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Weather Derivatives, Spatial Aggregation, and Systemic Risk: Implications for Reinsurance Hedging

Joshua D. Woodard and Philip Garcia

Previous studies identify limited potential efficacy of weather derivatives in hedging agricultural exposures. In contrast to earlier studies which investigate the problem at low levels of aggregation, we find that better weather hedging opportunities may exist at higher levels of spatial aggregation. Aggregating production exposures reduces idiosyncratic risk, leaving a greater proportion of the total risk in the form of systemic weather risk which can be effectively hedged using relatively simple weather derivatives. The aggregation effect suggests that the potential for weather derivatives in agriculture may be greater than previously thought, particularly for aggregators of risk such as reinsurers.

Key words: crop insurance, hedging, reinsurance, spatial aggregation, systemic risk, weather derivatives

Introduction

The failures of crop insurance markets in the form of high loss ratios, low participation rates, and the aversion of private insurance companies to bearing exposures have been documented extensively. Early explanations attributed these failures primarily to information asymmetries related to moral hazard and adverse selection (Chambers, 1989; Gardner, 1994; Goodwin and Smith, 1995; Just and Calvin, 1994; Nelson and Loehman, 1987; Quiggen, 1994; Quiggen, Karagiannis, and Stanton, 1994; Skees and Reed, 1986).[1] More recently, a different view has gained support that relates market failures to the inherent systemic nature of the risks in insuring agricultural production exposures (Duncan and Meyers, 2000; Mason, Hayes, and Lence, 2003; Miranda and Glauber, 1997).

Systemic risk in agricultural insurance markets stems from spatially correlated adverse weather events. Research on this explanation concentrates primarily on identifying the nature and magnitude of systemic risks (Mason, Hayes, and Lence, 2003; Miranda and Glauber, 1997) and on investigating ways in which the risks can be managed by utilizing private reinsurance and capital markets (Hayes, Lence, and Mason, 2003; Miranda and Glauber, 1997; Turvey, Nayak, and Sparling, 1999). Based on our review

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[1] Other explanations for low producer participation include crowding-out by other risk management tools and government programs (Schmitz, Just, and Furtan, 1994; Wright and Hewitt, 1994), heterogeneity in the financial conditions of farms (Leathers, 1994), and the whole-farm portfolio diversification effect (Schoney, Taylor, and Hayward, 1994).

of the literature, no empirical investigation of reinsurance hedging with weather derivatives (WDs) has been conducted to date.

A key characteristic of agriculture is that it is extremely weather sensitive, and the use of WDs in agriculture has received increased attention recently. Currently the WD market is the fastest growing derivative market in the world (Brockett, Wang, and Yang, 2005). According to the Chicago Mercantile Exchange (CME), the value of CME weather products grew ninefold in the first nine months of 2005, increasing from $2.2 billion in 2004 to $22 billion through September 2005, with trading volume surpassing 630,000 contracts. While numerous authors have suggested the potential of weather hedging in a reinsurance context on conceptual grounds (Glauber, 2004; Skees and Barnett, 1999), earlier research suggests that the potential effectiveness of WDs at the farm level may be limited (Vedenov and Barnett, 2004). Evaluation at low levels of aggregation, however, may not be relevant for reinsurers who are exposed to more aggregated risks, but no clear explanation has been offered to clarify why one might expect improved WD hedging performance at the reinsurance (i.e., aggregate) versus the primary (i.e., farm) level.

This study seeks to bridge these gaps in the literature by proposing that WD hedging may be more effective at higher levels of aggregation. Specifically, aggregating production exposures across space may reduce idiosyncratic (i.e., localized or region-specific) risk in the aggregate portfolio. A greater proportion of the aggregate portfolio's total risk may be left in the form of systemic weather risk relative to idiosyncratic risk, which may be effectively hedged using WDs. A conceptual model that supports this notion is developed. The hypothesis is investigated at varying levels of aggregation using Illinois corn over the 1971–2002 period at the Crop Reporting District (CRD) and state levels.

The hedging analysis assumes minimization of semivariance. An expected-shortfall measure of tail-risk is also evaluated. These measures of downside risk may be more relevant to reinsurers as they are typically more concerned with loss events. For several reasons, the hedging analysis focuses on seasonal temperature derivatives in lieu of more complex monthly precipitation and temperature derivatives used in previous studies. The interaction of temperature and precipitation during loss events, temperature autocorrelations, and high computation costs limit the potential benefits of more complex WDs. Also, transaction costs associated with negotiating over-the-counter (OTC) precipitation derivatives are likely high, and their potential for liquidity low relative to temperature derivatives. Further, the markets for the temperature derivatives traded at the CME are currently the most developed WD markets. The WDs employed here, which are highly consistent with the CME contracts in structure, appear to present a promising avenue for current research.

Weather Risk in Crop Insurance Markets

In contrast to earlier studies on failures in crop insurance markets, Miranda and Glauber (1997) propose that systemic weather risk poses a serious obstacle to the emergence of independent private crop insurance markets because widespread adverse weather induces significant correlations among individual farm-level yields. The authors estimate that U.S. crop insurer portfolios are between 20 and 50 times riskier than they otherwise would be if yields were independent. Thus, the lack of independence among individual yields causes crop insurers to bear substantially higher risk per unit of premium than other property liability and business insurers.

In order to induce insurers to underwrite crop insurance, insurers in the United States are provided reinsurance protection by the government under the Standard Reinsurance Agreement (SRA). The SRA imposes large administrative costs on the public. Moreover, the extent to which the SRA effectively transfers *systemic* risks from the insurer to the government is not known. Ineffective transfer of systemic risk under the SRA may impose additional costs on the government if insurers do not have the incentives to appropriately monitor and share in the risk of the policies they underwrite. Also, the current structure of the SRA is restrictive in terms of how insurers may price the policies they underwrite. All of these factors contribute to excess costs, whether implicit or explicit, generated by the absence of competitive and independent agricultural insurance markets.

