BASIS RISK AND WEATHER HEDGING EFFECTIVENESS

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Abstract

Basis risk has been cited as a primary concern for implementing weather hedges. This study investigates several dimensions of weather basis risk for the U.S. corn market at various levels of aggregation. The results suggest that while the degree of geographic basis risk may be significant in some instances, it should not preclude the use of geographic cross-hedging. In addition, the degree to which geographic basis risk impedes effective hedging diminishes as the level of spatial aggregation increases. In fact, geographic basis risk is actually negative in the case most representative of a reinsurance hedge, and the reduction in risk from employing straightforward temperature derivatives is significant. Finally, precipitation hedges are found to introduce additional product basis risk. The findings may be of interest to decision makers considering using exchange traded weather derivatives to hedge agricultural production and insurance risk.

Keywords

Weather Derivatives, Basis Risk, Spatial Aggregation, Insurance, Hedging Effectiveness

1 Introduction

Weather derivatives are mechanisms which can be used to manage the effects of weather related events on agricultural production. Most research pertaining to the management of weather risk in agriculture has focused on pricing issues (e.g., TURVEY, 2006; TURVEY, 2005; TURVEY, 2001; RICHARDS ET AL, 2004; CAMPBELL AND DIEBOLD, 2005), although a handful of studies have examined hedging effectiveness directly (e.g., VEDENOV AND BARNETT, 2004; WOODARD AND GARCIA, 2006). Previous weather hedging studies have assumed that sufficiently liquid derivative markets exist for the remote agricultural regions considered, and

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that hedgers can obtain reasonable prices on over-the counter (OTC) derivative products. These assumptions may not be realistic as sufficient historical data may not always exist and/or speculators may require risk premiums significantly in excess of those charged in more liquid but distant large-city markets. Yet, hedging with non-local contracts may introduce additional basis risk, as the payoffs from these contracts may not offset losses in the underlying exposure being hedged.

Basis risk has been cited as a primary concern for the implementation of weather hedges (see e.g., TURVEY, 2001; TURVEY 2006; DENG ET AL, 2007; BROCKETT ET AL, 2005). However, to our knowledge a systematic assessment of basis risk has not been conducted in the weather derivative literature. Investigation of the characteristics of basis risk may be crucially important if weather hedging instruments are to be widely adopted. An understanding of basis risk may be particularly important in the agricultural arena where the acceptance of weather derivatives has been impeded by a lack of knowledge concerning their use and performance. Thus, a systematic investigation of basis risk may assist decision makers when hedging.

We investigate several aspects of the basis risk problem for Illinois corn yields at the Crop Reporting District (CRD) and state levels for the period 1971 to 2005. Both precipitation and temperature derivatives are investigated. Following VEDENOV AND BARNETT (2004) and WOODARD AND GARCIA (2006), basis risk is examined for summer temperature and precipitation derivatives under the assumed objective of minimization of semi-variance. The expected shortfall measure of risk (DOWD AND BLAKE, 2006) is also investigated, and sensitivity analyses are conducted regarding assumptions about distributions of the underlying weather indexes, transaction costs, and preferences.

We extend the literature in several dimensions. First, we investigate basis risk for and across multiple geographic locations, including those for which exchange traded derivatives exist. To date, this has not been sufficiently addressed. Second, we investigate the influence

that spatial aggregation—of both the exposures being hedged as well as the hedging instruments—has on basis risk. Analysis at greater levels of spatial aggregation is of more interest to insurers. Motivation for investigation of this dimension emerges from research which questions the feasibility of producer risk management with weather derivatives in this market (VEDENOV AND BARNETT, 2004). Also, the notions that weather hedges are more likely suitable for re/insurers than individual producers (WOODARD AND GARCIA, 2006) and that re/insurers will inevitably play an important role if weather derivatives are to be widely adopted in agriculture further motivate investigation of this issue. Third, we investigate basis risk across products by comparing the effectiveness of precipitation and temperature derivatives. While earlier studies have focused on both types of instruments, comparisons of the two have not been conducted. Fourth, we investigate the sensitivity of our findings to alternative pricing assumptions. This may be particularly informative since much attention in the literature has been given to comparing alternative pricing methods, but little attention has been given to the extent to which the assumed method of pricing may affect hedging decisions.

2 Basis Risk

Basis risk is defined as the risk that the payoffs of a given hedging instrument do not correspond to shortfalls in the underlying exposure. Basis risk, for any given hedging horizon, can be categorized into three types: local, geographic, and product.

2.2 Local Basis Risk

Local basis risk refers to the degree to which a particular weather derivative is an imperfect hedge against shortfalls for a given exposure, where the underlying index on the weather derivative and the exposure being hedged correspond to the same geographic location. For instance, a corn producer in central Illinois may wish to hedge against drought using a weather contract derived from weather at a local county station. Even if the payoffs of the derivative accurately reflect local weather conditions, it may not provide a perfect hedge

because of an imperfect link between weather and the biological production process. Formally, we define *local basis risk* as

$$\sigma_k^{local} = E[f(y_{k,t} + h_k * \pi_{k,t} - E(y_k))] \quad (1)$$

where y is the value of the exposure being hedged, π is the profit per standardized unit of a given weather derivative, $f(x)$ is a function relating deviations in the value of a hedged position from the expected value of the exposure (e.g., expected square loss),[1] and h is the optimal hedge ratio in quantity of standardized weather derivative contracts per unit of exposure value which minimizes $\sigma_{local,k}$ for any given $f(x)$, t is a time index, and k is a location index.

2.3 Geographic Basis Risk

Often it may not be feasible to use a contract for the local area as measurement and monitoring may be too costly and more efficient markets may exist for larger cities. For example, the Chicago Mercantile Exchange (CME) offers temperature futures and options for several major international cities, which are among the most liquid and fairly priced contracts available. These cities often have relatively liquid over-the-counter (OTC) markets for precipitation derivatives as well as more exotic weather products. Extra basis risk may arise, however, when the weather derivative employed is derived from a non-local city as opposed to a local one. As JEWSON AND BRIX (2005) point out, there is usually a trade-off between basis risk and the price of the weather hedge.

Geographic basis risk is defined as the additional basis risk imposed by employing a non-local weather derivative. Formally

$$\sigma_{k,l}^{geo} = E[f(y_{k,t} + h_{k,l} * \pi_{l,t} - E(y_k)) - f(y_{k,t} + h_{k,k} * \pi_{k,t} - E(y_k))] \quad (2)$$

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[1] In this context, the function for expected square loss, $f(x) = E[\max(0, x)^2]$, would yield the semi-variance of a hedged position.

where all variables are previously defined, l is a location index for the non-local derivative, and $h_{l,k}$ denotes the optimal hedge ratio for the exposure in location k of a weather derivative derived from weather at location l. Thus, geographic basis risk is the additional risk that arises by using a non-local contract. While geographic basis risk is defined in terms of a particular site, it is possible for location indices to also be specified as a weighted set of locations to identify the effect of offsetting an exposure risk using weather derivatives from multiple non-local markets.

2.4 Product Basis Risk

Product basis risk refers to the difference in hedging effectiveness between alternative hedging instruments. Formally

$$\sigma_{k,l,i,j}^{prod} = E[f(y_{k,t} + h_{k,l,i} * \pi_{l,i} - E(y_k)) - f(y_{k,t} + h_{k,k,j} * \pi_{k,j} - E(y_k))] \quad (3)$$

where the indexes i and j refer to the type of weather derivative, and k and l may or may not refer to the same location(s). Product basis risk can refer, for example, to the difference in hedging effectiveness between precipitation and temperature derivatives.[2]

3 Weather Indexes

We examine temperature and precipitation derivatives. It is well accepted that high temperatures can significantly hinder corn development. Temperature derivatives and indexes based on Accumulated Cooling Degree Days (ACDD's) for the summer season: June, July, and August are used. Agronomic experiments indicate that cooling degree days (CDD's) are more relevant to crop yields than outright temperature measurements (SCHLENKER ET AL, 2006). It can be argued that temperature derivatives are likely the most feasible weather variable on which to structure weather contracts since temperature derivatives traded on the CME are written on ACDD indexes. The number of CDD's for a single day is defined as the amount by which the average temperature is above the reference temperature, sixty-five

[2] All weather hedges are in essence cross-hedges with different contract structures and delivery points.

degrees Fahrenheit. Explicitly, the number of CDD's on any day *d* is given by

$$CDD_d = Max(0, T_d - 65) \tag{4}$$

where T_d is the is the simple arithmetic average of the daily maximum and minimum temperatures on day *d*. The index of ACDD's on any day of the index period, *d,* is defined as

$$ACDD_d^{M,N} = \sum_{d=M-N}^{M} CDD_d, \quad d = M-N,...,M \tag{5}$$

where $M - N$ is the first day of the contract period and M is the expiration date.

The use of temperature derivatives alone is usually not a major shortcoming as atmospheric flow patterns that control much of the North American climate tend to be persistent (NAMIAS, 1986). On a large scale, average temperature and precipitation conditions for a given region tend to be highly negatively correlated in these extreme events. Temperature is also highly spatially correlated, while precipitation tends to be more dispersed. Since measurements are taken at discrete points in space (i.e., individual weather stations), temperature measurements are more representative of the surrounding region (for example, the county in which the temperature measurement was taken) than are precipitation measurements. In this sense, temperature measurements may be considered more reliable than precipitation measurements. From a hedging perspective, temperature derivatives may be naturally more suited for hedging crop production risk because their measurement entails less idiosyncratic effects than precipitation.

