Addressing Credit and Basis Risk Arising From Hedging Weather-related Risk with Weather Derivatives

Patrick L Brockett
Red McCombs School of Business
University of Texas at Austin
brockett@mail.utexas.edu

Linda L. Golden
Red McCombs School of Business
University of Texas at Austin
mkllg@mail.utexas.edu

Charles C Yang
School of Finance, Insurance, and Economics
Florida Atlantic University
Cyang1@fau.edu

Hong Zou
Department of Finance and Insurance
Lingnan University, Hong Kong

Abstract

Weather derivatives are a relatively recent innovation, but according to the Chicago Mercantile Exchange (CME), are the fastest growing derivative market today. They are used to manage weather related risks which previously were exclusively handled by insurance products, and represent the latest product in the continuing convergence of financial and insurance research and markets. A weather derivative pays-off based upon the realization of an underlying weather index, much like stock index based derivatives pays-off based upon a realization of the underlying stock index. The pay-off from a weather derivative can offset losses generated by adverse weather conditions. The use of these derivatives creates new risks, however, depending upon whether an exchange traded derivative or an over-the-counter (OTC) derivative is used. This paper examines the effectiveness of using a basis derivative strategy in conjunction with an exchange traded weather derivative to mitigate credit risk inherent in OTC transactions, and basis risk inherent in exchange-traded transactions. We examine the effectiveness of this strategy for summer and winter seasons, with both linear and nonlinear hedging instruments. Finally, we compare the effectiveness obtained using the CME and Risk Management Solutions, Inc. (RMS) weather indices. Results show that hedging methods are significantly more effective for winter than for summer, for both the CME and RMS weather indices, and for both linear and nonlinear basis derivative instruments. It is also found that the RMS regional weather indices are more effective than the CME weather indices for creating a basis hedging strategy, and that the effectiveness weather risk management can vary significantly by region of the country.

Keywords: **credit (default) risk, basis risk, weather risk management, hedging effectiveness**

1. Introduction

In 1997, with the deregulation of the energy and power industries in the US, energy companies faced increased financial exposure due to weather changes. While previously the regulated, monopolistic setting of the power industry allowed the financial consequences of weather risks to be absorbed in their allowed pricing, with deregulation such risks were now not necessarily compensated. To address this problem, the first weather related financial instrument was created[1].

Essentially, certain market participants saw they could address the adverse consequences of weather-related events in a manner similar to the securitization process used to mitigate the adverse consequences of commodity price risk in the commodity market. By measuring and indexing various weather recordings across the US, one could create financial instruments whose pay off values were dependent upon the level of the recorded underlying weather index.

Initially, only Over-the-Counter (OTC) trades on such derivative instruments were made; however in 1999, financial exchange-traded weather futures, and options on futures, began to be offered on the Chicago Mercantile Exchange (CME). While OTC transactions, being private transactions, carry credit risk (the potential of counter-party default on the contract), CME transactions are contracts traded on the open market, are marked to the market, are guaranteed by the exchange, and do not carry credit (default) risk.

On the other hand, by being constructed as standardized in form and in the location of the weather station reading underlying the weather index used for the CME contract, the weather derivative contracts traded on the CME possess a different risk:

[1] This was a weather derivative contract based on Heating Degree Days in Milwaukee between Koch Industries and Enron Corporation (see Climetrics, RMS Inc. at www.climetrics.com)

basis risk. Basis risk for a market participant using a particular weather-indexed derivative involves the possibility that the location of the source of weather data used to specify the weather index underlying the derivative contract may not precisely match the location of the enterprise's exposure to weather related loss. Thus, an underlying substantive characteristic (or basis) of the contract may not match the location of the source of risk.

Managing weather risk by trading weather derivatives is a rapidly growing business (c.f., Brockett, Wang, and Yang 2005**;** Golden, Wang and Yang 2007). Indeed, the US Department of Commerce estimates that almost one third of all businesses are affected by weather related risks[2], and in 2007 about 730,000 weather derivative contracts were traded worldwide[3]. The total value of weather contracts traded on the CME in 2006 was $45.2 billion (USA Today 2008).

In a weather derivative transaction, variables such as temperature, precipitation, wind or snow are measured and indexed covering a specified amount of time at a specified location. A threshold limit regarding the actionable level of the measured variable is agreed upon by the buyer and seller. If the threshold limit is exceeded during the set timeframe, the buyer receives payment. If the weather variable does not exceed the limit, the seller keeps the premium paid by the buyer.

The most common weather derivatives are contracts based on indices that involve Heating Degree Days (HDD) for the winter season and Cooling Degree Days (CDD) for the summer season. Using 65°F as the baseline, HDD and CDD values are determined by subtracting the day's average temperature from 65°F for HDD and subtracting 65°F

[2] See http://www.guaranteedweather.com
[3] According to the Weather Risk Management Association as quoted in USA Today 2008.

from the day's average temperature for CDD values. If the temperature exceeds 65°F in the winter the HDD is 0; if the temperature is lower than 65°F in the summer the CDD is 0 (since one does not need to heat in the winter if the temperature is above 65°F, and one does not need to cool in the summer if the temperature is below 65°F). The CME creates HDD and CDD derivative instruments based upon temperature index values centered in fifteen US cities (see Appendix I). Another company, Risk Management Solutions, Inc. (RMS)[4] also supplies CDD and HDD indices for the management of weather risk. RMS produces ten regional indices; each is created by averaging the temperature index values centered in ten chosen cities within the region. Derivative instruments can be created from the RMS indices as well.

Since the financial impact of short bursts of cold or hot weather can be absorbed by most firms, most weather derivatives accumulate the HDDs or CDDs over a specified contract period, such as, one week, one month, or a winter/summer season. To calculate the degree days over a multi-day period, one aggregates the daily degree measure for each day in that period (c.f., Golden, Wang and Yang 2007 for the requisite formulae and for further discussion).

Initially, energy companies were the main enterprises hedging weather risk by trading weather derivatives. Today, diverse enterprises such as resorts, hotels, restaurants, universities, governments, airlines, farming and others are using weather derivatives to manage risk. As the market for trading weather risk continues to grow, the enterprises who hedge weather risk using exchange-traded contracts want to minimize

[4] Risk Management Solutions, Inc. is the world's leading provider of products and services for the quantification and management of natural hazard risks.

their basis risk and conversely, those who hedge using OTC contracts want to minimize their credit (counterparty default risk).

Briys, Crouhy, and Schlesinger, 1993; Poitras, 1993; Moschini and Lapan, 1995; Vukina, Li, and Holthausen, 1996; Li and Vukina, 1998; Coble, Heifner, and Zuniga, 2000 have conducted studies related to the problem of optimal hedging of basis risk. Other studies have analyzed optimal hedging strategies when the hedging enterprise faces credit risk. (cf., Hentschel and Smith, 1997). Additional research has investigated the demand for insurance by policyholders who purchase insurance from credit-risky insurers but without consideration of basis risk (see, for example, Tapiero, Kahane, and Jacque, 1986; and Doherty and Schlesinger, 1990).

There is an OTC derivative instrument that mitigates the basis risk inherent in exchange-traded weather derivatives and lessens the hedger's credit risk exposure compared to just using an OTC weather derivative. The hedging instrument is called a basis derivative (cf., Considine, 2000; MacMinn, 2000). This OTC basis derivative combines a local temperature index and an exchange-traded temperature index to moderate the impact of the temperature difference between the location of the exchange-traded derivative and the local weather index. Using a basis derivative in conjunction with an exchange traded derivative can improve the basis risk exposure faced by the hedging enterprise. Although the hedging enterprise again faces credit risk (basis derivatives are traded OTC) the basis derivative instrument is expected to be less volatile, being the difference between the local index and the exchange traded index. This stability should lessen the enterprise's credit risk exposure compared to an OTC weather contract written directly on the local index.

