.247
	VaR (10%)	$32.69	$61.07	$68.69	$65.65	$73.48	$35.03	$36.07
	CE(γ=0.001)	$174.76	$170.14	$177.74	$177.88	$185.71	$174.94	$175.98
	CE(γ=0.005)	$146.73	$151.47	$159.07	$158.62	$166.45	$147.86	$148.89
	CE(γ=0.009)	$120.70	$137.05	$144.65	$143.44	$151.27	$122.97	$124.01
	RP(γ=0.001)	$7.52	$5.55	$5.55	$5.65	$5.65	$7.31	$7.31
	RP(γ=0.005)	$35.55	$24.22	$24.22	$24.90	$24.90	$34.39	$34.39
	RP(γ=0.009)	$61.57	$38.64	$38.64	$40.08	$40.08	$59.27	$59.27
Morris	Net Income	$118.77	$111.79	$120.58	$119.36	$126.85	$118.78	$118.35
	Sharpe Ratio	0.669	0.675	0.724	0.715	0.755	0.671	0.669
	VaR (10%)	-$56.36	-$16.80	-$8.01	-$18.30	-$10.82	-$55.24	-$55.68
	CE(γ=0.001)	$108.67	$104.56	$113.35	$111.67	$119.16	$108.79	$108.35
	CE(γ=0.005)	$71.28	$80.81	$89.60	$86.08	$93.57	$71.82	$71.38
	CE(γ=0.009)	$37.15	$63.19	$71.98	$66.84	$74.32	$38.12	$37.68
	RP(γ=0.001)	$10.11	$7.23	$7.23	$7.69	$7.69	$10.00	$10.00
	RP(γ=0.005)	$47.50	$30.98	$30.98	$33.28	$33.28	$46.96	$46.96
	RP(γ=0.009)	$81.62	$48.60	$48.60	$52.52	$52.52	$80.67	$80.67

Table 6.10 - Continued

		Farm Level (Average of Farms)						
Location	Indicator	No Hedge	MPCI (No Sub.)	MPCI (Subsidy)	GRP (No Sub.)	GRP (Subsidy)	Option (Local)	Option (Mpls.)
Preston	Net Income	$175.70	$159.93	$170.66	$180.70	$185.26	$175.71	$176.19
	Sharpe Ratio	0.893	0.848	0.906	0.969	0.994	0.895	0.900
	VaR (10%)	-$0.43	$17.13	$27.85	$29.69	$34.25	$0.07	$1.27
	CE(γ=0.001)	$165.05	$151.89	$162.62	$172.27	$176.83	$165.09	$165.66
	CE(γ=0.005)	$124.17	$125.24	$135.97	$143.71	$148.28	$124.36	$125.25
	CE(γ=0.009)	$80.37	$104.93	$115.66	$121.36	$125.92	$80.59	$81.83
	RP(γ=0.001)	$10.66	$8.04	$8.04	$8.43	$8.43	$10.62	$10.53
	RP(γ=0.005)	$51.53	$34.70	$34.70	$36.99	$36.99	$51.35	$50.94
	RP(γ=0.009)	$95.33	$55.00	$55.00	$59.34	$59.34	$95.12	$94.37
Rush City	Net Income	$58.99	$54.16	$63.51	$58.99	$59.52	$68.42	$74.11
	Sharpe Ratio	0.386	0.379	0.463	0.388	0.394	0.493	0.544
	VaR (10%)	-$92.56	-$46.04	-$36.69	-$91.24	-$90.10	-$38.40	-$32.71
	CE(γ=0.001)	$51.14	$49.06	$58.41	$51.24	$51.83	$63.01	$68.71
	CE(γ=0.005)	$22.30	$32.40	$41.75	$22.76	$23.58	$45.16	$50.86
	CE(γ=0.009)	-$4.64	$20.12	$29.47	-$3.93	-$2.92	$31.79	$37.49
	RP(γ=0.001)	$7.85	$5.10	$5.10	$7.75	$7.69	$5.40	$5.40
	RP(γ=0.005)	$36.69	$21.76	$21.76	$36.23	$35.94	$23.26	$23.26
	RP(γ=0.009)	$63.63	$34.04	$34.04	$62.92	$62.44	$36.62	$36.62

Then, how can we use weather options as a hedging tool in crop production? In the federal crop insurance program, private crop insurance companies provide insurance products to farmers as an agent of the government, and transfer most of the farmers' crop risk exposures to the government. However, the government does not hedge the risk exposures transferred from the crop insurance companies. This could be considered as social cost, because the potential losses caused by not hedging risk exposures would be covered with tax-payers money. Furthermore, the government also provides a significant portion of insurance premium to farmers in the form of government subsidy. Although idiosyncratic crop yield risk can be reduced by the government through aggregating the individual risk exposures at the county or higher level, the government still faces the systemic weather risk without any risk hedge.

Thus, we observe whether and how the government uses weather options as an effective risk management tool to reduce the social cost. Suppose that the government provides GRP products with subsidy to farmers, and hedges the crop risk exposures by purchasing weather options at the county level. Table 6.11 and 6.12 compare the net income and value at risk (VaR) of the government between no hedge, local station-based weather options hedge, and Minneapolis-based weather options hedge for soybean and corn, respectively, for our four counties. The net income of the government from the federal crop insurance program is computed as "GRP premium received from farmers – GRP indemnity payments paid to farmers – weather options premium paid to the option provider for risk hedge + weather options payoffs received from the option provider." We assume no other administrative costs in the calculation. The net income and VaR of the government is calculated over the 10,000 simulated county-level crop yields for each of the four counties. The only risk indicator we compare for the government is VaR. We do not measure Sharpe ratio of the government, because it is hard to evaluate the federal service cost to calculate Sharpe ratio. In addition, certainty equivalent and risk premium at various levels of risk for the government is not appropriate because the government is risk neutral.