Most estimates put the share of temperature derivatives as a percent of the entire weather market in excess of 90%. Nevertheless, we investigate precipitation contracts as well because of the attention they have attracted in the literature. This study considers cumulative precipitation (CP) contracts

$$CP_d^{M,N} = \sum_{d=M-N}^{M} P_d, \quad d = M-N,...,M \tag{6}$$

where P is daily precipitation measured in inches. Since most days do not experience any precipitation, there is no reason to truncate the daily precipitation measurements as is done with temperature.

While past studies have suggested that in some markets there may be potential benefits of using contracts that focus on shorter time intervals or specific events (TURVEY, 2001; TURVEY, 2007) we restrict attention to seasonal contracts. There are several reasons for this. First, month-to-month temperatures are typically autocorrelated (JEWSON AND BRIX, 2005), particularly in extreme events likely to result in widespread crop losses (NAMIAS, 1986). Second, with the small number of years of data available, using multiple derivative contracts increases the probability of over fitting the hedging parameters. Thus, including contracts for individual months or weeks may diminish the accuracy of the hedging estimates and further may not be necessary to achieve reasonable hedging effectiveness. Third, the seasonal contracts considered here are usually more liquid compared to their time disaggregated counterparts. Since research has demonstrated that transaction cost is a major impediment to the use of agricultural derivatives (LENCE, 1996; MATTOS, GARCIA, AND NELSON, FORTHCOMING), we opt to study more transaction-cost friendly instruments.

3.2 Derivative Pricing

All derivatives are priced using burn analysis (BA). BA is the simplest method for pricing weather derivatives, and is based on calculating what the contract would have paid out in the past based on the observed historical distribution.[3] It is attractive in that it does not require strong assumptions about the distribution of the underlying index, and it is straightforward to compute.[4]

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[3] The assumptions of BA are that the historical terminal index time series is stationary, and statistically consistent with the prevailing climate during the contract period (i.e., the historical distribution of weather accurately reflects the true underlying distribution), and that the values are independent across different years (JEWSON AND BRIX, 2005). Regressing the temperature indexes on a linear trend suggested no significant warming or cooling trends in our data.

[4] We offer BA as a sufficient pricing method. While a change in the contract price would uniformly shift the ex-post revenue of the buyer up or down, this would not affect the payment schedule and the correlation between losses and payoffs embedded in the contract structure (VEDENOV AND BARNETT, 2004).

3.3 Derivative Structures

Since research suggests that the relationship between yields and weather variables is non-linear and possibly quadratic (WOODARD AND GARCIA, 2006; AND VEDENOV AND BARNETT 2004), we restrict attention to hedging with option contracts. The pay-off, *p,* from a long call option is given by

$$p_t(I_t, K) = Max(0, D(I_t - K)) \tag{7}$$

and the profit, π, of an option position initiated on day *d* is given by

$$\pi_t(I_t, K) = Max[0, D(I_t - K)] - e^{r\left[\frac{M-d}{360}\right]} PREM_d(K) \tag{8}$$

where *t* is the year index, *I* is the weather index value in year *t*, *D* is the tick value measured in \$/*I*, *K* is the strike price, *r* is the risk-free rate, and *PREM* is the option price, or premium. The premium is compounded forward at the risk-free rate in order to account for opportunity costs of initiating the option position. Pricing entails simply determining the fair premium, or fair price, defined as the price such that the expected profit on the derivative is zero. The fair price is set equal to the discounted expected pay-off of the contract for any given *K*. Formally, on any day *d* before expiration of the contract, the premium equals:

$$PREM_d = e^{-r\left[\frac{M-d}{360}\right]} E_d(p) \tag{9}$$

where $E_d(\bullet)$ denotes the expectation on day *d.* Thus, pricing using BA simply consists of calculating the mean of the historical pay-offs, *p,* given a strike, *K.* If *d* is set at a point in time sufficiently prior to the realization of the index such that no information has been incorporated into the forecast of the ending distribution of the weather index, then BA should provide reasonable results. It is assumed that borrowing and lending occurs at the risk free rate. Put options are employed for precipitation hedges to protect against drought conditions, and are expressed similarly.

3.4 Hedging Analysis

Consistent with the focus of previous research, we restrict attention to hedging quantity risk

by assuming that all price risk is hedged prior using price derivatives (e.g., HAYES ET AL, 2004).[5] The hedge ratio and strike is estimated by minimizing the semi-variance (SV) of a portfolio consisting of a yield exposure and a weather derivative using a historical simulation (VEDENOV AND BARNETT, 2004). SV only measures deviations below the mean and thus is a measure of downside risk. The weight, or hedge ratio (contracts/$ acre), *h,* and strike price, *K*, are chosen by solving

$$\min_{h_{k,l},K_{k,l}} \quad \sum_t \left(\max\{\overline{Y_k} - [Y_{k,t}^{\det} + h_{k,l}\pi_{k,t}(K_{k,l})], 0\}\right)^2 \cdot \frac{1}{T} \tag{10}$$

where $Y_{k,t}^{\det}$ is detrended yields in bu/acre, $\overline{Y_k}$ is the long-run average detrended yield, *I* is the weather index being considered (*CP* or *ACCD*), *T=35* is the sample size, and $\pi_k(K)$ is the profit from a fairly priced call option with strike price *K* which pays $1 per unit of the weather index.[6] Optimal portfolios are estimated using a grid search over *h* and *K*.

The tick on the weather option is normalized to $1 per unit of the weather index for simplicity. This choice is arbitrary. In practice it would simply be rescaled to account for the tick of the particular contract. As noted, attention is restricted to quantity risk only as optimal portfolios are estimated when price and quantity decisions differ. Thus, the hedge ratio, *h*, is expressed in contracts per hedged revenue acre. For instance, suppose we are referring to an exposure of 1,000 acres which is hedged with price derivatives at $2.50/bu. If average yield is $\overline{Y_k}$, and the price derivative (e.g., a futures contract) is expressed in $/bushel standardized to 1 bushel per contract, then the optimal number of price derivatives in terms of the optimal

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[5] While it is true that there may be an interaction between market prices and observed weather, whether or not they are complements or substitutes in a risk management context is an empirical question we leave as an area of future research.

[6] As noted, the expected payoff of the option is discounted at the risk-free rate in order to obtain the fair option premium on any day *d* prior to expiration of the option. In our formulation, however, it is not necessary to define *d* explicitly since the expected payoff of the discounted option is simply equal to the discounted premium invested at the risk-free rate. Since we assume risk-free borrowing, and that the date, *d,* that the hedge is initiated has no effect on the expectation of the terminal index distribution, the results are invariant to the choice of *d.* For practical purposes, *d* is assumed to be some day sufficiently prior to the first day of the growing season such that no information about the coming season has been incorporated into the market's expectation of the terminal index distribution.

hedge ratio of the price derivative in bushels, say z, purchased would be $z \times 1000 \times \overline{Y}_k$. If the contracts were standardized, for example, at 5,000 bushels then the number of price derivatives purchased would simply be rescaled and expressed as $z \times 1,000 \times \overline{Y}_k \div 5,000$. The optimal weather hedge in terms of h would then be expressed as $h \times 1,000 \times \$2.50$. If, for example, the option paid $50 per tick of the underlying weather index, then it would be expressed as $h \times 1000 \times 2.5 \div 50$.

3.5 Risk Measures

The criterion used to evaluate basis risk is the root mean square loss (RMSL). RMSL is a simple function of SV,

$$RMSL_{k,l} = \sqrt{\sigma^2{}_{k,l}^{-}} \tag{11}$$

where $\sigma^2{}_{k,l}^{-}$ is the SV from equation (10). In terms of equations (1), (2), and (3), this is equivalent to substituting *RMSL* for *f(x)*.

In addition to expected net losses, agents may also be interested in the magnitude of losses given an extreme event occurs. Thus, expected shortfall (ES) is also reported (DOWD AND BLAKE, 2006).[7] ES is the probability weighted average of the worst α revenues. In the case of a discrete distribution, the ES is given by

$$ES_\alpha = \frac{1}{\alpha}\sum_{p=0}^{\alpha}(\text{pth worst outcome}) \times (\text{probability of pth worst outcome}) \tag{12}$$

and is reported for $\alpha \approx 6\%, 9\%$.[8] It can be interpreted as an expectation of yields in the case

[7] The ES measure used here is based on the return distribution, and is thus a modification of the measure reported in DOWD AND BLAKE (2006), which is calculated in terms of the loss distribution.

[8] Since the ES measurements are calculated using a historical simulation where each observation is assigned an equal probability of $1/T$ (T=35), ES 6% approximately equals the average of the two lowest valued observations, and ES 9% approximately equals the average of the three lowest observations. A subset of the results was replicated using simulation techniques to assess the sensitivity of this discretized technique. Several alternative parametric functional forms were estimated for the return distribution, and then numerical integration was used to estimate ES. The results were not materially different and further the discretized calculation was not biased compared to the parametric calculations.

that a tail event *does* occur, and thus is a preference free measure of tail-risk.[9] The expected shortfall measure is used rather than the Value-at-Risk (VaR), which provides an estimate of the worst loss that one might expect given a tail event does not occur, because the ES is subadditive making it less likely to produce puzzling and inconsistent findings in hedging applications. As DOWD AND BLAKE (2006) point out, subadditivity "reflects our expectation that aggregating individual risks should not increase overall risk, and this is a basic requirement of any 'respectable' risk measure, coherent or otherwise." Since the VaR is just a quantile and is not subadditive, instances may arise where the VaR of a portfolio is greater than the sum of the VaR's of its components.

