

## **REDUCING THE SOCIAL COST OF FEDERAL CROP INSURANCE: A ROLE FOR US GOVERNMENT HEDGING WITH WEATHER DERIVATIVES**

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### **Keywords**

crop insurance, geographic basis risk, hedging, implied social cost, spatial aggregation, weather derivatives

### **Abstract**

Previous studies have shown that weather derivatives are an effective means of hedging agricultural production risk. Yet, it is still unclear what role weather derivatives will play in agriculture as a risk management tool as compared with existing crop insurance programs which depend highly on government subsidies. This study compares the hedging cost and effectiveness of weather options and crop insurance for soybean in southern Minnesota. Our results show that the hedging effectiveness of weather options is limited at the farm level while the effectiveness increases as the level of aggregation increases. Thus, individual farmers will continue to prefer the federal crop insurance program to weather derivatives for their production risk management. However, the US government as an insurer, which currently does not hedge its risk exposures taken from farmers in the federal crop insurance program, could reduce the implied social cost in the form of un-hedged risk exposure by use of the weather options in the financial market.

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## I . Introduction

Weather events are a major source of crop production risk exposure. One method of hedging this risk exposure in the U.S. has been through the use of federal crop insurance. 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 costly asymmetric information problems: adverse selection, moral hazard, and verifiability (Hyde and Vercammen 1997; Skees and Reed 1986). In addition, the failure of crop insurance markets is closely related to the existence of systemic weather risk which stems from spatially correlated adverse weather events (Xu et al. 2009; Woodard and Garcia 2008). Miranda and Glauber (1997) argue that without government subsidies or reinsurance crop insurers would have to pass the cost of bearing the systemic risk through to farmers. One might conclude that government subsidies are a substitute for hedging the underlying weather risk.

As a result, the US 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 total premium(price), depending on the coverage level, and the federal government pays the rest of the premium. Insurance company losses are reinsured by the USDA and their administrative and operating expenses are reimbursed by the federal government. During fiscal 2008-2010, the cost of the government premium subsidy for farmers averaged \$5.06 billion (92% of the average total government cost). The next largest component was reimbursement of administrative and operating expenses to private insurance companies. Under the conditions of the Standard Reinsurance Agreement(SRA) participating insurance companies retain only about 20% of the business in their assigned (high) risk funds and the federal government assumes the balance of the high risk portfolio (Shields 2010). The risk exposure in these funds represents an important part of the social costs of the federal crop insurance program. In effect, the social cost includes the explicit and implicit costs that exist in the federal crop insurance program. The government subsidies are provided for farmers and insurance companies directly so that we consider the subsidies as explicit cost in this study. On the other hand, the high risk exposure which the government assumes but does not hedge is not direct

cost in normal weather seasons but the government should cover losses of insurance companies based on the SRA in the occurrence of large-scale disasters. Therefore, we consider the government's unhedged risk exposure as implicit or potential social cost.

Weather derivatives such as futures and options contracts, based on temperature and precipitation, have been suggested as a potential risk management tool. In contrast with crop insurance, the problems of asymmetric information do not exist in the weather derivatives market because weather derivatives insure against the weather events causing damage, not the damage itself. Systematic weather risk over larger geographic areas may also be effectively hedged using weather derivatives, which could reduce the need for government subsidies (Woodard and Garcia 2008). If the purpose is to reduce the social cost of weather risk management, the public policy question is: who should use weather derivatives - the farmer, the insurance company, or the government?

Previous studies have focused on weather options pricing because there is no agreed pricing mechanism for the options underlying nonstorable and nontradable assets such as weather indices (Huang et al. 2008; Odening et al. 2007; Cao and Wei 2004; Richards et al. 2004; Yoo 2003). In this regard, simulation methods have been widely used to price weather derivatives, as a generalized closed-form pricing mechanism has yet to be developed. Those studies also show that hedging effectiveness exists when using weather derivatives, yet the efficacy of weather derivatives is limited when hedging farm-level agricultural exposures and geographic basis risk is a primary concern (Woodard and Garcia 2007, 2008; Odening et al. 2007). Basis risk is generally defined as the hedging gap between the payoffs of a given hedging instrument and shortfalls in the underlying exposure, and geographic basis risk originates from the distance between the weather station for weather derivatives and the exposure location.

It remains unclear what role weather derivatives will play in agriculture. One reason for this uncertainty is the continuing popularity of crop insurance. That popularity is due significantly to the fact that the federal government subsidizes insurance premiums to keep farm premium rates low and to maintain private crop insurance companies with adequate reserves in case of widespread crop disasters. Yet, the rising cost of the federal crop insurance program has been an incentive for the government to seek alternative ways to

reduce that cost. To address that policy dilemma, we compare weather derivatives to crop insurance as a potential risk management tool. Unlike previous studies which compare weather derivatives to the no hedge alternative, several risk indicators are compared for alternative hedging tools using historical farm-level and county-level soybean yield data. No previous study has compared hedging cost and effectiveness directly between weather options and crop insurance. Based on comparisons of hedging effectiveness we find that the social cost of the federal crop insurance program could be reduced by selective use of weather options.

## II. Conceptual Framework

To analyze the hedging cost of weather options for crop agriculture, we integrate three models - a yield response model, a temperature process model, and a precipitation process model. The estimated yield response model identifies the weather-yield relationship and determines the optimal tick value (the indemnity payment per unit of adverse weather event) and the optimal hedge ratio of weather options as an efficient hedging instrument. Linear, quadratic, and Cobb-Douglas yield response functions are considered to estimate soybean yields on rainfall and temperature variables by OLS and to choose the model which fits the weather-yield relationship best. Although there are many other factors that potentially influence yields, if they are uncorrelated with weather variables, relatively simple models will provide reliable estimates of the weather-yield relationship (Richards et al. 2004).