Additionally, when the basis derivative instrument is used in conjunction with an exchange-traded derivative it should improve the hedging enterprise's basis risk position over the exchange-traded contract because it is calculated based on the difference between the specific location weather index and the closest regional location. By setting up mathematical models and varying the model parameters in a simulation study, Golden, Wang and Yang (2007) analyzed the joint impact of basis risk and the tradeoff between basis risk and credit (default) risk regarding the effectiveness of the linear and nonlinear hedging models. The actual indices used for trade, however, may behave slightly differently than the model-based indices, so it remains to examine the results for the real series and to ascertain if either of the two indices (CME or RMS) is superior regarding region, index or season.

Accordingly, this paper empirically analyzes the effectiveness of using linear and nonlinear[5] basis hedging instruments developed using either the CME or RMS weather indices. Effectiveness is examined by: region of the country, source of the weather index used (CME or RMS), season of the year (summer or winter), as well as examining any potential interactive effects such as region by index, season by index , region by season, or region by index by season.

2. Weather Hedging Models

We adopt the utility-based hedging models from Golden, Wang and Yang (2007) with some modifications. We assume the enterprise is attempting to hedge the negative effects weather-related events may have on the quantity demanded of their product or service. (e.g., energy producers need to hedge demand risk due to variations in the

[5] By linear hedging instruments we mean derivative contracts such as futures and forwards whose pay off is linear in structure. By nonlinear hedging instruments we mean derivative contracts such as options whose pay off is nonlinear (e.g., zero below the exercise threshold and linear thereafter).

quantity of energy demanded as a function of the weather, or a ski resort has interest in hedging against too many warm weather days, etc.) We assume that the risk in the quantity demanded (q) is mainly effected by a weather event, and we assume that the hedging enterprise wishes to choose weather derivatives to maximize an objective function defined to be the end of period terminal wealth.

To hedge against the risk of a weather related loss, an enterprise will choose one or a combination of the following strategies.

A. Use an OTC derivative that is location specific to the site facing the weather risk. This carries counterparty credit (default) risk but no basis risk.

B. Use an exchange-traded derivative based on a regional weather data index or based on one of CME's fifteen city weather index. This strategy carries basis risk but no credit (default) risk.

C. Employ a combination strategy and buy an exchange-traded derivative to mitigate the majority of the weather-related risk at minimal credit risk, and then supplement this with an OTC basis hedging derivative designed to decrease the enterprise's basis risk.

This third strategy, C, is intended to reduce the risk of weather-related loss while simultaneously improving the credit (default) risk by creating a hedge that corrects for the difference between CME traded derivatives and OCT local weather derivatives. Analyzing the effectiveness of this third strategy is the focus of this paper.

In order to analyze the impact of credit risk, we need to model the likelihood of counterparty default. To this end, let θ denote the proportion of the required payoff on a weather derivative that will actually be paid to the hedging enterprise. Here, we take θ as either 1 or 0 (i.e., the counterparty either performs entirely or fails to perform entirely). The probability distribution of θ is defined as $\Pr ob(\theta = 1) = p$ and $\Pr ob(\theta = 0) = 1 - p$. The default risk is represented by $\Pr ob(\theta = 0) = 1 - p$. The hedging enterprise and the weather derivative issuer may have different perceptions about the issuer's default risk, but through the process of resolving a price and entering into a weather derivative contract, they essentially agree to a subjective probability distribution for the issuer's default risk (possibly only implied). This subjective or market probability distribution is defined as $\Pr ob(\theta = 1) = p_s$ and for default risk $\Pr ob(\theta = 0) = 1 - p_s$. The subjectively agreed upon common non-default risk parameter p_s may or may not be the same as the "true" or real likelihood of non-default p.

Our analysis employs a mean-variance approximation to the hedger's utility based objective function; $u(W \mid \theta) = E(W \mid \theta) - \lambda\sigma^2(W \mid \theta)$, where W denotes the hedger's end of period wealth and $\lambda > 0$ denotes the hedger's risk aversion parameter. It is assumed that the market sets prices such that the observed prices reflect the expected value of the pay off including expenses and profit loadings (referred to as actuarially fair or unbiased pricing).

To compare the effectiveness of using of a basis derivative, we first consider the baseline situation, A above, wherein a linear OTC weather derivative contract drawn on a local weather index is used. Let T_l be the strike price of the contract, and let t_l denote the local weather index used to write the contract. Let $r_l^p = \max(T_l - t_l, 0)$ denote the payoff for a put option on the weather index, and $r_l^c = \max(t_l - T_l, 0)$ denote the payoff for a call option on the weather index. Let h_{l-ll} denote the hedge ratio used for the local weather forward derivative contract.

Without consideration of credit (default) risk, the final wealth resulting from a hedged forward contract with a price of $E[h_{l-ll}(T_l - t_l)]$ is simply $W = q - E[h_{l-ll}(T_l - t_l)] + h_{l-ll}(T_l - t_l)$ where q represents the (uncertain and weather related) demand quantity.[6] However, taking into consideration the possibility of credit (default) risk, this final wealth is

$$W = q - E[h_{l-ll}(\theta r_l^p - r_l^c)] + h_{l-ll}(\theta r_l^p - r_l^c)\,, \tag{1}$$

since default on the contract only occurs if the counterparty is forced to pay (when $T_l > t_l$), and in this situation default occurs with probability θ.

Suppose now that the weather related quantity of goods or services demanded of the enterprise employing the hedging strategy can be decomposed such that there is a portion which is systematically related to the local weather index and a portion which constitutes non-systematic or idiosyncratic non-weather dependent individual variation in demand (see, for example, Davis, 2001). This may occur, for example, because of the particular sensitivities of the hedging enterprise (e.g., better insulation, better snow plows, etc.). We express this relationship as $q = \alpha + \beta t_l + \varepsilon$, where $\varepsilon \sim N(0, \sigma_\varepsilon^2)$ is the non-systematic quantity risk, which is assumed to be independent of the weather indices. The optimal hedging problem is:

$$MAX_{h_l}\, E(W \mid \theta) - \lambda \sigma^2 (W \mid \theta)\,,$$

[6] We assume that the hedger's price risk has been totally hedged by other instruments. Thus, the weather hedging problem is equivalent to hedging the quantity risk only. The tick sizes of all the weather derivatives in this paper are assumed to be one.

subject to $\Pr ob(\theta = 1) = p_s$.

Performing the maximization using (1) we derive the optimal hedge ratio as[7]

$$h^*_{l-ll} = \frac{-p_s \beta\sigma_{t_l, r_l^p} + \beta\sigma_{t_l, r_l^c}}{p_s \sigma^2_{r_l^p} + \sigma^2_{r_l^c} + (p_s - p_s^2)\mu^2_{r_l^p} - 2p_s \sigma_{r_l^p, r_l^c}}. \tag{2}$$

In an unbiased market with prices set at their expected values, the mean-variance objective ($MAX_h E(W \mid \theta) - \lambda\sigma^2(W \mid \theta)$) is equivalent to a variance minimization objective ($MIN_h \sigma^2(W \mid \theta)$). The minimum variance of the hedger's final wealth when using the OTC contract and the linear local hedging strategy with credit risk is $V_{\min-ll} = Var[W(h^*_{l-ll})]$, subject to $\Pr ob(\theta = 1) = p$. That is,

$$\begin{aligned} V_{\min-ll} &= \beta^2\sigma^2_{t_l} + \sigma^2_\varepsilon + {h^*_{l-ll}}^2 p\sigma^2_{r_l^p} + {h^*_{l-ll}}^2\sigma^2_{r_l^c} + {h^*_{l-ll}}^2 (p - p^2)\mu^2_{r_l^p} \\ &- 2ph^{*2}_{l-ll}\sigma_{r_l^p, r_l^c} + 2h^*_{l-ll}\beta p\sigma_{t_l, r_l^p} - 2h^*_{l-ll}\beta\sigma_{t_l, t_l^c} \end{aligned}. \tag{3}$$