5 Data

The data used are Illinois Crop Reporting District (CRD) corn yields for 1971-2005. Illinois consists of nine CRD's. Temperature and precipitation data were collected for a location within each CRD as well as a handful of nearby major cities, including Kansas City, Chicago, Minneapolis, Des Moines, Cincinnati, and St. Louis. An attempt was made to select the most centralized location in each district (Table 1). Yield data were obtained from the National Agricultural Statistics Service website, and weather data from United States Historical Climatology Network (USHCN) website (WILLIAMS ET AL, 2006) and the National Climatic Data Center (NCDC). The state level (i.e. aggregated) yield and weather index measures were calculated as a simple average of the individual district yields and weather indexes.[10]

5.2 Temperature and Precipitation Correlations

Figure 1 presents average temperature and precipitation for each CRD during the period. In general, the climate in northwest Illinois is relatively cool and wet, while the southeast tends to be hotter and drier. Across CRD's, the correlation between average temperature (ACDD's) and precipitation (CP) for the period was -0.46, indicating that the hotter regions also tended

[9] The ES measure has also been referred to as the Conditional Tail Expectation, Expected Tail Loss, Tail VaR, Conditional VaR, Tail Conditional VaR, and Worst Conditional Expectation. Alternatively, ES can be interpreted as the utility of tail-risk for an agent with risk neutral tail-risk preferences.

[10] Replication of the results with a production weighted average did not materially change our findings.

Table 1: Selected Weather Stations, Illinois Crop Reporting Districts

District	City	County
D10 Northwest	Dixon	Lee
D20 Northeast	Ottawa	LaSalle
D30 West	LaHarpe	Hancock
D40 Central	Bloomington	McLean
D50 East	Hoopeston	Vermillion
D60 West Southwest	Whitehall	Greene
D70 East Southeast	Olney	Richland
D80 Southwest	Sparta	Randolph
D90 Southeast	Harrisburg	Saline

The Table presents the location for the local weather station selected in each Crop Reporting District.

to be drier. Temperature and precipitation are negatively correlated across years as well. For the whole sample, the average correlation of CP and ACDD's was -0.27. This negative correlation is even stronger during drought events. For example, during the fifteen hottest years in the sample—as measured by the average of the ACDD's for the local stations—the correlation between average local CP and ACDD's was -0.57, while during the coldest fifteen years the correlation was only -0.16. Thus, the payoffs from ACDD calls and CP puts are highly congruent during events likely to result in crop losses. For example, the four driest years in the sample—1983, 1984, 1988, and 1991—were also among the hottest years. During these years the average CP was 6.75 and average annual ACDD's were 1061.21 for the state. These values corresponded to approximately the 7th and 93rd percentiles of CP and ACDD measurements, respectively. Thus, although ACDD and CP derivatives are not perfect substitutes, because temperature and precipitation are highly negatively correlated in Illinois—particularly in drought events—they likely act as surrogates when protection is needed most.

5.3 Technology Change and Yield Trends

Failure to account for technological advancements yields may produce spurious results. To account for technology gains, yields are detrended using a simple linear trend model

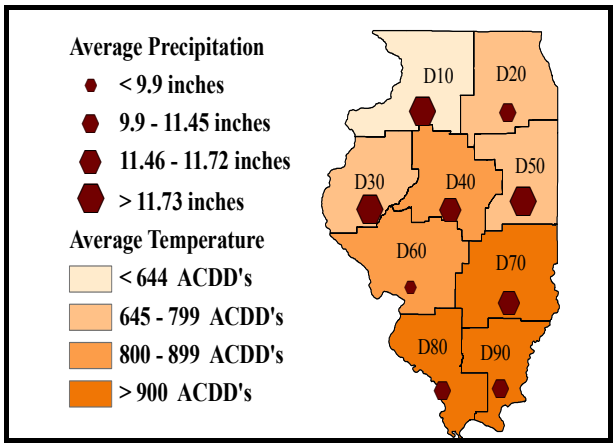
$$Y_t^{tr} = \alpha_0 + \alpha_1 t, \qquad t = 1971, 1972, ..., 2005 \tag{13}$$

Detrended yields to 2005 equivalents are calculated as

$$Y_t^{\det} = Y_t + \alpha_1 (2005 - t), \qquad t = 1971, 1972, ..., 2005 \tag{14}$$

where Y_t are observed yields and Y_t^{tr} are the corresponding yield trends.

Figure 1: Temperature and Precipitation, Illinois Crop Reporting Districts



The Figure presents the average summer temperature and precipitation measurements for the sample period, 1971-2005, at the local weather station selected in each Crop Reporting District.

6 Results and Discussion

Table 2 presents results for the unhedged yield exposures for Illinois CRD's for the period 1971 to 2005. Average yield, RMSL, and ES 6% and 9% are reported for each district as well as for the State level, or aggregated exposure.[11] The "Average of Districts" row represents the average of the district level statistics, and is provided as a basis of comparison for the State level exposure. The productivity varied among the individual districts. D40 Central was the most productive with an average yield of 162.82 bu/acre, while D90 Southeast was the least productive with 126.39 bu/acre. The RMSL varied 18.14 (D50) to 12.79 (D80). The State level RMSL was 12.84 compared to 14.76 for the Average of Districts, reflecting the fact that

[11] A decrease (increase) in the RMSL corresponds to a reduction (increase) in risk as a result of the addition of a weather derivative. In contrast, an increase (decrease) in the ES indicates a reduction (increase) in risk exposure from adding a weather derivative.

the individual yields are not perfectly correlated. Thus, some of the risk of the individual districts is "self diversified" as they are aggregated.

Table 2: Unhedged Exposures

	Average	RMSL	ES 6%	ES 9%
D10 NORTHWEST	156.52	14.02	110.60	117.98
D20 NORTHEAST	149.81	14.01	104.08	109.32
D30 WEST	158.22	16.00	107.20	109.87
D40 CENTRAL	162.82	16.28	108.61	115.47
D50 EAST	153.30	18.14	94.19	101.71
D60 WEST SOUTHWEST	160.83	13.52	114.89	123.00
D70 EAST SOUTHEAST	143.87	14.25	102.32	107.32
D80 SOUTHWEST	126.68	12.79	88.03	90.26
D90 SOUTHEAST	126.39	13.84	82.86	88.32
Average of Districts	148.72	14.76	101.42	107.03
State Level	148.72	12.84	106.64	112.96

The table presents results for unhedged corn yield exposures for the sample period, 1971-2005, in bu/acre. The RMSL is a measure of average downside deviation, while the ES statistics indicate the expectation of yields given a tail event occurs.

6.2 Local and Product Basis Risk

Next, we turn attention to the local basis risk (Equation 1), defined as the hedging effectiveness of a locally written derivative. Results for each district as well as the state level for a hedged portfolio with a local precipitation (CP) and degree day (ACDD) derivative are presented in Table 3. The "State Level" hedging results were obtained by constructing ACDD and CP indexes which were averages of the local indexes. The "Average of District" results were again obtained by averaging the district level statistics. Local basis risk is measured as the difference between the percentage change in the risk measure (RMSL, ES6%, or ES 9%) for the hedged versus unhedged exposure. For example, a percentage reduction in RMSL of 100% would imply no local basis risk for the instrument, while 0% would mean that the local basis risk of the instrument is high.

Hedging effectiveness varied greatly for local ACDD derivatives. Percentage reductions in RMSL ranged from 16.01% (D90) to 46.45% (D50) for the individual districts.

The "State Level" (aggregated) RMSL (reduction in RMSL) was 7.50 (41.56%), compared to 10.38 (28.95%) for the average of the individual districts. Thus, the hedging effectiveness of local ACDD derivatives at the aggregated level was about 30% better than what would have been implied by analyzing the individual districts. In addition, the variation in hedging effectiveness was high across the individual districts. The results concerning the relationship between hedging effectiveness and spatial aggregation are consistent with those obtained by WOODARD AND GARCIA (2006), which employed a different sample period. Analysis of the ES statistics identified similar results. The ES 6% (ES 9%) for the state portfolio hedged with ACDD derivatives was 127.81 (129.59) compared to 118.05 (121.45) for the average of the district portfolios, while the increase in the change in ES 6% (ES 9%) over the unhedged portfolio was 19.85% (14.72%) at the state level versus 16.40% (13.47%) for the average of the districts.

At the disaggregate level, the hedging effectiveness of CP compared to ACDD varied, but local basis risk for CP derivatives was higher on average compared to ACDD derivatives. For example, the average reduction in RMSL for the individual districts when hedging with ACCD derivatives was 28.95% versus 23.90% for CP contracts. Thus, for local contracts, additional product basis risk is imposed on average by using CP instead of ACDD.

This effect was even stronger at higher levels of spatial aggregation. At the state level the reduction in RMSL for CP derivatives (23.34%) was much lower than for ACDD derivatives (41.56%). More importantly, the spatial aggregation effect was not present for CP contracts. That is, the reduction in RMSL for the average of districts (23.90%) was very similar to that obtained for the state level portfolio (23.34%). This is due to the fact that share of idiosyncratic risk relative to systemic risk for CP is much higher than for ACCD in an aggregated portfolio. As suggested by the framework developed by WOODARD AND GARCIA (2006), this fact results in CP contracts having higher basis risk. Similar results were obtained for the ES measures regarding product basis risk for CP and ACDD derivatives.