Table 6.11 Weather Options Used by the Government at the County Level: Soybean

			County Level	
		No Hedge	Option	Option
Location	Indicator	(Subsidy)	(Local)	(Mpls.)
Luverne	Net Income	$ 0.57	$ 0.54	$ 1.58
	VaR (10%)	-$10.58	-$ 7.24	-$ 6.20
Morris	Net Income	-$ 1.88	-$ 1.87	-$ 2.31
	VaR (10%)	-$22.81	-$22.08	-$22.52
Preston	Net Income	$ 0.04	$ 0.04	$ 0.53
	VaR (10%)	-$ 0.84	-$ 0.47	$ 0.02
Rush City	Net Income	-$ 5.65	-$ 5.65	-$ 5.12
	VaR (10%)	-$34.39	-$33.34	-$32.38

Table 6.12 Weather Options Used by the Government at the County Level: Corn

			County Level	
		No Hedge	Option	Option
Location	Indicator	(Subsidy)	(Local)	(Mpls.)
Luverne	Net Income	$ 3.73	$ 3.68	$ 5.14
	VaR (10%)	-$14.67	-$ 9.27	-$ 7.81
Morris	Net Income	-$ 1.27	-$ 1.24	-$ 2.28
	VaR (10%)	-$35.99	-$32.86	-$33.89
Preston	Net Income	$ 1.26	$ 1.27	$ 1.52
	VaR (10%)	-$ 6.17	-$ 6.21	-$ 4.34
Rush City	Net Income	$ 0.57	$ 0.56	$ 1.25
	VaR (10%)	-$21.72	-$20.30	-$19.50

We find the government's VaR indicator improves from -\$10.58/acre with no hedge to -\$6.20/acre by using Minneapolis-based options in Luverne (Table 6.11). All other counties show improved VaR of the government by using either local station-based weather options or Minneapolis-based weather options to hedge soybean yield risk exposures. Table 6.12 also shows the improved VaR indicators of the government by using weather options to hedge corn yield risk exposures at the county level across the four locations. This confirms that weather options can be used by the government as an effective hedging tool at the county or higher level for reducing social cost.

Since local weather options based on our four specific counties are not traded due to liquidity and fair pricing problems in the market, we use Chicago Mercantile Exchange (CME) options based on several large reference cities near to the counties. Here we need to consider geographic basis risk which is caused by the difference between the weather index at a CME reference city and at a specific farm location. Geographic basis risk is measured as the difference in hedging effectiveness between local and non-local derivatives. When we compare our risk indicators between "Option (Local)" and "Option (Minneapolis)" in Table 6.10~6.12, the difference is very small both at the farm and county level. For example at Luverne in Table 6.10, Sharpe Ratio, VaR, CE(γ=0.001), and RP(γ=0.001) by using local weather options are 1.240, \$35.03, \$174.94, and \$7.31, respectively, and they are close to 1.247, \$36.07, \$175.98, and \$7.31 by using Minneapolis-based weather options. This implies that geographic basis risk is minimal in southern Minnesota. Woodard and Garcia (2007) also find that the geographic basis risk from hedging with non-local contracts is small when they compare hedging effectiveness between local options (based on nine Illinois Crop Reporting Districts) and non-local options (based on nearby major cities).

This result is interesting since the conventional wisdom is that geographic basis risk may be a large impediment to the implementation of weather hedges in the agricultural industry. It is likely due to the fact that Midwest area including Minnesota and Illinois have relatively homogeneous (or less variable) weather conditions across the counties when compared to other U.S. regions. In particular the correlations of daily temperature between Minneapolis and each of the four local stations in this study are higher than 90%. Even though daily precipitation tends to be less spatially correlated, growing season precipitation (on which our precipitation options are based) shows a relatively high correlation close to 50% between Minneapolis and each of the four local stations. The result here indicates that we can hedge local weather risk with Minneapolis-based weather derivatives in southern Minnesota, since the geographic basis risk is not large. However, this approach should be applied cautiously to other locations, crops, or other types of weather derivatives considering spatial correlation of crop losses and weather variables across the locations. For example, Odening, Musshoff, and Xu (2007) show the geographical basis risk is significantly large based on their study with only rainfall options for hedging wheat production risk in Brandenburg, Germany during 1993-2005.

Table 6.13 and 6.14 illustrate the effect of spatial aggregation by using weather options evidently where we compare farm level ("Average of Farms"), county level ("Average of Counties"), and four-county aggregate level ("Aggregated") for soybean and corn, respectively. The "Average of Farms" column statistics are calculated as the average of the individual 96 farm indicators in our four counties (24 farms for each of the four counties). The "Average of Counties" column statistics are calculated as the average of the individual four county indicators. The four-county "Aggregated" results are obtained by averaging the data across counties (i.e., aggregating) and then performing the analysis.

All risk indicators using Minneapolis-based options improve as the level of aggregation increases from the farm level to the four-county aggregate level. In Table 6.13 for soybean, Sharpe ratio and VaR by using Minneapolis-based weather options increase remarkably from 0.803 to 1.506 and from -$27.11 to $35.39, respectively, as the level of spatial aggregation increases, implying an increase in hedging effectiveness with spatial aggregation. Certainty equivalent and risk premium are also improved at all levels of risk aversion as the level of spatial aggregation increases. Table 6.14 shows that weather options hedging effectiveness increases with the level of spatial aggregation for corn, which is consistent to Table 6.13 for soybean. This implies that reinsurers including the government could reduce idiosyncratic or individual farm-level yield risk by aggregating individual production exposures and hedging the remaining systematic weather risk by using spatially-aggregated weather derivatives. As a result, weather derivatives could be considered as an effective hedging tool by the government to reduce the social cost of crop insurance.

Table 6.13 Weather Options Hedging Effectiveness and Spatial Aggregation for Soybean

This table compares the risk indicators (Sharpe Ratio, Value at Risk, Certainty Equivalent, Risk Premium) when using Local Station-based Weather Options and Minneapolis-based Weather Options at the farm level, county level, and multi-county level in order to show the spatial aggregation effect. Sharpe Ratio is calculated under the assumption of risk free rate of 0.05. Value at Risk (VaR) is measured at the 10% confidence interval. Certainty Equivalent (CE) and Risk Premium (RP) are measured at the three different levels of risk aversion (γ=0.001, 0.005, 0.009).

