Weather Derivatives: *An Attractive Additional Asset Class*

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While still a relatively young market, the popularity of weather derivatives has experienced a rapid escalation in recent years. The weather derivatives market was introduced during the mid 1990s in the midst of the deregulation of the energy industry in the United States. Market surveys report an increase of market turnover from 695 trades for US$1.8 billion notional value in 1999 to 4,517 trades for US$3.5 billion in 2003.[1] The growth of the weather derivatives market was enhanced by the presence of an organized market for weather derivatives at the Chicago Mercantile Exchange (CME), which started to trade temperature weather derivatives contracts of 10 U.S. cities in 1979. This has since expanded to 15 U.S. cities and 5 European cities with turnover of 7,239 trades for US$0.7 billion notional value in 2003.

Extant literature attributes the rapid growth in the weather derivatives market to the deregulation of the energy and electricity markets.[2] While the importance of weather risk on the revenue generated by electricity and energy companies is apparent, it is also important to recognize that a large number of other industries are exposed to weather risks. Indeed, Challis [1999] and Hanley [1999] estimate that around US$1 trillion of the US$7 trillion U.S economy is sensitive to weather risks. Globally, Auer [2003] points out that "around four-fifths of all economic activity world-wide is directly or indirectly affected by the weather" (p. 1). However, despite the broad range of industries affected by weather risks, a significant portion of weather derivatives are traded against temperature-related variables. Moreno [2000] claims that temperature-based derivative contracts are the most widely traded weather derivatives. Indeed, Cao, Li, and Wei [2003] report that "more than 80 percent of all the weather derivatives contracts are traded against temperature variables ... accounting for more than 90 percent of the total value in any given year" (p. 2).

The high concentration of temperature-based contracts is somewhat perplexing given the significant effect imposed by other non-temperature weather variables on the volatility of companies' revenues within a wide range of industries. Exhibit 1 outlines the impact of weather risks on various industries. This study examines the role of non-standardized contracts in serving as a hedge instrument for company revenues. Non-standardized contracts are defined as weather derivatives contracts that are constructed to fit the need of a particular industry or corporate clients and are traded on the Over-The-Counter (OTC) market rather than an organized exchange such as the CME. Additionally, the potential of weather derivatives as an alternative asset class in portfolio management is analyzed. Extending prior studies, the weather derivatives contracts examined here are not confined to temperature-based contracts.

EXHIBIT 1
Sectors Affected by Weather Risks

Element	Beneficial to	Detrimental to
Frost	Energy, retail	Construction, production, crops
Heat	Utilities, beverages, water	Insurance, crops, energy
Sun	Leisure, tourism, retail	Cinemas, video rentals
Rainfall	Crops, hydro plants	Food and beverages
Downpour	Retail	Crops, insurance, dredging
Wind	Windparks	Insurance, airlines
Snow	Ski resorts, snowmobiles	Airports, transport
Waves	Wave power generation	Offshore construction, transport
Fog	Airports	Airlines, transport, insurance

Companies from a wide range of industries are able to hedge more accurately against the volatility of their revenues, costs, or margins by resorting to non-standardized weather derivatives contracts. For example, the impact of weather risks on agricultural companies varies throughout a calendar year, with a precipitation-based weather derivatives providing a hedge against volatility of revenues caused by either too much or too little rainfall. Additionally, the conventional analyses of the ability of weather derivatives contracts to serve as a risk transfer mechanism have largely been conducted on single-variable weather derivatives contracts, such as temperature-based contracts. However, companies' revenues are often exposed to more than one weather risk factor. This article proposes the use of a basket of weather derivatives contracts to more accurately hedge against a number of weather variables that directly affect the volatility of revenues.

The role of weather derivatives in portfolio management is also examined in this study. Extending the work of Cao, Li, and Wei [2003] who analyze the role of the temperature-based contract, this article investigates the role of both temperature- and non-temperature-based contracts on portfolio management. The results documented in this study demonstrate adding weather derivatives into conventional portfolio produces significant diversification benefits and enhances the efficient frontier line of the conventional portfolio.[3] These benefits allow the market maker to diversify the systematic risk involved in writing non-standardized contracts by repackaging these contracts and including these contracts as part of existing portfolios, in order to enhance diversification and increase returns.

