

***The Performance of Weather Derivatives
in Managing Risks of Specialty Crops***

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Practitioner's Abstract

California specialty crop growers are exposed to extreme price volatility, as well as considerable yield volatility caused by fluctuations in temperature, precipitation, and other specific weather events. Weather derivatives do provide a promising market-based solution to managing risks for specialty crops. While previous weather derivatives research has focused on the pricing of weather options, little if any research has been conducted evaluating the hedging effectiveness of these instruments in practical risk management settings. Therefore, this research examines the hedging effectiveness of weather derivative strategies for nectarines, raisin grapes, and almonds in Central California. Estimates of the yield-weather relationships for these crops are found to be non-linear, suggesting a straddle strategy (long put and long call) in weather options. Simulation results also suggest that specialty crop producers can improve their net income distribution through the use of weather derivative strategies. This is particularly true when the correlation between price and yields is low.

Introduction

Specialty crop growers in California endure a pain-staking, year-round effort of growing and harvesting a variety of crops, thus making production practices one of the most labor-intensive and capital-demanding forms within agriculture. Along with this, there are few in the agricultural economy that face the extreme volatility in price and yield that specialty crop growers do. For example, over the past 20 years the coefficient of variation of revenue per acre, as shown in table 1, is much greater for certain specialty crop growers in California than for more traditional crops grown in the Midwest. Given the large amount of resources required for specialty crops and the extreme fluctuations in price and yield, growers have expressed demand for some form of risk management tool (Blank and McDonald). Despite this, there are few risk management alternatives for California specialty crop growers outside of crop diversification, off-farm employment, and maintaining capital reserves. Weather derivatives, however, do provide a promising market-based solution to managing risks for California specialty crop growers.

Weather derivatives are contingent securities that promise payment to the holder based on the difference between an underlying weather index – accumulated snowfall, rainfall, or “degree days” over a specified period – and an agreed strike value. Because weather represents a common source of volume risk for agribusinesses of all types, weather derivatives are a potentially valuable tool for risk management. In fact, according to a 1998 survey of California growers, 46.9% of growers ranked weather-related risks as the most important they face, followed by 32.0% citing output price risk (Blank). As well, preliminary results from a recent survey administered to members of the California Kiwi Growers Association indicate that these growers see fluctuations in temperature as being their greatest risk to yields, and ultimately revenue.¹

¹ This preliminary survey was administered as part of an ongoing research project with the USDA Risk Management Agency (RMA) examining the use of weather derivatives for managing risks of specialty crops.

While previous research on weather derivatives has focused on understanding the stochastic processes of temperature indices, as well as appropriate pricing models for pricing temperature based weather derivatives (Turvey; Richards, Manfredo, and Sanders 2002, 2003, and 2004), little if any research has been conducted evaluating the hedging effectiveness of these instruments in practical risk management settings. Indeed, if weather derivatives are to be a viable risk management tool for California specialty crop growers, the hedging performance of these instruments must be understood. However, evaluating the hedging effectiveness of weather derivatives is not as straightforward as is with (say) a futures hedge, where it is determined by a casual examination of the R-squared from a regression of historic cash prices on futures prices (Leuthold, Junkus, and Cordier; Martinez-Garmendia and Anderson; Ederington). Given that weather phenomenon create volumetric risks, hedging effectiveness is mostly driven by the relationship between yields and weather. Richards, Manfredo, and Sanders (2003) found that for California nectarines, that the relationship between yields and temperature (cooling degree day index or CDD) is non-linear (quadratic), thus complicating the evaluation of hedging performance. Furthermore, basis risk is primarily driven by the relationship between a temperature index at a reference weather station and an individual grower's farm location. Thus, the nature of each grower's basis risk becomes an important element in defining a hedging strategy with weather derivatives, and evaluating its ultimate performance (Castelino; Moschini and Lapan; Castelino, Francis, and Wolf).

Given this, the overall objective of this research is to evaluate the risk management performance of a temperature based weather derivative in managing the volatility of net income for various California specialty crop enterprises. In doing this, we specifically examine how appropriate option strategies, given the empirical weather-yield relationships, effects the distribution of net income for a variety of crop enterprises. If the use of these option strategies help reduce net income variability, increase mean returns, or both, relative to unhedged returns, then a weather derivative based on temperature would appear to be a valuable risk management tool for California specialty crop producers.

The remainder of the paper is presented as follows. First, using University of California crop budgets, representative specialty crop enterprises are developed for nectarines, raisin grapes, and almonds. Second, we provide a description of the weather and yield data used in developing relationships defining the yields of these crops as a function of a temperature index (cooling degree days - CDD) for Fresno, California. Next, we describe the Monte Carlo simulation model used to estimate the revenue distribution of these representative crop enterprises both with and without the use of weather derivatives. In evaluating the resulting net income distributions, we measure the risk management performance of weather derivatives by their ability to 1) reduce downside risk exposure (e.g., VaR), 2) obtain mean variance efficiency (e.g., the Sharpe Ratio), and 3) maximize utility (e.g., a certainty equivalent approach). The results provide practical insight into the usefulness of weather derivatives.