Options	Indicator	Average of Farms	Four Counties Average of Counties	Aggregated
Local-based	Net Income	$133.93	$134.69	-
	Sharpe Ratio	0.799	1.221	-
	VaR (10%)	-$27.85	$13.43	-
	CE (γ=0.001)	$125.02	$130.21	-
	CE (γ=0.005)	$91.70	$112.29	-
	CE (γ=0.009)	$59.44	$94.36	-
	RP (γ=0.001)	$8.92	$4.48	-
	RP (γ=0.005)	$42.23	$22.40	-
	RP (γ=0.009)	$74.50	$40.33	-
Minneapolis-based	Net Income	$134.34	$135.09	$130.95
	Sharpe Ratio	0.803	1.229	1.506
	VaR (10%)	-$27.11	$14.11	$35.39
	CE (γ=0.001)	$125.46	$130.65	$128.17
	CE (γ=0.005)	$92.28	$112.87	$117.02
	CE (γ=0.009)	$60.15	$95.11	$105.82
	RP (γ=0.001)	$8.88	$4.44	$2.78
	RP (γ=0.005)	$42.06	$22.22	$13.92
	RP (γ=0.009)	$74.19	$39.98	$25.13

Table 6.14 Weather Options Hedging Effectiveness and Spatial Aggregation for Corn

Options	Indicator	Four Counties		
		Average of Farms	Average of Counties	Aggregated
Local-based	Net Income	$175.70	$165.45	-
	Sharpe Ratio	0.799	1.237	-
	VaR (10%)	-$34.16	$19.46	-
	CE (γ=0.001)	$160.53	$158.86	-
	CE (γ=0.005)	$106.51	$132.59	-
	CE (γ=0.009)	$55.37	$106.59	-
	RP (γ=0.001)	$15.17	$6.59	-
	RP (γ=0.005)	$69.19	$32.85	-
	RP (γ=0.009)	$120.33	$58.85	-
Minneapolis-based	Net Income	$176.04	$165.79	$156.10
	Sharpe Ratio	0.802	1.242	1.604
	VaR (10%)	-$33.65	$20.11	$51.51
	CE (γ=0.001)	$160.89	$159.22	$152.69
	CE (γ=0.005)	$106.94	$133.03	$138.53
	CE (γ=0.009)	$55.86	$107.10	$118.30
	RP (γ=0.001)	$15.15	$6.57	$3.42
	RP (γ=0.005)	$69.10	$32.76	$17.57
	RP (γ=0.009)	$120.18	$58.68	$37.80

Chapter Ⅶ

Conclusion

Summary and Implications

We analyze weather derivatives as a potential risk management tool for soybean and corn production in southern Minnesota compared with unsubsidized crop insurance for solving the problems of asymmetric information and systemic weather risk. For this purpose we price the growing degree days and precipitation options by a daily simulation method that is based on the estimated temperature and precipitation process models. Hedging cost and several risk indicators are compared between weather options and crop insurance in various scenarios. Based on this analysis we observe how weather options can be used as an effective risk hedging tool and whether the social cost that exists in the federal crop insurance program can be reduced by using weather derivatives.

We find that the MPCI premium with no federal subsidy is much higher than the weather option premium at the same 100% coverage level. Main reason of the higher MPCI premiums compared with weather options is that MPCI premium is calculated at the individual farm level which reflects larger yield variability, while the weather option premium is calculated at the county level which removes the individual farmer's yield variability. However, when we compare the weather option premiums with GRP premiums at the 100% coverage level with no subsidy, the gaps between the two premiums are much smaller. This is because both weather options and GRP premiums are measured at the same county level.

Against our expectation based on the conventional wisdom and previous studies, geographic basis risk is not significant in hedging our local weather risk with non-local CME weather options based on Minneapolis. This result is consistent to Woodard and Garcia (2007) for Illinois Crop Reporting District corn yields. It is likely due to the fact that the Midwest area including Minnesota and Illinois has relatively homogeneous (or less variable) weather conditions and crop yields across the counties compared to other U.S. regions. The result indicates that we can hedge local weather risk with non-local exchange market weather derivatives in southern Minnesota. However, it should be applied cautiously to other locations, crops, or other types of weather derivatives, considering spatial correlation of weather variables between a specific farm location and a weather index reference point.

The hedging effectiveness of using weather options is limited at the farm level compared with crop insurance products. This is because weather options insure against adverse weather events causing damage at the county level, while crop insurance protects farmers against the loss of their crops directly at the farm level as well as at the county level. Vedenov and Barnett (2004) also suggest there is only limited efficacy of weather derivatives in hedging disaggregated production exposures mainly due to large yield variability. Thus, individual farmers will continue to use crop insurance with government subsidy for their production risk management.

However, we observe that the hedging effectiveness of using weather options increases as the level of spatial aggregation increases from farm level to county level to multi-county aggregate level. Woodard and Garcia (2008) confirm that better weather hedging opportunities may exist at higher levels of spatial aggregation. This implies that the government as a reinsurer can reduce idiosyncratic yield risk by aggregating the individual risk exposures at the county or higher level, and hedge the remaining systemic weather risk by purchasing weather options in the financial market. As a result, weather derivatives could be used by the government as a hedging tool to reduce the social cost of the federal crop insurance program, since the government currently does not hedge their risk exposures in the program.

Suggestions for Further Research

First of all, this study can be extended to more variable crops grown in regions such as southern or western states to observe stronger hedging effectiveness of using weather derivatives compared with crop insurance. We focus on soybean and corn grown in southern Minnesota in this study. Southern Minnesota, which is located in the Corn Belt, is the relatively homogeneous and highly productive region compared with western or southern states in the United States. Weather conditions are relatively less variable so that production losses for corn and soybean have historically occurred only infrequently in southern Minnesota. Thus, the hedging effectiveness of using weather derivatives would be smaller in our locations than in the non-homogeneous regions. If we compare the hedging effectiveness of using weather derivatives and crop insurance for more variable and weather sensitive crops (such as Texas cotton or Kansas wheat), the hedging effectiveness of using weather derivatives will be greater for the crops in the non-homogeneous regions.

Second, to calculate the price of weather options we use the risk-neutral valuation method, which discounts the payoffs of the options at expiry by the risk free rate, under the assumption that the market price of weather risk is zero in this study. If there is no correlation between the weather index and an aggregate market index, then the market price of weather risk must be zero. In our four locations in southern Minnesota where weather indices are relatively less variable compared with many other states during the most years, we find the correlations between the weather index and an aggregate market index are not statistically significant except Chisago county.

However, in other regions where weather conditions are highly variable, we need to consider the market price of weather risk to calculate weather option premiums more accurately. Two different pricing models can be applied to reflect the market price of weather risk: the equilibrium asset pricing model (Cao and Wei, 2004; Richard, Manfredo, and Sanders, 2004) and the Martingale method (Huang, Shiu, and Lin, 2008).

