# Reducing the Social Cost of Federal Crop Insurance: A Role for Government Hedging with Weather Derivatives

Wonho Chung*

## 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 government subsidizes a high proportion of the costs of crop insurance for participating farmers and private crop insurance companies. Farmers pay

* Research Fellow Korea Rural Economic Institute

only 33-62% of the total premium, 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 (Shields, 2010, p. 11). Under the conditions of the Standard Reinsurance Agreement 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, p. 12). 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 including the government subsidies and the government's unhedged risk exposure.

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 in 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.

## 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 hedging 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 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 over fitting the hedging parameters and may diminish the accuracy of the hedging estimates (Woodard and Garcia, 2007).

## 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

$$dT_t = \mu dt + \sigma dz \tag{1}$$

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

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

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 in (3),

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

where $t$ is the time variable, measured in days, and the $\gamma$ terms are parameters. We let $t$ denote January 1, January 2, etc. 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 $\varphi$. The random shock is assumed to be distributed as $\ln(\varphi)\sim N(\theta, \delta^2)$, 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

$$dT_t = (\kappa(T_t^m - T_t) - \lambda\theta)dt + \sigma dz + \varphi dq \tag{4}$$

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

## 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

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

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

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

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, 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 α and β are derived by maximum likelihood estimation.

# Methodology

The empirical analysis is comprised of estimating the yield response model to determine the optimal hedging 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.

## 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 ($\mathrm{Max}T_t^L$), daily low temperature ($\mathrm{Min}T_t^L$), and daily precipitation ($prec_tL$), 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

$$\mathrm{GDD}_t = \frac{\mathrm{Max}[\mathrm{Min}[\mathrm{MinT}_t,86],50] + \mathrm{Max}[\mathrm{Min}[\mathrm{MaxT}_t,86],50]}{2} - 50\,.$$

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 1941-2007. NASS provides the county-level yields per planted acre from 1972 onward, while they provide the county-level yields per harvested acre from 1941 onward. We calibrate the yields per planted acre before 1972 based on the yields per harvested acre. 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.

## 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 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 MPCI premium for each of the four counties as an average of MPCI 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. MPCI 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. Yet, 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 MPCI, 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.

## 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. The farmer's expected negative exponential utility function is specified as $E[U(\pi)] = E[-\exp(-\gamma\pi)]$. Here exp( · ) 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 (University of Illinois). Total production cost is estimated based on county-level yields and costs using the 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 obtained by solving the expected negative exponential utility function 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. 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, as the same utility function and the same degree of risk aversion are assumed for both crop insurance and the weather option hedge. 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, Rf 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.

## 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 location are not traded due to liquidity and fair pricing problems. 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).

## 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 1). Since the four selected counties show similar results to one another for some of the model estimating stage, we report the empirical results for two representative locations (Luverne and Preston) to illustrate variations in the data. Full results for all tables are available from the authors upon request. 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. Second, a higher than average yield level is predicted to optimize the yield response function.

Table 1. 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.

| Location | Coefficient | | | | | F | $R^2$ | 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 |
| 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 |

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

Based on the estimated quadratic function, we select a 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. For example, the optimal strike level ($R_t^*$) for the precipitation option in the quadratic function is obtained by solving, $\hat{\beta}_0 + \hat{\beta}_1 R_t^* + \hat{\beta}_3 (R_t^*)^2 = 0$. The resulting optimal tick value is $Tick^* = \hat{\beta}_1 + 2\hat{\beta}_3 (R_t^*)$.

Table 2. Temperature Process Model Parameters for Daily Low Temperature

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

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. Subscript “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 |

| Parameter | Luverne | | Preston | |
|---|---|---|---|---|
| | Estimate | S.E. | Estimate | S.E. |
| $\lambda$ | 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

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 2 are significant at the 5% level. These estimated parameters explain reasonably well 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 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 3. Precipitation Process Model Parameters

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

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

$P_t$, $P_t$(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), α and β 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 estimated parameters of the precipitation process model in Table 3 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 β 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 4. Simulated Weather Option Prices

| Location | Precipitation Options | | GDD Options | | Both Options | |
|---|---|---|---|---|---|---|
| | Put (%) | Call (%) | Put (%) | Call (%) | w/Basis Risk | w/o Basis Risk |
| Luverne | | | | | | |
| Strike[a/] | 8.09 | 15.58 | -[c/] | -[c/] | | |
| Tick[b/] | $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.

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 4. 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 5. 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(%)[a/] | Coverage (Gov. Subsidy) | Price(%)[a/] | Coverage (Gov. Subsidy) | Price(%)[a/] |
| Luverne (Avg. APH 10Y = 45.0 bu./acre)c/ | 44% | \$ 4.24 (1.19%) | 85%(38%)[b/] | \$12.15 (3.42%) | 85%(59%)[b/] | \$ 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 (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 APH 10Y is the average of the county-level soybean yields during 1997-2006.

In Table 5 the prices of weather options are compared to those of MPCI and GRP. The prices of weather options and GRP are calculated at the county level, while MPCI premiums are calculated at the farm level. 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 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.

The approximate MPCI 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 MPCI premiums compared with weather options is that the MPCI premium is calculated at the individual farm level, which reflects larger yield variability. The weather option premium is calculated at the county level, 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 6 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, 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 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.

Table 6. Hedging Effectiveness

| 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[a/] | 1.226 | 1.322 | 1.381 | 1.387 | 1.449 | 1.240 | 1.247 |
| | VaR(10%)[b/] | \$32.69 | \$61.07 | \$68.69 | \$65.65 | \$73.48 | \$35.03 | \$36.07 |
| | CE[c/](ɣ=0.001) | \$174.76 | \$170.14 | \$177.74 | \$177.88 | \$185.71 | \$174.94 | \$175.98 |
| | CE(ɣ=0.005) | \$146.73 | \$151.47 | \$159.07 | \$158.62 | \$166.45 | \$147.86 | \$148.89 |
| | CE(ɣ=0.009) | \$120.70 | \$137.05 | \$144.65 | \$143.44 | \$151.27 | \$122.97 | \$124.01 |
| | RP[c/](ɣ=0.001) | \$7.52 | \$5.55 | \$5.55 | \$5.65 | \$5.65 | \$7.31 | \$7.31 |
| | RP(ɣ=0.005) | \$35.55 | \$24.22 | \$24.22 | \$24.90 | \$24.90 | \$34.39 | \$34.39 |
| | RP(ɣ=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 (ɣ=0.001, 0.005, 0.009).

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 MPCI 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 MPCI 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. MPCI insures the highly variable individual farm-level yields relatively better than weather derivatives 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, mainly due to the hedging gap caused by local basis risk (an imperfect weather-yield relationship). 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 weather risk management.

Table 7. 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 |

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 7 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.

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

Table 8. Government Use of Weather Options at the County Level

| | | 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 |

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?

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 8 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 the 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 6 and 8, 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 with Minneapolis-based weather derivatives in southern Minnesota where geographic basis risk is not large. 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.

## Conclusions

Social cost includes the explicit and implicit costs that exist in the 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 government is the re-insurer 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.

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