Miranda and Glauber (1997) suggest that area yield reinsurance contracts may permit crop insurers to cover most of their systemic crop loss risk, reducing their risk exposure to levels typically experienced by conventional property liability insurers.[2] Given the ability to hedge their systemic risk, crop insurers may be less averse to insuring crop production independently, lessening the need for government intervention and increasing the efficient functioning of agricultural insurance markets.

Hayes, Lence, and Mason (2003),[3] as well as Miranda and Glauber, investigate the effectiveness of area yield derivatives in hedging crop insurance risk. Although area yield contracts did trade for a short time in an exchange setting, they eventually failed due to insufficient trading volume. A major problem was that market-makers were largely uninterested in taking the other side of such specialized contracts because they were unable to offset the resulting risk. This does not appear to be the case for weather derivatives. The potential for liquidity in WD markets is greater due to the number of market agents with naturally opposing hedge preferences (e.g., electrical utilities).

Hayes, Lence, and Mason (2003) also evaluate the hedging effectiveness of price derivatives. The primary risk factor in crop insurance, however, is not price but rather widespread adverse weather events such as drought and extreme temperatures during critical growing periods. In addition, plant disease and infection can be intensified by adverse weather.

While researchers have suggested that WDs may be useful for hedging systemic risk, the use of WDs by producers is questionable. For example, Vedenov and Barnett (2004) analyze the efficiency of WDs as primary hedging instruments for corn, soybeans, and cotton in the United States at the CRD level of aggregation. Based on relatively complex nonlinear combinations of monthly (June, July, and August) precipitation and temperature indexes, Vedenov and Barnett's results suggest only the limited efficacy of WDs in hedging disaggregated production exposures.[4]

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[2] Most insurance markets have some degree of systemic risk. For example, life insurance may be sensitive to interest rates, and health insurance markets may be sensitive to health care cost inflation. Agricultural insurance markets, however, are unique in that the degree of systemic risk is so high that private markets have failed to develop without extreme government intervention.

[3] Hayes, Lence, and Mason (2003) investigate reinsurance hedging for the Risk Management Agency (RMA), the government agency which administers the federal crop insurance program. Although the RMA is technically a reinsurer, it is likely that the high degree of systemic risk in agricultural insurance markets exposes private insurers and reinsurers to the same fundamental problem. Because the exposure to systemic risk is similar, we do not differentiate between hedging by the insurer and the reinsurer in the discussion.

[4] Vedenov and Barnett (2004) assess the hedging effectiveness of WDs at the CRD level and make the assumption that farmer-level yield risk is accurately reflected in CRD-level yield risk. They conclude that typical farmer yields are likely much riskier than CRD yields.

This study builds on earlier research in two important dimensions. First, hedging effectiveness of WDs is investigated at varying levels of spatial aggregation. Yields evaluated at low levels of aggregation (e.g., farm or CRD level) are likely much riskier than those at higher levels (e.g., state level) because the potential degree to which idiosyncratic risks self-diversify increases as the level of aggregation increases. Yet, high temperature spatial correlations induce significant correlations among low-level yield exposures. Thus, relatively more risk may be left in the form of systemic weather risk, and the hedging effectiveness of WDs may increase as the level of aggregation is increased. Analysis of aggregated yields also may be more relevant from the reinsurers' viewpoint as aggregate yield risk more accurately embodies their systemic risk.

Second, we investigate straightforward seasonal temperature WDs in lieu of complex monthly temperature and precipitation WDs. Persistence in weather conditions may induce a high degree of collinearity between precipitation and temperature (Namias, 1983, 1986; Wolfson, Atlas, and Sud, 1987). This, along with the fact that U.S. weather conditions during the summer tend to be autocorrelated (Jewson and Brix, 2005), increases the probability of misspecifying weather hedges involving multiple underlying indexes (Vedenov and Barnett, 2004). The current work simplifies the analysis by investigating seasonal (June, July, and August) temperature WDs that correspond to the important growth and development stages of the crops.

The Conceptual Model

Idiosyncratic effects may self-diversify when aggregated, leaving a greater proportion of the total risk in the form of weather risk. Thus, WD hedging may be more effective for aggregate rather than disaggregate yield exposures. The magnitude of the spatial aggregation effect depends on the relative correlations of weather and idiosyncratic yield effects across locations. To illustrate, assume yields can be decomposed into two effects, weather effects ($\mathbf{W}$) and all other effects (ε), which may be correlated. Consider a simple model of crop yields which allows for nonlinear terms:

$$Y_{t,k} = \alpha_k + f_k(\mathbf{W}_{t,k}) + \varepsilon_{t,k}, \tag{1}$$

where t is the time index, k is the location index, $\mathbf{W}_{t,k}$ is a vector of weather variables, $f_k(\mathbf{W}_{t,k})$ represents the systemic weather component of yields, $\varepsilon_{t,k}$ represents the idiosyncratic risk component, and $E[\varepsilon_{t,k}] = 0$. Summing across k locations gives:

$$E\left[\sum_k Y_{t,k}\right] = \sum_k \alpha_k + E\left[\sum_k f_k(\mathbf{W}_{t,k})\right] + E\left[\sum_k \varepsilon_{t,k}\right] \tag{2}$$

and

$$\operatorname{Var}\left[\sum_k Y_{t,k}\right] = \operatorname{Var}\left[\sum_k f_k(\mathbf{W}_{t,k})\right] + \operatorname{Var}\left[\sum_k \varepsilon_{t,k}\right] + \operatorname{Cov}\left[\sum_k f_k(\mathbf{W}_{t,k}), \sum_k \varepsilon_{t,k}\right]. \tag{3}$$

If the $\varepsilon_{t,k}$'s are relatively less positively correlated than the $f_k(\mathbf{W}_{t,k})$'s across locations, then, as the individual yields are summed, more variation in yields may be able to be attributed to the weather effects at larger levels of spatial aggregation. Hence, WD hedging may be more effective at larger levels of spatial aggregation.