Table 3: Local and Product Basis Risk

	D10		D20		D30		D40		D50		D60		D70		D80		D90		Average of Districts		State Level (Aggregate)	
	CP	ACCD	CP	ACCD	CP	ACCD	CP	ACCD	CP	ACCD	CP	ACCD	CP	ACCD	CP	ACCD	CP	ACCD	CP	ACCD	CP	ACCD
Hedge Ratio	22.40	0.48	9.20	0.26	16.20	0.14	12.40	0.20	6.00	0.20	7.20	0.09	3.00	0.22	4.60	0.14	13.00	0.12	10.44	0.21	6.00	0.20
Optimal Strike	6.20	820.00	8.80	880.00	9.80	790.00	8.60	910.00	13.40	820.00	10.80	300.00	14.60	1050.00	12.80	1230.00	8.00	1070.00	10.33	874.44	13.00	940.00
Average	156.52	156.52	149.81	149.81	158.22	158.22	162.82	162.82	153.30	153.30	160.83	160.83	143.87	143.87	126.68	126.68	126.39	126.39	148.72	148.72	148.72	148.72
RMSL	9.95	9.32	10.82	11.09	11.62	12.19	12.63	8.72	12.72	10.60	10.42	8.81	12.71	10.79	9.94	10.74	10.02	11.18	11.20	10.38	9.85	7.50
% Reduction RMSL	29.05%	33.52%	22.77%	20.86%	27.37%	23.82%	22.43%	46.45%	29.86%	41.56%	22.93%	34.80%	10.80%	24.32%	22.27%	16.01%	27.60%	19.20%	23.90%	28.95%	23.34%	41.56%
ES 6%	127.76	130.07	118.61	112.75	127.46	117.08	126.67	139.06	120.11	120.33	134.06	135.35	110.12	115.56	98.33	92.17	98.80	100.05	117.99	118.05	123.52	127.81
ES 9%	130.24	131.48	120.42	119.17	128.96	124.34	129.22	141.50	123.79	124.02	135.34	137.93	112.64	116.16	101.01	97.71	100.99	100.73	120.29	121.45	125.09	129.59
% Change ES 6%	15.52%	17.61%	13.96%	8.33%	18.90%	9.22%	16.63%	28.04%	27.52%	27.76%	16.69%	17.81%	7.62%	12.94%	11.70%	4.70%	19.24%	20.74%	16.34%	16.40%	15.82%	19.85%
% Change ES 9%	10.39%	11.44%	10.15%	9.00%	17.38%	13.17%	11.91%	22.54%	21.71%	21.94%	10.03%	12.13%	4.96%	8.24%	11.92%	8.26%	14.35%	14.05%	12.39%	13.47%	10.74%	14.72%

The table presents results of the local hedging analysis under the assumed objective of minimization of SV. Estimates are obtained by optimizing the objective with respect to the hedge ratio and optimal strike. Results are presented for each district, D10-D90, as well as the state level exposure when hedging yields with a locally derived CP and ACCD derivative. "Average of Districts" statistic values are obtained by averaging the individual district statistic values and is provided to serve as a basis of comparison to the "State Level" results. Statistics measuring changes in RMSL and ES are calculated relative to the unhedged exposures. A decrease (increase) in the RMSL corresponds to a reduction (increase) in risk as a result of the addition of a weather derivative. In contrast, an increase (decrease) in the ES indicates a reduction (increase) in risk exposure from adding a weather derivative.

Table 3 illustrates that the changes in the ES measures were always greater for ACDD derivatives compared to CP derivatives, and that the spatial aggregation effect was not present for CP derivatives. In fact, the change in ES 6% (ES 9%) for CP derivatives was actually greater on average at the district level, 16.34% (12.39%), than at the state level, 15.82% (10.74%). This effect is again due to the fact that the degree of idiosyncratic risk is high for precipitation contracts.

6.3 Geographic and Product Basis Risk

The results for geographic basis risk for RMSL and ES are presented in Tables 4 and 5. Geographic basis risk was measured as the difference in hedging effectiveness between local and non-local derivatives (Equation 2), and percentage geographic basis risk was defined similarly except percentage differences are used. Positive values of geographic basis risk in Tables 4 and 5 imply that hedging with non-local as opposed to local contracts introduces extra basis risk. Negative values of geographic basis risk mean that the non-local derivatives were actually more effective hedging instruments.

The first row of results refers to the state level analysis, and the fourth row presents results for the average of the districts. The second and third row present results for two representative districts, D20 and D50. The columns indicate the location for the derivative. The first column represents unhedged exposure, the second column is for the portfolio of the exposure and a derivative written on local weather, and the remaining columns present the hedging results when a non-local derivative is used for hedging. The "Average of Cities" column measures the average of the results when hedging with individual city contracts. The last column, "All Cities", displays hedging results where the derivative used was constructed as an equally weighted portfolio of the individual cities. The cities chosen for the analysis were Kansas City, Chicago, Minneapolis, Cincinnati, Des Moines, and St. Louis. All cities have exchange traded ACDD contracts on the CME except St. Louis. The percentage reductions in RMSL (ES 6% and 9%) are again measured relative to the unhedged exposure.

Table 4: Geographic and Product Basis Risk (RMSL)

			Local	Kansas City		Chicago		Minneapolis		Des Moines		Cincinnati		St. Louis		Average of Cities		All Cities	
State Level	Unhedged	CP	ACCD	CP	ACCD	CP	ACCD	CP	ACCD	CP	ACCD	CP	ACCD	CP	ACCD	CP	ACCD	CP	ACCD
RMSL	12.84	9.85	7.50	9.28	9.10	11.83	8.59	11.23	8.17	11.70	8.17	11.96	8.39	11.15	7.22	11.19	8.27	9.10	7.07
% Reduction RMSL	-	23.34%	41.56%	27.71%	29.14%	7.85%	33.09%	12.53%	36.40%	8.92%	36.40%	6.90%	34.71%	13.18%	43.79%	12.85%	35.59%	29.10%	44.94%
Geographic basis risk (RMSL)	-	-	-	-0.56	1.59	1.99	1.09	1.39	0.66	1.85	0.66	2.11	0.88	1.30	-0.29	1.35	0.77	-0.74	-0.43
% Geographic basis risk (RMSL)	-	-	-	-4.37%	12.42%	15.48%	8.47%	10.80%	5.17%	14.42%	5.17%	16.43%	6.86%	10.16%	-2.23%	10.49%	5.97%	-5.77%	-3.38%
D20 Northeast																			
RMSL	14.01	10.82	11.09	10.04	11.38	10.80	10.63	12.34	11.45	11.53	11.45	12.98	9.15	12.38	9.57	11.68	10.60	9.16	10.00
% Reduction RMSL	-	22.77%	20.86%	28.36%	18.82%	22.92%	24.12%	11.92%	18.32%	17.75%	18.32%	7.40%	34.71%	11.68%	31.71%	16.67%	24.33%	34.64%	28.62%
Geographic basis risk (RMSL)	-	-	-	-0.78	0.29	-0.02	-0.46	1.52	0.36	0.70	0.36	2.15	-1.94	1.56	-1.52	0.86	-0.49	-1.66	-1.09
% Geographic basis risk (RMSL)	-	-	-	-5.58%	2.04%	-0.15%	-3.26%	10.86%	2.54%	5.02%	2.54%	15.38%	-13.85%	11.10%	-10.85%	6.10%	-3.47%	-11.87%	-7.76%
D50 East																			
RMSL	18.14	12.72	10.60	13.19	13.04	15.13	13.20	16.00	13.41	16.78	13.41	17.46	12.66	15.78	10.47	15.73	12.70	11.32	11.20
% Reduction RMSL	-	29.86%	41.16%	27.28%	28.10%	16.56%	27.20%	11.78%	26.07%	7.49%	26.07%	3.71%	30.21%	13.01%	42.28%	13.30%	29.99%	37.58%	38.25%
Geographic basis risk (RMSL)	-	-	-	0.47	2.44	2.41	2.61	3.28	2.81	4.06	2.81	4.74	2.06	3.06	-0.13	3.00	2.10	-1.40	0.60
% Geographic basis risk (RMSL)	-	-	-	2.58%	13.46%	13.31%	14.37%	18.09%	15.49%	22.38%	15.49%	26.15%	11.35%	16.86%	-0.72%	16.56%	11.57%	-7.72%	3.32%
Average of Districts																			
RMSL	14.76	11.20	10.38	11.03	11.03	13.52	10.92	13.21	10.44	13.64	10.44	13.67	10.51	13.42	9.77	13.08	10.52	11.12	9.47
% Reduction RMSL	-	23.90%	28.95%	25.36%	25.14%	8.22%	25.80%	10.27%	29.24%	7.73%	29.24%	7.78%	28.80%	9.06%	33.60%	11.40%	28.64%	24.16%	35.59%
Geographic basis risk (RMSL)	-	-	-	-0.17	0.65	2.31	0.54	2.00	0.06	2.44	0.06	2.46	0.13	2.21	-0.61	1.88	0.14	-0.08	-0.91
% Geographic basis risk (RMSL)	-	-	-	-1.46%	3.81%	15.68%	3.15%	13.63%	-0.29%	16.17%	-0.29%	16.12%	0.15%	14.84%	-4.65%	12.50%	0.31%	-0.26%	-6.64%

The table presents results of the geographic hedging analysis under the assumed objective of minimization of SV. Estimates are obtained by optimizing the objective with respect to the hedge ratio and optimal strike. Each column represents results of hedging with a CP or ACCD instrument from the corresponding location. The "Average of Cities" column is obtained by averaging the results obtained by hedging with all non-local city contracts. The "All Cities" column presents results from hedging the exposure with an equally weighted weather index of all non-local cities. The first row of results, "State Level", presents results from the aggregated yield exposure. The second row of results, "Average of Districts", is obtained by averaging the individual district statistic values and is provided to serve as a basis of comparison to the "State Level" results. Individual district level results are suppressed. Statistics measuring changes in RMSL are calculated relative to the unhedged exposures. Geographic basis risk is measured as the difference in hedging effectiveness between hedging the exposure with the local and non-local contract. A decrease (increase) in the RMSL corresponds to a reduction (increase) in risk as a result of the addition of a weather derivative.