We turn now to the exchange traded weather hedging alternative involving the use of an exchange-traded linear contract. This contract involves basis risk, so we also add an adjustment compensating for basis risk via a basis derivative risk hedge that "corrects" for the difference $t_l - t_e$ between the local weather index t_l required for the hedging enterprise and the index t_e used by the exchange in creating a traded derivative. This "correction" is done by creating an OTC contract with strike price T_d based on the difference in indices t_d ($t_d = t_l - t_e$). The resulting hedging model (for strategy C) is

$$\begin{aligned} W &= q - E[h_{e-lb}(T_e - t_e)] - E[h_{d-lb}(\theta r_d^p - r_d^c)] \\ &+ h_{e-lb}(T_e - t_e) + h_{d-lb}(\theta r_d^p - r_d^c) \end{aligned}, \tag{4}$$

---

[7] Details of this and other optimizations which are not provided in the paper can be obtained from the authors.

where $r_d^p = \max(T_d - t_d, 0)$ and $r_d^c = \max(t_d - T_d, 0)$ with the put and call derivate designation being symbolized by superscripts. Here. h_{e-lb} and h_{d-lb} are the hedge ratios of the exchange-traded weather futures contract and the basis weather forward, respectively. The optimal hedging problem in strategy C involves optimally selecting a hedge ratio for both the exchange traded derivative and for the basis derivative simultaneously; i.e., $MAX_{h_{e-lb}, h_{d-lb}} E(W \mid \theta) - \lambda\sigma^2(W \mid \theta)$, subject to $\Pr ob(\theta = 1) = p_s$.

Upon maximization, the optimal linear basis hedge ratios are determined to be

$$h_{d-lb}^* = \frac{\beta\sigma_{t_l,t_e}(p_s\sigma_{t_e,r_d^p} - \sigma_{t_e,r_d^c}) + \beta\sigma_{t_e}^2(\sigma_{t_l,r_d^c} - p_s\sigma_{t_l,r_d^p})}{\sigma_{t_e}^2[p_s\sigma_{r_d^p}^2 + (p_s - p_s^2)\mu_{r_d^p}^2 + \sigma_{r_d^c}^2 - 2p_s\sigma_{r_d^p,r_d^c}] - (p_s\sigma_{t_e,r_d^p} - \sigma_{t_e,r_d^c})^2} \tag{5}$$

and

$$h_{e-lb}^* = \frac{\beta(p_s\sigma_{t_e,r_d^p} - \sigma_{t_e,r_d^c})(\sigma_{t_l,r_d^c} - p\sigma_{t_l,r_d^p}) + \beta\sigma_{t_l,t_e}[p_s\sigma_{r_d^p}^2 + \sigma_{r_d^c}^2 + (p_s - p_s^2)\mu_{r_d^p}^2 - 2p_s\sigma_{r_d^p,r_d^c}]}{\sigma_{t_e}^2[p_s\sigma_{r_d^p}^2 + (p_s - p_s^2)\mu_{r_d^p}^2 + \sigma_{r_d^c}^2 - 2p_s\sigma_{r_d^p,r_d^c}] - (p_s\sigma_{t_e,r_d^p} - \sigma_{t_e,r_d^c})^2}. \tag{6}$$

Similarly, the minimum variance of the final wealth when using linear basis hedging is $V_{\min-lb} = Var[W(h_{e-lb}^*, h_{d-lb}^*)]$, subject to $\Pr ob(\theta = 1) = p$. That is,

$$\begin{aligned} V_{\min-lb} &= \beta^2\sigma_{t_l}^2 + \sigma_\varepsilon^2 + {h_{e-lb}^*}^2\sigma_{t_e}^2 + {h_{d-lb}^*}^2 p\sigma_{r_d^p}^2 + {h_{d-lb}^*}^2\sigma_{r_d^c}^2 \\ &+ {h_{d-lb}^*}^2(p - p^2)\mu_{r_d^p}^2 - 2ph_{d-lb}^{*2}\sigma_{r_d^p,r_d^c} - 2h_{e-lb}^*\beta\sigma_{t_l,t_e} + 2h_{d-lb}^*\beta p\sigma_{t_l,r_d^p} \, . \\ &- 2h_{d-lb}^*\beta\sigma_{t_l,r_d^c} - 2h_{e-lb}^*h_{d-lb}^*p\sigma_{t_e,r_d^p} + 2h_{e-lb}^*h_{d-lb}^*\sigma_{t_e,r_d^c} \end{aligned} \tag{7}$$

Turning now to the nonlinear local and basis hedging models (i.e., those involving instruments with nonlinear payoff functions such as put and call options) we write

$$W = q - E(\theta h_{l-nl}r_l^p) + \theta h_{l-nl}r_l^p, \tag{8}$$

and

$$W = q - E(\theta h_{d-nb}r_d^p) - E(h_{e-nb}r_e^p) + h_{e-nb}r_e^p + \theta h_{d-nb}r_d^p. \tag{9}$$

where nl and nb denote the nonlinear local hedging and the nonlinear basis hedging respectively. In a manner similar to the derivations in Golden, Wang and Yang (2007) and to the derivation of (2)-(3) and (5)-(7), we can obtain the optimal nonlinear hedge ratios and the nonlinear local and basis minimum final wealth variances:

$$h^*_{l-nl} = \frac{-\beta\sigma_{t_l, r_l^{p*}}}{\sigma^2_{r_l^{p*}} + (1-p_s)\mu^2_{r_l^{p*}}}, \tag{10}$$

$$h^*_{d-nb} = \frac{\beta\sigma_{t_l, r_e^{p*}}\sigma_{r_e^{p*}, r_d^{p*}} - \beta\sigma_{t_l, r_d^{p*}}\sigma^2_{r_e^{p*}}}{\sigma^2_{r_e^{p*}}\sigma^2_{r_d^{p*}}(1-p_s\rho^2_{r_e^{p*}, r_d^{p*}}) + (1-p_s)\sigma^2_{r_e^{p*}}\mu^2_{r_d^{p*}}}, \tag{11}$$

$$h^*_{e-nb} = \frac{(p_s-1)\beta\mu^2_{r_d^{p*}}\sigma_{t_l, r_e^{p*}} + p_s\beta\sigma_{t_l, r_d^{p*}}\sigma_{r_e^{p*}, r_d^{p*}} - \beta\sigma_{t_l, r_e^{p*}}\sigma^2_{r_d^{p*}}}{\sigma^2_{r_e^{p*}}\sigma^2_{r_d^{p*}}(1-p_s\rho^2_{r_e^{p*}, r_d^{p*}}) + (1-p_s)\sigma^2_{r_e^{p*}}\mu^2_{r_d^{p*}}}, \tag{12}$$

$$\begin{aligned} V_{\min-nl} &= \beta^2\sigma^2_{t_l} + \sigma^2_\varepsilon + {h^*_{l-nl}}^2 p\sigma^2_{r_l^{p*}} + {h^*_{l-nl}}^2 (p-p^2)\mu^2_{r_l^{p*}} \\ &+ 2h^*_{l-nl}\beta p\sigma_{t_l, r_l^{p*}} \end{aligned}, \tag{13}$$

and

$$\begin{aligned} V_{\min-nb} &= \beta^2\sigma^2_{t_l} + \sigma^2_\varepsilon + {h^*_{e-nb}}^2\sigma^2_{r_e^{p*}} + {h^*_{d-nb}}^2 p\sigma^2_{r_d^{p*}} + {h^*_{d-nb}}^2(p-p^2)\mu^2_{r_d^{p*}} \\ &+ 2h^*_{e-nb}\beta\sigma_{t_l, r_e^{p*}} + 2h^*_{d-nb}\beta p\sigma_{t_l, r_d^{p*}} + 2h^*_{e-nb}h^*_{d-nb}p\sigma_{r_e^{p*}, r_d^{p*}} \end{aligned}, \tag{14}$$

where, r_l^{p*}, r_e^{p*} and r_d^{p*} are the payoffs of the put options with optimal strike prices[8].