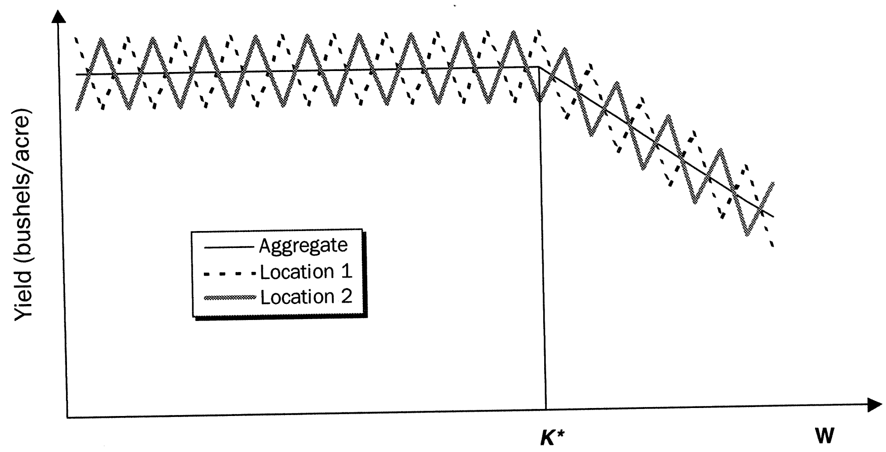

Figure 1. Spatial aggregation effect and weather hedging

To illustrate, consider an extreme case. Suppose there are two locations and the $\varepsilon_{t,k}$'s are perfectly negatively correlated, $f_k(\mathbf{W}_{t,k})$'s are perfectly positively correlated, and $\mathrm{Cov}[f_k(\mathbf{W}_{t,k}), \varepsilon_{t,j}] = 0, \forall j, k$. In this case the variance of aggregate yields reduces to:

$$(4) \qquad \mathrm{Var}\left[\sum_k Y_{t,k}\right] = \mathrm{Var}\left[\sum_k f_k(\mathbf{W}_{t,k})\right],$$

and all variation in yields can be attributed to weather events. This risk can be potentially hedged with a WD equal in size but opposite in direction to the underlying systemic weather effect, $f_k(\mathbf{W}_{t,k})$. Figure 1 depicts such a situation in which the two locations are aggregated. In this case, if $\mathbf{W}$ can be approximated by a weather index, the risk of the aggregated exposure can be hedged more effectively with a call option on the index with strike price K^* than can either of the individual exposures. This framework supports the notion that while WDs may not be useful for individual producers, they may still prove useful in hedging systemic risks borne by aggregators of risk.

Of course, this may not always be the case. At the other extreme, consider two locations where the $\varepsilon_{t,k}$'s are perfectly positively correlated, the $f_k(\mathbf{W}_{t,k})$'s are perfectly negatively correlated, and $\mathrm{Cov}[f_k(\mathbf{W}_{t,k}), \varepsilon_{t,j}] = 0, \forall j, k$. Here, the variance of aggregate yields reduces to:

$$(5) \qquad \mathrm{Var}\left[\sum_k Y_{t,k}\right] = \mathrm{Var}\left[\sum_k \varepsilon_{t,k}\right],$$

and thus all variation in aggregate yields is attributed to idiosyncratic effects and none of the aggregate risk can be hedged using WDs.

While both cases are unrealistic, they illustrate the aggregation argument. If weather events across locations are highly correlated, but other yield effects are relatively less correlated, then relatively more variation (i.e., risk) in yields can be attributed to weather events as yields are aggregated. Empirically, the relevant question for the reinsurer is whether the differences in the correlations of weather effects and other yield effects are significant enough to observe substantial differences in WD hedging effectiveness as the level of aggregation increases.

There are good reasons to believe WD hedging may be more effective as the level of aggregation is increased. First, aggregating yields should have a diversifying effect across locations. Popp, Rudstrom, and Manning (2005), for instance, find that the risk of farm-level yields is substantially higher than county-level yields. This is partly due to the diversifying effect as yields are aggregated over individual farms.[5] Second, weather events tend to be highly spatially correlated. For example, the average correlation between the temperature indexes used in this study (described below) across locations was 0.755.[6]

Yields, Weather Indexes, Derivatives, and Pricing

Failure to account for technological advancements in crop production can produce misleading hedging results. Significant trends in historical yields may produce spurious hedge ratios which are not representative of the underlying optimal hedge ratio distribution. To account for changes in technology, district-level yields are detrended using a simple log-linear trend model (Vedenov and Barnett, 2004):[7]

$$\log(Y_t^{tr}) = \alpha_0 + \alpha_1(t - 1971), \quad t = 1971, 1972, \ldots, 2002. \tag{6}$$

Detrended yields to 2002 equivalents are calculated as:

$$Y_t^{\det} = Y_t \frac{Y_{2002}^{tr}}{Y_t^{tr}}, \quad t = 1971, \ldots, 2002, \tag{7}$$

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

The negative effect of temperature stress on corn yields during the summer season is well accepted (Dixon et al., 1994; Kaufmann and Snell, 1997; Monjardino, Smith, and Jones, 2005; Teigen, 1991). Moreover, temperature derivatives are likely the most feasible weather variable on which to structure weather contracts from a transaction cost standpoint. Thus temperature derivatives are adopted for this study. The temperature variables used are accumulated cooling degree days (ACDDs) for the summer season: June, July, and August. Agronomic experiments indicate that cooling degree days (CDDs) are more relevant to crop yields than outright temperature measurements (Schlenker, Hanemann, and Fisher, 2006). Further, the temperature derivatives traded on the CME are written on ACDD indexes. The number of CDDs for a single day is defined as the amount by which the average temperature is above the reference temperature, 65° Fahrenheit. Explicitly, the number of CDDs on any day t is given by:

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[5] Preliminary analysis strongly suggested the presence of a self-diversifying aggregation effect. The average correlation among individual district detrended yields was 0.746. Also, the data suggest that the variance of aggregate yields was significantly less than the variance of the individual yields.