Data and Methods

Weather and Yield Data

The weather data used for this study are from the U.S. National Climatic Data Center (NCDC) for a weather station located at the Fresno Air Terminal in Fresno, CA. Estimates of the temperature data process are obtained using 30 years of daily average temperatures (1970-2000). These data are used to first define the weather process itself (see Richards, Manfredo, and Sanders, 2004 and 2002) and then used in an equilibrium pricing model to derive the prices of both a call and put option on a weather index (see Richards, Manfredo, and Sanders, 2004). In defining the weather process, all daily observations in the data set are used. But the particular CDD index used in the pricing model describes only the May through July window. Specifically, the CDD index is defined as the cumulative sum of the extent to which daily average temperatures exceed a 65 degree Fahrenheit benchmark:

$$(1) \quad CDD = \sum_{t=1}^T \max(0, w_t - 65),$$

where w_t is the average daily temperature on day t measured in degrees Fahrenheit. Although this temperature series is not directly applicable to any particular grower, primarily because it is gathered at the Fresno Air Terminal, the proximity of many growers to Fresno and the relative topographical homogeneity of the surrounding area (the San Joaquin Valley) should minimize the basis risks that would likely exist for growers located farther away from the weather station.

We examine the hedging effectiveness of weather derivatives for three specialty crops grown in Central California: nectarines, raisin grapes, and almonds. Annual county-average (Fresno County) yields and prices for these crops were obtained from the California Department of Food and Agriculture as reported by the Fresno County Agricultural Commissioner's office for the period 1980-2001. This yield data is used in estimating a relationship between the above weather index and yields for these crops. Enterprise budget data for nectarines, raisin grapes, and almonds grown in Central California were obtained for the most recent year published (2001) by the University of California – Davis Cooperative Extension. These enterprise budgets are used in developing the Monte Carlo simulation models such that the distribution of net revenue of these enterprises can be examined both with and without the use of a weather derivative hedging strategy.

Yield Temperature Relationship

Hedging effectiveness depends on the correlation of the underlying state variable, the CDD index, with key measures of economic interest – revenue, cost, or profit. In the case of an energy producer, Hull argues that the ability to effectively hedge both price and volume risks can be determined by estimating a regression model of their profit on power prices and a CDD or HDD index. This very reasoning suggests that a regression model of yields on a CDD index calculated over a critical growing period can serve the same purpose. Therefore, we estimate simple temperature-yield models for nectarines, raisin grapes, and almonds in order to determine if weather derivatives are likely to form part of an effective hedging program. A regression model

for these crops is estimated that includes a CDD index calculated over the 92-day May to July period when yield potential is determined (w), the square of w and a linear time trend to explain yields (y) such that:

$$(2) \quad y_i = \beta_0 + \beta_1 w + \beta_2 w^2 + \beta_3 t + \varepsilon_i.$$

Estimating these yield models involves many practical considerations. First, because reliable yield data for Fresno County crops are available for only the last twenty years, yield models must be as parsimonious as possible to capture the underlying temperature-yield relationship. Second, for most agricultural products, yield is a function of both temperature and precipitation. However, preliminary estimates of (2) found no significant relationship between yields and precipitation. Conversations with local agronomists indicated that this is to be expected as most orchards and vineyards are irrigated and excess rainfall does not appear to hamper fruit development and maturation.² The results obtained by estimating these yield models provide an initial measure of the usefulness of weather derivatives for hedging yield risk. That is, if the estimated parameters are significantly different from zero, then weather derivatives are likely to be useful hedging tools. The yield-weather relationship defined in equation (2) is also used in the simulation model described below.

Risk Management Strategy Simulations and Measures of Hedging Effectiveness

Farm-level simulation models for nectarines, raisin grapes, and almonds are constructed based on the enterprise budget data published by the University of California – Davis Cooperative Extension Service. Because we restrict our attention to one class of financial instruments – CDD options – our primary interest lies in determining how weather-yield relationships determine the appropriate type of hedge transaction. Clearly, the analysis does not include a wider variety of risk management strategies such as enterprise diversification or geographic diversification that are potentially available to all growers. Nonetheless, the recommendations that emerge should provide the basis for future research on how weather derivatives can be made more effective in protecting U.S. specialty crop growers' cash flow. As a first step, however, it is necessary to define “effective” when evaluating these risk management strategies.

Hedging effectiveness is evaluated in the same way for each case-study/crop enterprise examined. Specifically, for each commodity and derivative strategy, we compare performance according to the ability to mitigate risk or, more formally, achieve an efficient risk-return tradeoff. In order to keep our data requirements to a level that each grower is likely to have available (on the assumption that growers are the ultimate audience), and to keep the results as general as possible, we consider only net income from a single commodity enterprise and do not attempt to model whole-farm profit. Our measures of risk – return efficiency consist of: (1) the Sharpe Ratio, (2) a 5% Value-at-Risk (VaR) estimate, and (3) a certainty equivalent measure. These alternative measures are necessary for several reasons.

² It is important to remember that the weather index variable, ω , is the CDD index over the 92-day May to July period. Excess precipitation which occurs during the blooming period for tree fruits and nuts may indeed ultimately affect yields. However, the blooming period for both nectarines and almonds does not occur during this time period.

First, growers tend to hold differing notions of risk. Whereas measures based on statistical notions of a distribution of returns hold meaning for some, others are more interested in the probability of a loss. Second, some measures are easier to calculate and explain to growers than others. Third, different risk management strategies have different information requirements. While growers that maintain capital reserves to tide them through market downturns would be more interested in a VaR measure, others that choose projects based on their risk-return profiles would rather use a mean-variance based measure. Finally, if there is strong agreement in the rankings implied by each of our measures, then this provides corroborating evidence in favor of the superiority of one risk management strategy over another (Gloy and Baker).