Finally, we can consider different approaches or assumptions in estimating yield response models to improve the design of risk management using weather derivatives. For example, the design and pricing of weather derivatives up to now is strongly based on an assumption that the dependence structure between crop yields and weather variables remains unchanged over time. However, there could be temporal changes in the weather yield relationship. Bokusheva (2011) employs two different approaches, the dynamic regression analysis[2] and the copula approach[3], to measure dependence in joint distribution of yield and weather variables. He suggests that temporal changes might become more pronounced in next decades due to both climate change and more rapid technological adjustments. Thus, future research could consider a dynamic analysis in estimating yield response models to determine optimal pricing and hedging ratio of weather derivatives.

[2] Bokusheva (2011) presents the model specification with the effect of time on the parameters measuring the sensitivity of the farms' yields to a particular weather variable. Three alternative functional forms are employed: linear, logarithmic, and quadratic.

[3] A copula is a function that relates a joint cumulative distribution function to the distribution functions of the individual variables. It provides an alternative way to model joint distributions of crop yield and weather variables with great flexibility in terms of marginal distributions and dependence structure. Bokusheva concentrates on two explicit copulas – the Clayton and Gumbel copulas which are relevant for modeling joint distributions with asymmetric dependence structures.

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Appendix I: Derivation of the Likelihood Function for Temperature Process

Our stochastic differential equation (3.31) is composed of two parts: mean-reverting Brownian motion and discrete jumps. Let's consider the mean-reverting Brownian motion part first: $dWt = \kappa\,(W_t^m - Wt)\,dt + \sigma\,dz$. This Brownian motion follows a normal distribution with mean of $\kappa\,(W_t^m - Wt)$ and variance of σ^2. We know the probability distribution of our normally distributed Brownian motion is give by:

$$P(W_t) = \frac{1}{\sqrt{2\pi\sigma^2}} \times \exp\left(\frac{-(dW_t - \kappa(W_t^m - W_t))^2}{2\sigma^2}\right) \tag{A.1}$$

where exp represents the exponential function. Remember the likelihood function is the product of the individual probabilities taken over all T observations. Then, the likelihood function is given by:

$$L(W_1, W_2, ..., W_T) = P(W_1)\cdot P(W_2)\cdots P(W_T) = \frac{1}{(\sqrt{2\pi\sigma^2})^T} \times \exp\left(-\sum_{t=1}^{T}\frac{(dW_t - \kappa(W_t^m - W_t))^2}{2\sigma^2}\right). \tag{A.2}$$

Taking the logarithm of both sides yields the log-likelihood function:

$$\ln L(W_1, ..., W_T) = -\frac{T}{2}\ln(2\pi) + \sum_{t=1}^{T}\ln\left[\frac{1}{\sqrt{\sigma^2}}\exp\left(\frac{-(dW_t - \kappa(W_t^m - W_t))^2}{2\sigma^2}\right)\right]. \tag{A.3}$$

Now we move to the unexpected discrete jumps in our temperature process. The discrete jumps occur according to a Poisson process q with average arrival rate λ and the jumps size φ which is distributed as $\ln(\varphi) \sim N(\theta, \delta^2)$. We know the probability distribution of our Poisson process is given by:

$$P(n;\lambda) = \frac{\lambda^n \exp^{-\lambda}}{n!}, \tag{A.4}$$

where n is the number of jumps from 0 to N. The likelihood function is then given by:

$$L(n_1, ..., n_T) = P(n_1)\cdot P(n_2)\cdots P(n_T) = \sum_{t=1}^{T}\sum_{n=0}^{N}\frac{\lambda^n \exp^{-\lambda}}{n!}. \tag{A.5}$$

Thus, the log-likelihood function of the Poisson process is:

$$\ln \mathrm{L}(\mathrm{n}_1,\ldots,\mathrm{n}_\mathrm{T}) = -\mathrm{T}\lambda + \sum_{\mathrm{t}=1}^{\mathrm{T}}\sum_{\mathrm{n}=0}^{\mathrm{N}}\frac{\lambda^{\mathrm{n}}}{\mathrm{n}!} \qquad \text{(A.6)}$$

Combing (A.3) and (A.6) yields the log-likelihood function:

$$\ln L(W) = -T\lambda - \frac{T}{2}\ln(2\pi) + \sum_{t=1}^{T}\ln[\sum_{n=0}^{N}\frac{\lambda^n}{n!}\frac{1}{\sqrt{\sigma^2}}\times\exp(\frac{-(dW_t - \kappa(W_t^m - W_t))^2}{2(\sigma^2)})]. \qquad \text{(A.7)}$$

Finally, we include the mean and variance of the jump size, θ and δ^2, into (A.7) when the discrete jumps occur:

$$\ln L(W) = -T\lambda - \frac{T}{2}\ln(2\pi) + \sum_{t=1}^{T}\ln[\sum_{n=0}^{N}\frac{\lambda^n}{n!}\frac{1}{\sqrt{\sigma^2+\delta^2 n}}\times\exp(\frac{-(dW_t - (\kappa(W_t^m - W_t) - n\theta))^2}{2(\sigma^2+\delta^2 n)})]. \qquad \text{(A.8)}$$