Soybean is used in this analysis, as soybean yield data is both nonstationary and highly variable, which makes it a good test of the approach. The data series is detrended to correct for the general upward trend in yields before analyzing the impact of weather on yield. Following Turvey's (2001) yield response model, we use 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 temperatures are typically auto-correlated. Second, using multiple derivative contracts based on monthly weather indices increases the probability of overfitting the hedging parameters and may diminish the accuracy of the hedging estimates (Woodard

and Garcia 2007).

## 1. Temperature Model

Weather derivatives are evaluated mostly 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. We construct our temperature process model using mean-reverting Brownian motion with log-normal jumps and seasonal volatility (Richards et al. 2004; Yoo 2003).

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

$$(1) \quad dT_t = \mu dt + \sigma dz$$

where  $\mu$  is the drift rate per unit of time ( $dt$ ),  $\sigma$  is the standard deviation of the process, and  $dz$  is an increment of a standard Weiner process with zero mean and variance of  $dt$ . The process in (1) is rewritten by including a mean-reversion term as:

$$(2) \quad dT_t = \kappa(T_t^m - T_t)dt + \sigma dz$$

where  $\kappa$  is the rate of mean reversion, and  $T_t^m$  is the instantaneous mean of the process.  $T_t^m$  is set up to accommodate seasonality, auto-regression, and time trend as:

$$(3) \quad T_t^m(T_t, t) = \gamma_0 + \gamma_1 \sin(2\pi t / 365) + \gamma_2 \cos(2\pi t / 365) + \gamma_3 t + \sum_{j=1}^p \rho_j T_{t-j}$$

where  $t$  is the time variable, measured in days, and the  $\gamma$  terms are parameters. We let  $t$  denote 1, 2, 3, ..., 24,837 for September 1, 1940 to August 31, 2008 (data period). 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 Bayesian Information Criterion.

To address the unexpected discrete jumps, we assume that discrete jumps occur according to a Poisson process  $q$  with average arrival rate  $\lambda$  and a random percentage shock  $\phi$ . The random shock is assumed to be distributed as  $\ln(\phi) \sim N(\theta, \delta^2)$ , where  $\theta$  is the mean jump size and  $\delta^2$  is the variance of the jump (Jorion 1988). The Poisson process is distributed as  $dq = 0$  with probability  $1 - \lambda dt$  and 1 with probability  $\lambda dt$ . Combining this with (1) - (3), the stochastic differential equation for the temperature process accommodating mean reversion and jump diffusion is:

$$(4) \quad dT_t = (\kappa(T_t^m - T_t) - \lambda\theta)dt + \sigma dz + \phi dq$$

The parameters ( $\kappa, \sigma, \lambda, \theta, \delta$ ) of the weather process model in (4) are derived by maximum likelihood estimation.

## 2. Precipitation Model

A combination of a Markov chain and a gamma distribution function has been recognized as a simple and effective approach in generating daily precipitation data for many environments (Geng et al. 1986; Richardson and Wright 1984). 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  $X_t = 0$  if day  $t$  is dry, or  $X_t = 1$  if day  $t$  is rainy. If we assume that  $X_t$  follows a first-order Markov process, then the probability of rainfall occurrence at day  $t$  ( $P_t$ ) can be written as:

$$(5) \quad P_t = P_{t-1} \cdot P_t(W/W) + (1 - P_{t-1}) \cdot P_t(W/D), \text{ for } t = 1, 2, \dots, n$$

where  $P_t(W/W)$  is the transition probability from rainfall at day  $t-1$  to rainfall at day  $t$ , and  $P_t(W/D)$  is the transition probability from dryness at day  $t-1$  to rainfall at day  $t$ .

The second part of the precipitation process is a nonnegative 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:

$$(6) \quad f(Y_t | X_t = 1) = \frac{Y_t^{\alpha-1} \exp(-Y_t / \beta)}{\beta^\alpha \Gamma(\alpha)}, \quad Y_t, \alpha, \beta > 0$$

where  $\alpha$  and  $\beta$  are distribution parameters, and  $\Gamma(\alpha)$  is the gamma function of  $\alpha$ .

Since it is known that the rainfall pattern depends on the seasonality in a year, a Markov chain can best be applied for each month separately (Geng et al. 1986). The estimation of the transitional probabilities  $P_t(W/W)$  and  $P_t(W/D)$  are obtained directly from the historical daily rainfall assuming that the homogeneity condition holds for rainfall within a month and we have at least twenty years of data (Richardson and Wright 1984). The gamma distribution parameters  $\alpha$  and  $\beta$  are derived by maximum likelihood estimation.

### III. Methodology

The empirical analysis is comprised of estimating the yield response model to determine the optimal hedge ratio of weather options, pricing the weather options to determine the cost of hedging, and evaluating the hedging effectiveness as measured by several risk indicators: certainty equivalent, risk premium, Sharpe ratio, and value-at-risk.