Value-at-Risk, or VaR, is now widely accepted as a measure of a firm's exposure to market-based risk from a variety of sources. Manfredo and Leuthold provide a review of VaR applications in agriculture and discuss some of the practical matters involved in calculating and using VaR as a risk measure. Essentially, VaR measures the maximum amount a firm can expect to lose at a certain confidence level for a certain period of time. Defining risk in this way provides a very intuitive notion of the monetary equivalent of the risk a grower faces as it immediately converts a notion of spread or dispersion into a dollar-equivalent figure. With such an intuitive notion of risk, the results of this study will be much easier to describe to growers who are used to either not considering quantitative measures of risk, using rules of thumb, or simply defining risk as the likelihood of bankruptcy. However, VaR considers only a "safety first" measure of risk and not the inherent tradeoff between risk and return typical of more formal criteria based on the assumption of expected utility maximization.

The Sharpe Ratio, defined as the coefficient of variation of a strategy's return relative to the risk-free asset, is one such criteria (Sharpe). Formally, if the difference between the return to strategy j and the risk-free asset is: $D_j = k_j - k_f$, and the mean (μ_j) and the standard deviation (σ_j) of D_j are calculated in the usual way, then the Sharpe Ratio is:

$$(3) \quad S_j = \mu_j / \sigma_j,$$

so that an investor with the ability to borrow and lend at the risk-free rate maximizes expected utility by choosing the strategy with the largest value of S_j . However, given that the Sharpe ratio suffers from the usual criticisms of all mean-variance measures (e.g., it assumes the distributions are entirely characterized by their first two moments) and that it does not consider different degrees of risk aversion, a more formal expected utility metric is also considered – a certainty equivalent (CE).

Intuitively, a strategy's CE value is the guaranteed amount of money a decision maker would take (or units of utility) to remain indifferent between this offer and participating in a venture with some probability of failure. Assuming a rational decision maker is risk averse, the utility of expected return is a concave function, or the utility of expected return is everywhere greater than the expected utility of returns to a risk venture. To reflect this concavity, we use a negative exponential utility function, where the degree of risk aversion (ρ) is set to reflect a range of attitudes toward risk. The particular form of the exponential utility function used is:

$$(4) \quad U(\pi_i) = k_0 - k_1 e^{-\rho \pi_i},$$

where π_i is the level of net income in state i , k_0 and k_1 are calibrated in order to force U to lie on $[0,1]$. By simulating the level of net income over 10,000 draws from the yield and price distributions described below, and calculating the mean of the resulting empirical distribution, we find the expected utility of profit as:

$$(5) \quad E[U(\pi_i)] = \sum_i \Pr_i (k_0 - k_1 e^{-\rho \pi_i}),$$

where \Pr_i is the probability of state i . With this expected utility function, it is a simple matter to invert (5) and calculate the CE value associated with any given strategy i :

$$(7) \quad CE_i = -\left(\frac{1}{\rho}\right) \ln\left(\frac{k_0 - EU}{k_1}\right).$$

By comparing CE values among strategies, we evaluate the relative effectiveness of using weather derivatives to manage output risk under a variety of risk aversion assumptions in a way that is entirely consistent with expected utility maximization. With this approach, we provide growers a menu of informed choices, which will allow them to choose an evaluation method that is consistent with the way their organization defines and manages risk.

All simulations are conducted using the @Risk modeling software. Although @Risk allows for the definition of virtually unlimited number of random variables, we consider only randomness in three variables: (1) CDD, (2) yield and (3) price. Yields are specified as stochastic functions of the cumulative CDD value according to the relationship estimated in the yield-temperature relationship above in equation (2). A standard normal error term is appended to this function in order to capture the inherent randomness of the regression function. A distribution for the CDD index value at harvest is found using the estimation tool in the BestFit software program. A variety of goodness-of-fit tests are used to determine the preferred distribution, with selection based on Chi-square and Komolgorov-Smirnov statistic.³ The preferred CDD distribution, which is the same for each crop as they are assumed to be located near the Fresno air terminal weather station, is determined to be inverse-Gauss with a mean of 1064.51 and a standard deviation of 154.47. Farm-level prices for each commodity are also assumed to be random variables. Therefore, correlation coefficients between annual yields and prices are estimated using Pearson's correlation estimate:

$$(8) \quad r_i = \frac{\sum_t (y_{it} - \bar{y}_{it})(p_{it} - \bar{p}_{it}) / (T - 1)}{(s_{yi})(s_{pi})},$$

where r_i is the estimated sample correlation coefficient, s_y is the sample standard deviation of yields and s_p is the sample standard deviation of prices. For each commodity, the price

³ In some cases, the Chi-square and Komolgorov-Smirnov statistics produced different results, so the selection of a preferred statistic is potentially important. Sensitivity analysis with this choice, however, revealed little qualitative difference in the conclusions reached using distributions ranked among the top three.

distribution is estimated using a historical price series from 1980 –2001 for Central California obtained from USDA-ERS *Fruit and Tree Nuts: Situation and Outlook Yearbook*. As with the CDD distribution, BestFit is again used to estimate and test for the preferred price distribution for each commodity. Table 2 provides a summary of each price distribution for the selected crops. Based on these distributions for prices and yields, a number of different risk management strategies are modeled for each commodity.