Appendix II-1: Detrended County-Level Soybean Yield Series

Year (t)	Luverne		Morris		Preston		Rush City	
	Harvested	Planted	Harvested	Planted	Harvested	Planted	Harvested	Planted
1972	32.0	31.9	17.0	16.9	29.0	28.6	20.0	19.1
1973	27.5	27.5	25.4	25.2	26.3	24.8	21.5	21.2
1974	22.6	22.6	17.7	17.6	18.6	18.0	10.1	9.4
1975	32.1	32.0	21.6	21.5	22.6	22.5	15.0	14.3
1976	18.0	17.8	9.9	9.7	21.8	21.7	12.5	10.8
1977	34.5	33.5	23.3	23.1	32.1	31.7	19.2	19.0
1978	34.3	34.2	25.3	25.1	30.0	29.8	19.0	18.8
1979	30.9	30.8	24.4	24.1	26.3	26.2	21.7	21.3
1980	31.7	31.6	23.9	23.8	25.4	25.2	21.8	21.7
1981	31.6	31.3	27.1	27.0	27.7	27.6	19.2	18.7
1982	29.6	28.4	26.6	26.2	24.8	24.3	18.1	17.4
1983	29.0	29.0	26.1	25.9	25.0	25.0	21.0	20.6
1984	28.6	28.3	26.4	26.2	23.8	23.6	19.0	18.8
1985	27.3	27.1	22.1	21.4	20.3	20.0	19.5	19.2
1986	24.5	24.3	23.9	23.9	25.9	25.7	23.0	22.6
1987	31.2	30.8	24.3	24.0	30.5	30.2	24.1	24.1
1988	28.4	28.2	11.6	11.2	19.2	18.8	16.3	15.6
1989	30.3	30.1	25.6	25.3	28.0	27.9	18.2	18.1
1990	28.4	28.0	23.7	23.2	27.5	25.9	20.1	19.1
1991	28.0	27.5	27.5	26.9	29.1	28.5	19.8	19.0
1992	20.3	19.5	17.6	17.5	20.6	20.2	12.5	11.6
1993	7.9	7.2	15.3	13.3	18.3	18.2	13.0	12.6
1994	31.1	31.1	21.6	20.7	28.3	28.0	18.9	18.8
1995	28.6	28.0	25.1	24.7	30.4	29.9	18.6	17.9
1996	28.9	28.6	21.6	21.2	25.5	25.2	13.8	13.6
1997	27.2	27.1	24.4	24.3	28.2	28.1	19.4	19.1
1998	30.2	30.0	24.6	24.2	28.4	27.7	22.9	22.7
1999	32.5	32.1	24.9	24.6	27.4	26.7	22.0	21.8
2000	30.8	30.3	25.1	24.7	26.9	26.5	18.6	18.2
2001	27.8	27.6	23.0	22.7	19.6	19.4	17.7	17.6
2002	28.1	27.9	25.0	24.8	29.0	28.8	25.4	25.1
2003	24.6	24.5	19.5	19.4	18.5	18.4	14.3	14.2
2004	25.6	25.5	18.7	18.6	22.7	22.5	14.7	14.5
2005	32.7	32.3	22.9	22.5	31.1	30.8	20.3	20.1
2006	32.3	31.9	21.5	21.2	27.4	27.1	21.8	21.5
2007	30.8	30.6	22.3	22.1	26.5	26.4	15.3	15.2
2008	28.0	27.7	20.3	20.0	22.1	21.8	15.4	15.2
Mean	28.3	28.0	22.3	22.0	25.5	25.2	18.5	18.1
S.D.	4.95	4.98	4.09	4.16	3.91	3.86	3.56	3.70

Appendix II-2: Detrended County-Level Corn Yield Series

Year (t)	Luverne		Morris		Preston		Rush City	
	Harvested	Planted	Harvested	Planted	Harvested	Planted	Harvested	Planted
1972	96.0	95.5	69.0	68.2	102.0	101.3	86.0	84.9
1973	86.9	86.5	84.5	83.9	103.3	102.6	83.2	82.0
1974	34.0	33.7	45.1	44.5	66.9	66.2	40.6	38.9
1975	66.1	65.1	66.9	66.4	82.9	82.4	58.4	56.0
1976	34.6	33.7	29.4	28.8	75.6	74.6	42.0	41.2
1977	89.9	88.9	78.6	77.1	102.6	101.6	85.9	85.0
1978	89.3	89.0	79.2	78.3	105.3	104.9	68.4	67.3
1979	85.5	85.0	67.3	67.3	94.9	94.4	71.1	70.2
1980	79.3	78.7	72.0	71.6	86.3	85.2	74.0	73.4
1981	82.4	82.2	79.2	79.2	104.7	103.2	68.5	67.7
1982	78.8	77.9	71.3	70.5	85.1	83.9	68.9	68.5
1983	52.4	51.9	58.3	58.3	80.3	78.1	68.5	67.9
1984	73.4	73.2	70.0	69.4	88.6	88.1	71.3	70.7
1985	75.0	73.6	64.2	62.5	80.2	78.7	73.9	72.1
1986	84.6	82.6	69.4	66.3	99.3	97.2	78.8	77.1
1987	83.9	83.9	72.6	72.2	97.4	96.8	81.3	79.1
1988	51.5	51.0	35.4	34.0	50.3	49.8	34.1	33.1
1989	80.2	79.5	73.7	71.5	92.5	91.3	69.2	68.8
1990	71.7	71.6	65.1	64.0	90.2	89.1	73.1	72.4
1991	63.1	62.4	64.1	63.6	91.4	90.0	65.7	55.4
1992	67.0	66.0	57.2	56.8	70.0	69.1	60.5	57.6
1993	35.4	25.8	35.7	25.1	51.3	50.8	37.0	35.6
1994	80.5	78.7	70.4	70.1	92.6	90.8	71.5	69.5
1995	60.3	59.1	52.1	51.4	77.3	76.4	67.2	59.7
1996	66.7	66.1	61.5	60.7	77.3	76.8	62.9	62.4
1997	65.4	64.9	69.0	68.4	90.1	89.0	71.7	69.8
1998	77.6	77.2	76.3	75.7	100.1	98.7	82.8	82.1
1999	77.8	77.0	71.9	71.5	92.6	91.6	74.1	72.7
2000	78.9	78.4	72.9	72.5	86.6	85.7	67.6	65.9
2001	63.7	63.2	62.0	61.0	74.5	73.6	64.2	63.0
2002	69.9	69.1	73.3	72.5	91.4	90.2	83.3	82.2
2003	69.2	68.4	67.1	66.6	85.1	84.5	60.1	59.6
2004	73.6	73.5	63.4	63.3	93.2	93.2	67.6	67.3
2005	87.0	87.0	71.5	70.7	103.3	103.2	73.7	73.1
2006	74.8	74.6	66.6	66.1	92.3	91.6	64.8	64.2
2007			57.8	57.1	89.5	88.9	52.1	49.5
2008			62.3	61.1	88.8	87.5	76.6	75.4
Mean	71.6	70.7	65.0	64.0	87.5	86.5	67.6	66.0
S.D.	15.4	16.1	12.3	13.0	13.2	13.1	12.9	13.1