A HEDGING INSTRUMENT FOR THE AUSTRALIAN AGRICULTURAL CHEMICAL INDUSTRY

Prior to the introduction of weather derivatives, agricultural companies were only able to hedge against price risk caused by the volatility of their revenues by using commodity futures contracts.[4] The recent introduction of weather derivatives provides these companies with a contract to hedge the risks associated with variable production volume due to the level of annual rainfall. While temperature has been a significant factor affecting the energy industry, agricultural companies may want to hedge against other weather variables, such as rainfall.[5]

The effects of rainfall on agricultural industries have long been documented. Orlove, Chiang, and Cane [2000] state that following an abnormally low rainfall period, farmers adjust and moderate their planting pattern. Further, the 2002 report by the Wisconsin Agricultural Statistics Service reports that corn and soybean farmers reduce their planting volume if they anticipate a lower than normal rainfall. On the other hand, extremely high rainfall translates to higher probability that the crops will incur disease.[6] Consequently, the demand for crop-protection chemicals is expected to be affected by rainfall conditions that influence both the volume of planting and the need for pre-harvest treatments.

This section discusses the fundamentals underlying the construction of non-standardized weather derivatives based on rainfall. Such a weather derivatives contract would allow agricultural crop-protection chemical producers to hedge against rainfall-driven sales volatility. As an example, we take a precipitation-based weather deriv-

EXHIBIT 2
Adjusted R-Squared and Pearson Correlation

	Sales vs. Annual Rainfall		Log(Sales) vs. Log(Ann. Rainfall)	
	Pearson Corr.	**Adj R-Sq.**	**Pearson Corr.**	**Adj R-Sq.**
Central West Region	0.32°	8.93	0.33	8.02°

atives contract written for an agricultural chemical company to hedge their rainfall risk in the Central West region of New South Wales, Australia. The dataset of dollar value spent on crop protection chemical per non-irrigated hectare (*Sales*) is obtained from ABARE and covers the period between June30, 1990, and June 30, 2002.[7]

Exhibit 2 reports the Pearson correlation between the actual and the logged value of *Sales* and the values of *annual rainfall*. The double-log specification is selected as it can be interpreted as the percentage change in *Sales* for every 1% increase or decrease in the annualized rainfall. The results documented in Exhibit 2 demonstrate that the two variables are, at best, weakly correlated. This finding is further supported by the small adjusted R-squared value from the regression of *Sales* (log *Sales*) on *annual rainfall* (log of *annual rainfall*) as reported in Exhibit 2. The adjusted R-squared is a measure of explanatory power and quantifies the ability of the annual rainfall variable to explain variation in *Sales*. The results show that *annual rainfall* explains only around 9% of the variation in *Sales*. The weak correlation and low adjusted R-squared documented indicate that crop protection chemical producers would not be able to efficiently hedge their volume risk using swap contracts that are benchmarked against an annual rainfall variable.

The lack of explanatory power attributed to annual rainfall in explaining variations in *Sales* is largely due to the variable impact of rainfall on the sales of crop-protection chemicals throughout a calendar year. The effect of rainfall varies throughout the different stages of the cropping cycle. In order to account for such variations, it is important to weight the impact of rainfall on *Sales* corresponding to different stages of crop maturation. The monthly weightings are the regression coefficients in the following equations:

$$\ln(Sales_t) = \alpha + \sum_{i=1}^{18} \beta_i \ln R_{i,t} + \varepsilon_t \qquad (1)$$

where the independent variable, annual accumulated rainfall, has been decomposed into monthly variables. R_i denotes the monthly accumulated rainfall for month i. The estimation covers the period between 1990 and 1997. The years from 1998 to 2001 inclusive are held out from the estimation period and are used to generate forecasts to asses the robustness of the results over an out-of-sample period. The independent variables represent the combination of months that best explain the variations in the log value of *Sales*. The combination with the minimum Akaike Information Criterion (AIC) is selected. This information criterion is given by the following equation:

$$AIC = (n)\ ln\left(\frac{SSE}{n}\right) + 2p \qquad (2)$$

where n is the number of observations, SSE denotes the error sum of squares, and p represents the number of parameters in the model. As the number of parameters in the regression model increases, there will be a reduction of the error sum of squares. Also, as a consequence of an increase in the number of parameters, further error is introduced into the model via the estimation of the additional parameters. The AIC penalizes the introduction of extra parameters by balancing the reduction of the SSE with the increased error from the estimation process. The β_i coefficients of the monthly accumulated rainfall variables from the selected model represent the weights allocated for the various months. Exhibit 3 reports the weights allocated to each of the selected months for our New South Wales Central West example.[8]