The risk management strategies used in the evaluation of hedging yield losses associated with adverse temperatures are: (1) buying a CDD call option, which rises in value if the number of cooling degree days rises above the strike level, (2) buying a CDD put, which rises in value if the cumulative CDD index falls below the strike level, and (3) a long straddle consisting of a long call and a long put, both with the same strike CDD value. Strike values for the CDD index are set at the average CDD value over the May – July time period over the 1970 – 2000 sample time frame. Option prices for the CDD call and put are equilibrium option prices estimated in Richards, Manfredo, and Sanders (2004) for at-the-money options (puts and calls). Hedge ratios (the number of contracts to purchase) are determined for each commodity by multiplying the marginal increase in yield for a one CDD change in temperature by an estimate of the net selling margin (see equation 2 and table 3). In this way, we approximate the incremental effect on profit produced by a one-unit change in the temperature index. For each commodity case study, the “best” strategy depends upon the shape of weather-yield function. However, simulation results are presented for all three strategies in order to provide some indication of the differences in performance that can arise based on the nature of the yield function. Each of these strategies represents a realistic description of the types of approaches growers may take in using weather derivatives to manage the risk of either volume or quality reduction associated with either excessive, or insufficient heat. Although the strategies are similar for each commodity, the performance of each differs significantly.

Results

Yield-Weather Relationship

Table 3 presents the estimates of the yield-weather function specified in equation (2). The coefficients of determination are reasonably high for so few observations and the estimated parameters adhere to prior expectations of sign and significance. These results lead to a tentative conclusion that a weather derivative based on this CDD index would be a valuable risk management tool for growers of these crops in Fresno County. However, the temperature-yield functions were found to be concave in nature suggesting that yields rise as temperature increases up to an optimal point, then yields are negatively affected as the season average temperature increases. This finding is consistent with prior expectations (Garcia, Offutt, and Pinar). Consequently, growers will want to buy a call option on the CDD index if they expect the cumulative CDD value to be below the optimal point, but buy a put if they expect to be above. Given that they likely do not have any *a priori* expectations as to the entire season’s average temperature, a potential strategy may be to buy a long straddle, ideally with the strike price equal to the optimal CDD level indicated by their respective yield function.

Clearly, the estimates of equation (2) are only indirect measures of hedging effectiveness. On the other hand, simulation models provide more direct evidence of the likely impact on not only the dispersion of net income, but also on the risk-return tradeoff to various weather derivative-based risk management strategies. Thus, if improvements in risk-return performance (Sharpe ratio), VaR, or expected utility (CE) are evident with use of weather derivatives, then this constitutes evidence, beyond that provided in table 3, that weather derivatives can be an effective risk management tool. We consider each of the described hedging strategies (long call, long put, and long straddle) for each of the three specialty crops (nectarines, raisin grapes, and almonds).

Nectarine Risk Model

Table 4 shows adjusted net income values based on the University of California – Davis crop budgets, as well as a comparison of each risk measure between the base (unhedged) scenario versus three risk management strategies incorporating weather derivatives. Based on the estimated weather-yield model for nectarines (table 3), the initial strategy involves buying a CDD put option at a strike value equal to the long-run season average CDD of 1047. This strategy is chosen as growers are most likely to be on the upward-sloping portion of the yield function in a typical year (figure 1). Consequently, yields are reduced if temperatures generate a CDD value below 1047, but are higher for CDD values above 1047 up to a maximum of 1245. Based on the summary statistics in table 4, it is clear that the put strategy is modestly effective in this case. Although mean net income is lower in the hedged scenario, as we would expect given the necessity to pay a significant option premium, the VaR is 3.61% higher and the certainty equivalent value is 32.99% higher compared to the unhedged scenario. Interpreting the difference between the CE value and the level of expected net income as a risk averse growers' willingness to pay for risk management services, we find that this premium is \$517.12, suggesting that the grower would be willing to pay about \$500 per acre for protection similar to that provided by the weather derivative. As well, the Sharpe ratio – a measure of the risk-return tradeoff implied by a given strategy – is improved by 3.94% under the put option hedge compared to the unhedged case. This result suggests that weather options may be effective in changing the shape of the net income distribution, but are an expensive means of doing so.

Next, we simulated an out-of-the-money call-option buy. Assuming a grower's average yield is below the peak of the yield curve, a long call option protects the grower from yield shortfalls only in the case of extremely hot weather. Perhaps surprisingly, the potential cost of hot weather occurring causes the expected call payoff to be higher than the payoff to the put so that expected net income actually rises 19.76% relative to the unhedged case. Among the other metrics, however, only the Sharpe ratio rises (due to the increase in net income) as both VaR and CE are significantly lower than in the unhedged case. An intermediate result is produced by buying both a put and a call at the 1047 strike price. The results in table 4 show that this "long straddle" improves net income considerably (19.21%), and has a more marked effect on the Sharpe Ratio (+14.63%) and CE (+37.03%) values. Consequently, if the goal is risk reduction, then either a put or straddle strategy is recommended for nectarines.

Raisin Grape Risk Model

The raisin grape simulation results (table 5) show a significantly different pattern of results to that of nectarines. For raisin grapes, a put option strategy is entirely dominated by not hedging at all. By buying put options on the CDD index, average net income is slightly lower (-0.12%), the standard deviation of net income is higher so the Sharpe ratio is significantly reduced (-2.00%), the VaR is below zero (-\$24.94) and the CE value is lower by -0.63%. Alternatively, a call option strategy produces marginal improvements in expected net income (+5.01%) and CE value (+5.00%), and also yields a higher Sharpe ratio (+2.79%) and improved VaR (+100.57%) measures. However, a long straddle completely dominates that of a put option strategy, and also provides considerable improvement over the long call. Most notably, using a straddle increases the Sharpe ratio by 8.32% and the VaR by 344.53%. While the improvement in net income is about the same as that provided by the call hedge (+4.89%), the CE measure does register a slight improvement. Combining each of these outcomes, it is clear that a more complicated hedge strategy than either a straight put or call produces significant gains in both risk and return. This result is likely due to the shape and structure of the weather-yield relationship. Whereas in the nectarine case the optimal CDD level is significantly above the long-run average, raisin grapes reach their maximum yield at a CDD value of 1066.5 – very close to long-term average for this time period (figure 2). Therefore, if both the put and the call are at the money, or nearly so, then growers receive a similar amount of protection from CDD variation in either direction.