Table 5- Geographic and Product Basis Risk (ES)

Geographic Basis Risk			Local	Kansas City		Chicago		Minneapolis		Des Moines		Cincinnati		St. Louis		Average of Cities		All Cities	
State Level	Unhedged	CP	ACCD	CP	ACCD	CP	ACCD	CP	ACCD	CP	ACCD	CP	ACCD	CP	ACCD	CP	ACCD	CP	ACCD
ES 6%	106.64	123.52	127.81	122.84	122.92	112.38	125.48	116.25	128.77	111.46	128.77	112.77	124.04	114.47	127.37	115.03	126.23	123.97	127.98
ES 9%	112.96	125.09	129.59	124.05	125.59	115.49	126.99	119.32	129.51	114.30	129.51	116.81	125.60	119.11	128.65	118.18	127.64	126.47	130.44
% Change ES 6%	-	15.82%	19.85%	15.18%	15.27%	5.38%	17.66%	9.01%	20.75%	4.51%	20.75%	5.75%	16.32%	7.34%	19.44%	7.86%	18.36%	16.25%	20.01%
% Change ES 9%	-	10.74%	14.72%	9.82%	11.18%	2.24%	12.42%	5.64%	14.65%	1.19%	14.65%	3.41%	11.19%	5.44%	13.89%	4.62%	13.00%	11.97%	15.47%
% Geographic basis risk (ES 6%)	-	-	-	0.64%	4.59%	10.45%	2.19%	6.81%	-0.90%	11.31%	-0.90%	10.08%	3.53%	8.49%	0.41%	7.96%	1.49%	-0.42%	-0.16%
% Geographic basis risk (ES 9%)	-	-	-	0.92%	3.54%	8.50%	2.30%	5.10%	0.07%	9.55%	0.07%	7.33%	3.53%	5.30%	0.83%	6.12%	1.72%	-1.23%	-0.75%
Average of Districts																			
ES 6%	101.42	117.99	118.05	118.09	118.44	107.42	117.45	108.98	118.41	105.69	118.41	107.37	118.22	108.63	119.89	109.36	118.47	116.98	120.01
ES 9%	107.03	120.29	121.45	120.22	120.57	110.06	120.34	113.12	121.60	109.73	121.60	111.03	120.86	112.83	122.98	112.83	121.33	119.99	123.54
% Change ES 6%	-	16.34%	16.40%	16.44%	16.79%	5.92%	15.80%	7.45%	16.76%	4.21%	16.76%	5.87%	16.56%	7.11%	18.21%	7.83%	16.81%	15.34%	18.33%
% Change ES 9%	-	12.39%	13.47%	12.32%	12.65%	2.84%	12.44%	5.70%	13.62%	2.53%	13.62%	3.74%	12.93%	5.42%	14.90%	5.42%	13.36%	12.11%	15.43%
% Geographic basis risk (ES 6%)	-	-	-	-0.10%	-0.39%	10.42%	0.59%	8.89%	-0.36%	12.13%	-0.36%	10.47%	-0.17%	9.23%	-1.81%	8.51%	-0.42%	1.00%	-1.94%
% Geographic basis risk (ES 9%)	-	-	-	0.07%	0.82%	9.55%	1.03%	6.69%	-0.15%	9.87%	-0.15%	8.66%	0.55%	6.97%	-1.43%	6.97%	0.11%	0.28%	-1.95%

The table presents results of the geographic hedging analysis under the assumed objective of minimization of SV. Estimates are obtained by optimizing the objective with respect to the hedge ratio and optimal strike. Each column represents results of hedging with a CP or ACCD instrument from the corresponding location. The "Average of Cities" column is obtained by averaging the results obtained by hedging with all non-local city contracts. The "All Cities" column presents results from hedging the exposure with an equally weighted weather index of all non-local cities. The first row of results, "State Level", presents results from the aggregated yield exposure. The second row of results, "Average of Districts", is obtained by averaging the individual district statistic values and is provided to serve as a basis of comparison to the "State Level" results. Individual district level results are suppressed. Statistics measuring changes in ES are calculated relative to the unhedged exposures. Geographic basis risk is measured as the difference in hedging effectiveness between hedging the exposure with the local and non-local contract. An increase (decrease) in the ES indicates a reduction (increase) in risk exposure from adding a weather derivative.

First, we consider the state level results. The results for ACDD derivatives varied but hedged reasonably well in all cases. Reductions in RMSL when hedging with non-local city derivatives ranged from 29.14% for Kansas City to 43.79% for St. Louis. On average, the reduction in RMSL was 35.59% when hedging with individual non-local city contracts compared to 41.56% when hedging with a derivative derived from an equally weighted index of the local indexes. That is, geographic basis risk in terms of RMSL was 5.97%. Thus, hedging effectiveness was only about 15% better when hedging with a derivative written on an index of the average of local indexes compared to the *individual* non-local city derivatives.

Interestingly, the derivative written on the average of the non-local indexes actually performed *better* than a derivative on an index of the average of the local indexes, as the percentage reduction in RMSL was 44.94% when hedging the state level exposure with a derivative derived from an index of the average of the non-local city indexes versus 41.56% when hedging the state level exposure with a derivative written on an index of the average of the local indexes. Thus, the hedging effectiveness was about 8% better when hedging with a non-local average index derivative relative to the implied hedging effectiveness of a derivative written on an average index of the local indexes. This result was slightly unexpected. It is likely due to the fact that aggregating the hedging instruments across such a large geographic area results in a portfolio that has a very high systemic component, which can be associated with production shortfalls, relative to idiosyncratic component. Since the non-local cities are spread out over a larger geographic area than are the local weather stations, the degree to which the idiosyncratic components self diversify is likely greater in the case of the former.

The same effect was present with CP derivatives. On average, ACDD contracts performed better than CP contracts. Interestingly though, the aggregation effect *in terms of the hedging instruments* was very strong when hedging with an index of all non-local cities. The reduction in RMSL at the state level when hedging with individual non-local city

contracts was 12.85% on average, whereas it was 29.10% when hedging with a portfolio of all cities. Again, this is likely due to the fact that the idiosyncratic components of the derivative returns, which can not be related to production, are much less correlated for the non-local contracts than for the local contracts because they are spread out over a larger geographic area.

Analysis of the district results (Table 4-second through fourth rows) leads to similar findings regarding geographic basis risk and the effect of aggregating across non-local contracts. On average, the geographic basis risk from hedging with non-local contracts was small, and the hedging effectiveness of a portfolio of non-local contracts was more effective than a portfolio of local contracts. The effects regarding spatial aggregation across exposures was also consistent with the results found earlier (Table 3) which compared the state level and average of district results. The hedging effectiveness was stronger for the state level exposure compared to the individual districts in virtually all cases, and was also stronger on average. The results varied somewhat for the individual districts, but overall the results were similar. While geographic basis risk for individual districts was generally higher for the disaggregated exposures than for the state level exposure, the degree of geographic basis risk was not prohibitive.

The ES results were consistent with those from the RMSL statistics (Table 5). The ACCD contracts performed better than CP contracts and the results concerning aggregation across exposures and across hedging instruments was consistent overall with the findings above. Importantly, the ES results again indicate that the geographic basis risk from hedging a state level exposure with an equally weighted portfolio of non-local contracts actually resulted in *negative* basis risk.

6.4 Implications

These results are striking since the conventional wisdom is that geographic basis risk may be a large impediment to the implementation of weather hedges. The results here indicate that

that is not necessarily so, and in fact that it may be *better* to hedge with a portfolio of non-local contracts than with a portfolio of local contracts, even before accounting for transaction costs. Further, the degree to which these hedges are effective is substantial. Specifically, the use of simple seasonal temperature derivatives can reduce downside risk by about half, and can also decrease the severity of major shortfalls significantly. For instance, the expectation of yields in the worst 6% of cases for the state level exposure was 106.64 bu/acre for an unhedged exposure. This increased over 20% to 127.98 bu/acre equivalent when hedging with simple seasonal temperature derivatives from non-local cities. The results also indicate that on average temperature based derivatives perform better than precipitation contracts. They also corroborate those found in WOODARD AND GARCIA (2006) in that hedging effectiveness was greater at higher levels of spatial aggregation in the exposure, indicating that the most likely users will be re/insurers.

7 Sensitivity Analysis

Much of the weather derivative literature has focused on issues regarding how best to determine the fair price of a given derivative and how to estimate the market price of risk, however, little effort has focused on investigating the impact alternative pricing assumptions have on the utility of weather hedges. The purpose of this sensitivity analysis is to assess the impact that alternative assumptions about the distribution of the underlying weather indexes and the market price of risk has on the hedging results.

7.2 Alternative Pricing Frameworks

There are multiple ways to price weather derivatives, including inter-seasonal methods, where the terminal index distribution is estimated *explicitly*, and intra-seasonal methods, where the ending distribution of the weather index is specified *implicitly.* Additionally, since weather is non-tradable, models have also been developed to explicitly account for the market price of risk.

Pricing with inter-seasonal models simply entails integrating the derivative payoff

function over the assumed weather index distribution to obtain the derivative's expected payoff. This payoff is then discounted at the risk-free rate to obtain the "fair" market price. Intra-seasonal pricing models in essence perform the same function, except that the ending distribution is treated as a forecast of the "true" ending distribution. The advantage in intra-seasonal models is that they can incorporate new information about the current season into the distribution forecast, whereas inter-seasonal models can only incorporate historical ending values of the index. Nevertheless, intra-seasonal models ultimately imply a particular ending distribution. Intra-seasonal models usually specify a daily process which is then aggregated over time to obtain an ending index value. Usually, Monte Carlo integration is performed to obtain the estimate of the ending index distribution (see e.g., RICHARDS ET AL, 2004; AND CAO AND WEI, 2004), however, in some cases an analytical solution may exist. With an estimate of the index distribution in hand, intra-seasonal models proceed exactly as inter-seasonal models: the derivative payoff function is integrated over the assumed index distribution and discounted at the risk-free rate to obtain a price.