Controlling for variations in the impact of rainfall on the different stages of crop maturation significantly increases the ability of the derivative contract to act as a hedge against the volatility in the demand for crop-protection chemicals. The results reported in Exhibit 4 demonstrate that, during the estimation periods, the settlement levels of the rainfall contracts exhibit a high correlation against the variations in sales volume of the crop-protection chemicals. The Pearson correlation

EXHIBIT 3
Weights Allocated to the Selected Months

January	April	July	August	October	February	May
0.08	–0.04	0.13	0.06	0.15	0.09	0.17

EXHIBIT 4
In-Sample and Out-of-Sample Tests

	Pearson Correlation	Adjusted R-Squared
In-Sample	0.94	84.81%
Out-of-Sample	0.97	55.38%

increases from 0.33 to 0.94, whereas the adjusted R-squared increases from 8.02% to 84.81%.

In order to ensure the robustness of the results, the correlation between the settlement values of the rainfall contracts and the sales volume during the out-of-sample period (1998, 1999, 2000, and 2001) is examined. The results for the out-of-sample test are found to be consistent. The results reported in Exhibit 4 document a Pearson correlation of 0.97 and an adjusted R-squared of 55.38%[9]

A HEDGING INSTRUMENT FOR THE AUSTRALIAN WINE INDUSTRY

In the last five years, the Australian wine industry has experienced very rapid growth. Wine production has increased by 52% between 1998 and 2003, with export volumes increasing by 170% to AUD$2.4 billion in value.[10] The rapid increase in Australian wine production indicates a growing demand for financial instruments that allow winegrape producers to hedge against weather risks. Jackson and Spurling [1992] identify weather risks as one of the most significant factors that affect the quality and the quantity of grape production. The significance of weather risks is further pronounced by the announcement in the 1998 Australian Wine and Grape Industry report that they account for 42% of the loss in Australian Chardonnay grape production. Responding to the need for risk management, many studies have proposed the introduction of financial derivatives that allow participants in the wine industry to hedge some of the risks involved.

Taylor [2000] proposes the use of wine forward contracts to hedge against price volatility. Winkler, Kliewer, and Lider [1974] propose the use of temperature derivatives that are benchmarked against the *Degree Day Index*. Consistent with the *Heating Degree Day* (HDD) and the *Cooling Degree Day* (CDD), the Degree Day Index captures a one-sided deviation from a threshold level. While extensive literature has, in general, agreed on the methodology, there are disparities on what the appropriate level of the threshold should be. The level of the threshold determines the level of acceptable temperature. Gladstone [1965] proposes the use of 19°C as the upper limit while Boehm [1970] finds that the use of 8°C provides a better base temperature between the period of budburst and flowering. Aney [1974] proposes an alternative index which utilizes Thornthwaite's potential evapotranspiration index as an arbiter of climatic suitability for grape growing. This method was later challenged by Jackson and Spurling [1992]. Other indices include the Mean Average Range (Dry and Smart [1984]) and the Sunshine Index (Becker [1985]).

Interestingly, the existing wine indices that measure the weather desirability are all benchmarked against a single weather variable. This is highly perplexing given that the wine industry is exposed to a number of risks from weather. Gladstone [1992] argues that temperature, sunshine, humidity, and rainfall are the dominant weather risks that confront the wine industry. Happ [1999] and Smart [2001] suggest that temperature above 30°C and below 20°C could have an adverse effect on winegrape production. McCarthy and Coombe [1985] and Bravdo and Hepner [1987] point out the danger of water stress on the quality of winegrapes. Jackson and Spurling [1992] state that excessive rainfall increases the likelihood of disease.

Moreover, Coombe [1987] warns against the generalization of the relationship between climate and wine quality. Hedberg [2000] asserts that, while grapevines can survive at very low temperatures, the new spring growth

EXHIBIT 5
Weighted Coefficients

	ATMin	ATMax	ATVol	ExRain	ShrRain
January	-	-	-	-	-
February	-	0.42	-	0.68	-
March	-	-	-	0.16	-
April	-	-	-	-	-
May	-	-	-	-	-
June	0.21	-	0.36	-	0.24
July	-	-	0.31	-	-
August	0.18	0.26	-	-	0.12
September	0.24	-	0.33	-	-
October	-	-	-	-	-
November	0.37	-	-	0.16	0.64
December	-	0.32	-	-	-

EXHIBIT 6
Contribution Ratios of the Underlying Weather Variables

		AnnATMin	AnnATMax	AnnATVol	AnnExRain	AnnShrRain
	Mean	28.98%	27.74%	36.27%	5.55%	1.46%
Barossa	**Median**	29.03%	26.77%	33.95%	0.00%	0.00%
	Std Dev	8.95%	9.46%	11.66%	11.11%	3.24%

is very sensitive to low temperatures. Hofacker, Alleweldt, and Khader [1976] assert that the growth of berries exhibits greater dependence on precipitation than on the temperature during the shoot, interflorescence development, and flowering stages.