[6] In addition, preliminary analysis strongly supported the spatial aggregation hypothesis. Preliminary analysis was conducted by regressing individual district detrended yields on the temperature and temperature^2 indexes for all districts. The average of the district adjusted R^2s was 0.366, compared to 0.526 for aggregated yields. The average correlation of the temperature effects across all districts was 0.72, and the average correlation of the residuals was 0.52.

[7] This procedure does not impose any distributional assumptions on the residuals but removes their central tendency (Vedenov and Barnett, 2004). While OLS is inefficient when errors are not normally distributed, the econometric properties of an uninterrupted series independent variable, as well as the level of skewness typical of corn yields, can permit OLS to generate better crop yield coefficient estimates than many robust regression methods (Swinton and King, 1991).

$$CDD_t = \mathrm{Max}(0, T_t - 65), \tag{8}$$

where T_t is the average temperature on day t. The average temperature is the simple arithmetic average of the daily maximum and minimum temperatures. The index of ACDDs on any date t is simply defined as:

$$ACDD_t^{M,N} = \sum_{t=M-N}^{M} CDD_t, \quad t = M - N, \ldots, M, \tag{9}$$

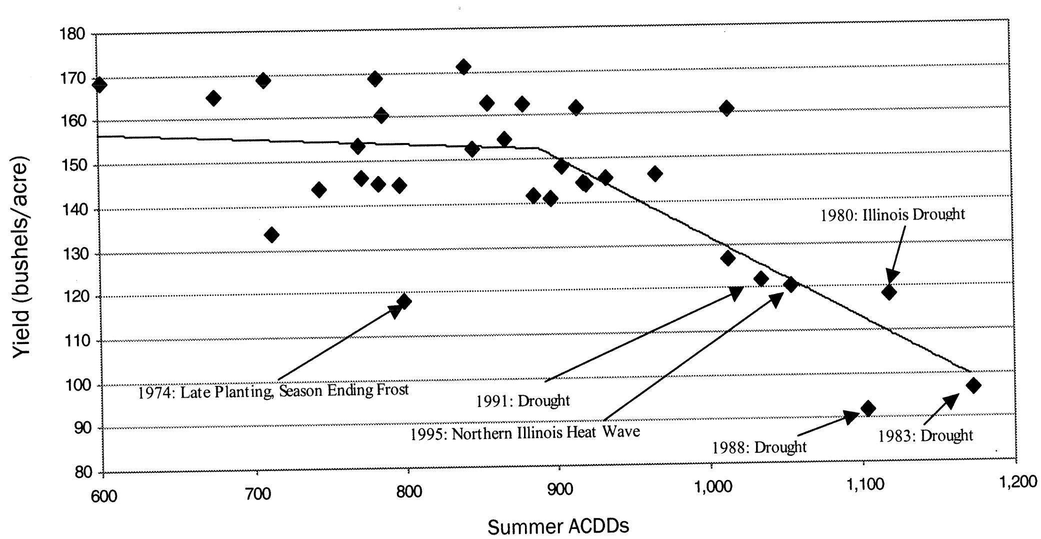
where $M - N$ is the first day of the contract period, and M is the expiration date.

Although precipitation is also an important risk factor in crop yields, we restrict analysis to temperature derivatives due to the higher potential for liquidity in temperature derivatives. For instance, from October 14, 1997 to April 15, 2001, temperature derivatives represented over 98% of all WDs (Brockett, Wang, and Yang, 2005). Further, we use summer season contracts as opposed to more time-disaggregated contracts (e.g., monthly). The use of time-aggregated temperature derivatives may not be a major shortcoming as atmospheric flow patterns that control much of the North American climate tend to be persistent (Namias, 1983, 1986; Wolfson, Atlas, and Sud, 1987). In particular, during extreme drought events—those most likely to result in widespread crop losses—this persistence phenomenon causes heat and precipitation conditions to interact, resulting in a self-perpetuating event across both time and space. On a large scale, average temperature and precipitation conditions for a given region are highly negatively correlated in these extreme events. The use of a seasonal index is further motivated by the fact that in the U.S. corn growing regions, month-to-month temperatures are typically autocorrelated (Jewson and Brix, 2005) during the summer season.[8]

Figure 2 displays aggregate detrended Illinois state corn yields for 1971–2002, with the x-axis ordered by summer season ACDDs. The hottest years, those in which ACDDs exceeded approximately 900, corresponded roughly to the driest years. In fact, four of the five hottest years were also drought years. Furthermore, all droughts corresponded to temperatures in excess of 900 ACDDs. Consequently, it appears that temperature derivatives may act as a suitable substitute in hedging precipitation risk when it is most needed.

Hedging yield risk with WDs becomes a difficult problem for two reasons. First, there is a high degree of yield variability that cannot be attributed to potentially tradable weather indexes. For instance, while yields are systemically related to summer ACDDs, there is still considerable yield variability that cannot be ascribed to ACDDs. For example, large yield shortfalls may be due to other events not related to ACDDs, such as in 1974 when late planting and an early season-ending frost were responsible for large yield shortfalls (figure 2). Second, the relationship between weather and yields is likely nonlinear and quadratic. In figure 2, a trend line is obtained by plotting the fitted

[8] While investigation of more time-disaggregated derivatives may improve hedging effectiveness, analysis of more specific contracts raises concerns regarding the usefulness of instruments traded on market exchanges. Splitting the "contract space" into a large number of highly specific contracts frequently reduces market activity and willingness of traders to participate. Hence, the benefits of potentially improved hedging effectiveness are likely offset by limited liquidity which adds transaction costs and further market risk. In a practical sense, it is important to note this focus is consistent with industry practices and recent literature that identifies a movement toward more market-based weather derivatives (Roth, Ulardic, and Trueb, 2007). It is also of value to note that the use of well-specified "generic" contracts like those proposed in this study should not dampen their usefulness. Hedgers almost always use generic contracts and estimate basis risk to meet their firm-specific risk management needs. Turvey (2001) provides a discussion of the use and pricing of more time- and event-specific structures.



Sources: Yield data were obtained from the USDA's National Agricultural Statistics Service (1971–2002). Temperature data were obtained from the U.S. Historical Climatology Network.