#### 1. Data

Weather data is obtained from the Minnesota Climatology Working Group. In order to analyze a cross-section of the southern Minnesota region, we use weather data from four dispersed measurement stations, Luverne, Morris, Preston, and Rush City which map into the southwest, northwest, southeast, and northeast points of the region. For each location ( $L$ ), daily high temperature ( $\text{Max}T_t^L$ ), daily low temperature ( $\text{Min}T_t^L$ ), and daily precipitation ( $\text{prec}_t^L$ ) are obtained for the period from September 1, 1940 to August 31, 2008 ( $t = 1$  to 24,837).

For the temperature-based weather call/put option, the standard measure of growing-degree-day (GDD) for a particular day is calculated as:

$$(7) \quad GDD_t = \frac{\text{Max}[\text{Min}[\text{Min}T_t, 86], 50] + \text{Max}[\text{Min}[\text{Max}T_t, 86], 50]}{2} - 50$$

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 and precipitation data are the cumulative daily measures during June-August.

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 yields (per planted acre) are obtained from the National Agricultural Statistics Service (NASS) and Risk Management Agency (RMA), respectively, for the four selected counties (towns): Rock County (Luverne), Stevens County (Morris), Fillmore County (Preston), and Chisago County (Rush City). NASS provides the county-level yields for 68 growing seasons from 1941-2008. The farm-level yields are provided by RMA for 23 growing seasons from 1984-2006. We select 24 representative farms reporting at least 17 years out of 23 years to evaluate the crop insurance and weather options at the farm level.

TABLE 1. Statistics of GDD and Rainfall during June-August for Luverne, Morris, Preston, and Rush City, 1941-2008

Variable/Region	Mean	Max.	Min.	S.D.	Kurtosis	Skewness
GDD (degree)						
Luverne	1,804	2,075	1,437	140.7	0.25	-0.58
Morris	1,679	1,971	1,283	136.1	0.31	-0.48
Preston	1,726	2,048	1,359	132.2	0.01	-0.23
Rush City	1,611	1,862	1,258	140.3	-0.42	-0.36
Rainfall (inch)						
Luverne	10.75	22.92	2.18	3.75	0.93	0.61
Morris	10.71	16.22	3.96	2.99	-0.84	-0.24
Preston	13.54	23.64	5.81	4.45	-0.58	0.28
Rush City	12.59	22.45	2.85	3.67	-0.46	0.39



TABLE 2. County-level Soybean Yields(Bushels per Planted Acre) in the Four Counties, MN, 1941-2008

City(County)	Mean	Max.	Min.	S.D.	Kurtosis	Skewness
Luverne(Rock)	29.1	52.4	10.1	11.7	-1.13	0.21
Morris(Stevens)	23.9	42.7	6.8	10.5	-1.39	0.29
Preston(Fillmore)	28.6	56.4	10.9	11.5	-0.71	0.47
Rush City(Chisago)	19.6	41.6	4.5	8.3	-0.37	0.48

## 2. Valuation of Weather Options and Crop Insurance

Valuation of the weather option premium is carried out by daily simulation. The option value is calculated by averaging the discounted payoffs of the option over 10,000 weather values by Monte Carlo simulation based on the estimated parameters in the weather process models. The advantages of daily simulation are to produce more accurate results based on a considerably large number of simulated values and to incorporate possible weather forecasts (such as mean reversion or extreme events) into the pricing model.

A risk-neutral valuation method is used which discounts the payoffs of the options at expiration 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 2006). To observe the correlation, we use the annual personal income data (to represent the aggregate market index) and annualized GDD and precipitation residuals for each of the four counties. There is a statistically significant correlation between personal income and weather series residuals for only Chisago County. Odening et al. (2007) also shows that there is no (or negligible) correlation between rainfall indexes and stock market returns for the precipitation option. In addition, Turvey (2005) argues that the market price of weather risk should be zero in equilibrium because of spatial arbitrage.

To compare with the hedging cost and effectiveness of weather options, two crop insurance plans, multiple peril crop insurance (MPCI) and the group risk plan (GRP) are considered because both plans protect individual farmers against production risk caused by adverse weather. MPCI provides farmers with

farm-level indemnities while GRP insures farmers at the county level. Crop insurance premiums are obtained from the crop insurance calculator based on farm location, actual production history (APH), and coverage levels (University of Illinois). We calculate the MPCCI premium for each of the four counties as an average of MPCCI premiums of the 24 representative farmers for each county while the GRP premiums are same for all farmers in the same county.

There is no hedging instrument which provides 100 percent coverage to farmers. MPCCI insures each farmer's crop from 50 to 85 percent of his or her APH yield while GRP insures each farmer's crop from 70 to 90 percent of his or her county APH yield. On the other hand, weather derivatives induce a hedging gap, caused by the imperfect relationship between crop yield and weather variables. Therefore, we calculate the weighted hedging costs for MPCCI, GRP, and weather options by adjusting each cost by the corresponding coverage ratio in order to compare the hedging cost at the same coverage level.

### 3. Hedging Effectiveness

Using a stochastic expected utility framework, the hedging effectiveness of weather options is evaluated by comparing several simulated risk indicators: certainty equivalent (CE), risk premium (RP), Sharpe ratio (SR), and value-at-risk (VaR) among alternative hedging strategies. We assume that the farmer has a negative exponential utility function whose expectation is specified as:

$$(8) \quad E[U(\pi)] = E[-\exp(-\gamma\pi)]$$

where  $\exp(\cdot)$  is an exponential function,  $\gamma$  is the degree of risk aversion, and  $\pi$  is the profit. The advantage of this utility function is that the degree of concavity ( $\gamma$ ) is independent of profit ( $\pi$ ). This implies that the utility function shows constant absolute risk aversion for  $\gamma > 0$ , regardless of the profit or loss level. The certainty equivalent (CE) and risk premium (RP) are measured based on the negative exponential utility function.