Almond Risk Model

Given that optimal almond yield is attained at a CDD level of 1,157 degrees (figure 3), one would expect a put option strategy to be more effective than either a call or a straddle, given the high option premiums that must be paid. Like nectarines, almond prices and yields move opposite of each other, so weather derivatives must be particularly effective to show any incremental benefit. Moreover, almond prices and yields are more normally distributed, so there is a lower likelihood of an inherent bias toward needing either upside or downside revenue protection in any given year. Despite this fact, put options appear to be dominated by a simple call strategy and, to a greater extent, a more complex long straddle. Closer inspection of the yield function in figure 3 provides a reason for this seeming paradox. Whereas a high CDD value produces nectarine yields of nearly half their maximum, in a similar year almond yields fall to almost nothing. Given that almonds are particularly sensitive to excessive heat, it is understandable that protection against high temperatures will have more value than protection against low. In fact, the results in table 6 show that a CDD call option strategy can improve expected net income by 12.37% over an unhedged program, and improve the Sharpe ratio, and CE by 3.66% and 10.79% respectively. Despite this, the call option strategy does cause the VaR to decline relative to the unhedged strategy (-6.35%). Put options, however, reduce expected net income by -0.70%, the Sharpe ratio by -0.17% , VaR by -2.97% and CE value by -0.85%. Combining both upward and downward insurance through a long straddle appears to capture the best of both simple strategies as net income is expected to rise by 11.67%, the Sharpe ratio by 9.06%, VaR by 2.14% and CE by fully 14.02%. Interestingly, the high premiums associated with a long straddle do provide considerable benefits through the mean of net income, and this

strategy also appears to concentrate the distribution of net income somewhat as each of the risk-return and safety measures are vastly improved relative to the unhedged benchmark.

Implications for Hedging Strategies

Based on the intersection of risk management outcomes across this set of commodities, it is possible to come up with a set of reasonably general implications. First, it is clear that effectiveness of each strategy, and hence the choice of a preferred strategy, is critically dependent on agronomic factors such as the shape of the yield function and the distribution of yields. If prices and yields are negatively skewed, then there is a lower likelihood of adverse revenue outcomes, so option strategies designed to prevent against such events are less likely to be economically viable. Positively skewed revenues, on the other hand, suggest that option based strategies will be more effective in mitigating net income loss due to weather-borne yield loss.

More importantly, however, if the yield function is strongly concave in temperature, then there will be a greater likelihood that options strategies will be effective in limiting the damage from either excessively high or low temperatures. Clearly, the non-linear nature of the temperature-yield relationship suggests that relatively complex trading strategies are likely appropriate. Namely, these results suggest that a grower should implement a straddle strategy in which he or she simultaneously buys a put and a call with strike CDD values set at the optimal level indicated by the yield model. The yield function, however, embodies only physical relationships whereas our interests concern economic risks.

Addressing economic risks means that characteristics of the market into which each product is sold also impacts the desirability of weather derivatives as there may be a significant “natural hedge” in many products. Even if yields are strongly related to temperature, if prices rise by enough to compensate for any reduction in yield, then growers will be better off accommodating or accepting risk than paying option premiums to mitigate the revenue damage. Indeed, this is seen in the simulation results presented. The Pearson correlation coefficient estimates between price and yield for nectarines is -0.70 , -0.032 for raisin grapes, and -0.39 for almonds. Considering the results for nectarines in table 4, there is some improvement in the CE, Sharpe ratio, and the 5% VaR with all of the three hedging strategies. However, the strong negative correlation between price and yield (i.e., the natural hedge) makes any hedging strategy less desirable because of the added cost of risk management (e.g., the option premium). However, with raisin grapes where there is a negligible negative correlation between price and yield, we see much improvement in the various evaluation measures, especially with the call option and long straddle strategies. This is particularly true with respects to improvement in VaR. Therefore, it is critical that specialty crop growers understand their specific price-yield correlation when considering the use of weather derivatives in managing yield risks. Although most specialty crop production areas are relatively geographically concentrated, and therefore subject to highly correlated weather risks, many specialty crop markets are highly dependent on global supply and demand factors. For example, prices of apples, citrus, kiwi, avocados, and to a lesser extent grapes, are all largely determined in world markets, whereas prices for highly perishable and non-traded summer fruits such as peaches, plums, and nectarines depend upon domestic market conditions. Consequently, weather derivatives are more likely to be effective in

hedging net income risk for products that are subject to a high degree of import competition (and hence a greater likelihood for low correlations between yield and price).