Figure 2. Illinois state corn yields (bushels/acre), 1971–2002

values from regressing yields on ACDDs for the highest (above 900) and lowest (below 900) observed ACDDs separately. For Illinois corn, it appears that yields are quadratically related to ACDDs, suggesting the potential advantage in hedging applications of an options contract which can be nonlinearly related to an ACCD index. In this analysis we include swaps as well as options in order to investigate the degree to which nonlinear weather effects exist in yields.

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 as determined by observed historical distributions.[9] It is attractive because it does not require strong assumptions about the distribution of the underlying index, and it is simple to compute.[10] Pricing is conducted by integrating the derivative payoff function over the distribution of the empirical distribution of the inter-year ending value of the weather index. The expected payoff is then discounted back to obtain the derivative price. BA assumes that the appropriate discount rate is the risk-free rate. While some studies have investigated the use of equilibrium models to estimate the discount rate (e.g., Cao and Wei, 2004; Richards, Manfredo, and Sanders, 2004), Turvey (2005) argues that the market price of risk should be zero (and thus the discount rate will equal the risk-free rate) in equilibrium because of spatial arbitrage.

[9] The assumptions of BA are that the historical 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.

[10] Pricing estimates were also obtained by estimating a parametric functional form for the weather index and numerically integrating the option payoff over the estimated distribution similar to the approach used by Vedenov and Barnett (2004). The pricing was impacted only slightly. Burn analysis prices were not found to be biased on average relative to the estimated index prices.

Our analysis also assumes all pricing and hedging is conducted prior to realizations of the current season. Although more complex intra-year models exist (e.g., Richards, Manfredo, and Sanders, 2004; Turvey, 2005), they should correspond closely to inter-year index pricing models if the processes underlying the daily model are well specified, and if the pricing is conducted at a point in time at which information about the current index value has not been incorporated into the market's expectation of the ending index distribution.

The payoff, f, from a long swap contract is given by:

$$f(ACDD) = D(ACDD - K), \tag{10}$$

where $ACDD$ is the index, D is the tick value measured in \$/ACCD, and K is the strike price of the contract (Jewson and Brix, 2005)—i.e., the contract pays \$$D$ per ACCD above the chosen strike price K. The payoff is a linear function of the index. The buyer is swapping a certain exposure, K, to the index for an uncertain exposure, $ACDD$, and thus the term "swap." Most swaps are costless (i.e., there is no premium, and the payoff equals the profit). If the swap contract is to be traded without a premium, then the strike must be set at a value such that the expected payoff is zero—i.e., $K_F = E(ACDD)$, where K_F is known as the "fair strike." Pricing of a swap thus entails determining the fair strike. Pricing a zero-cost linear swap using BA simply involves setting the fair strike equal to the historical average of the index. Most exchange-traded swap contracts—such as those traded on the CME—are costless, settled daily, and are technically known as futures contracts. Most OTC zero-cost swap contracts are settled at the end of the contract and are known as forwards. This study uses derivatives which are settled as forwards and assumes that borrowing and lending exist at the risk-free rate. Settlement method would be unlikely to change the qualitative results in a significant way.

The payoff, p, from a long call option is denoted by:

$$p(ACDD, K) = \text{Max}\big(0, D(ACDD - K)\big), \tag{11}$$

and the profit, π, is given by:

$$\pi(ACDD, K) = \text{Max}\big(0, D(ACDD - K)\big) - P(K), \tag{12}$$

where P is the option price, or premium. For options, pricing entails simply determining the fair premium, or fair price, which is defined whereby the expected profit on the contract is zero. The fair price is equal to the expected payoff of the contract, or $P = E(p)$, and pricing using BA simply consists of calculating the mean of the historical payoffs, p, given a strike, K.

Hedging Analysis and Risk Measures

Following Vedenov and Barnett (2004), the hedge ratio is determined by minimizing the semivariance (SV) of a portfolio consisting of yields and a WD, restricting attention to quantity risk alone. This assumes all price risk is previously hedged using price derivatives and implies the estimated hedge ratio below can be scaled by the hedged price to arrive at a standardized hedged revenue per acre exposure. SV, which only measures deviations below the mean, reflects downside risk.

Formally, for swaps, the hedge ratio (w) is chosen by solving:

$$\underset{w_k}{\mathrm{Min}} \sum_t \left\{ \mathrm{Max}\left[\overline{Y}_k - \left(Y_{t,k}^{\det} + w_k f_{t,k} \right), 0 \right] \right\}^2, \tag{13}$$

where w is the hedge ratio measured in contracts/acre, $Y_{t,k}^{\det}$ is detrended yield in bushels/acre, $\overline{Y}_k$ is the long-run average detrended yield, and $f_{t,k}$ is the return on the swap contract which pays $1 per ACDD. Here the index k refers to either an individual district or an aggregate-level exposure.

For options, the hedge ratio (contracts/acre), v, and strike price, K, are chosen by solving:

$$\underset{w_k, K_k}{\mathrm{Min}} \sum_t \left(\mathrm{Max}\left\{ \overline{Y}_k - \left[Y_{t,k}^{\det} + v_k \pi_k(K_k) \right], 0 \right\} \right)^2, \tag{14}$$

where $\pi_k(K)$ is the profit of an ACDD call option with strike price K. The hedging effectiveness of weather derivatives is examined by comparing portfolios with and without derivatives at different levels of aggregation. Hedging effectiveness is evaluated using hypothetical ACDD derivatives written for the locations identified in table 1. A single derivative is chosen for the individual districts as well as for the state-level exposure. The state-level (i.e., aggregated) yield and ACDD index measures were calculated as a simple average of the individual district yields and ACDD indexes.[11]

In the context of the discussion above regarding alternative pricing methods, since the assumed objective is minimization of risk, the choice of pricing method will not alter the risk-minimizing hedge because a change in the contract price will uniformly shift the ex post revenue of the hedger up or down in all states of nature. Therefore, in this framework, alternative pricing methods will not affect the payment schedule of the derivative or the correlation between crop revenue losses and derivative payoffs (Vedenov and Barnett, 2004).