Profit is calculated as crop revenue less total production cost per planted acre, where crop revenue is the product of uncertain yield and price. Uncertain crop yields are simulated based on the estimated yield response model and simulated weather processes with the assumption of a normally

distributed error term in the yield response model. Crop price is taken from maximum price elections set by the RMA every year. Total production cost is estimated based on county-level yields and costs using the FINBIN farm financial database provided by Center for Farm Financial Management. Payoffs from hedging instruments (such as crop insurance and weather options) are included in crop revenues and hedging costs are added to production costs.

The certainty equivalent (CE) value is obtained by solving the expected negative exponential utility function (8) for  $\pi$ , which becomes  $CE(\pi) = (1 / \gamma) \ln E[U(\pi)]$ . The risk premium (RP) equals  $E(\pi) - CE(\pi)$ . The CE and RP measures have been used in the traditional expected utility model by assuming the decision maker is an expected utility maximizer with a Bernoulli utility function. The Sharpe ratio (SR) is defined as  $\{E(R) - R_f\} / \sigma(R)$ . Here  $E(R)$  is the expected rate of return from the crop production,  $R_f$  is the risk-free rate of return (0.05 in this study), and  $\sigma(R)$  is the standard deviation of the crop production returns. The value-at-risk (VaR) is measured using Monte Carlo simulation at the 90% confidence level.

#### 4. Geographic Basis Risk and Spatial Aggregation

Weather options are priced using 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 remote location are not traded due to liquidity and fair pricing problems. Instead, the Chicago Mercantile Exchange (CME) offers weather options and futures for several major international cities. Thus, geographic basis risk may arise when we use the CME options instead of OTC options. To measure the geographic basis risk for each county, we compare the hedging effectiveness of CME options (based on the Minneapolis weather index) with OTC options (based on each local weather index) because there is no geographic basis risk in using the OTC options.

Woodard and Garcia (2007) show that the use of spatial aggregation diminishes the degree to which geographic basis risk impedes effective hedging. We also observe the improvement of hedging effectiveness by using weather options as the level of aggregation increases (from the farm level, to the county level, to the four-county level).

## IV. Empirical Results

Three alternative yield response models are estimated: linear, quadratic, and Cobb-Douglas. The quadratic yield response model fits the relationship between crop yield and the two weather variables best (Table 3)<sup>1</sup>. 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). In addition, not all estimated coefficients of the models are statistically significant, which means some weather variables with insignificant coefficient cannot be used to hedge the yield risk. For example, neither  $\beta_2$  nor  $\beta_4$  for Luverne is significant and so we cannot use weather options underlying GDD since there is no significant relationship between soybean yield and GDD for Luverne. On the other hand, Preston and Rush City can use weather options underlying both rainfall and GDD even though  $\beta_4$  for GDD is not significant but  $\beta_2$  is still significant at 5%. This implies that there exists some relationship between soybean yield and GDD for Preston and Rush City even though the relationship is not as significant as that between soybean yield and rainfall.

TABLE 3. Quadratic Yield Response Model for Soybean

$$Y_t = \beta_0 + \beta_1 R_t + \beta_2 G_t + \beta_3 R_t^2 + \beta_4 G_t^2 + \varepsilon_t$$

$Y_t$  is the detrended crop yield (bushels per planted acre),  $R_t$  is the deviation of the cumulative daily rainfall for growing season (June to August), and  $G_t$  is the deviation of the cumulative daily growing-degree-day (GDD) for growing season.

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<sup>1</sup> In estimating the yield response model, we considered various types of variables with rainfall and GDD such as interaction terms but the variables are not significant and do not improve the model fit. Previous studies (Thompson, 1988; Tannura, et al., 2008) also estimate the quadratic yield response model used in this study.

Location	Coefficient					F	R <sup>2</sup>	S.E.	Obs.
	$\beta_0$ (S.E.)	$\beta_1$ (S.E.)	$\beta_2$ (S.E.)	$\beta_3$ (S.E.)	$\beta_4$ (S.E.)				
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