The hedging effectiveness of the linear and nonlinear basis hedging is measured by

$$\frac{V_{\min-ll} - V_{\min-lb}}{V_{\min-ll}} \tag{15}$$

and

[8] The optimal strike prices were determined by simulation.

$$\frac{V_{\min-nl} - V_{\min-nb}}{V_{\min-nl}} \qquad (16)$$

respectively. These ratios express the extent to which the use of the basis derivative in conjunction with an exchange traded derivative (strategy C) has reduced the uncertainty in final wealth compared to the simpler hedging strategy A that uses a local weather index with associated credit (default) risk. While the formulae to this point are general, in the numerical empirical results which follow we shall assume a strong dependence of demand on weather ($\sigma_\varepsilon^2 = 0$) and, by rescaling if necessary, that $\beta = 1$.

3. Weather Data Used for Empirical Analysis[9]

The CME offers futures and options on futures for fifteen selected cities throughout the United States (see Appendix I). The CME selected these cities because of population, variability in their seasonal temperatures, and their extensive use in OTC derivative trading. On the other hand, the RMS framework is comprised of ten indices made up of data gathered from ten regions with ten cities in each region. The RMS selected these regions because they represent significant meteorological patterns, predominant weather risk trading places, population, and correlations with other weather stations throughout the regions. To construct a weather index for a particular region, RMS collects HDD and CDD data from ten city weather stations within the region and averages them.[10]

There are 100 separate city weather records used in the RMS data set. Of these, 13 are locations that are also used by the CME derivative products, (and hence would have no basis risk when compared to the CME index). Accordingly, we have used the 87

[9] Data provided by Earth Satellite Corporation, the weather data provider to the CME and RMS.
[10] The RMS regional indices are not currently exchange traded, however OTC contracts can be created using them.

remaining city locations for the comparative assessment of basis risk hedging effectiveness. The most common contract terms in the weather derivative market are seasonal (summer season and winter season), monthly, and weekly.[11] In this paper, we only consider seasonal contracts.[12] The CME index is either an HDD or CDD index for the particular city being traded. We compare the RMS indices with the CME indices to determine which index provides better basis hedging results.

4. Results

The analysis presented in this paper concerns the effectiveness of basis hedging under the assumption that the subjective perceived counterparty default risk probability p_s (which was incorporated into the weather derivative contract's price) is the same as the actual likelihood of default p, that is, when the market implied default risk is the true default risk.[13] For the CME index, concerning the computation of the basis hedging effectiveness for a basis derivative centered at any of the 87 local cities, there would be fifteen different CME based city indices (with derivative instruments) against which the basis hedging effectiveness could be compared. CME table entries in Appendix II are the maximum comparison measurements obtained using the fifteen CME city indices. This is done because the closest of the fifteen cities geographically may not be the best city index to use for basis risk hedging.

---

[11] See Climetrix, RMS, at www.climetrix.com.

[12] Winter season is November 1 through March 31, and summer season is May 1 through September 30. April and October are often referred to as the shoulder months, and not considered in this paper.

[13] Three alternative default risk levels were considered: $\Pr ob(\theta = 0) = 1 - p$ = 0.10, 0.05, and 0.01. There was no statistically significant difference between the effectiveness of basis risk hedging in either the linear or nonlinear hedging scenario across the three default risk levels, and hence in all that follows only the results for the default risk level p=.05 are presented. Also examined was the scenario wherein the hedger assumed there would be no default risk and the market actually had default risk (a mismatch between the subjective assessment of risk and the true risk). These latter results are not presented here but are available from the authors.

Similarly, in computing an RMS index for any given city, there are ten measurements of basis hedging effectiveness obtained by using the ten RMS regional weather indices and the RMS basis hedging effectiveness for a city is defined as the maximum of these ten measurements. Appendix II presents the computed effectiveness measure for the 87 cities in the summer and winter seasons using both the CME and RMS weather indices and utilizing both linear and nonlinear basis hedging.

A three-way Analysis of Variance (ANOVA) ascertained if region of the country, season of the year, or the weather index used (CME or RMS) had a statistically significant impact on the effectiveness of using basis risk derivatives with respect to hedging the uncertainty in final wealth. Separate ANOVAs were carried out for linear hedging [equation (15)] and nonlinear hedging [equation (16)] effectiveness. Also considered was the possibility of interaction effects (e.g., it might be that RMS is more effective in the Northeast during the winter, etc.), so interactions were also assessed statistically. The outcomes of these analyses are presented in Table 1.

Table 1. ANOVA of the Effectiveness of Basis Risk Hedging According to Region, Index and Season for Linear (forwards and futures) Hedging Instruments and Nonlinear (options) Hedging Instruments.

Source	DF	Sum of Squares	F-Value	p <
Linear Hedging Effectiveness[a]				
Model[b]	39	27.00	2.48	.0001
Region	9	14.71	5.86	.0001
Index	1	2.74	9.81	.0019
Season	1	3.07	11.01	.0010
Region x Index	9	1.12	0.45	.9082
Region x Season	9	4.23	1.68	.0921
Index x Season	1	0.59	2.12	.1464
3-way interaction	9	0.53	0.21	.9928
Error	308	85.99		
Non-Linear Hedging Effectiveness [c]				
Model[d]	39	14.28	6.10	.0001
Region	9	7.33	13.57	.0001
Index	1	1.28	21.24	.0001
Season	1	3.89	64.69	.0001
Region x Index	9	0.59	1.09	.3681
Region x Season	9	0.60	1.12	.3492
Index x Season	1	0.37	6.21	.0132
3-way interaction	9	0.22	0.41	.9271
Error	308	18.50		

[a] The dependent variable is the effectiveness measure (15)
[b] $R^2 = 0.24$
[c] The dependent variable is the effectiveness measure (16)
[d] $R^2 = 0.44$

As can be observed, the models incorporating region, season and index explain a highly significant amount of the variance in the effectiveness of hedging uncertainty in both the linear hedging and nonlinear hedging contexts (p<.0001). Moreover, the main effects of region, index used and season were all statistically significant for both linear and nonlinear hedging methods. This implies that that the levels of basis risk hedging effectiveness differed significantly across regions, seasons, and indices used. For example, the average effectiveness measure for the CME index in the winter season in the Northeast region is much higher than the average effectiveness for the CME index in the winter season in the Southeast region. Figure 1 presents the average effectiveness measure for linear basis risk hedging across seasons and across regions, and Figure 2 presents the same information for nonlinear basis risk hedging.