The tick, D, is standardized to $1 per unit of the weather index for simplicity, but the choice is arbitrary. In practice, it can be rescaled to account for the tick of the particular contract. As noted, attention is restricted to quantity risk only, and optimal portfolios are estimated assuming price and quantity decisions are made separately. The hedge ratio, w or v, is expressed in contracts per hedged revenue acre. For instance, consider an exposure of 1,000 acres which is hedged with price derivatives at $2.50/bushel. If average yield is $\overline{Y}_k$, and the price derivative (e.g., a futures contract) is expressed in $/bushel standardized to one bushel per contract, then the optimal number of price derivatives in terms of the optimal hedge ratio of the price derivative in bushels (say z) purchased is $z \times 1{,}000 \times \overline{Y}_k$. If the price derivatives are standardized at 5,000 bushels per contract, 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 can then be expressed as $h \times 1{,}000 \times \$2.50$. If the option paid $50 per tick of the underlying weather index, then it is expressed as $h \times 1{,}000 \times 2.5 \div 50$. Thus, the weather hedge ratio need only be scaled by the hedged price, acres, and tick of the WD.

The criterion used to evaluate the change in risk exposure is the root mean squared loss (RMSL). RMSL is a simple function of SV:

[11] The choice of weighting scheme for the districts is not central to the findings. The analysis was also conducted using a production-weighted average and the results were not materially different.

Table 1. Selected Weather Stations for Illinois Crop Reporting Districts

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

$$RMSL_k = \sqrt{\frac{1}{T}\sigma_{\bar{k}}^2}, \tag{15}$$

where $T = 32$ is the sample size, and $\sigma_{\bar{k}}^2$ is the SV from equations (13) and (14).

In addition to expected net losses, agents also may be interested in the magnitude of losses given an extreme event occurs. Thus, expected shortfall (ES) is also reported (Dowd and Blake, 2006).[12] ES is the probability weighted average of the worst α outcomes. In the case of a discrete distribution, the ES is given by:

$$ES_\alpha = \frac{1}{\alpha}\sum_{p=0}^{\alpha}(p\text{th worst outcome}) \times (\text{probability of } p\text{th worst outcome}), \tag{16}$$

and is reported for $\alpha = 6\%, 9\%$. The ES measurements are calculated using a historical simulation where each observation is assigned an equal probability of $1/T$. Therefore, ES 6% equals the average of the two lowest valued observations, and ES 9% equals the average of the three lowest observations.[13] It can be interpreted as an expectation of yields in the case that a tail event *does* occur, and thus is a preference-free measure of tail-risk.[14] The expected shortfall measure is used rather than the value-at-risk (VaR), which provides an estimate of the worst loss one might expect given a tail event does not occur, because it is subadditive—making it less likely to produce puzzling and inconsistent findings in hedging applications (Dowd and Blake, 2006).

Data

The data used in this study are Illinois CRD corn yields for 1971–2002. Illinois consists of nine CRDs. Temperature data were collected for a location within each CRD. 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 the United States Historical Climatology Network website (Williams et al., 2006).

[12] The ES measure used here is based on the revenue distribution, and hence is a modification of the measure reported in Dowd and Blake (2006) which is calculated in terms of the loss distribution.

[13] The ES statistics were also estimated using numerical integration after first estimating the distribution of the hedged or unhedged exposure. The results using this method were not materially different.

[14] 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.

Results and Discussion

The results of the hedging analysis appear in tables 2 and 3. All estimates are obtained by minimizing SV as outlined above assuming a constant price of $2.50/bushel.[15] Results are first presented for the full sample (1972–2002, table 2), and then for the second half (1987–2002, table 3) subsample period which provides an out-of-sample dimension to the analysis. Out-of-sample estimates in table 3 are obtained by applying the in-sample solution for the first half of the sample to the second half of the sample.

Within the tables the "average of districts" column statistics are calculated as the average of the individual district statistics. The "average of districts" results serve as a basis of comparison to the "state (aggregated)" portfolio statistics. The "state (aggregated)" results are obtained by averaging the data across districts (i.e., aggregating) and then performing the analysis. Notice, if the weather effects captured by an ACCD index across districts are relatively uncorrelated and/or the other factors affecting yields are strongly correlated, then the "state (aggregated)" results will closely mirror the "average of districts" results. Substantial differences in the risk-reducing effectiveness of WDs for the "state (aggregated)" portfolio compared to the "average of districts" portfolio reveal that the risk reduction offered by WDs at the aggregate level is stronger than by hedging the individual districts separately. For instance, in table 2, the RMSL of the state portfolio when hedging with a call option was 22.56 versus 32.08 for the average district-level result, indicating the hedging effectiveness obtained when hedging an aggregated exposure is greater than by hedging at the individual district level.

Statistics measuring changes in RMSL and ES are calculated relative to the unhedged yield exposures. If the change in RMSL resulting from the addition of a WD is negative (positive), then the WD is risk reducing (risk increasing), whereas for the ES a positive (negative) change implies a reduction (increase) in risk.

The results for the full sample are reported in table 2. The return is the same for all hedged and unhedged portfolios in-sample, a direct result of fair option pricing. Hedging effectiveness varied widely across districts, with reductions in RMSL (change in ES 6%) ranging from 11.45% ($23.88) in the Southwest D80 region and 20.48% ($15.58) in the East Southeast D70 region when hedging with swaps, to 41.76% ($67.76) for the Southeast D90 region when hedging with call options. The large variability indicates that at low levels of aggregation there is a high degree of idiosyncratic risk present in crop yields.

Hedging with options was consistently more effective than hedging with swaps due to the presence of strong nonlinear temperature effects. The superior performance of options, which is illustrated in figure 2, is consistent across risk measures. For example, in table 2, the "state (aggregated)" portfolio reduction in RMSL (change in ES 6%) was 43.31% ($59.91) when hedging with options compared to 31.88% ($46.37) when hedging with swaps.