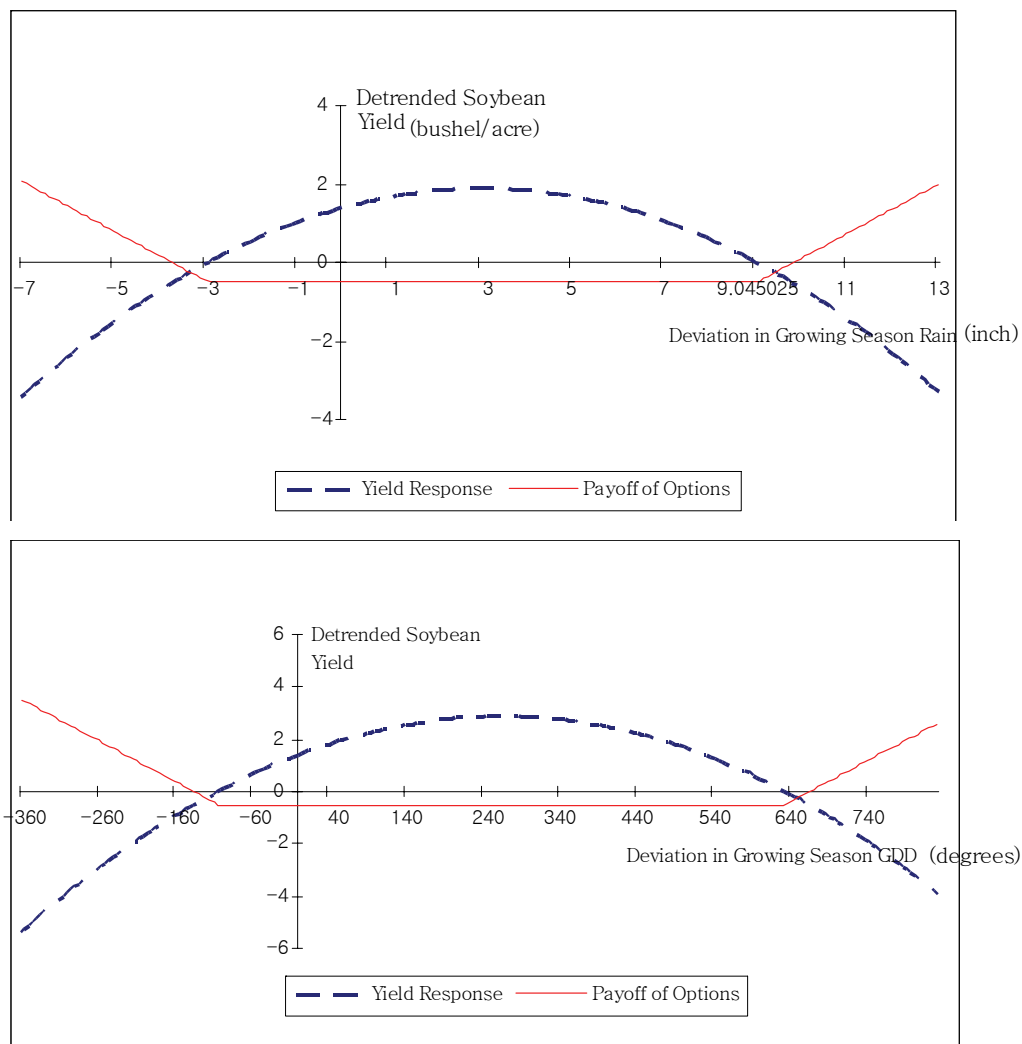
\*\* Significant at 5% level

\* Significant at 10% level

There are two distinguishing characteristics of the estimated quadratic function. First, large deviations (in either direction) from the historical mean precipitation and temperature tend to depress yields. This implies that either too humid (too hot) or too dry (too cold) weather will depress yields. Second, a little higher than average precipitation and temperature is predicted to optimize the yield response function. For example at Luverne, to optimize the quadratic yield response function for rainfall, we rewrite the function  $Y_t = 1.99 + 0.33R_t - 0.15R_t^2$  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.

The negative quadratic curve in Figure 1 shows the estimated quadratic yield response function for Preston, one of our four counties, graphically. The two distinguishing characteristics of the estimated quadratic function explained in Table 3 are observed more clearly. For rainfall in the first figure, either below -3 inches or above 9.045 inches from the average rainfall depresses yields and the optimal amount of rainfall to maximize yield is 3 inches higher than the average. Based on the estimated quadratic function, we select a long 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. The optimal strike and tick values of the options are also determined based on the estimated parameters.

FIGURE 1. Estimated Soybean Yield Response Functions and Strangle Hedging Strategies in Fillmore County (Preston)



Option prices by the daily simulation method are calculated over 10,000 simulated weather processes using the estimated parameters. Most of the parameters of the daily low temperature process model reported in Table 4 are significant at the 5% level<sup>2</sup>. These estimated parameters explain reasonably well

<sup>2</sup> Since the four selected counties show similar results to one another, we report the results for Luverne and Preston. Full results for all tables are available from the author upon request.

the seasonal temperature process in southern Minnesota where the standard deviation of winter temperature during December-February is about twice as large as that of summer temperature during June-August. The average arrival rate ( $\lambda$ ), the variance of the jump ( $\delta^2$ ), and the variance of the process ( $\sigma^2$ ) are much larger in winter than in summer. The rate of mean reversion ( $\kappa$ ) 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 result of the daily high temperature process model is not reported since it is similar 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 4. Temperature Process Model Parameters for Daily Low Temperature

$$dT_t = (\kappa(T_t^m - T_t) - \lambda\theta)dt + \sigma dz + \phi dq$$

Parameters  $\kappa$ ,  $\lambda$ ,  $\theta$ ,  $\delta^2$ ,  $\sigma^2$  represent the rate of mean reversion, average arrival rate, mean jump size, variance of the jump, and variance of the Brownian motion process, respectively. Subscripts “s” and “w” stand for summer and winter, respectively.

Parameter	Luverne		Preston	
	Estimate	S.E.	Estimate	S.E.
$\kappa$	0.12**	0.00	0.10**	0.00
$\kappa_s$	0.16**	0.00	0.14**	0.00
$\kappa_w$	0.10**	0.00	0.09**	0.00
$\lambda$	0.08**	0.02	0.46**	0.07
$\lambda_s$	0.01	0.01	0.19**	0.07
$\lambda_w$	0.33**	0.11	0.44**	0.16
$\theta$	-0.33**	0.07	-0.80**	0.08
$\theta_s$	-0.19*	0.10	-0.57**	0.12
$\theta_w$	-0.55**	0.16	-0.63**	0.19
$\delta^2$	3.72**	0.06	4.00**	0.07
$\delta_s^2$	2.68**	0.08	2.88**	0.09
$\delta_w^2$	4.38**	0.13	4.82**	0.15
$\sigma^2$	3.88**	0.03	4.73**	0.04
$\sigma_s^2$	3.04**	0.05	3.70**	0.06
$\sigma_w^2$	4.70**	0.08	5.79**	0.10

\*\* Significant at 5% level

\* Significant at 10% level

The estimated parameters of the precipitation process model in Table 5 explain the historical precipitation process 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 ( $P(W/D)$ ) and from rainfall to rainfall ( $P(W/W)$ ) are higher, and the  $\beta$  parameter of the gamma distribution (which determines the extent of extremely heavy rainfall) are larger for Preston and Rush City compared to Luverne and Morris.