Figure 1 Average Effectiveness Of Linear Basis Hedging

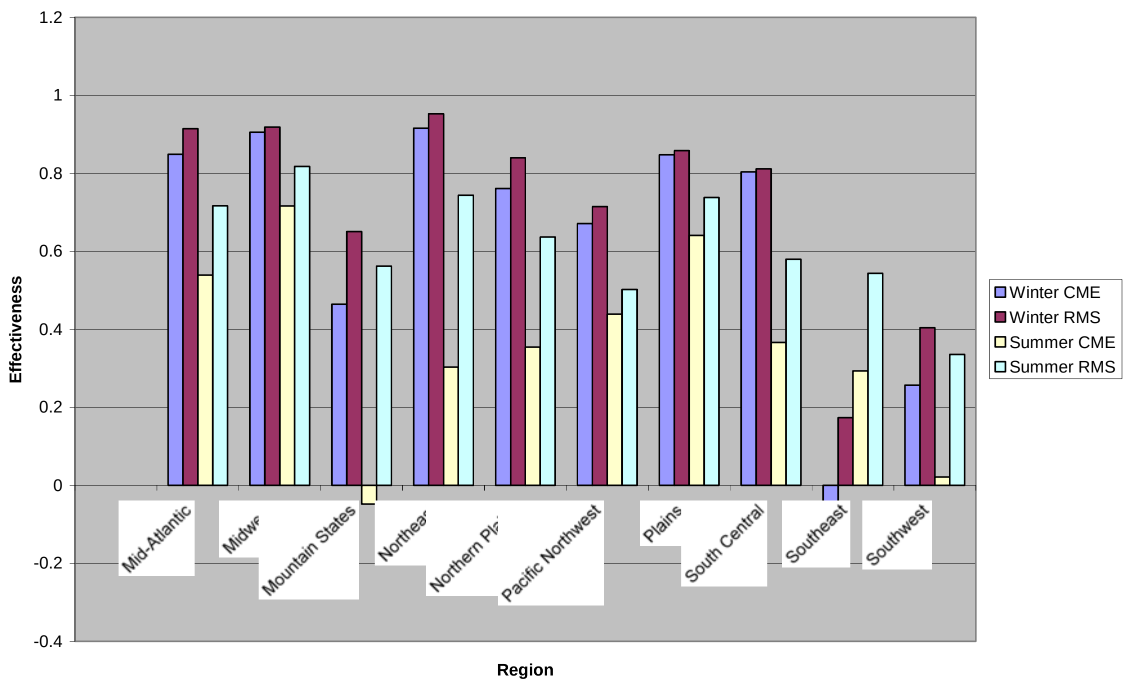
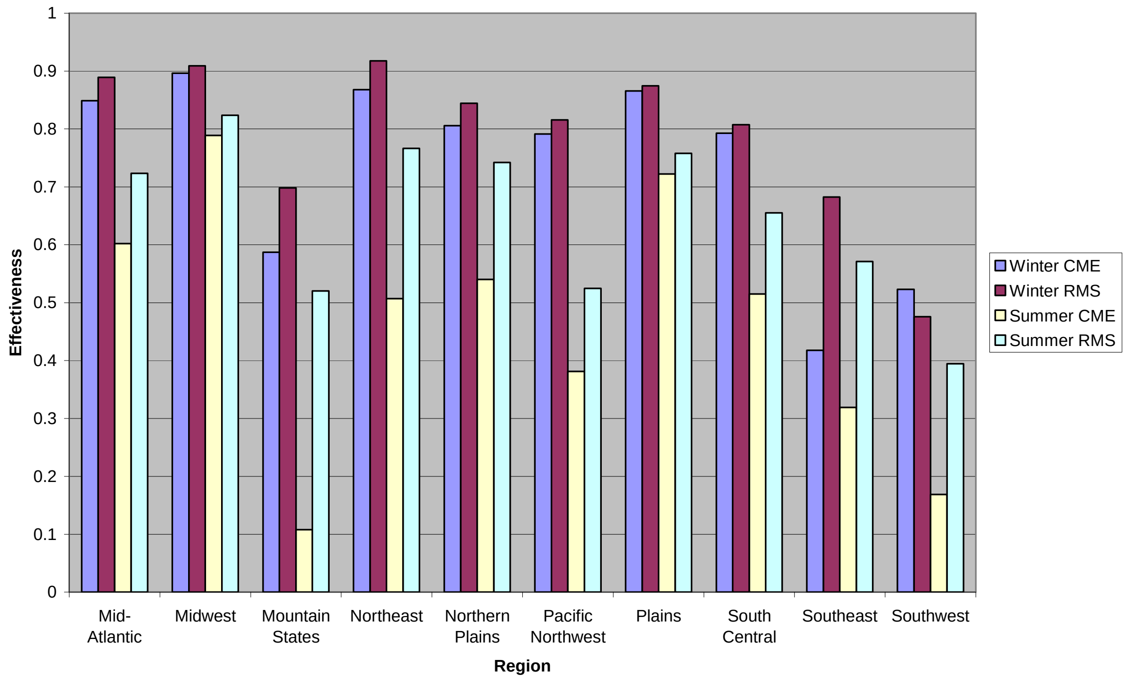


Figure 2 Average Effectiveness of Nonlinear Basis Hedging



From the ANOVA table we observe that there was also a marginally significant interaction between region and season for linear hedging instruments and a significant interaction between index used and season for nonlinear hedging instruments. All other interaction effects were not statistically significant.

To illustrate the seasonal effect on hedging effectiveness using linear derivatives, Figure 3 presents the difference in linear basis hedging effectiveness for the winter and summer seasons. We observe that the linear basis hedging for the winter season is generally more effective than for the summer season. Similarly, Figure 4 shows the difference between the effectiveness for the CME index using nonlinear hedging instruments, and again shows that basis risk hedging is more effective during the winter than during the summer. The ANOVA results show these differences are significant.

Figure 3: The difference in CME linear basis risk hedging effectiveness between winter and summer seasons (LHE_{winter} - LHE_{summer}).
(Miami, FL with a value of -6.13 is not shown in this figure.)

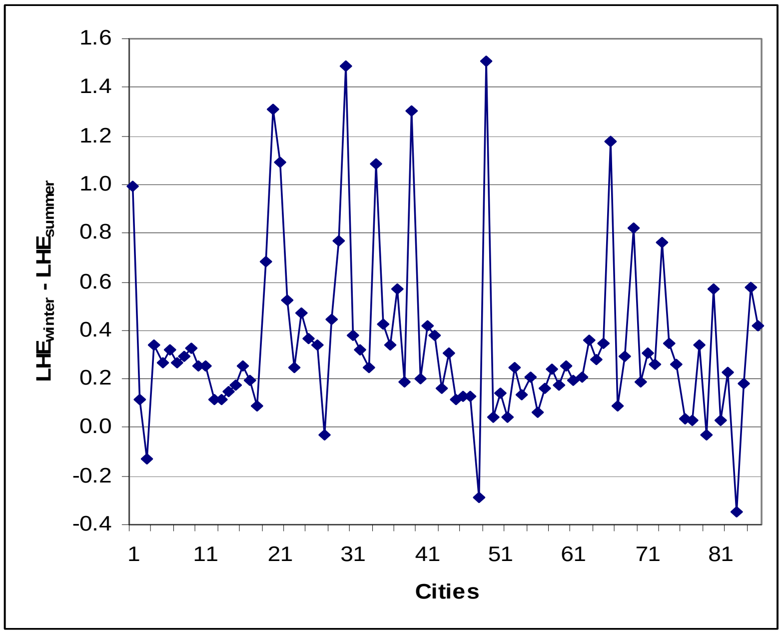
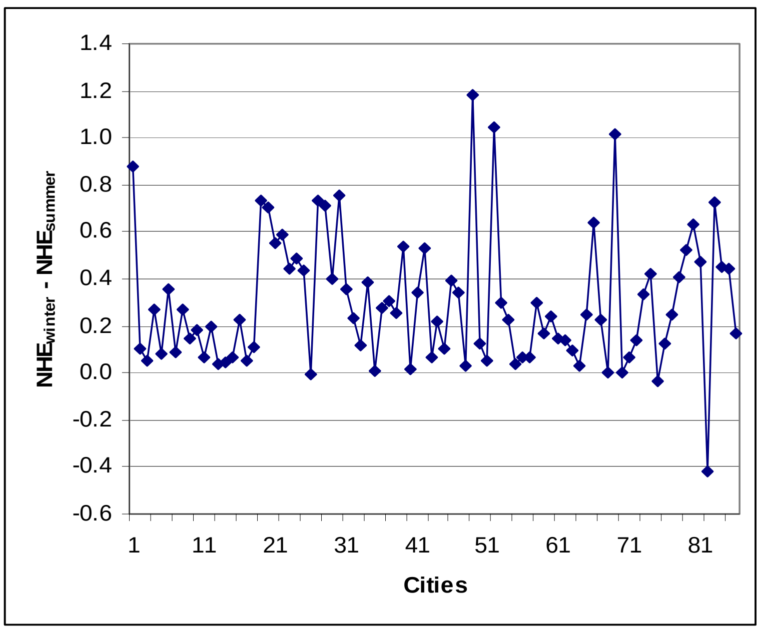


Figure 4: The difference in CME nonlinear basis risk hedging effectiveness between winter and summer seasons (NHE_{winter} – NHE_{summer}).
(Miami, FL with a value of -1.27 is not shown in this figure.)