Next, attention is turned to investigation of the spatial aggregation effect. The unhedged portfolio results for the full sample (table 2) show that the RMSL is lower for the "state (aggregated)" portfolio than for the "average of districts" portfolio ($39.80 vs. $45.42), and results for ES 6% and 9%, respectively, are higher under the "state (aggregated)" portfolio ($235.38 and $255.18) compared to the "average of districts"

[15] Similar to previous research, the results are presented in terms of revenues assuming a constant price. Evaluation of price-quantity risk interactions is an interesting area for future research.

Table 2. Hedging Results: In-Sample Estimates, 1971–2002

	Districts					
Description	D10	D20	D30	D40	D50	D60
Unhedged						
Average Yield	152.09	147.44	151.81	158.60	144.36	157.66
RMSL	43.07	42.06	48.90	50.42	52.97	42.89
ES 6%	240.56	237.91	224.41	235.23	201.04	251.92
ES 9%	258.39	246.09	235.74	252.45	216.20	277.84
Hedged - Swap						
Hedge Ratio (contracts/acre, $1 tick)	0.17	0.19	0.26	0.31	0.33	0.28
Swap Fair Strike	644.26	803.91	798.75	851.04	804.03	907.38
RMSL	36.62	35.78	39.71	35.94	33.94	28.33
Change RMSL	-6.45	-6.29	-9.19	-14.48	-19.04	-14.56
% Change RMSL	-14.97	-14.95	-18.80	-28.72	-35.94	-33.95
ES 6%	268.96	265.89	253.94	276.25	263.69	318.32
ES 9%	281.75	268.19	273.14	292.36	270.04	326.55
Change ES 6%	28.41	27.98	29.53	41.03	62.65	66.40
Change ES 9%	23.36	22.10	37.40	39.91	53.85	48.72
Hedged - Call Option						
Hedge Ratio (contracts/acre, $1 tick)	2.44	0.69	0.59	0.73	0.56	0.39
Optimal Call Strike	864.96	875.89	876.00	920.78	819.00	929.68
RMSL	28.15	34.54	37.08	32.74	32.00	30.05
Change RMSL	-14.91	-7.53	-11.82	-17.68	-20.98	-12.84
% Change RMSL	-34.63	-17.90	-24.17	-35.06	-39.59	-29.93
ES 6%	296.46	254.24	265.16	290.69	263.34	314.05
ES 9%	304.80	273.51	274.00	306.76	271.39	319.75
Change ES 6%	55.90	16.33	40.75	55.46	62.30	62.13
Change ES 9%	46.41	27.42	38.26	54.31	55.19	41.91

Notes: The table presents results of the hedging analysis for a $2.50/bushel corn price. Estimates were obtained by minimization of semivariance with respect to the WD hedge ratio (WD hedge ratio and optimal strike) when hedging with swaps (options). The optimal hedge ratio and strike are defined as the SV-minimizing hedge ratio and strike. Statistics measuring changes in RMSL and ES are calculated relative to the unhedged revenue exposures. "Average of Districts" column statistic values were obtained by averaging the individual district statistic values and are provided to serve as a basis of comparison to the "State (aggregated)" results. A decrease (increase) in the RMSL corresponds to a reduction (increase) in risk as a result of the addition of a WD. In contrast, an increase (decrease) in the ES indicates a reduction (increase) in risk exposure from adding a WD.

(table extended . . . →)

portfolio ($221.48 and $235.55). As implied by these findings, yield risk "self-diversifies" to some extent in the aggregate portfolio.

Yet, a comparison of unhedged portfolios does not allow us to determine whether WD hedging is more effective at larger levels of aggregation. For this we must examine the hedged portfolios. We restrict attention to portfolios hedged with options for the remainder of the discussion. The results from the swap hedging analysis, however, lead to similar conclusions.

All estimates of hedging effectiveness support the aggregation argument. Reduction in the RMSL for the "state (aggregated)" portfolio for the full sample (43.31%) was

Table 2. Extended

Description	Districts [extended] D70	D80	D90	Average of Districts	State (aggregated)
Unhedged					
Average Yield	139.80	123.89	126.29	144.66	144.66
RMSL	43.07	41.07	44.34	45.42	39.80
ES 6%	227.55	192.83	181.33	221.48	235.38
ES 9%	241.14	195.22	196.93	235.55	255.18
Hedged - Swap					
Hedge Ratio (contracts/acre, $1 tick)	0.27	0.15	0.30	0.25	0.27
Swap Fair Strike	1,000.38	1,092.37	994.53	877.40	877.40
RMSL	34.25	36.36	29.35	34.47	27.11
Change RMSL	-8.82	-4.70	-14.99	-10.95	-12.69
% Change RMSL	-20.48	-11.45	-33.80	-23.67	-31.88
ES 6%	243.14	216.71	230.44	259.71	281.75
ES 9%	258.27	222.80	234.68	269.75	284.68
Change ES 6%	15.58	23.88	48.57	38.23	46.37
Change ES 9%	17.13	27.59	37.75	34.20	29.49
Hedged - Call Option					
Hedge Ratio (contracts/acre, $1 tick)	0.69	0.18	0.54	0.76	0.68
Optimal Call Strike	1,056.00	943.00	1,014.00	922.15	953.48
RMSL	32.94	35.40	25.82	32.08	22.56
Change RMSL	-10.13	-5.67	-18.52	-13.34	-17.23
% Change RMSL	-23.51	-13.81	-41.76	-28.93	-43.31
ES 6%	257.82	221.10	249.64	268.06	295.29
ES 9%	264.94	227.23	253.43	277.31	302.31
Change ES 6%	30.26	28.28	67.76	46.57	59.91
Change ES 9%	23.80	32.01	56.51	41.76	47.13

greater than for the average of the districts (28.93%), an improvement in hedging effectiveness of approximately 50% over what is implied by separate evaluation of the individual districts on average. The intuition behind this result is that the weather effects are strongly correlated across the districts while the other effects are relatively less correlated. Thus, the aggregated exposure is highly systemic and a substantial portion of this can be effectively managed using WDs. The ES measure leads to similar conclusions. For instance, the full-sample results indicate an ES 6% increase of $59.91 for the state portfolio, compared to $46.57 for the averaged district portfolios.