Appendix II-3: Calibrated County-Level Soybean Yields per Harvested Acre

Year	Luverne		Morris		Preston		Rush City	
(t)	Uncalibrated	Calibrated	Uncalibrated	Calibrated	Uncalibrated	Calibrated	Uncalibrated	Calibrated
1941	33.9	33.6	36.8	36.7	37.1	36.6	27.9	27.9
1942	30.1	29.8	24.1	23.8	26.0	25.6	22.3	22.0
1943	28.8	28.5	17.7	17.3	33.9	33.4	17.2	16.7
1944	34.0	33.8	31.3	31.1	38.9	38.5	35.1	35.3
1945	32.7	32.4	32.1	31.9	24.9	24.6	18.9	18.5
1946	35.4	35.2	32.8	32.7	34.0	33.5	15.3	14.8
1947	24.7	24.3	23.0	22.7	23.1	22.8	18.5	18.1
1948	33.0	32.7	34.1	33.9	26.0	25.6	17.9	17.4
1949	27.4	27.1	28.8	28.6	35.8	35.4	27.7	27.7
1950	18.8	18.5	24.0	23.7	27.7	27.4	8.4	7.6
1951	29.9	29.6	28.5	28.3	20.1	19.8	24.4	24.2
1952	29.0	28.7	24.0	23.7	27.6	27.3	22.2	21.9
1953	31.2	30.9	29.8	29.6	29.9	29.5	26.1	26.0
1954	28.8	28.5	27.2	27.0	33.6	33.2	23.9	23.7
1955	25.1	24.7	24.8	24.5	23.8	23.5	20.4	20.0
1956	24.4	24.1	24.0	23.7	31.8	31.4	21.3	20.9
1957	36.3	36.1	23.3	23.0	36.5	36.1	24.9	24.7
1958	20.4	20.0	17.0	16.5	27.4	27.0	16.2	15.6
1959	25.2	24.9	13.7	13.2	30.7	30.3	21.0	20.7
1960	31.1	30.8	21.3	21.0	22.1	21.8	14.1	13.5
1961	34.1	33.8	23.4	23.1	33.0	32.6	18.8	18.4
1962	29.6	29.3	15.2	14.7	24.8	24.4	17.2	16.7
1963	27.7	27.4	29.5	29.4	31.4	31.0	18.0	17.5
1964	24.7	24.4	14.4	13.9	20.1	19.8	12.9	12.2
1965	20.7	20.4	17.6	17.2	23.1	22.8	10.3	9.6
1966	28.2	27.9	20.6	20.2	26.0	25.7	18.0	17.5
1967	23.2	22.9	15.6	15.2	21.0	20.7	15.4	14.9
1968	19.5	19.1	17.5	17.0	24.9	24.6	17.3	16.8
1969	31.8	31.5	19.2	18.8	28.7	28.3	10.6	9.8
1970	26.0	25.7	17.7	17.3	31.2	30.8	21.8	21.5
1971	23.4	23.1	18.4	18.0	24.5	24.2	15.3	14.7
1972	32.0	31.7	17.0	16.6	29.0	28.6	20.0	19.6
1973	27.5	27.2	25.5	25.2	26.5	26.2	21.6	21.3
1974	22.6	22.3	17.8	17.4	18.8	18.5	10.1	9.4
1975	32.1	31.8	21.8	21.5	23.0	22.7	15.2	14.6
1976	17.9	17.6	10.1	9.5	22.3	22.0	12.7	12.0
1977	34.4	34.2	23.6	23.3	32.9	32.5	19.5	19.1
1978	34.3	34.0	25.7	25.4	30.9	30.6	19.4	19.0
1979	30.9	30.6	24.9	24.6	27.3	27.0	22.1	21.9

Appendix II-3: Continued

Year	Luverne		Morris		Preston		Rush City	
(t)	Uncalibrated	Calibrated	Uncalibrated	Calibrated	Uncalibrated	Calibrated	Uncalibrated	Calibrated
1980	31.6	31.4	24.5	24.2	26.5	26.1	22.3	22.0
1981	31.5	31.3	27.8	27.6	29.0	28.6	19.7	19.3
1982	29.5	29.2	27.3	27.1	26.0	25.7	18.6	18.1
1983	29.0	28.7	26.8	26.6	26.4	26.1	21.6	21.3
1984	28.5	28.2	27.2	27.0	25.2	24.9	19.7	19.3
1985	27.3	27.0	22.8	22.5	21.6	21.3	20.2	19.8
1986	24.5	24.2	24.8	24.5	27.6	27.2	23.9	23.6
1987	31.2	30.9	25.1	24.9	32.6	32.2	25.1	24.9
1988	28.4	28.1	12.0	11.5	20.7	20.4	17.0	16.5
1989	30.3	30.0	26.6	26.3	30.2	29.8	19.0	18.6
1990	28.3	28.0	24.7	24.4	29.7	29.4	21.0	20.7
1991	28.0	27.6	28.6	28.4	31.5	31.1	20.7	20.4
1992	20.3	20.0	18.3	17.9	22.4	22.1	13.2	12.5
1993	7.9	7.4	16.0	15.6	20.0	19.7	13.7	13.1
1994	31.1	30.8	22.6	22.3	30.9	30.6	19.9	19.5
1995	28.6	28.3	26.4	26.1	33.3	32.9	19.7	19.3
1996	28.9	28.6	22.7	22.3	28.1	27.7	14.6	14.0
1997	27.2	26.8	25.6	25.4	31.1	30.7	20.5	20.2
1998	30.2	29.9	25.9	25.7	31.3	31.0	24.3	24.1
1999	32.4	32.2	26.2	26.0	30.3	29.9	23.4	23.1
2000	30.7	30.4	26.5	26.3	29.9	29.5	19.8	19.4
2001	27.8	27.5	24.3	24.0	21.8	21.6	18.9	18.5
2002	28.1	27.8	26.4	26.2	32.4	32.0	27.1	27.0
2003	24.6	24.3	20.6	20.3	20.7	20.4	15.3	14.7
2004	25.5	25.2	19.8	19.4	25.4	25.1	15.7	15.2
2005	32.6	32.4	24.3	24.0	34.9	34.5	21.8	21.5
2006	32.3	32.0	22.8	22.5	30.9	30.5	23.4	23.1
2007	30.7	30.4	23.7	23.4	29.9	29.5	16.4	15.9
2008	28.0	27.7	21.6	21.2	24.9	24.6	16.6	16.1
Mean	28.2	27.9	23.3	23.0	27.9	27.5	19.3	18.9
S.D.	4.84	4.88	5.27	5.36	4.76	4.71	4.69	4.88