Since weather is inherently non-tradable, some have suggested that it is not appropriate to discount the expected payoff of the option at the risk-free rate when determining the price. That is, the market price of risk should be incorporated into the price of the derivative. Both RICHARDS ET AL (2004) AND CAO AND WEI (2004) employ procedures that directly estimate the market price of risk using equilibrium models. The implication of a positive market price of risk is that the derivative will now have a risk premium (positive or negative), and the expected payoff from holding the option is no longer equal to zero.

BA assumes that the market price of risk is zero (i.e., that the expected payoff is discounted at the risk-free rate to obtain the price) and that the "true" terminal, or ending, distribution of the relevant weather index is equivalent to the observed empirical distribution. Here, we perform sensitivity analyses to assess the possible effects alternative distributional assumptions and different levels of risk premiums may have on hedging effectiveness.

7.3 Index Pricing Methods: Intra- vs. Inter-seasonal Models

Above, we used BA to price all derivatives since it is relatively straightforward to use and requires minimal assumptions about the distribution of the underlying weather index. Notice, BA is the equivalent to integrating the derivative payoff function over the empirical distribution of the underlying weather index and discounting the price at the risk-free rate. Inter-seasonal index pricing is similar except that it allows the weather distribution to be of any form. For instance, the analyst may have a good reason to believe that the underlying distribution follows a lognormal distribution. In this case, the derivative payoff function would be integrated over the desired lognormal distribution to obtain the expectation of the derivative payoff. This expectation is discounted at the risk-free rate to obtain the fair price.

A shortcoming of inter-seasonal index pricing models is that they do not incorporate information about the current index realization. For example, if pricing is to be conducted mid-season, intra-seasonal models are necessary. Intra-seasonal models take the estimation one step further and attempt to use daily models to aid in estimation of the ending, or terminal, index distribution. Stochastic processes are estimated, and in turn provide an estimate of the terminal distribution. From here the derivative payoff is integrated over the estimated distribution to obtain the fair price. Nevertheless, it is important to realize that intra-seasonal models ultimately imply a particular ending distribution of the underlying index. When the ending distributions in the intra- and inter-seasonal models are analogous, similar results will emerge.

Results from using BA should correspond closely to intra-seasonal models when the process generating daily results is well specified,[12] the market price of risk is zero, and pricing

[12] Since intra-seasonal pricing can allow for the incorporation of new information, these models are more likely to be beneficial in dynamic hedging contexts or situations in which the hedge is being placed midseason after information has been realized which may affect the market's expectation of the terminal distribution of the index. The use of daily models does have drawbacks though. Namely, that the risk of misspecifying the daily weather process is high. When estimates from a misspecified daily model are aggregated to obtain estimates of an accumulated index, small errors in the daily model can have a multiplying effect (CAMPBELL AND DIEBOLD, 2005) rendering estimates of the index distribution potentially worse than those that can be obtained by using the historical index values. In practice, continuous repositioning of hedging positions also increases transaction costs.

is conducted before any information about the next index realization has been incorporated into the distribution forecast. Indeed, RICHARDS ET AL (2004) find that BA estimates are comparable to those obtained from their complex pricing representation when the market price of risk is zero.[13] Since our analysis assumes the hedge is placed before the season starts, we investigate the sensitivity of our finding to different inter-seasonal specifications by allowing the ending distribution to take alternative functional forms.

7.4 Equilibrium Models, the Market Price of Risk, and Risk Premiums

Since weather itself is not a tradable asset, the no-arbitrage framework that is used to price other derivatives breaks down. In this case, numerous authors (see e.g., RICHARDS ET AL, 2004) have argued for the importance of considering the market price of risk in pricing weather derivatives. In essence, when the market price of risk is not equal to zero, then the expected payoff of the derivative should be discounted back at something other than the risk-free rate, which is equivalent to the derivative having a risk premium. Some authors have proposed using equilibrium models to estimate the market price of risk (e.g., RICHARDS ET AL, 2004; CAO AND WEI, 2004). Unfortunately, difficulties in selecting the appropriate aggregate dividend process and utility function limit their feasibility. Thus, while equilibrium models may be more theoretically "valid" than models that simply discount the expected payoff at the risk-free rate, they are virtually never used in practice (JEWSON AND BRIX, 2005).

TURVEY (2005) argues that the market price of risk should be zero when spatial aggregation provides an opportunity to develop a risk-free portfolio in a CAPM framework. For large city markets where fairly liquid markets for the derivatives exist, this seems

[13] RICHARDS ET AL (2004) find BA option premiums which are only about 6%-7% higher than their estimated model when the options are fairly priced. TURVEY (2005), on the other hand, finds BA premiums which are significantly higher than those obtained from his Black-Sholes type stochastic pricing method. It should be noted, however, that Turvey appears to fail to detrend the index used to obtain his BA estimates, while his stochastic estimation does take into account the apparent trend embodied in his data. Failure to account for a trend in the BA pricing estimation would cause the volatility to be overestimated and as a result the BA prices would be biased upward relative to a properly specified distribution. RICHARDS ET AL (2004) also fail to account for a trend in their BA estimates, which could bias their BA estimates upward, but the trend in their data set was not as extreme as in TURVEY's (2005). Nevertheless, if the index trend is accounted for appropriately there is no reason to believe a priori that BA should produce estimates which are biased one way or the other relative to any given alternative pricing procedure.

reasonable. For illiquid rural weather stations, however, significant risk premiums for the derivatives may exist. Notice, the hedger's desire to avoid paying these risk premiums is the primary motivation for considering geographic cross hedges. If the hedger has to pay a risk premium on hedging instruments derived from illiquid rural markets, but not on large city markets, this is equivalent to saying that the hedger incurs lower transaction costs when using geographic cross hedges. If the impact of risk premiums is significant, this further motivates the case for using geographic cross hedges. Thus, an inquiry into the performance of weather hedges under alternative risk premiums warrants attention.

7.5 Utility and Hedging

Since BA assumes the derivative is fairly priced there is no need to consider utility models because the choice of hedging instrument will not affect the expected return. If the derivatives being compared have different expected returns, then analyzing risk alone will not be sufficient since a change in the contract price will affect expected return. Thus, analysis must be carried out using utility based models.

In their analysis of dairy hedging with weather derivatives, DENG ET AL (2007) assume the producer values returns using a the mean variance criterion (MV). The mean semi-variance criterion (MSV) may be a better approximation of utility when the investor values losses differently than gains and the return distribution is not symmetric (MARKOWITZ, 1991). In the context of crop losses, the MSV may be a more appropriate utility approximation because of the negative skew typical in the crop yield distributions. Here, we employ the MSV to assess the sensitivity of the main results to alternative pricing assumptions regarding the distribution of the underlying weather index and different risk premium specified in terms of varying transaction costs. The MSV is similar to the MV except the variance of returns is replaced by two times the semi-variance (ESTRADA, 2004)

$$MSV = E(R) - A \times \sigma^{2-} \tag{15}$$

where R is the portfolio return and A is a risk aversion coefficient.

To carry out the analysis, we compare the results obtained using BA pricing to those obtained by using index pricing to assess the effect that the assumed distributional form has on the pricing of the option. Three alternative distributional forms for the weather index are estimated from a set of thirty-seven different possible standard functional forms. The three distributions with the highest average ranking among the Anderson-Darling, Kolmogorov-Smirnov, and Chi-Squared statistics were selected for analysis.

The option premium is estimated as the discounted value of the expected pay-off of the option. For call options

$$PREM_d = e^{-r\left[\frac{M-d}{360}\right]} \int_{-\infty}^{\infty} Max[D(I_t - K), 0] g_d(I) \mathrm{d}I \tag{16}$$

where $g_d(I)$ is the estimated probability distribution of the weather index I at expiration M, and the expectation of the index and the pricing is taken on day d. Prices are estimated using Monte Carlo integration. Estimation for put options follows similar reasoning.