Consequently, the production risks would be better represented by a basket of weather derivative contracts that cover multiple weather variables. Additionally, the proposed contracts place different weight on the impact of weather risks on winegrape production throughout different months in the calendar year. The sample utilized in this study represents grape yield and weather data from the Barossa region of South Australia. The grape yield data differentiates between the yield contributing to either white or red wine, and the sample covers the period between 1981 and 2002. The grape yield sample is obtained through the Australian Bureau of Statistics (ABS). The weather data is obtained from the Australian Bureau of Meteorology (BOM) and covers the period between 1980 and 2002.

In order to decide on the composition of the basket of contracts that efficiently serve as a hedging mechanism for winegrape production, a number of factors need to be identified. First, the weather risks that confront winegrape production need to be identified based on conjectures and hypotheses set out by prior literature. Higher than expected temperature (*ATMax*), lower than expected temperature (*ATMin*), excessive temperature volatility (*ATVol*), excessive rainfall (*ExRain*), and shortage of rainfall (*ShrRain*) are utilized as the weather variables that serve as the benchmark for the winegrape hedging contracts. The variables are constructed in a manner similar to the Heating Degree Day (HDD) and Cooling Degree Day (CDD) contracts traded on the CME.[11]

Second, in order to identify the months that significantly effect winegrape production, the grape yield variable is regressed against each of the weather variables separately. All possible monthly combinations are examined for each weather variable with combinations that exhibit the lowest AIC selected as the base model. The coefficients of the selected models are weighted so that the sum of the coefficients is equal to one. The standardized weighted values of the coefficients represent the weight imposed on each month and represent the quan-

EXHIBIT 7
In-Sample and Out-of-Sample Tests

	Adjusted R-Squared	Pearson Correlation
In-Sample	0.36	-0.61
Out-of-Sample	-	-0.90

EXHIBIT 8
Weather Portfolio

Location	Position	Index
Melbourne	Short Put	Temperature & Sunshine
Melbourne	Short Call	CDD (18 C)
Paris	Short Put	HDD (18 C)
Osaka	Short Collar	True Avg Temp
Fukushima	Short Call	Snow Depth
Sydney	Long Swap	HDD (18 C)
Townsville Aero	Short Call	Precipitation
Sacramento Airport	Short Call	Cold Days
Kassel, Nuerburg, Hannover	Long Swap	Freezing Days
Frankfurt	Short Swap	Average Temp
Schiphol	Short Call	Freezing Days
Memphis, Nashville, Chattanooga, Knoxville	Long Swap	HDD (65 F)
Toronto	Short Put	HDD (18 C)
Memphis, Nashville, Chattanooga, Knoxville	Long Swap	CDD (65 F)
Denmark	Long Swap	Wind Speed
US	Long Swap	Wind Speed
Spanish Hydro Index	Short Put	Res. Level
Australian Stream Flow	Short Put	Stream Flow
Tokyo	Short Collar	True Avg Temp
WPI Spain	Short Put	Wind Index
Essen	Short Put	HDD (18 C)
Essen	Short Put	2 Coldest Days
De Bilt	Short Call	Precipitation > 19mm
WPI Australia	Long Swap	WPI
Kairi Australia Rain	Short Call	Precipitation
Chicago	Short Put	HDD (65 F)

tified impact of the weather variable on the winegrape production for that month. They are utilized to compute a contribution ratio for the annualized value of the weather variables. The monthly weightings of the weather variables are reported in Exhibit 5, while the contribution ratios of the annualized weather variables are reported in Exhibit 6.