Appendix II-4: Calibrated County-Level Corn Yields per Harvested Acre

Year	Luverne		Morris		Preston		Rush City	
(t)	Uncalibrated	Calibrated	Uncalibrated	Calibrated	Uncalibrated	Calibrated	Uncalibrated	Calibrated
1941	162.2	164.7	246.0	254.9	126.1	125.0	90.0	88.8
1942	169.6	172.5	175.7	180.3	129.8	128.7	79.7	78.3
1943	150.4	152.4	140.6	143.2	130.6	129.4	72.3	70.8
1944	154.6	156.8	153.6	157.0	119.3	118.3	75.8	74.3
1945	100.0	99.7	124.0	125.5	93.2	92.3	59.2	57.4
1946	112.1	112.4	112.9	113.8	104.2	103.2	57.2	55.3
1947	88.4	87.6	91.5	91.0	93.5	92.6	68.1	66.5
1948	122.9	123.7	132.5	134.5	105.6	104.6	85.5	84.2
1949	88.0	87.1	86.4	85.7	93.7	92.8	77.6	76.2
1950	69.0	67.3	68.5	66.7	82.8	81.9	41.8	39.6
1951	75.7	74.3	68.9	67.1	85.1	84.2	58.4	56.6
1952	85.6	84.7	93.0	92.6	99.1	98.2	78.8	77.4
1953	89.2	88.4	81.8	80.7	87.5	86.6	73.5	72.0
1954	76.7	75.4	75.6	74.1	95.8	94.8	68.6	66.9
1955	77.0	75.8	81.0	79.9	72.6	71.8	69.6	68.0
1956	74.1	72.7	77.2	75.9	101.8	100.8	84.8	83.5
1957	82.2	81.2	70.4	68.6	97.3	96.3	81.3	79.9
1958	59.9	57.8	68.9	67.1	86.0	85.1	77.9	76.5
1959	63.6	61.7	50.7	47.8	91.7	90.8	72.1	70.6
1960	69.9	68.3	72.3	70.7	79.9	79.0	61.5	59.7
1961	78.5	77.2	75.3	73.8	98.5	97.5	73.8	72.3
1962	76.0	74.7	56.1	53.5	88.3	87.4	80.8	79.4
1963	77.5	76.3	72.6	70.9	100.8	99.9	74.2	72.7
1964	77.7	76.5	45.9	42.6	58.8	58.0	57.4	55.5
1965	70.7	69.2	55.4	52.8	87.7	86.8	67.7	66.0
1966	74.6	73.2	71.5	69.9	101.7	100.7	86.5	85.2
1967	76.0	74.7	56.6	54.0	80.3	79.5	74.8	73.3
1968	77.3	76.0	66.1	64.1	89.4	88.5	76.6	75.1
1969	94.7	94.2	67.4	65.5	96.0	95.0	66.7	65.0
1970	72.4	70.9	71.9	70.2	99.1	98.2	84.1	82.7
1971	77.8	76.6	71.9	70.3	97.0	96.1	80.5	79.1
1972	96.0	95.6	69.0	67.2	102.0	101.0	86.0	84.7
1973	87.9	87.1	85.7	84.9	103.8	102.9	83.5	82.1
1974	34.8	31.5	46.4	43.2	67.5	66.7	40.9	38.7
1975	68.3	66.6	69.7	67.9	84.1	83.2	59.0	57.1
1976	36.1	32.9	31.0	26.9	77.0	76.2	42.6	40.4
1977	94.9	94.4	83.7	82.8	104.9	103.9	87.4	86.1
1978	95.0	94.5	85.3	84.4	108.1	107.1	69.8	68.1
1979	91.8	91.1	73.2	71.7	97.8	96.8	72.7	71.1

Appendix II-4: Continued

Year	Luverne		Morris		Preston		Rush City	
(t)	Uncalibrated	Calibrated	Uncalibrated	Calibrated	Uncalibrated	Calibrated	Uncalibrated	Calibrated
1980	85.7	84.8	79.0	77.8	89.2	88.3	75.9	74.4
1981	89.8	89.1	87.8	87.1	108.7	107.7	70.4	68.8
1982	86.5	85.6	79.6	78.4	88.6	87.7	71.0	69.4
1983	57.9	55.7	65.6	63.6	83.8	83.0	70.8	69.2
1984	81.7	80.7	79.4	78.2	92.9	91.9	73.8	72.3
1985	84.1	83.1	73.4	71.8	84.3	83.4	76.8	75.3
1986	95.4	94.9	79.9	78.8	104.6	103.6	82.0	80.6
1987	95.2	94.7	84.1	83.2	103.0	102.0	84.8	83.4
1988	58.7	56.6	41.3	37.7	53.3	52.6	35.6	33.3
1989	91.9	91.3	86.5	85.7	98.3	97.4	72.5	70.9
1990	82.7	81.7	76.8	75.5	96.1	95.2	76.7	75.3
1991	73.1	71.6	76.1	74.7	97.5	96.6	69.0	67.4
1992	78.0	76.8	68.3	66.4	74.9	74.1	63.7	62.0
1993	41.4	38.5	42.8	39.4	55.0	54.3	39.0	36.8
1994	94.6	94.1	84.8	84.0	99.6	98.6	75.6	74.1
1995	71.2	69.6	63.0	60.8	83.3	82.4	71.1	69.5
1996	79.0	77.8	74.8	73.3	83.4	82.6	66.7	65.0
1997	77.9	76.6	84.3	83.4	97.5	96.5	76.2	74.7
1998	92.8	92.2	93.6	93.3	108.5	107.5	88.1	86.9
1999	93.3	92.7	88.7	88.0	100.6	99.7	79.0	77.6
2000	95.0	94.5	90.1	89.6	94.2	93.3	72.1	70.5
2001	77.0	75.7	77.0	75.6	81.2	80.3	68.6	67.0
2002	84.7	83.8	91.3	90.9	99.8	98.9	89.1	87.9
2003	84.2	83.2	84.0	83.1	93.1	92.2	64.5	62.7
2004	89.8	89.1	79.6	78.4	102.2	101.2	72.6	71.0
2005	106.6	106.6	90.1	89.5	113.4	112.3	79.2	77.8
2006	91.9	91.3	84.1	83.2	101.4	100.5	69.7	68.1
2007	87.4	86.6	73.2	71.6	98.5	97.5	56.1	54.2
2008	98.2	97.9	79.3	78.1	97.9	96.9	82.6	81.3
Mean	86.1	85.2	82.1	81.1	94.2	93.2	71.6	70.1
S.D.	23.9	25.0	31.1	33.0	14.6	14.6	12.2	12.4