The hedging effectiveness results were also stronger for the "state (aggregated)" portfolio than for any of the individual districts. As shown in table 2, the 43.31% reduction in RMSL under the state portfolio was greater than for any of the individual district portfolios, with the next closest being 41.76% for D90. Also, the hedging effectiveness for the individual districts varied widely across districts, where reductions in RMSL ranged from 41.76% for D90 to 13.81% for D80.

Table 3. Hedging Results of Historical Simulation: Out-of-Sample Estimates, 1987–2002

Hedged: Call Option	Average of Districts	State (aggregated)
RMSL	25.56	19.65
Change RMSL	-5.93	-6.78
% Change RMSL	-16.85	-25.66
ES 6%	268.41	291.85
ES 9%	279.96	296.17

Note: The table presents out-of-sample estimates for the second half of the data period (1987–2002) when hedging with call options. Out-of-sample estimates are obtained by applying the optimal hedge estimated from the first half of the data period to the second.

The out-of-sample results lead to similar conclusions.[16] The out-of-sample estimates for the second half (table 3) of the sample period show reductions in RMSL of 25.66% for the state portfolio versus 16.85% for the averaged district portfolios. The change in ES as well as the level of ES was greater for the state portfolio in all out-of-sample cases. Specifically, table 3 reports the ES 6% (9%) was $291.85 ($296.17) for the state portfolio versus $268.41 ($279.96) for the averaged district portfolios. On average, the hedging effectiveness for the out-of-sample results in this study, which employs simple seasonal temperature contracts, is comparable to the results obtained by Vedenov and Barnett's (2004) analysis, which employs complex combinations of monthly precipitation and temperature derivatives. This suggests that although substantial amounts of yield risk can be hedged using WDs, the marginal benefit of more complex instruments for weather hedges may not be large, particularly when their components are correlated.

Based on our findings, aggregating individual production exposures has the effect of reducing idiosyncratic yield risk, leaving a greater proportion of the aggregated portfolio's total risk in the form of systemic weather risk, a substantial portion of which can be effectively hedged using WDs. These results support the notion that WDs may be more useful than previously thought, particularly for aggregators of risk such as reinsurers. In addition, the results show that the use of relatively simple temperature contracts can achieve reasonable hedging effectiveness.

Conclusion

This study investigates whether WDs are more effective for hedging yield exposures at large versus small levels of aggregation. Using relatively simple contract structures similar to those traded on the CME, we demonstrate their potential in hedging yield risk. Risk reduction is substantial for the aggregated portfolio as the RMSL can be reduced by almost half, and the ES can be increased by about 25% relative to an unhedged portfolio. The analysis builds on earlier research in some important dimensions.

[16] In-sample estimates of two subperiods, 1971–1986 and 1987–2002, were highly consistent with the out-of-sample estimates. For example, separate analysis of the in-sample subperiods (not reported) revealed reductions in RMSL ranging from 3.88% (26.02%) in the first half of the sample, to 42.59% (4.68%) in the second half for district D20 (D80), whereas the state portfolio RMSLs ranged only from 40.24% to 58.66%. A complete set of in-sample estimates for the subperiods is available from the authors on request.

We establish a simpler but clearer link between yields and temperature indexes and highlight how market agents may employ relatively simple WDs to hedge yield risk. Also, we establish a link between temperatures and yields at a higher level of aggregation than in previous studies. The high performance of the temperature contracts in hedging systemic risk is related to three factors: the autocorrelations in month-to-month temperatures (Jewson and Brix, 2005), the highly negative correlations between temperature and precipitation in extreme events (Namias, 1983, 1986; Wolfson, Atlas, and Sud, 1987), and the nonlinear response of yields to temperatures (Dixon et al., 1994; Vedenov and Barnett, 2004) which emerges most noticeably at higher levels of aggregation.

This study provides two important contributions. First, a conceptual basis is established for the notion that WD hedging may be more effective at the reinsurance versus the primary level, suggesting the potential of WDs for reinsurers. Second, the empirical evidence substantiates the presence of the aggregation effect which supports the proposition that WDs may provide benefits for aggregators of risk such as reinsurers. Further, the use of simple temperature derivatives may provide risk management benefits which are reasonably effective and also more consistent than those provided by complex multivariate WDs. Given the problems that systemic weather risk has caused in crop insurance markets, and also considering that crop insurance is now widespread with more than 75% of corn and soybeans planted in 2003 insured (Coble et al., 2004), our findings may be of interest to market-makers, reinsurers, and policy makers. In addition, the aggregation effect outlined here may also be applicable to other domains such as natural gas consumption.

Several qualifications are in order. First, the study only considers WDs written on local and relatively remote weather stations. It is likely the transaction costs associated with negotiating WDs in the OTC market on remote weather stations would entail high transaction costs and render these contracts infeasible. Yet, WDs written on ACDD indices for major international cities are traded on the CME. Given the great potential liquidity for these CME contracts and the high degree of spatial correlation in temperatures, an assessment of geographical basis risk for larger areas using CME contracts may be a worthwhile area of future research.

The analysis does not consider actual reinsurer portfolios, but rather only establishes the basis for the spatial aggregation effect in yield hedging applications involving WDs. It is likely, however, that yield risk is a reasonable proxy for reinsurer risk. For instance, Hayes, Lence, and Mason (2003) conclude that the RMA's reinsurance risk stems mostly from yield, or quantity, risk. Still, future research of WD hedging with special attention to specification of the reinsurer portfolio is needed. This may also include addressing price risk, which is not considered here. Given the growing popularity of revenue products and the interaction between prices and yields at the aggregate level, optimal hedging of the reinsurer portfolio may involve simultaneous determination of optimal hedge ratios with both price and weather derivatives. More complex weather derivative structures could also be investigated.

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