Summary and Conclusions

Weather derivatives hold great promise of offering specialty crop growers a means of transferring weather-borne risk to financial markets without the support or backing of government. While previous studies have examined the underlying stochastic processes of weather (temperature) indices, and subsequently appropriate pricing models for weather options, this study specifically considers the hedging effectiveness of these instruments. In doing this, this study examines the relationship between yields on select specialty crops and an underlying temperature index for Fresno, California. As well, the study develops a series of stochastic simulation models based on representative financial information. The results show that simple long-put, long-call and long-straddle option strategies can indeed be effective in increasing expected net income, improving the risk-return tradeoff as measured by the Sharpe ratio, raising the Value-at-Risk of a representative grower, and increasing the certainty equivalent value of random net income relative to an unhedged benchmark. The effectiveness of a weather derivative based risk management program, however, depends critically upon the nature of the weather-yield relationship and the correlation between yields and prices. Weather derivatives are likely to be more effective the more concave is the yield function, and the less correlated are prices and yields. That is, if a strong natural hedge exists for a particular crop, then it is difficult to duplicate the extent of the hedge provided by “mother nature” and the “invisible hand” working in tandem.

To the extent that this research demonstrates that weather derivatives are potentially effective risk management tools for California fruit growers, they can expect to experience significant improvements in economic welfare, both directly if we assume they are inherently risk averse, and indirectly through a greater ability to plan, invest, and manage cash flow. Uncertainty causes inefficiency throughout the entire industry as growers are forced to adopt sub-optimal operating practices in order to manage the total business and financial risks they face. While crop rotations, growing multiple types and varieties of produce, and geographic diversification are likely to remain important means of managing risk, weather derivatives can allow growers more flexibility in designing their internal risk management programs and enable them to avoid practices that otherwise lead to inefficient operating practices. Perhaps most important, growers who use weather derivatives as part of a broader risk management strategy will be able to hold smaller capital reserves to cover potential losses, thus freeing up resources for more productive investments in irrigation technology, packing facilities, or new variety development programs.

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Table 1: Volatility of Revenue for Selected Crops (1980 – 2001)

	Average Revenue	Standard Deviation	Coefficient of Variation
Iowa Corn	\$287.96	\$54.55	0.19
Kansas Wheat	\$113.77	\$19.57	0.17
Illinois Soybeans	\$234.51	\$30.70	0.13
Idaho Potatoes	\$1,663.34	\$244.85	0.15
CA Nectarines	\$4,663.78	\$851.34	0.18
CA Raisin Grapes	\$2,281.20	\$701.75	0.31
CA Almonds	\$1,559.65	\$547.16	0.35

Source: USDA-NASS; USDA-ERS

Table 2. Price Distributions for Nectarines, Raisin Grapes, and Almonds

	Nectarines (\$/box)	Raisin Grapes (\$/ton)	Almonds (\$/pound)
Distribution^a	Weibull	Triangular	Lognormal
Minimum	\$2.85	\$119.80	\$0.49
Maximum	\$12.67	\$338.50	\$2.83
Mean	\$6.56	\$236.71	\$1.28
Std. Deviation	\$1.49	\$44.21	\$0.48

^a For nectarines, the preferred price distribution was Extreme Value. However, this distribution admits the possibility of negative prices, which clearly cannot occur. Consequently, the chosen distribution reflects an implicit choice constraint that all realizations are positive.

Table 3. Empirical Hedge Ratios: Weather (CDD) Relationship to Yield

Variable ^a	<u>Nectarines</u>		<u>Raisin Grapes</u>		<u>Almonds</u>	
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Const.	-5.025*	-2.01	16.74	-1.38	-1870.23	-0.66
t	-0.044	-1.55	0.115	2.165	N.A.	N.A.
w ₁	27.471*	2.956	48.422	2.115	5.557	1.042
w ₁ ²	-11.028*	-2.63	-22.707	-2.13	-0.002	-1.97
R ²	0.618		0.641		0.291	

^a In the above table, t is a linear time-trend variable and w_1 is the value of the CDD index at the end of the sample period. Yield (y) is defined as tons per acre for raisin grapes, boxes per acre for nectarines, and pounds per acre for almonds.

Table 4. Risk Management Simulation Results: California Nectarines (2001)

	Unhedged	Call Hedge	% Δ	Put Hedge	% Δ	Straddle ^c	% Δ
CDD	1066.01	1066.01		1066.01		1066.01	
Price (\$ / box)	\$6.58	\$6.58		\$6.58		\$6.58	
Yield (boxes / acre) ^d	916.65	916.65		916.65		916.65	
Derivative Strategies: ^{a,b}							
Put Premium				\$231.98		\$231.98	
Call Premium		\$229.33				\$229.33	
Put Payoff				\$229.66		\$229.66	
Call Payoff		\$312.10				\$312.10	
Hedge Ratio		4.34		4.34		4.34	
Net Income	\$418.83	\$501.60	19.76%	\$416.51	-0.55%	\$499.29	19.21%
Risk Measures:							
Sharpe Ratio	0.38	0.40	5.98%	0.39	3.94%	0.43	14.63%
5% VaR	-\$1,362.11	-\$1,484.40	-8.98%	\$1,312.91	3.61%	-\$1,328.81	2.67%
Certainty Equivalent	-\$150.14	-\$207.13	-37.95%	-\$100.61	32.99%	-\$94.55	37.03%

^a The option premium is calculated using the equilibrium model explained in Richards, Manfredo, and Sanders (2004). The value for the call option (1 contract) is \$52.89, and 53.50 for a put option. The strike CDD level is 1,047.

^b The hedge ratio is determined by calculating the marginal profit per CDD: $h = (\partial y / \partial w) * (p - c)$, where h is the hedge ratio, p is the average price per box, c is the average cost per box, y is yield and w is the CDD value (see table 3). The value of h implies that we purchase $1/h$ weather options to implement the hedge.

^c The straddle strategy involves the simultaneous purchase of both a put and a call at the same strike CDD level: 1,047. The optimal (yield maximizing) CDD level is 1,245.21.