TABLE 5. Precipitation Process Model Parameters

$$P_t = P_{t-1} \cdot P_t(W/W) + (1 - P_{t-1}) \cdot P_t(W/D), \text{ for } t = 1, 2, \dots, n$$

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

$P_t$ ,  $P_t(W/W)$ , and  $P_t(W/D)$  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 gamma distribution function,  $Y_t$  is the amount of precipitation (given  $X_t=1$  when day  $t$  is rainy),  $\alpha$  and  $\beta$  are distribution parameters. Subscripts 6, 7, and 8 stand for June, July, and August, respectively.

Parameter	Luverne	Morris	Preston	Rush City
$P(W/D)_6$	0.27	0.33	0.31	0.33
$P(W/D)_7$	0.23	0.30	0.28	0.29
$P(W/D)_8$	0.21	0.26	0.27	0.28
$P(W/W)_6$	0.44	0.48	0.48	0.50
$P(W/W)_7$	0.34	0.40	0.37	0.38
$P(W/W)_8$	0.37	0.40	0.42	0.38
$\alpha_6$	0.61	0.63	0.61	0.62
$\alpha_7$	0.61	0.63	0.61	0.62
$\alpha_8$	0.62	0.64	0.62	0.61
$\beta_6$	17.95	13.81	18.43	15.74
$\beta_7$	17.84	14.60	18.57	16.50
$\beta_8$	16.23	13.16	17.21	17.99



The option prices obtained by applying the daily simulation method over 10,000 simulated GDD and precipitation processes are reported for Luverne and Preston in Table 6. The tick values and option prices are measured in 2007 dollars in order to compare with the 2007 crop insurance premiums. In order to observe the relative option price level, the prices are reported as the percent of the 2007 soybean revenue in parenthesis. The with (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 without (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 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 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 costs for weather options and crop insurances at the same coverage levels. Simulated total prices for Preston are \$3.45 per acre (or 0.99% of revenue) with basis risk and \$15.68 per acre (or 4.51% of revenue) without basis risk.

TABLE 6. Simulated Weather Option Prices

Location	Precipitation Options		GDD Options		Both Options	
	Put (%)	Call (%)	Put (%)	Call (%)	w/Basis Risk	w/o Basis Risk
Luverne						
Strike <sup>a/</sup>	8.09	15.58	- <sup>c/</sup>	- <sup>c/</sup>		
Tick <sup>b/</sup>	\$8.11	\$8.11	-	-		
Price	\$2.79 (0.78%)	\$1.45 (0.41%)	-	-	\$4.24 (1.19%)	\$9.64 (2.72%)
Preston						
Strike	10.61	22.59	1,622	2,358		
Tick	\$4.41	\$4.41	\$0.11	\$0.11		
Price	\$1.67 (0.48%)	\$0.13 (0.04%)	\$1.65 (0.47%)	\$0.00 (0.00%)	\$3.45 (0.99%)	\$15.68 (4.51%)

a/ 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 inches and the unit of strike for GDD options is degree days.

b/ Tick value is the indemnity payment 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.

c/ Not available because we do not purchase the options based on the estimated yield response functions.

In Table 7, the prices of weather options are compared to those of two crop insurance products, MPCI and GRP. The prices of weather options and GRP are calculated at the county level, while MPCI prices are calculated at the farm level. For crop insurance prices, the 85% coverage variable means that the premium(price) is calculated at the 85% coverage level, the highest level in the MPCI plan, and 100% 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 are the amounts paid by the farmer, which is assumed to be 62% of total premium. The remaining 38% is the government subsidy, as set by the Agricultural Risk Protection Act of 2000. Subsidy rates vary by coverage level and type of insurance. The GRP at the 85% coverage level is provided with 59% subsidy rate so that farmers pay only 41% of the total premium. The last row of each location is the total premium at the 100% coverage level, assuming no subsidy is provided.

TABLE 7. Prices of Weather Options and Crop Insurance

Location	Weather Option		MPCI (Price Election: \$7.00/bu. in 2007)		GRP (Price Election: \$7.00/bu. in 2007)	
	Coverage	Price (%) <sup>a/</sup>	Coverage (Gov. Subsidy)	Price (%) <sup>a/</sup>	Coverage (Gov. Subsidy)	Price (%) <sup>a/</sup>
Luverne (Avg. APH 10Y = 45.0 bu./acre) <sup>c/</sup>	44%	\$ 4.24 (1.19%)	85% (38%) <sup>b/</sup>	\$12.15 (3.42%)	85% (59%) <sup>b/</sup>	\$ 5.44 (1.53%)
	100%	\$ 9.64 (2.72%)	100% (38%)	\$14.29 (4.03%)	100% (59%)	\$ 6.40 (1.80%)
			100% ( 0%)	\$23.06 (6.50%)	100% ( 0%)	\$15.61 (4.40%)
Preston (Avg. APH 10Y = 44.6 bu./acre)	22%	\$ 3.45 (0.99%)	85% (38%)	\$17.17 (4.93%)	85% (59%)	\$ 3.17 (0.91%)
	100%	\$15.68 (4.50%)	100% (38%)	\$20.20 (5.80%)	100% (59%)	\$ 3.73 (1.07%)
			100% ( 0%)	\$32.58 (9.36%)	100% ( 0%)	\$ 9.10 (2.61%)

a/ Prices represented as a percent (in the parenthesis) are calculated as a percent of the soybean revenue 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 APH 10Y is the average of the historical county-level soybean yields during 1997-2006.