Appendix III: Time Trending Variables

Year	t_1	t_2	t_3
1941	0	0	0
1942	1	0	0
1943	2	0	0
1944	3	0	0
1945	4	0	0
1946	5	0	0
1947	6	0	0
1948	7	0	0
1949	8	0	0
1950	9	0	0
1951	10	0	0
1952	11	0	0
1953	12	0	0
1954	13	0	0
1955	14	0	0
1956	15	0	0
1957	16	0	0
1958	17	0	0
1959	18	0	0
1960	18	1	0
1961	18	2	0
1962	18	3	0
1963	18	4	0
1964	18	5	0
1965	18	6	0
1966	18	7	0
1967	18	8	0
1968	18	9	0
1969	18	10	0
1970	18	11	0
1971	18	12	0
1972	18	13	0
1973	18	13	1
1974	18	13	2
1975	18	13	3
1976	18	13	4
1977	18	13	5
1978	18	13	6
1979	18	13	7
1980	18	13	8
1981	18	13	9
1982	18	13	10
1983	18	13	11
1984	18	13	12
1985	18	13	13
1986	18	13	14
1987	18	13	15
1988	18	13	16
1989	18	13	17
1990	18	13	18
1991	18	13	19
1992	18	13	20
1993	18	13	21
1994	18	13	22
1995	18	13	23
1996	18	13	24
1997	18	13	25
1998	18	13	26
1999	18	13	27
2000	18	13	28
2001	18	13	29
2002	18	13	30
2003	18	13	31
2004	18	13	32
2005	18	13	33
2006	18	13	34
2007	18	13	35
2008	18	13	36

Appendix IV: Comparison of Hedging Effectiveness of Crop Insurance and Weather Options for Corn

This table compares the risk indicators (Sharpe Ratio, Value at Risk, Certainty Equivalent, Risk Premium) when using alternative hedging strategies (No Hedge, MPCI with No Subsidy, MPCI with Subsidy, GRP with No Subsidy, GRP with Subsidy, Local Station-based Weather Options, and Minneapolis-based Weather Options) at the farm level. Sharpe Ratio is calculated under the assumption of risk free rate of 0.05. Value at Risk (VaR) is measured at the 10% confidence interval. Certainty Equivalent (CE) and Risk Premium (RP) are measured at the three different levels of risk aversion (γ=0.001, 0.005, 0.009).

		Farm Level (Average of Farms)						
Location	Indicator	No Hedge	MPCI (No Sub.)	MPCI (Subsidy)	GRP (No Sub.)	GRP (Subsidy)	Option (Local)	Option (Mpls.)
Luverne	Net Income	$248.52	$229.48	$242.21	$232.08	$249.32	$248.47	$249.93
	Sharpe Ratio	1.259	1.290	1.367	1.283	1.387	1.273	1.281
	VaR (10%)	$49.75	$72.22	$84.95	$63.22	$80.46	$52.56	$54.02
	CE(γ=0.001)	$234.63	$218.87	$231.60	$221.00	$238.24	$234.90	$236.36
	CE(γ=0.005)	$186.55	$187.42	$200.15	$187.29	$204.53	$188.13	$189.59
	CE(γ=0.009)	$142.43	$165.78	$178.51	$163.28	$180.52	$145.33	$146.79
	RP(γ=0.001)	$13.89	$10.61	$10.61	$11.09	$11.09	$13.57	$13.57
	RP(γ=0.005)	$61.97	$42.06	$42.06	$44.79	$44.79	$60.34	$60.34
	RP(γ=0.009)	$106.09	$63.70	$63.70	$68.80	$68.80	$103.14	$103.14
Morris	Net Income	$180.96	$165.54	$180.80	$180.61	$195.59	$180.99	$179.95
	Sharpe Ratio	0.669	0.673	0.732	0.727	0.783	0.673	0.670
	VaR (10%)	-$64.00	-$6.08	$9.17	$3.82	$18.80	-$61.51	-$62.55
	CE(γ=0.001)	$160.96	$151.81	$167.06	$166.68	$181.66	$161.33	$160.30
	CE(γ=0.005)	$89.10	$111.34	$126.59	$125.25	$140.23	$90.91	$89.88
	CE(γ=0.009)	$17.65	$85.39	$100.64	$98.38	$113.36	$21.06	$20.02
	RP(γ=0.001)	$19.99	$13.73	$13.73	$13.92	$13.92	$19.65	$19.65
	RP(γ=0.005)	$91.86	$54.21	$54.21	$55.35	$55.35	$90.07	$90.07
	RP(γ=0.009)	$163.30	$80.15	$80.15	$82.23	$82.23	$159.93	$159.93

Appendix IV – Continued

		Farm Level (Average of Farms)						
Location	Indicator	No Hedge	MPCI (No Sub.)	MPCI (Subsidy)	GRP (No Sub.)	GRP (Subsidy)	Option (Local)	Option (Mpls.)
Preston	Net Income	$176.31	$154.05	$168.45	$182.01	$191.89	$176.32	$176.58
	Sharpe Ratio	0.710	0.644	0.720	0.823	0.877	0.711	0.714
	VaR (10%)	-$36.96	-$15.68	-$1.27	$20.01	$29.89	-$36.38	-$35.55
	CE(γ=0.001)	$160.79	$142.27	$156.68	$170.77	$180.64	$160.85	$161.17
	CE(γ=0.005)	$106.18	$106.60	$121.01	$136.63	$146.50	$106.47	$107.03
	CE(γ=0.009)	$57.31	$82.15	$96.55	$112.90	$122.77	$57.82	$58.60
	RP(γ=0.001)	$15.53	$11.77	$11.77	$11.24	$11.24	$15.47	$15.41
	RP(γ=0.005)	$70.14	$47.44	$47.44	$45.39	$45.39	$69.86	$69.55
	RP(γ=0.009)	$119.00	$71.90	$71.90	$69.11	$69.11	$118.50	$117.98
Rush City	Net Income	$97.01	$89.77	$105.41	$104.20	$115.90	$97.01	$97.70
	Sharpe Ratio	0.538	0.595	0.706	0.641	0.720	0.539	0.543
	VaR (10%)	-$91.65	-$15.13	$0.51	-$21.49	-$9.79	-$91.32	-$90.52
	CE(γ=0.001)	$85.00	$83.18	$98.82	$96.80	$108.50	$85.04	$85.74
	CE(γ=0.005)	$40.36	$63.19	$78.83	$73.63	$85.32	$40.53	$41.26
	CE(γ=0.009)	-$2.95	$49.50	$65.14	$57.11	$68.81	-$2.73	-$1.97
	RP(γ=0.001)	$12.01	$6.58	$6.58	$7.40	$7.40	$11.97	$11.96
	RP(γ=0.005)	$56.65	$26.58	$26.58	$30.58	$30.58	$56.48	$56.44
	RP(γ=0.009)	$99.96	$40.27	$40.27	$47.09	$47.09	$99.75	$99.66