^d The estimated Pearson correlation coefficient between price and yield is -0.70 .

Table 5. Risk Management Simulation Results: California Raisin Grapes (2001)

	Unhedged Call Hedge % Δ			Put Hedge % Δ		Straddle ^c % Δ	
CDD	1065.73	1065.73		1065.73		1065.73	
Price (\$ / ton)	\$231.34	\$231.34		\$231.34		\$231.34	
Yield (tons / acre) ^d	10.94	10.94		10.94		10.94	
Derivative Strategies: ^{a,b}							
Put Premium				\$147.08		\$147.08	
Call Premium		\$148.78				\$148.78	
Put Payoff				\$145.91		\$145.91	
Call Payoff		\$197.99				\$197.99	
Hedge Ratio		2.78		2.78		2.78	
Net Income	\$982.36	\$1,031.57	5.01%	\$981.19	-0.12%	\$1,030.40	4.89%
Risk Measures:							
Sharpe Ratio	1.55	1.59	2.79%	1.52	-2.00%	1.68	8.32%
5% VaR	\$17.72	\$35.53	100.57%	-\$24.94	-240.81%	\$78.75	344.53%
Certainty Equivalent	\$885.50	\$929.75	5.00%	\$879.90	-0.63%	\$939.05	6.05%

^aThe option premium is calculated using the equilibrium model explained in Richards, Manfredo, and Sanders (2004). The value for the call option (1 contract) is \$52.89, and 53.50 for a put option. The strike CDD level is 1,047.

^bThe hedge ratio is determined by calculating the marginal profit per CDD: $h = (\partial y / \partial w) * (p - c)$, where h is the hedge ratio, p is the average price per box, c is the average cost per box, y is yield and w is the CDD value (see table 3). The value of h implies that we purchase $1/h$ weather options to implement the hedge.

^cThe straddle strategy involves the simultaneous purchase of both a put and a call at the same strike CDD level: 1,047. The optimal (yield maximizing) CDD level is 1,066.50.

^dThe estimated Pearson correlation coefficient between price and yield is -0.032.

Table 6. Risk Management Simulation Results: California Almonds (2001)

	Unhedged	Call Hedge	% Δ	Put Hedge	% Δ	Straddle ^c	% Δ
CDD	1066.11	1066.11		1066.11		1066.11	
Price (\$ / box)	\$1.28	\$1.28		\$1.28		\$1.28	
Yield (boxes / acre) ^d	1281.99	1281.99		1281.99		1281.99	
Derivative Strategies: ^{a,b}							
Put Premium				\$132.25		\$132.25	
Call Premium		\$130.74				\$130.74	
Put Payoff				\$129.62		\$129.62	
Call Payoff		\$176.86				\$176.86	
Hedge Ratio		2.47		2.47		2.47	
Net Income	\$372.68	\$418.80	12.37%	\$370.06	-0.70%	\$416.17	11.67%
Risk Measures:							
Sharpe Ratio	0.59	0.61	3.66%	0.59	-0.17%	0.64	9.06%
5% VaR	-\$585.50	-\$622.66	-6.35%	-\$602.87	-2.97%	-\$572.96	2.14%
Certainty Equivalent	\$274.46	\$304.07	10.79%	\$272.13	-0.85%	\$312.95	14.02%

^a The option premium is calculated using the equilibrium model explained in Richards, Manfredo, and Sanders (2004). The value for the call option (1 contract) is \$52.89, and 53.50 for a put option. The strike CDD level is 1,047.

^b The hedge ratio is determined by calculating the marginal profit per CDD: $h = (\partial y / \partial w) * (p - c)$, where h is the hedge ratio, p is the average price per box, c is the average cost per box, y is yield and w is the CDD value (see table 3). The value of h implies that we purchase $1/h$ weather options to implement the hedge.

^c The straddle strategy involves the simultaneous purchase of both a put and a call at the same strike CDD level: 1,047. The optimal (yield maximizing) CDD level is 1,157.64.

^d The estimated Pearson correlation coefficient between price and yield is -0.39.