The approximate MPCCI premiums for soybean at the 100% coverage level with no government subsidy are \$23.06/acre at Luverne and \$32.58/acre at Preston. These premiums are much higher than the corresponding weather option premiums of \$9.64/acre (Luverne) and \$15.68/acre (Preston) at the 100% coverage level. The main reason for the higher MPCCI premiums compared with weather options is that the MPCCI premium is calculated at the individual farm level, which reflects larger yield variability. The weather option premium is calculated at the county level based on the weather indices in the county weather station, which removes the individual farmer's idiosyncratic yield variability. When the weather option premiums are compared 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 county level. The GRP premiums at the 100% coverage level without subsidy for Luverne and Preston are \$15.61/acre and \$9.10/acre, respectively.

In Table 8 we compare hedging effectiveness indicators when using alternative hedging strategies at the farm level to analyze weather options as a more efficient risk management tool for farmers at Luverne. The hedging effectiveness for the other locations is similar. The seven alternative hedging strategies include: no hedge, MPCCI with no subsidy, MPCCI 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 use the average of the individual 24 farm risk indicators in each location based on 10,000 simulated yields and corresponding cost estimates for each individual farm.

The hedging effectiveness of weather options compared with a no hedge position at the farm level is limited. Higher values for the Sharpe ratio, value-at-risk, and certainty equivalent, and a lower risk premium all imply greater hedging effectiveness. Most of the risk indicators that use weather options at the farm level are not significantly improved compared with the no hedge alternative and they are worse when compared with both the MPCCI and GRP hedges. For example, when using local weather options at Luverne, the Sharpe ratio, VaR, certainty equivalent at  $\gamma=0.005$ , and risk premium at  $\gamma=0.005$  are 1.240, \$35.03, \$147.86, and \$34.39, respectively. These are slightly improved from the values obtained with no hedge (1.226, \$32.69, \$146.73, and \$35.55). They are worse than those derived from using MPCCI with no

government subsidy (1.322, \$61.07, \$151.47, and \$24.22). Vedenov and Barnett (2004) also find there is only limited efficacy of weather derivatives in hedging disaggregated production exposures due to large yield variability at the farm level. MPCl insures the highly variable individual farm-level yields relatively better than weather derivatives because MPCl 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, mainly due to the hedging gap caused by local basis risk (an imperfect weather-yield relationship) in the weather options. These results are consistent with the previous literature, which shows that weather options are not an effective hedging tool for individual farmers implying that farmers will continue to prefer federal crop insurance for their weather risk management.

TABLE 8. Hedging Effectiveness at the Farm Level

Location	Indicator	Farm Level (Average of Farms)						
		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 <sup>a/</sup>	1.226	1.322	1.381	1.387	1.449	1.240	1.247
	VaR (10%) <sup>b/</sup>	\$32.69	\$61.07	\$68.69	\$65.65	\$73.48	\$35.03	\$36.07
	CE <sup>c/</sup> ( $\gamma=0.001$ )	\$174.76	\$170.14	\$177.74	\$177.88	\$185.71	\$174.94	\$175.98
	CE ( $\gamma=0.005$ )	\$146.73	\$151.47	\$159.07	\$158.62	\$166.45	\$147.86	\$148.89
	CE ( $\gamma=0.009$ )	\$120.70	\$137.05	\$144.65	\$143.44	\$151.27	\$122.97	\$124.01
	RP <sup>c/</sup> ( $\gamma=0.001$ )	\$7.52	\$5.55	\$5.55	\$5.65	\$5.65	\$7.31	\$7.31
	RP( $\gamma=0.005$ )	\$35.55	\$24.22	\$24.22	\$24.90	\$24.90	\$34.39	\$34.39
	RP( $\gamma=0.009$ )	\$61.57	\$38.64	\$38.64	\$40.08	\$40.08	\$59.27	\$59.27

a/ Sharpe Ratio is calculated under the assumption of risk free rate of 0.05.

b/ Value-at-risk is measured at the 10% confidence interval.

c/ Certainty equivalent and risk premium are measured at the three different levels of risk aversion ( $\gamma=0.001$ , 0.005, 0.009).

If individual farmers are not the likely primary users of weather options, then how might these options play a role in weather risk management? In order to address this question, we note that hedging effectiveness increases as spatial aggregation increases. Table 9 illustrates the effect of spatial aggregation on hedging effectiveness by using weather options where farm level (Average of Farms), county level (Average of Counties), and four-county

aggregate level (Aggregate) are compared for soybean. The Average of Farms statistics are calculated as the average of the individual 96 farm indicators in the four counties (24 farms for each of the four counties). The Average of Counties statistics are calculated as the average of the individual four county indicators. The four-county Aggregate results are obtained by averaging the data across counties 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. The 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. The certainty equivalent and risk premium are also improved at all levels of risk aversion as the level of spatial aggregation increases.