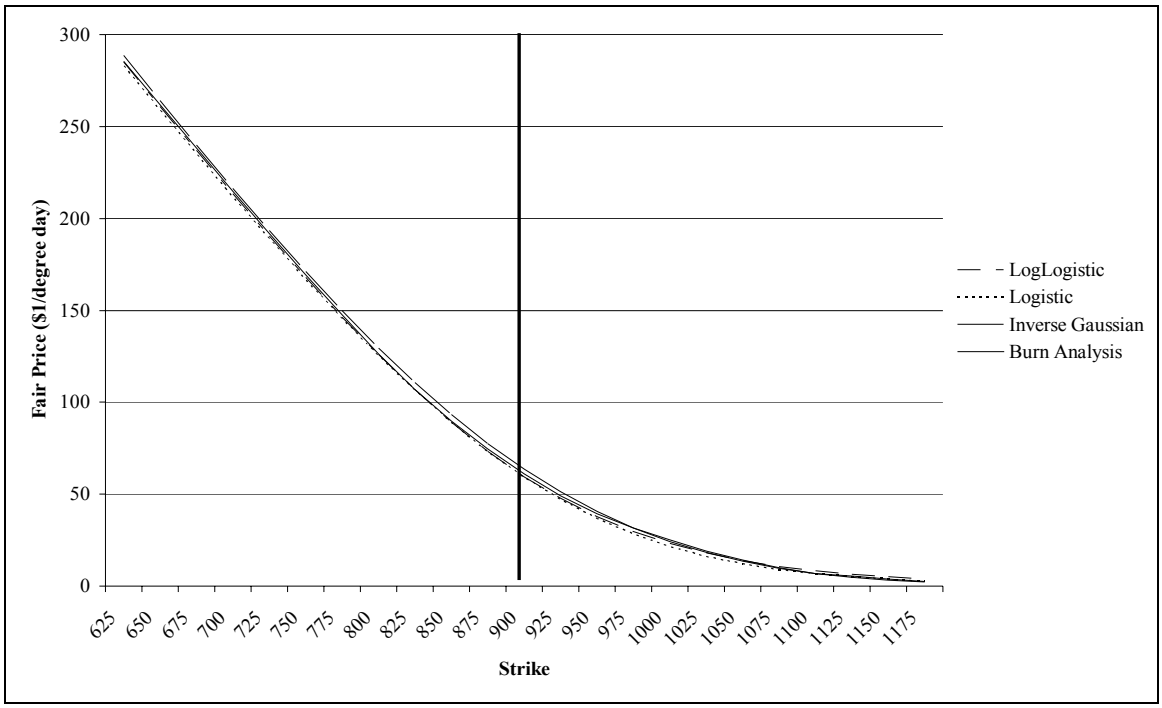
Second, we investigate the effect that risk premium may have on the utility of the weather hedge. A risk premium is levied on the option premium as a function of the expected pay-off. Thus, the option premium including the risk premium is equal to

$$PREM_{d,\gamma} = (\gamma + e^{-r\left[\frac{M-d}{360}\right]}) \int_{-\infty}^{\infty} Max[D(I_t - K), 0] g_d(I) \mathrm{d}I \tag{17}$$

where γ is the risk premium. The risk premium is levied in this way so that it is invariant to the number of days to expiration.

We investigate the implications of our pricing assumptions using the MSV criterion at differing levels of risk aversion. For brevity, we restrict attention to the case of hedging the state level exposure with a call option derived from an equally weighted index of non-local city ACDD's.

Figure 2: Call Option Prices, Average of Cities (Non-Local) ACDD Index



7.6 Sensitivity Analysis Results: Index Distributions

The Logistic, LogLogistic, and Inverse Gaussian specifications were the best, second-best, and third-best fitting distributions for the index considered. Figure 2 shows the fair price of an "All Cities" ACDD call option at different strike prices for the three alternative functional forms as well as for the BA specification (i.e., the empirical distribution). All distributions yield prices which are nearly perfectly correlated across strikes. Figure 3, which shows the differences between the prices using the estimated parametric distribution and the BA price, presents a somewhat clearer picture of the relationships among the distributions. The absolute difference from the BA price was always less than $4/contract and was greatest for the deepest in-the-money strikes. There is no uniform relationship between BA and the other specifications. In some cases BA results in lower prices, while in others the price is higher. Figure 4, which shows percentage differences from the BA price, again illustrates that the difference varies according to the strike price. In general, the more in-the-money the option strike, the smaller the difference among alternative distributions of the underlying index.

Figure 3: Call Option Value, Difference from Burn Price, Average of Cities (Non-local) ACDD Index

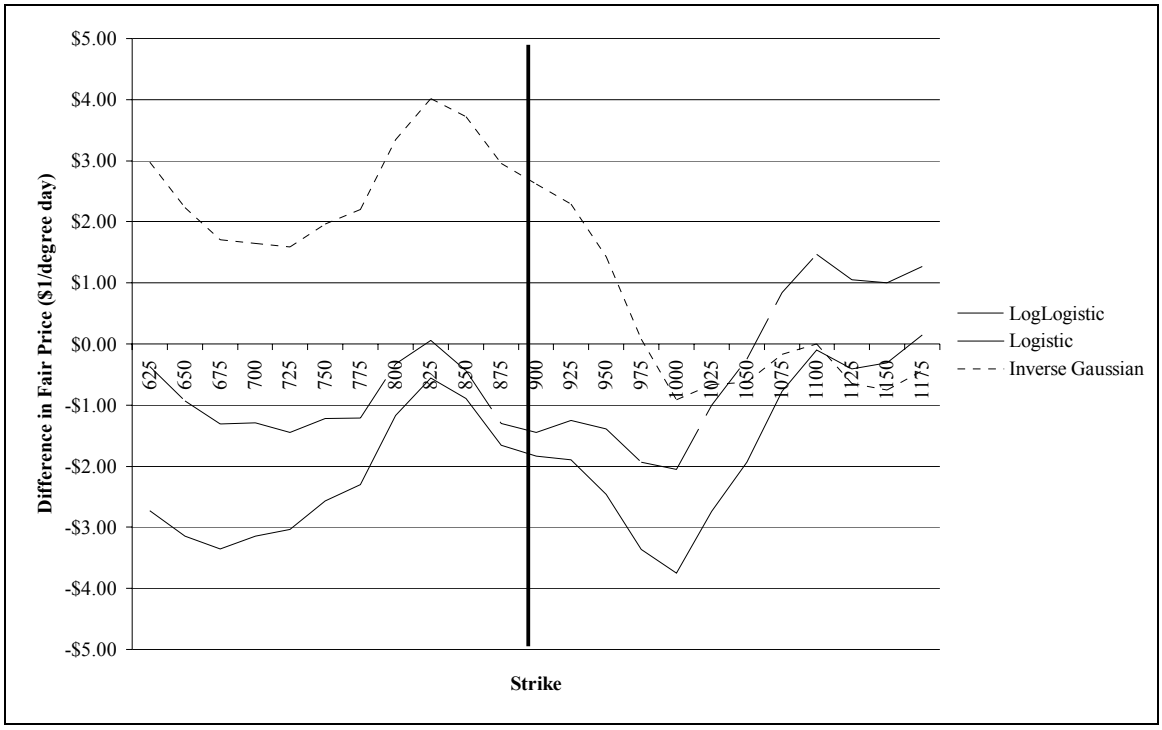


Figure 4: Call Option Value, % Difference from Burn Price, Average of Cities (Non-local) ACDD Index

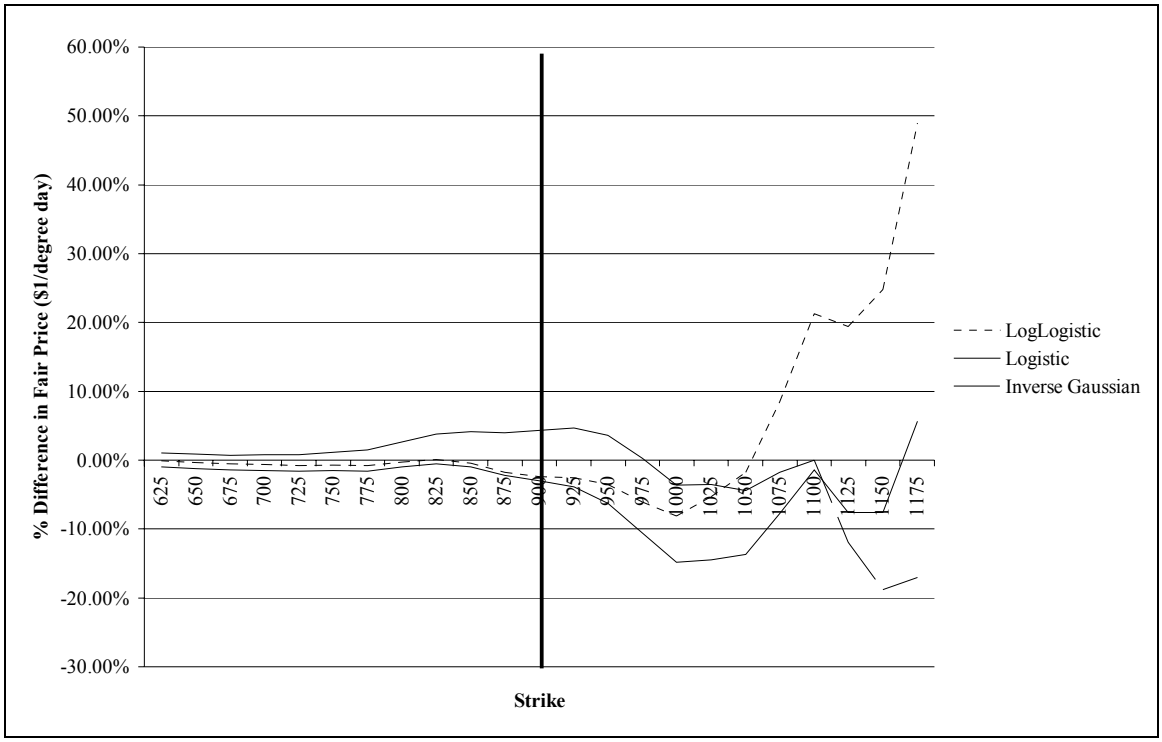


Table 6: Mean Semi-Variance Results, Pricing Distribution Sensitivity

	LogLogistic	Logistic	Inverse Gaussian	Burn
A=0.01				
Hedge Ratio	0.177	0.196	0.134	0.154
Optimal Strike	940.000	940.000	940.000	940.000
Option Price	$41.51	$40.59	$44.60	$42.86
Average	148.953	149.160	148.482	148.715
RMSL	7.179	7.412	7.175	7.068
% Reduction RMSL	44.10%	42.28%	44.13%	44.96%
ES 6%	127.070	126.470	128.224	127.817
ES 9%	130.763	130.569	129.518	130.604
MSV	148.438	148.610	147.967	148.216
A=0.02				
Hedge Ratio	0.165	0.174	0.143	0.154
Optimal Strike	940.000	940.000	940.000	940.000
Option Price	$41.51	$40.59	$44.60	$42.86
Average	148.938	149.111	148.468	148.715
RMSL	7.095	7.154	7.099	7.068
% Reduction RMSL	44.75%	44.29%	44.72%	44.96%
ES 6%	127.554	127.346	128.049	127.817
ES 9%	130.845	130.944	129.868	130.604
MSV	147.931	148.087	147.460	147.716
A=0.03				
Hedge Ratio	0.161	0.166	0.146	0.154
Optimal Strike	940.000	940.000	940.000	940.000
Option Price	$41.51	$40.59	$44.60	$42.86
Average	148.933	149.093	148.462	148.715
RMSL	7.080	7.100	7.082	7.068
% Reduction RMSL	44.87%	44.71%	44.85%	44.96%
ES 6%	127.708	127.667	127.904	127.817
ES 9%	130.871	130.992	130.004	130.604
MSV	147.429	147.581	146.957	147.217

The table presents results for the MSV analysis for four alternative weather index distributions. The MSV is maximized with respect to the hedge ratio. The results for hedging the state level exposure with the non-local city ACDD index are presented. "Burn" corresponds to the empirical distribution. The indexes were selected based on their average ranking according to the Kolmogorov-Smirnov, Anderson-Darling, and Chi-Squared statistics. Three levels of risk aversion, *A*, are evaluated.