5. Effectiveness of the CME Indices Compared to RMS Indices for Basis Hedging

The difference in the linear basis hedging effectiveness for winter and summer seasons using the CME and the RMS indices is displayed in Figures 5 and 6. Consistent with the significant main effect of index in the ANOVA, we observe that, in general, linear basis hedging is more effective using weather derivatives written on the RMS indices than the CME indices. For the winter season, linear basis hedging is more effective using weather derivatives written on the RMS indices for 67 of the 87 cities; and there are nearly 30 cities whose linear basis hedging effectiveness is at least 0.10 higher using the RMS indices than using the CME indices. The difference is only 0.05 or less for 13 of the 20 cities whose linear basis hedging effectiveness is higher using the CME indices. The difference in linear basis hedging effectiveness between the CME and the RMS indices is more pronounced for the summer season. The linear basis hedging model is more effective using weather derivatives written on the RMS indices for 80 of the 87 cities for the summer season; and there are more than 60 cities whose linear basis hedging effectiveness is at least 0.10 higher using the RMS indices.

Figure 5: The difference in linear basis hedging effectiveness between the CME and the RMS winter season indices ($LHE_{RMS} - LHE_{CME}$).

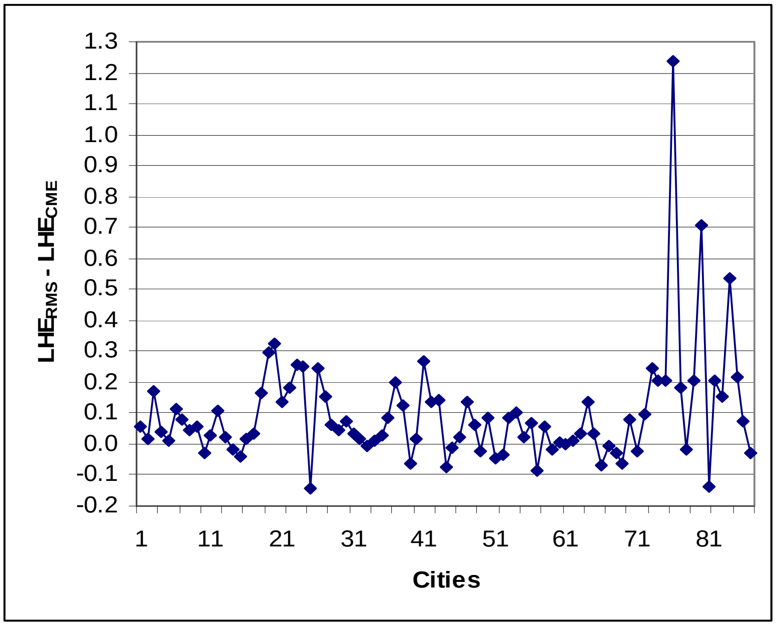
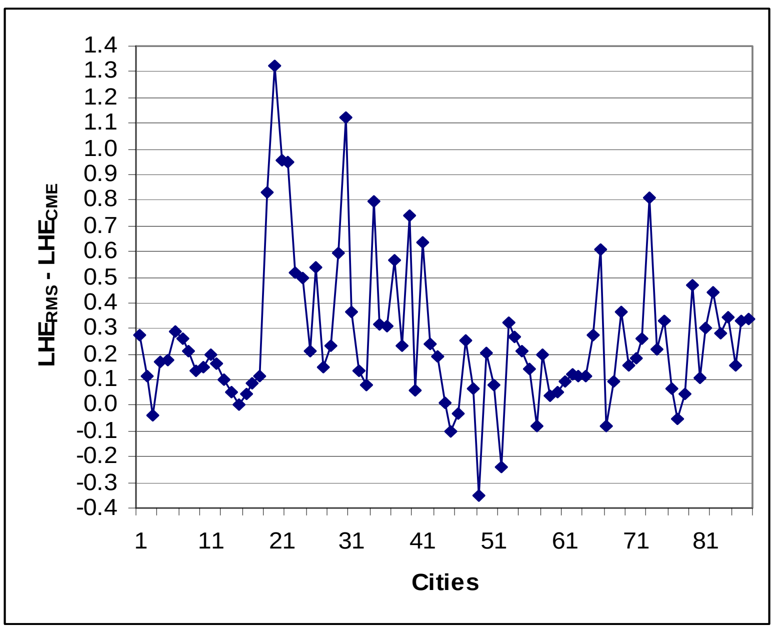


Figure 6: The difference in the linear basis hedging effectiveness between the CME and the RMS summer season indices ($LHE_{RMS} - LHE_{CME}$).



Similar results apply to the nonlinear basis hedging model. The difference in the nonlinear basis hedging effectiveness between the CME and the RMS indices for winter and summer seasons is displayed in Figures 7 and 8. Generally, the nonlinear basis hedging is also more effective using weather derivatives written on the RMS indices than the CME indices. In addition, the difference exhibits a pattern similar to the linear basis hedging model effectiveness. The nonlinear basis hedging model is more effective using weather derivatives written on the RMS indices for 64 of the 87 cities for the winter season, and 75 of the 87 cities for the summer season.

Figure 7: The difference in nonlinear basis hedging effectiveness between the RMS and the CME winter season indices ($NHE_{RMS} - NHE_{CME}$).

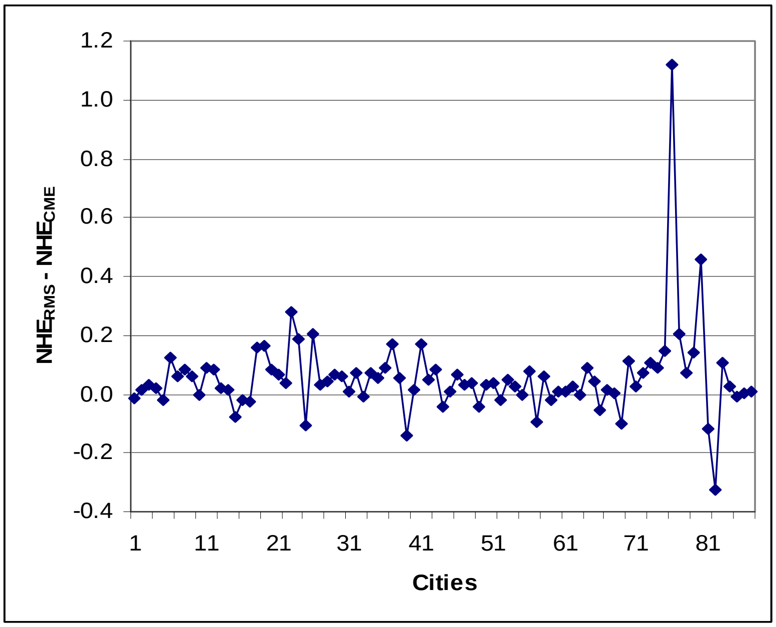
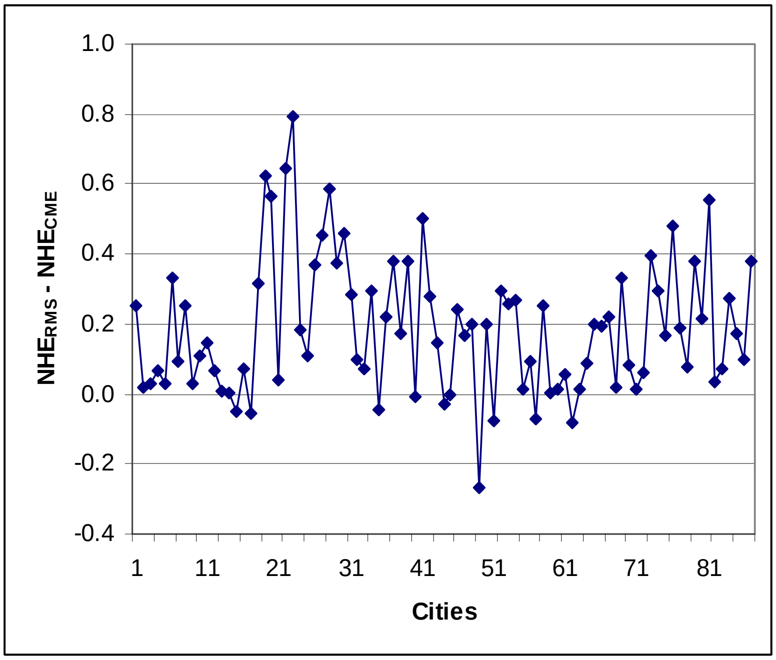


Figure 8: The difference in nonlinear basis hedging effectiveness between the RMS and the CME summer season indices ($NHE_{RMS} – NHE_{CME}$).