TABLE 9. Hedging Effectiveness and Spatial Aggregation

Options	Indicator	Four Counties		
		Average of Farms	Average of Counties	Aggregate
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 ( $\gamma=0.001$ )	\$125.46	\$130.65	\$128.17
	CE ( $\gamma=0.005$ )	\$92.28	\$112.87	\$117.02
	CE ( $\gamma=0.009$ )	\$60.15	\$95.11	\$105.82
	RP ( $\gamma=0.001$ )	\$8.88	\$4.44	\$2.78
	RP ( $\gamma=0.005$ )	\$42.06	\$22.22	\$13.92
	RP ( $\gamma=0.009$ )	\$74.19	\$39.98	\$25.13

In the federal crop insurance program, private crop insurance companies provide insurance products to farmers as an agent of the government and they transfer most of that crop risk exposure to the government. However, in the past the government has not hedged these risk exposures. Rather, government has simply tried to diversify the idiosyncratic risks by spatially aggregating the crop yield risks across farmers. This implies a significant social cost, because the potential losses caused by not hedging risk exposures would need to be covered by taxpayers. 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 systematic weather risk

without a risk hedge. How might the government use weather options as a risk management tool to reduce the implied social cost?

TABLE 10. Government Use of Weather Options at the County Level

Location	Indicator	County Level		
		No Hedge (Subsidy)	Option (Local)	Option (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

Suppose that the government provides GRP products with subsidy to farmers and hedges those crop risk exposures by purchasing weather options at the county level. In Table 10, we compare the net income and value-at-risk of the government between a no hedge position, a local station-based weather option hedge, and a Minneapolis-based weather option hedge for the four counties. The net income of the government realized from the federal crop insurance program is computed as: the GRP premium received from farmers minus the GRP indemnity payments paid to farmers minus the weather option premium paid to the option provider for the risk hedge plus the weather option payoffs received from the option provider. Let us assume no other administrative costs in this 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. Here the only risk indicator used for comparison is the VaR. The Sharpe ratio of the government is not measured because it is difficult to evaluate the federal service cost in order to calculate the Sharpe ratio. In addition, the certainty equivalent and risk premium at various levels of risk for the government is not used because the government is assumed to act as a risk-neutral agent.

The government's VaR improves from -\$10.58/acre with no hedge to -\$6.20/acre by using Minneapolis-based options in Luverne. All other counties

show improvements in the VaR of the government by using either local station-based weather options or Minneapolis-based weather options to hedge yield risk. This implies that the government, as a reinsurer, could reduce idiosyncratic risk by aggregating farm-level production exposures and hedging the remaining systematic weather risk with spatially-aggregated weather derivatives. As a result, weather options might be used by the government as an effective hedging tool at the county level (or higher levels of aggregation) for the purpose of reducing the social cost of crop insurance.

Since local weather options based on the four specific counties are not traded due to liquidity and fair pricing problems in the market, the CME option is used 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, where geographic basis risk is measured as the difference in hedging effectiveness between local and nonlocal derivatives. When comparing risk indicators between Option (Local) and Option (Minneapolis) in Tables 8 and 10, the difference is small. 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 nonlocal contracts is small when comparing hedge effectiveness between local options.

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 the Midwest has relatively homogeneous (less variable) weather conditions across 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 0.90. Even though daily precipitation tends to be less spatially correlated, growing season precipitation shows a relatively high correlation that is close to 0.50 between Minneapolis and each of the four local stations. This result indicates that local weather risk can be effectively hedged to produce soybean with Minneapolis-based weather derivatives in southern Minnesota where geographic basis risk is not large. However, this approach should be applied cautiously to other locations, crops, or other types of weather derivatives after considering spatial correlation of crop losses and weather variables across locations.

## V. Conclusions

Social cost includes the explicit and implicit costs that exist in the US federal crop insurance program including government insurance program subsidies and the government's unhedged risk exposure. When hedging cost and effectiveness of weather options and crop insurance are compared for soybean farmers in southern Minnesota, the hedging effectiveness of using weather options is limited at the farm level as compared to crop insurance products. This is because weather options insure against adverse weather events that cause damage, while crop insurance protects farmers against their crop losses directly. This is further evidence that individual farmers will continue to prefer using crop insurance with the government premium subsidy rather than weather derivatives as a weather risk management strategy. However, the US government is the reinsurer in the crop insurance program and it currently does not fully hedge the weather risk exposure. Historical simulation is used to demonstrate that the government could reduce social cost due to the unhedged risk exposure by designing a program that uses weather options at the county or higher levels of aggregation in the financial market. The government could use this approach to selectively reduce its risk exposure and the need to subsidize the crop insurance program.

This study could be applied to our crop insurance program in Korea in the same way as in the US program. Our government as a reinsurer for private crop insurance companies covers losses of insurance companies in case of loss ratio<sup>3</sup> exceeding 180% based on the reinsurance contract between the government and insurance companies. Similar to US government, our government does not hedge its own high risk exposure. Even though the unhedged high risk exposure will not be considered as explicit social cost in normal seasons, our government should compensate for large-scale losses of private insurance companies using tax payers' money when the loss ratio exceeds 180%. Our government as a hedger of its high risk exposure could purchase reinsurance from international reinsurance companies but the reinsurance premium would be relatively expensive compared to weather option

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<sup>3</sup> The loss ratio is the ratio of total losses incurred in claims divided by the total premiums earned.



premium. In this context, weather derivatives could be used as an efficient hedging instrument for our government.

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