Table 6 presents hedging results of the MSV analysis for the three alternative functional forms of the ACDD index distribution. The MSV is maximized subject to the hedge ratio. Three different levels of risk aversion are evaluated, A = 0.01, 0.02, 0.03. The implied trade-off between RMSL and return for the MSV specification varies depending on the level of

RMSL. For example, when RMSL = 15 bu/acre, this implies that for A = 0.03 the agent is willing to give up 0.45 bu/acre in expected return to decrease RMSL by 1 bu/acre; at a level of A = 0.01 the agent is willing to give up 0.15 bu/acre in expected return to obtain a 1 bu/acre reduction in RMSL. Choosing the appropriate level of A is somewhat contentious. NELSON AND ESCALANTE (2004) suggest that parameter values within the range of [0.000004, 0.346574] may be reasonable for a MV specification, while DILLON AND SCANDIZZO (1978) estimate using survey data for risk-averse producers that values in the range of (0, 0.06] may be more appropriate.

At the highest level of risk aversion, A=0.03, only marginal differences arise in the magnitude of the utility maximizing hedge ratio and the resulting risk reduction. The hedge ratio (MSV) varied little across pricing methods, ranging from 0.166 (147.581) for the Logistic distribution to 0.146 (146.957) for Inverse Gaussian distribution. Changes in RMSL, ES 6%, and ES 9% across distributions were virtually zero. At the lowest level of risk aversion, A=0.01, larger differences arose but did not have a qualitatively significant impact. The hedge ratios did vary somewhat, ranging from 0.196 for Logistic to 0.134 for Inverse Gaussian, however, the effects on the risk reduction effectiveness of the hedges were small. For example, the reduction in RMSL ranged only from 42.28% to 44.96%, and the ES 6% (ES 9%) ranged only 1.754 (1.245) bu/acre. Thus, the effects of differences in prices across alternative assumptions of the distributional form of the underlying weather index on hedging were small. It is also important to note that there was no bias one way or another for the BA price results relative to the other functional forms; the results obtained for BA were roughly an average of those obtained across the parametric distributions.

7.7 Sensitivity Analysis Results: Risk Premiums

Next we turn attention to estimating the effect that the presence of risk premiums have on the utility maximizing hedge, and in turn how this affects the risk reduction effectiveness of the hedge. Table 7 presents the results of the MSV analysis for the unhedged exposure

Table 7- Mean Semi-Variance Results, Risk Premium

	Unhedged	γ=0	γ=10%	γ=30%	γ=50%
A=0.01					
Hedge Ratio	-	0.154	0.108	0.024	0.000
Optimal Strike	-	940.000	940.000	940.000	940.000
Average	148.715	148.715	148.252	148.406	148.715
RMSL	12.842	7.068	7.704	11.447	12.842
% Reduction RMSL	-	44.96%	40.01%	10.86%	0.00%
ES 6%	106.643	127.817	125.727	112.053	106.643
ES 9%	112.959	130.604	128.150	117.405	112.959
MSV	147.066	148.216	147.659	147.095	147.066
A=0.02					
Hedge Ratio	-	0.154	0.130	0.087	0.045
Optimal Strike	-	940.000	940.000	940.000	940.000
Average	148.715	148.715	148.160	147.600	147.755
RMSL	12.842	7.068	7.237	8.413	10.324
% Reduction RMSL	-	44.96%	43.65%	34.49%	19.61%
ES 6%	106.643	127.817	127.505	123.225	116.328
ES 9%	112.959	130.604	128.996	125.927	120.168
MSV	145.417	147.716	147.112	146.185	145.623
A=0.03					
Hedge Ratio	-	0.154	0.137	0.107	0.080
Optimal Strike	-	940.000	940.000	940.000	940.000
Average	148.715	148.715	148.128	147.334	147.011
RMSL	12.842	7.068	7.144	7.721	8.697
% Reduction RMSL	-	44.96%	44.37%	39.87%	32.27%
ES 6%	106.643	127.817	127.948	124.755	122.011
ES 9%	112.959	130.604	129.286	127.205	124.420
MSV	143.768	147.217	146.597	145.545	144.742

The table presents results for the MSV analysis for unhedged portfolio and for the hedged portfolio at four different levels of risk premiums. The MSV is maximized with respect to the hedge ratio. The results for hedging the state level exposure with the non-local city ACDD index are presented. Three levels of risk aversion, A, are evaluated.

as well as the hedged exposure at four different risk premium levels, γ = 0%, 10%, 30%, and 50%, as well as for three different levels of risk aversion, *A* = 0.01, 0.02, and 0.03.[14]

The results indicate that the presence of risk premiums can significantly alter the magnitude of the utility maximizing hedge ratio and can severely diminish its risk reduction potential. As expected, the effects are most noticeable at lower levels of risk aversion, because at high levels of risk aversion the utility maximization problem simply reduces to minimization of

[14] RICHARDS ET AL, (2004) find that their option fair price can be distorted as much as 30% by a risk premium.

semi-variance.[15] For A = 0.01 the effects of a risk premium are substantial. For example, at γ = 50% the hedge is no longer desirable, as the utility maximizing hedge is zero. At γ = 30% the effects are still substantial; the optimal hedge ratio is only 0.024 versus 0.154 when γ = 0%. More importantly, the effectiveness of the utility maximizing hedge is severely diminished at this risk premium level as the reduction in RMSL is only 10.86% versus 44.96% when there is no risk premium. Further, the increase in ES 6% (ES 9%) relative to the unhedged exposure was only 5.41 (4.45) bu/acre when γ = 30% versus 21.17 (17.65) bu/acre for the fairly priced option. That is, the increase in ES 6% (ES 9%) for the option premium including the risk premium was only 25.55% (25.20%) of that for the option premium without any risk premium.

The effects are diminished at low levels of γ and higher levels of A. Even at moderate levels though the effects are non-trivial; at a moderate level of risk aversion, A = 0.02, and γ = 30% the reduction in RMSL (increase in ES 6% and 9%) is only 76.71% (78.22% and 73.60%) of that for the case with no risk premium.

Overall, the results indicate that the presence of risk premiums can significantly erode the hedging effectiveness of weather hedges. In the context of the earlier hedging analysis, this implies that the hedging effectiveness of the local contracts is likely overstated, further motivating the use of geographic cross hedges.

8 Conclusions

Basis risk is an often cited, yet rarely investigated, issue regarding the implementation of weather hedges. The conventional wisdom is that geographic basis risk will always be positive. The results here indicate that this may not always be the case. When hedging is implemented using non-local derivatives for a weather variable that is highly spatially correlated hedging effectiveness may be as good as, if not better than, what can be obtained

[15] Since a change in the price of the derivative has no effect on the covariance between the exposure being hedged and the derivative payoffs, the presence of a risk premium will have no effect on the estimated optimal hedge ratio and strike if the objective is minimization of risk, with no reference to return.

using locally derived contracts. The results also lend further support to the notion that relatively simple contracts can be employed to obtain reasonable hedging effectiveness. Precipitation derivatives were also shown to be less effective than temperature contracts, a finding that is attributable to differences in the degree of spatial correlation of those indexes.

The findings also corroborate those in WOODARD AND GARCIA (2006) as hedging was shown to be more effective at greater levels of aggregation. Weather hedges were more effective at greater levels of spatial aggregation indicating that the most likely end-users will be re/insurers rather than individual producers. The sensitivity analysis indicates that the assumptions of the underlying distributions are not critical here as long as the hedge is being placed sufficiently prior to realizations of the index. The sensitivity analysis also suggested that the presence of a significant risk premium may have a large effect on the utility of the hedge. Since derivatives on illiquid rural weather stations are likely to have a higher risk premium than large city markets, this finding further motivates the use of geographic cross hedges.

Future research should focus on incorporating more complex pricing models to investigate dynamic weather hedging situations. Also, given that aggregators of risk, such as re/insurers and large agribusiness companies, are the most likely end-users of weather derivatives in agriculture, future work should put greater focus on the specification of the risks they face and on identification of the instruments which may be of the most benefit to them. This may include investigation of the interaction between price and quantity hedging instruments, investigation of the interaction between different types of weather hedges (e.g. temperature and precipitation jointly), and comparison of different time aggregated derivatives (e.g. seasonal vs. monthly).

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