Exhibit 7 reports a Pearson correlation of −0.61 for the in-sample period (1981 to 1999) between the settlement of the basket of weather derivatives and the grape yield. The negative correlation is expected as the weather derivatives are correlated with the low levels of grape yield. Variation in the settlement of the weather derivatives, however, explains only 36.49% of the variation in

EXHIBIT 9

Performance of Weather Derivatives as an Additional Asset Class

Assets	Expected Return (annualized)	Standard Deviation of Return (annualized)	Correlation of Return			
			Equities	Bonds	Real Estate	Weather
1 Equities	10%	16%	100%	21%	55%	0%
2 Bonds	5%	6%	21%	100%	25%	0%
3 Real Estate	7%	12%	55%	25%	100%	0%
4 Weather	18%	26%	0%	0%	0%	100%

EXHIBIT 10

Performance of the Optimal Portfolios

Portfolio	Initial Investment Spectrum	Including Weather
Equities	32%	19%
Bonds	57%	52%
Real Estate	11%	9%
Weather	0%	20%
Expected Return	6.82%	8.75%
Standard Deviation	7.52%	7.54%
Sharpe Ratio	0.52	0.78

the grape yield. Again, this modest adjusted R-squared is to be expected as weather derivatives are used to hedge against the low grape yield and therefore capture only a one-sided variation in the grape yield. In order to ensure the robustness of the results over different time periods, settlement values are estimated for the out-of sample period (2000 to 2002). Exhibit 7 reports the in-sample and out-of-sample Pearson correlations, as well as the in-sample adjusted R-squared. The results for the out-of-sample analysis are consistent with those of the in-sample.[12]

THE ROLE OF WEATHER DERIVATIVES IN PORTFOLIO MANAGEMENT

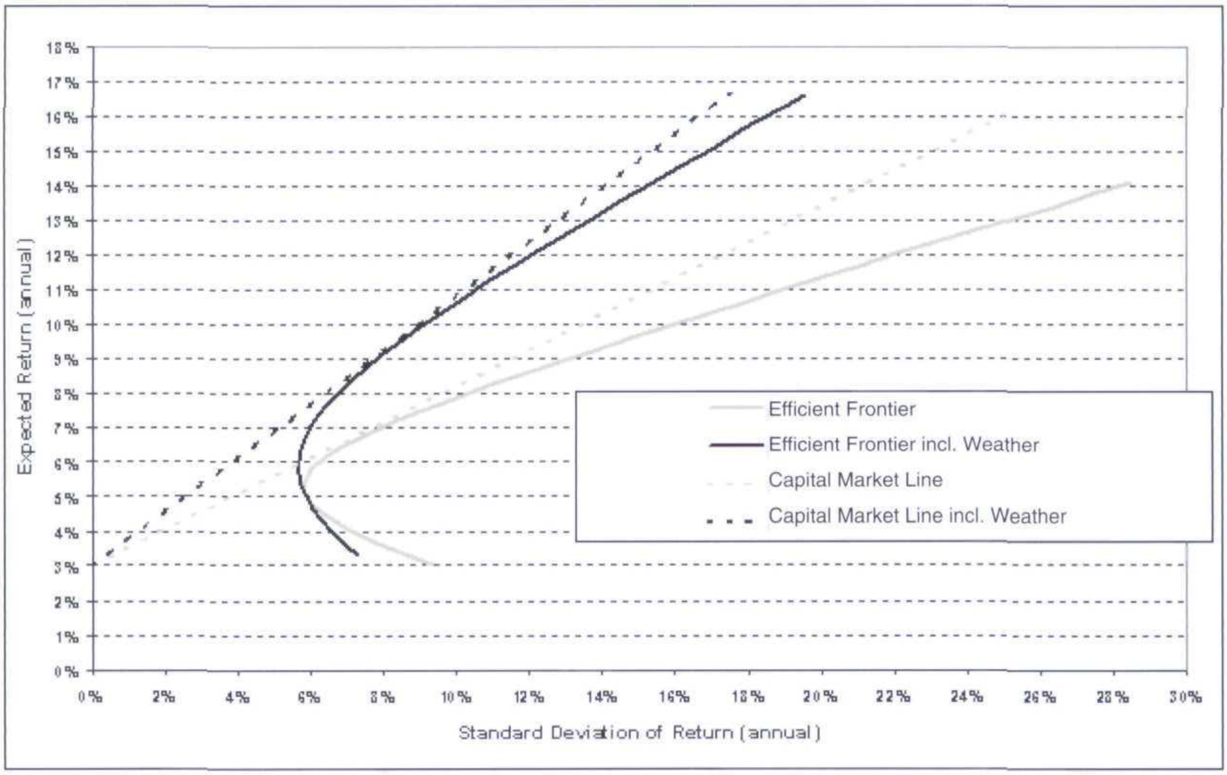
The negative correlation between various sectors adversely affected by weather exposure, in addition to low correlation between weather variables, suggests that the incorporation of weather derivatives into conventional portfolios should provide significant diversification benefits. This study examines the impact of including a number of different weather derivatives contracts into a conventional portfolio. Exhibit 8 outlines the 26 weather derivatives contracts which represent the constituent of the potential weather portfolio.