6. Conclusion

This paper has explored the effectiveness of using a basis derivative hedging strategy (involving either linear or nonlinear derivative instruments) in an attempt to mitigate both credit and basis risks inherent in OTC and exchange-traded weather derivatives. We find, using actual weather data, that linear and nonlinear basis hedging are both much more effective for the winter season than for the summer season, a finding which should be of use to potential hedgers deciding whether or not to use weather derivatives and how to implement a weather derivative strategy.

This article shows that the effectiveness of hedging using a basis risk derivative varies significantly across regions of the country. Moreover, concerning the effectiveness difference between the two most popular types of standardized weather indices, generally the RMS regional indices are more effective than the CME city indices for implementing a basis hedging strategy. These results have important implications for determining which type of index to use to create a hedging strategy to control weather related financial consequences for enterprises contemplating weather risk management in different parts of the United States and in different seasons.

References

Briys, E., M. Crouhy, and H. Schlesinger, 1993, Optimal Hedging in a Futures Market with Background Noise and Basis Risk, *European Economic Review*, 37: 949-960.

Brockett, Patrick L., Mulong Wang, Chuanhou Yang, 2005, "Weather Derivatives and Weather Risk Management," *Risk Management and Insurance Review*, 8(1): 127-140.

Coble, K. H., Heifner, R. G., and Zuniga, M., 2000, Implications of Crop Yield and Revenue Insurance for Producer Hedging, *Journal of Agricultural and Applied Economics*, 25(2): 432-452.

Considine, G., 2000, Introduction to Weather Derivatives, Weather Derivatives Group, Aquila Energy (Available at www.cme.com/weather/introweather.pdf).

Davis, M., 2001, Pricing Weather Derivatives by Marginal Value, *Quantitative Finance*, 1: 1-4

Doherty, N., and H. Schlesinger, 1990, Rational Insurance Purchasing: Consideration of Contract Nonperformance, *Quarterly Journal of Economics*, 105: 243-253.

Golden, Linda L., Mulong Wang and Chuanhou Yang, 2007, Handling Weather Related Risks through the Financial Markets: Considerations of Credit Risk, Basis Risk, and Hedging, *Journal of Risk and Insurance*, 74(2): 319-346.

Hentschel, L., and C. W. Smith, Jr., 1997, Derivatives regulation: Implications for central banks, *Journal of Monetary Economics*, 40: 305--346.

Li, D., and Vukina, T., 1998, Effectiveness of Dual Hedging with Price and Yield Futures, *Journal of Futures Markets*, 18(5): 541-561.

MacMinn, R. D., 1999, Risk and Choice: A Perspective on the Integration of Finance and Insurance, *Risk Management and Insurance Review*, 3: 69-79.

Moschini, G., and H. Lapan, 1995, The hedging Role of Options and Futures under Joint Price, Basis and Production Risk, *International Economic Review*, 36: 1025-1049.

Poitras, G., 1993, Hedging and Crop Insurance, *Journal of Futures Markets*, 13(4): 373 388.

Tapiero, C., Y. Kahane, and L. Jacque, 1986, Insurance Premiums and Default Risk in Mutual Insurance, *Scandinavian Actuarial Journal*, December: 82-97.

USA Today (2008), Weather Derivatives becoming hot commodities, *USA Today Online* http://www.usatoday.com/weather/forcast/2008-06-09-weather-derivative_N.htm?csp=34 posted 6/9/2008

Vukina, T., D. Li, and D. Holthausen (1996), Hedging with Crop Yield Futures: A Mean-Variance Analysis, *American Journal of Agricultural Economics*, 78: 1015-1025.

Appendix I: The CME Trading Cities and Weather Stations

Station Name	Symbol	Region	State	City
Atlanta Hartsfield International Airport	ATL	Southeast	GA	Atlanta
Boston Logan International Airport	BOS	Northeast	MA	Boston
Chicago O'Hare International Airport	ORD	Midwest	IL	Chicago
Cincinnati Northern Kentucky Airport	CVG	Midwest	KY	Covington
Dallas-Fort Worth International Airport	DFW	South Central	TX	Dallas
Des Moines International Airport	DSM	Plains	IA	Des Moines
Houston Bush Intercontinental Airport	IAH	South Central	TX	Houston
Kansas City International Airport	MCI	Plains	MO	Kansas City
Las Vegas McCarran International Airport	LAS	Southwest	NV	Las Vegas
Minneapolis-St. Paul International Airport	MSP	Northern Plains	MN	Minneapolis
New York La Guardia Airport	LGA	Northeast	NY	New York
Philadelphia International Airport	PHL	Mid-Atlantic	PA	Philadelphia
Portland International Airport	PDX	Pacific Northwest	OR	Portland
Sacramento Executive Airport	SAC	Southwest	CA	Sacramento
Tucson International Airport	TUS	Southwest	AZ	Tucson

Appendix II: The Effectiveness of Basis Risk Hedging for 87 cities

			Linear Hedging of Basis Risk				Nonlinear Hedging of Basis Risk			
			Winter		Summer		Winter		Summer	
Region	State	City name	CME	RMS	CME	RMS	CME	RMS	CME	RMS
Mid-Atlantic	NJ	Atlantic City	0.88	0.94	-0.1	0.16	0.9	0.89	0.03	0.28
Mid-Atlantic	MD	Baltimore	0.88	0.9	0.77	0.89	0.88	0.89	0.78	0.8
Mid-Atlantic	WV	Charleston	0.68	0.85	0.81	0.76	0.82	0.86	0.77	0.8
Mid-Atlantic	NJ	Newark	0.91	0.95	0.57	0.74	0.91	0.93	0.64	0.7
Mid-Atlantic	PA	Pittsburgh	0.92	0.93	0.66	0.83	0.91	0.88	0.83	0.86
Mid-Atlantic	VA	Richmond	0.8	0.91	0.48	0.77	0.8	0.93	0.44	0.77
Mid-Atlantic	VA	Roanoke	0.8	0.89	0.53	0.8	0.72	0.78	0.63	0.72
Mid-Atlantic	VA	Dulles	0.89	0.93	0.59	0.81	0.85	0.93	0.59	0.84
Mid-Atlantic	PA	Williamsport	0.88	0.93	0.55	0.69	0.85	0.91	0.71	0.74
Midwest	OH	Columbus	0.94	0.91	0.69	0.84	0.93	0.92	0.74	0.85
Midwest	MI	Detroit	0.93	0.96	0.68	0.87	0.84	0.93	0.77	0.92
Midwest	MI	Grand Rapids	0.76	0.86	0.64	0.8	0.81	0.9	0.62	0.68
Midwest	IN	Indianapolis	0.95	0.97	0.83	0.94	0.94	0.97	0.91	0.91
Midwest	KY	Louisville	0.88	0.86	0.73	0.79	0.85	0.87	0.81	0.81
Midwest	WI	Madison	0.94	0.9	0.77	0.77	0.94	0.87	0.88	0.83
Midwest	WI	Milwaukee	0.93	0.95	0.68	0.73	0.94	0.92	0.71	0.78
Midwest	IL	Peoria	0.91	0.94	0.71	0.8	0.92	0.89	0.87	0.81
Mountain States	ID	Boise	0.52	0.68	0.43	0.55	0.42	0.58	0.31	0.63
Mountain States	WY	Casper	0.51	0.8	-0.2	0.66	0.66	0.83	-0.1	0.55
Mountain States	WY	Cheyenne	0.51	0.84	-0.8	0.52	0.7	0.78	-0	0.56
Mountain States	CO	Colorado Springs	0.54	0.68	-0.6	0.41	0.76	0.82	0.2	0.24
Mountain States	CO	Grand Junction	0.24	0.42	-0.3	0.66	0.61	0.65	0.02	0.67
Mountain States	ID	Pocatello	0.47	0.73	0.22	0.74	0.46	0.74	0.02	0.81
Mountain States	CO	Pueblo	0.36	0.61	-0.1	0.38	0.45	0.64	-0	0.15
Mountain States	NV	Reno	0.58	0.44	0.21	0.42	0.77	0.66	0.34	0.45
Mountain States	UT	Salt Lake City	0.52	0.77	0.18	0.72	0.36	0.57	0.37	0.74
Mountain States	NV	Winnemucca	0.39	0.54	0.41	0.56	0.68	0.71	-0.1	0.4
Northeast	NY	Albany	0.91	0.97	0.46	0.7	0.91	0.95	0.2	0.79
Northeast	VT	Burlington	0.9	0.95	0.13	0.73	0.79	0.86	0.4	0.77
Northeast	NH	Concord	0.89	0.96	-0.6	0.52	0.88	0.94	0.12	0.58
Northeast	CT	Hartford	0.94	0.97	0.56	0.92	0.94	0.95	0.59	0.87
Northeast	NY	New York City	0.95	0.96	0.63	0.76	0.87	0.94	0.63	0.73
Northeast	NY	New York City	0.91	0.9	0.66	0.74	0.85	0.84	0.73	0.8
Northeast	ME	Portland	0.95	0.95	-0.1	0.66	0.84	0.91	0.45	0.75
Northeast	RI	Providence	0.93	0.96	0.51	0.83	0.88	0.93	0.87	0.82
Northeast	NY	Rochester	0.86	0.95	0.52	0.83	0.85	0.94	0.57	0.79