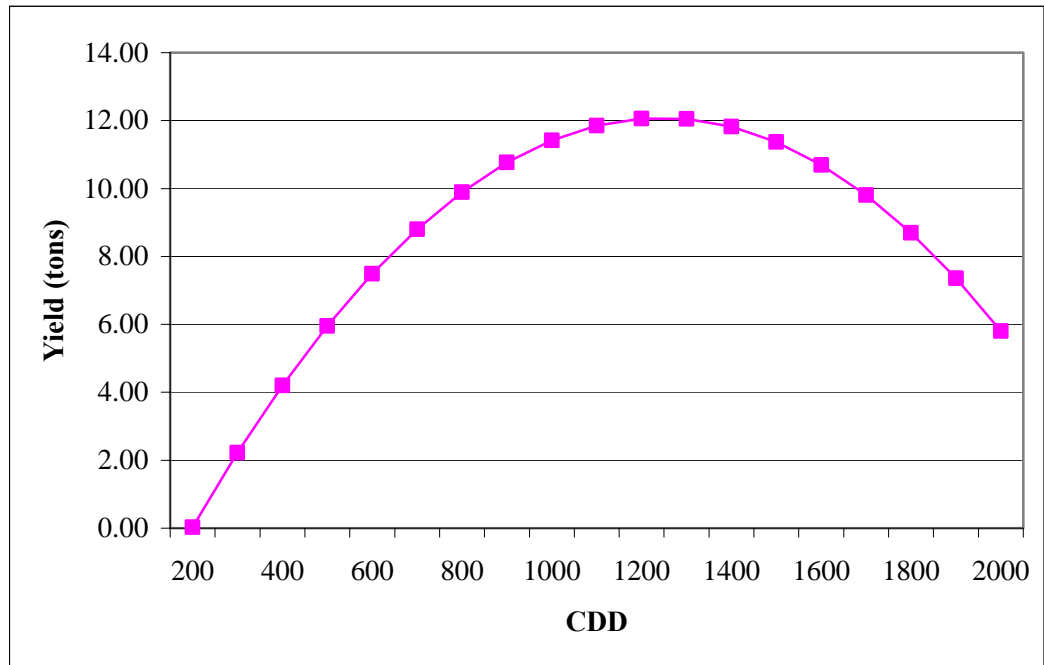


Figure 1. Nectarine Yield-CDD Function

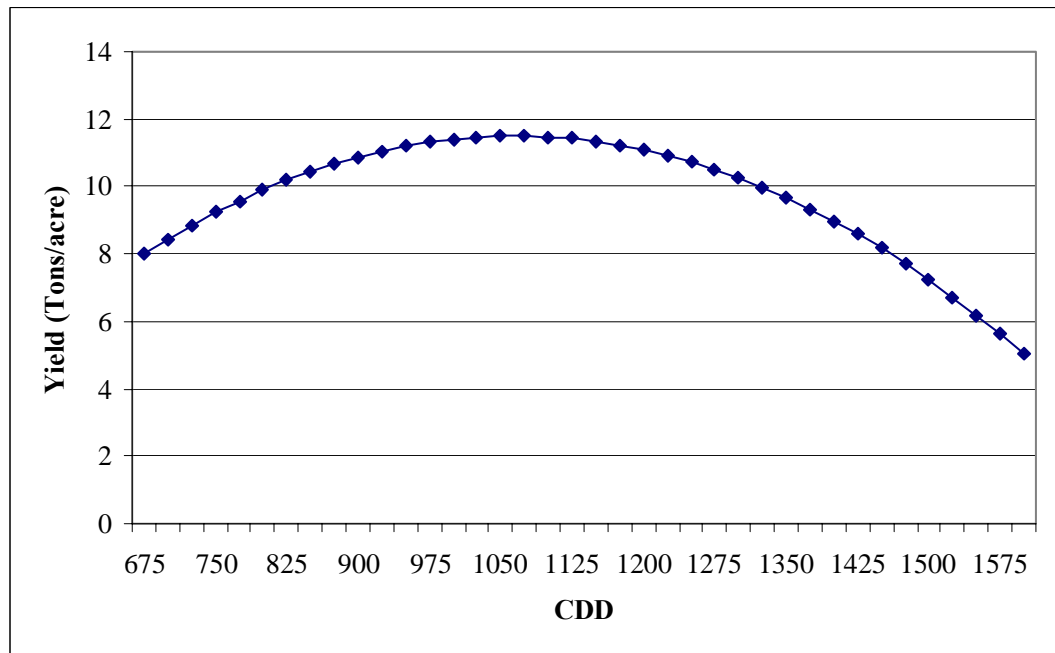


Figure 2. Raisin Grape Yield – CDD Function

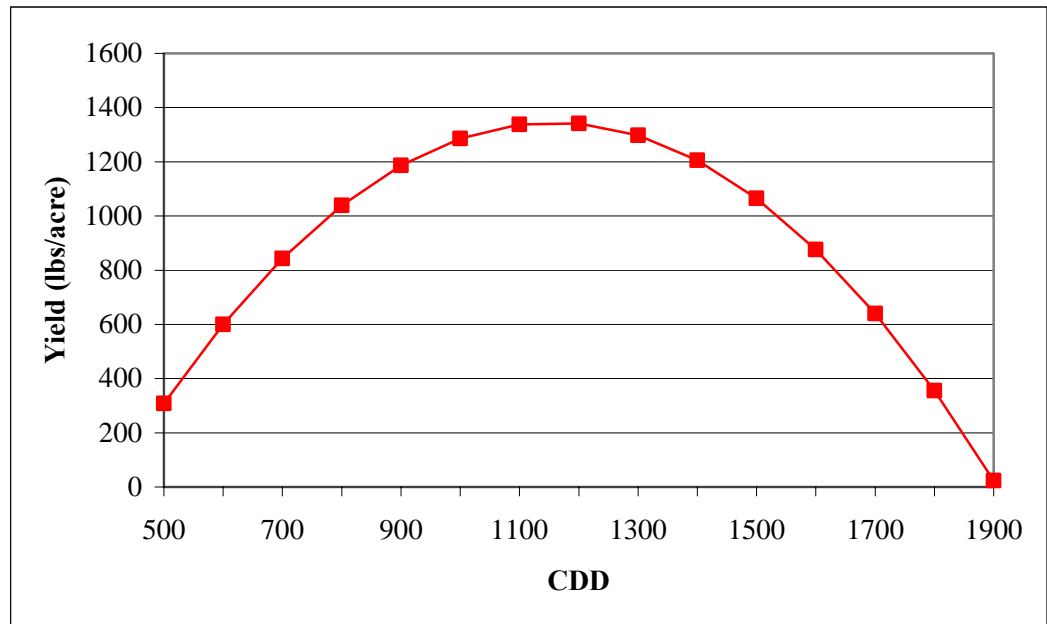


Figure 3. Almond Yield – CDD Function