Exhibit 9 reports the expected returns of weather derivatives contracts and the conventional asset classes. The expected returns and standard deviations of the three asset classes equity, bonds, and real estate are partly based on historical observations of indices for these asset classes. For equity, the MSCI World Equity Index was used: for bonds, the Salomon Brothers Investment Grade Bond Index; and for real estate, the EPRA Index from the European Public Real Estate Association (all monthly observations). The assumed returns of the asset classes are based partly on five-year historical observations and partly on current market expectations. Weather derivatives contracts are assumed to exhibit minimal correlation with other asset classes.

Exhibit 10 compares the performance of the optimal portfolio in the absence and the presence of weather deriv-

EXHIBIT 11

Impact of the Weather as an Additional Asset Class on Efficient Frontier and Capital Market Line



atives. The optimal portfolio is computed in accordance with modern portfolio theory (see Markowitz [1952]). The results reported in Exhibit 10 demonstrate that, by including weather derivatives, the expected return of the optimal portfolio is increased from 6.82% to 8.75%. Additionally, the Sharpe ratio is increased from 0.52 to 0.78.[13] This ratio is a performance measure for portfolios and is essentially a reward-to-variability ratio.[14] From Exhibit 10, we observe that including weather derivatives increases the standard deviation of the optimal portfolio only marginally, from 7.52% to 7.54%. Exhibit 11 depicts the impact of weather as an additional asset on efficient frontier and capital market line of the optimal portfolios.

CONCLUSIONS

The results documented in this article suggest that non-standardized contracts serve as a more efficient risk transfer mechanism than do standardized contracts. Relaxing the assumption that weather risks are constant throughout the calendar year significantly increases the ability of weather derivatives to serve as a hedging instrument against the volatility in demand for crop-protection chemicals. Also, by recognizing that companies are often exposed to more than one weather risk simultaneously, we examine an example from the wine industry that highlights the use of multi-variable weather derivatives contracts to hedge against variable production that is affected by weather. Additionally, this article demonstrates that including weather derivatives in a conventional portfolio enhances the performance of the portfolio while maintaining a low standard deviation.

While it appears that non-standardized weather derivatives contracts allow for better risk transfer as compared to standardized contracts, critics express concern over the lack of liquidity in markets that trade the majority of these non-standardized contracts. Evidently, this lack of liquidity contributes to the difficulty in finding counterparties to these contracts. However, our results suggest a solution to this problem. That solution would involve institutional investors writing non-standardized contracts for their corporate clients. By recognizing that incorporating weather derivatives will enhance the performance of conventional portfolios, institutions could repackage these non-standardized contracts and offer them as an additional asset class to be included in a conventional portfolio.

ENDNOTES

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[1]2003 Weather Risk Management Survey, Weather Risk Management Association (WRMA) and Pricewaterhouse Coopers, May 2003.

[2]These studies include Challis [1999], Hanley [1999], Alaton, Djehiche, and Stillberger [2002], and Cao and Wei [2003].

[3]All of our conclusions are based on historical data. Readers should recognize that the results might change for future periods and might not necessarily hold for other regions that are not examined in this article.

[4]For studies on commodity futures, see Ho [1984] and Luo [1998].

[5]Li and Sailor [1995] suggest that temperature is the most significant weather variable explaining U.S electricity and gas demand.

[6]Ohio State University Extension Bulletin 741 and Iowa Commercial Pesticide Applicator Manual.

[7]ABARE is the leading government data provider for the Australian agricultural and resource sector.

[8]These weightings are applicable only for the period under observation and the region examined in this study.

[9]The significantly higher Pearson correlation relative to the adjusted R-squared indicates that while the two variables are highly correlated, the ability of the constructed weather derivatives contract to explain the dependent variable is constrained by some degree by noise.

[10]Australian Wine and Grape Industry [2003], Australian Bureau of Statistics.

[11]The historical average value for each variable is selected as the threshold level.

[12]Given the small number of observations for the out-of-sample period, the adjusted R-squared are not computed.

[13]All results are computed using the historical data on the weather variables outlined in Exhibit 7. It is important for readers to recognize that the results might change when applying datasets from different observation periods and different weather variables.

[14]See Sharpe [1966, 1975] for further information regarding the Sharpe ratio.

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