			Linear Hedging of Basis Risk				Nonlinear Hedging of Basis Risk			
			Winter		Summer		Winter		Summer	
Region	State	City name	CME	RMS	CME	RMS	CME	RMS	CME	RMS
Northern Plains	MT	Billings	0.66	0.86	0.09	0.65	0.66	0.83	0.36	0.74
Northern Plains	ND	Bismarck	0.79	0.91	0.6	0.83	0.83	0.88	0.57	0.74
Northern Plains	MN	Duluth	0.86	0.8	-0.5	0.29	0.88	0.74	0.34	0.72
Northern Plains	ND	Fargo	0.88	0.89	0.67	0.73	0.89	0.91	0.88	0.87
Northern Plains	MT	Helena	0.44	0.7	0.02	0.65	0.62	0.78	0.27	0.77
Northern Plains	MT	Missoula	0.58	0.72	0.21	0.44	0.79	0.84	0.26	0.54
Northern Plains	SD	Rapid City	0.79	0.93	0.63	0.81	0.75	0.83	0.68	0.83
Northern Plains	MN	Rochester	0.97	0.89	0.66	0.67	0.94	0.9	0.72	0.69
Northern Plains	SD	Sioux Falls	0.88	0.86	0.76	0.66	0.89	0.89	0.78	0.78
Pacific Northwest	OR	Eugene	0.71	0.73	0.58	0.55	0.7	0.77	0.31	0.55
Pacific Northwest	ID	Lewiston	0.54	0.68	0.42	0.67	0.86	0.89	0.52	0.69
Pacific Northwest	OR	Medford	0.38	0.44	0.66	0.73	0.59	0.63	0.56	0.76
Pacific Northwest	WA	Olympia	0.8	0.78	-0.7	-1.1	0.88	0.84	-0.3	-0.6
Pacific Northwest	OR	Pendleton	0.7	0.79	0.65	0.86	0.81	0.84	0.68	0.88
Pacific Northwest	OR	Salem	0.85	0.8	0.71	0.78	0.86	0.89	0.8	0.73
Pacific Northwest	WA	Seattle	0.63	0.6	0.59	0.35	0.8	0.78	-0.3	0.05
Pacific Northwest	WA	Spokane	0.74	0.82	0.49	0.81	0.83	0.89	0.54	0.79
Pacific Northwest	WA	Yakima	0.69	0.79	0.55	0.82	0.79	0.81	0.57	0.84
Plains	MO	Columbia	0.87	0.89	0.66	0.87	0.89	0.89	0.85	0.87
Plains	KS	Dodge City	0.59	0.65	0.53	0.66	0.65	0.73	0.58	0.67
Plains	IA	Dubuque	0.93	0.84	0.77	0.68	0.95	0.86	0.88	0.81
Plains	NE	North Platte	0.71	0.77	0.47	0.67	0.74	0.8	0.44	0.69
Plains	NE	Omaha	0.91	0.89	0.74	0.77	0.91	0.89	0.73	0.74
Plains	IL	Springfield	0.9	0.91	0.65	0.7	0.92	0.93	0.68	0.7
Plains	MO	St. Louis	0.92	0.92	0.72	0.82	0.93	0.94	0.78	0.84
Plains	KS	Topeka	0.96	0.97	0.75	0.87	0.94	0.97	0.8	0.72
Plains	KS	Wichita	0.84	0.88	0.48	0.6	0.86	0.86	0.76	0.78
South Central	LA	Baton Rouge	0.69	0.83	0.41	0.52	0.63	0.72	0.6	0.69
South Central	AR	Little Rock	0.86	0.89	0.51	0.79	0.88	0.93	0.64	0.83
South Central	TX	Lubbock	0.82	0.75	-0.4	0.25	0.78	0.72	0.14	0.33
South Central	LA	New Orleans	0.73	0.72	0.64	0.56	0.7	0.71	0.48	0.7
South Central	OK	Oklahoma City	0.86	0.83	0.57	0.67	0.86	0.86	0.85	0.87
South Central	TX	San Antonio	0.87	0.81	0.05	0.42	0.89	0.79	-0.1	0.2
South Central	LA	Shreveport	0.83	0.91	0.64	0.79	0.84	0.95	0.84	0.92
South Central	OK	Tulsa	0.77	0.75	0.46	0.64	0.76	0.78	0.69	0.7
Southeast	AL	Birmingham	0.81	0.91	0.55	0.81	0.85	0.92	0.71	0.77
Southeast	SC	Charleston	0.63	0.88	-0.1	0.68	0.72	0.83	0.39	0.79
Southeast	NC	Charlotte	0.61	0.82	0.27	0.49	0.79	0.87	0.37	0.66

			Linear Hedging of Basis Risk				Nonlinear Hedging of Basis Risk			
			Winter		Summer		Winter		Summer	
Region	**State**	**City name**	**CME**	**RMS**	**CME**	**RMS**	**CME**	**RMS**	**CME**	**RMS**
Southeast	MS	Jackson	0.64	0.84	0.38	0.71	0.68	0.83	0.72	0.89
Southeast	FL	Miami	-6.2	-4.9	-0	0.04	-1.7	-0.6	-0.5	0.04
Southeast	AL	Mobile	0.64	0.82	0.61	0.56	0.6	0.8	0.47	0.66
Southeast	TN	Nashville	0.77	0.76	0.75	0.79	0.77	0.84	0.52	0.6
Southeast	NC	Raleigh	0.67	0.88	0.34	0.81	0.75	0.89	0.34	0.72
Southeast	FL	Tampa	-0.1	0.58	-0.1	0	0.32	0.77	-0.2	0.01
Southwest	NM	Albuquerque	0.6	0.46	0.03	0.33	0.55	0.43	-0.1	0.47
Southwest	CA	Bakersfield	0	0.21	-0	0.41	0.5	0.17	0.03	0.07
Southwest	CA	Fresno	0.52	0.67	0.29	0.57	0.11	0.21	0.53	0.6
Southwest	CA	Long Beach	-0.4	0.12	-0.1	0.28	0.72	0.75	-0	0.26
Southwest	CA	Los Angeles	0.15	0.37	-0	0.13	0.65	0.64	0.2	0.37
Southwest	AZ	Phoenix	0.53	0.61	-0	0.29	0.79	0.79	0.34	0.44
Southwest	AZ	Winslow	0.42	0.39	0	0.34	0.34	0.34	0.17	0.55