AMERICAN ASSOCIATION OF WINE ECONOMISTS

AAWE WORKING PAPER
No. 5

IDENTIFICATION OF STOCHASTIC PROCESSES FOR AN ESTIMATED ICEWINE TEMPERATURE HEDGING VARIABLE

Don Cyr and Martin Kusy

April 2007

www.wine-economics.org

AAWE
Working Paper No. 5

Identification of Stochastic Processes for an Estimated Icewine Temperature Hedging Variable

Don Cyr, Associate Professor and Martin Kusy, Professor
Department of Finance, Operations and Information Systems
Brock University, St. Catharines, Canada

Contact Information

Don Cyr
Faculty of Business
Brock University
500 Glenridge Avenue
St. Catharines, Ontario
Canada L2S 3A1
Tel: 905-688-5550 (ext 3136)
e-mail: dcyr@brocku.ca

I. Introduction

Weather derivatives represent a relatively new form of financial security with payoffs contingent on weather indices based on climatic factors. These contracts provide firms with the ability to manage unforeseen climatic changes that create risk in terms of the variability of earnings and costs. The potential for their use in a wide variety of industries is great as it has been estimated that approximately one-seventh of the industrialized economy is weather sensitive (Hanley, 1999). A recent survey for example, conducted by the U.S. Department of Commerce in 2004 estimates that approximately 30% of the total GDP of the United States is exposed to some type and degree of weather risk (Finnegan, 2005). A brief listing of affected industries includes not only agriculture and utilities but also the entertainment industry, beverage, construction and apparel industries.

Weather derivatives include various instruments such as swaps, options and option collars with payoffs dependent upon a wide variety of underlying weather –related variables such as average temperature, heating and cooling degree days, maximum or minimum temperatures, precipitation, humidity, sunshine and even temperature forecasts. Temperature related contracts are however the most prevalent, accounting for 80% of all transactions (Cao and Wei, 2004) with standardized contracts trading on the Chicago Mercantile Exchange for major U.S. cities.

As a result the interest in and use of weather derivatives is growing at a phenomenal rate from an estimated $500 million in notional value in 1998 (Finnegan 2005) to $45.2 billion in March 2006 based upon a recent survey of the Weather Risk Management Association. Much of this growth has occurred in the last few years and recent statistics indicate that the notional value of trading in standardized contracts on the Chicago Mercantile Exchange rose from 2.2 billion in 2004 to 22 billion in 2005. The recent growth in weather derivative arrangements is also being fueled by hedge funds which are beginning to add weather contracts in order to further diversify their investments. (Ceniceros, 2006)

Although the use of weather derivatives is potentially widespread it would appear that firms in many sectors of the economy have not yet established a hedging policy or even ascertained their full exposure to weather risk. Their potential use in the viticulture industry for example has seen limited applications, mainly involving the mitigation of risk in retail sales, due to climate conditions. The use of these instruments in hedging quality and quantity in grape growing has yet to be seen on a widespread basis. Although the lack of liquidity for specialized weather derivative contracts appears to be the main reason for their lack of use, other issues include uncertainties as to the pricing of these securities. In addition, the availability of useful historical weather data and the definition of an appropriate underlying variable that is the source of uncertainty, also adds to their complexity.

The Niagara region of Ontario, Canada represents the largest producer of icewine in the world with icewine significantly contributing to the revenues of many of the over 85 wineries in the region. Its production however is quite sensitive to the occurrence of relatively low temperatures during the winter months, when the grapes employed for icewine are harvested in a frozen state. Cyr and Kusy (2005) explored the potential use of weather derivatives for hedging the risks inherent in icewine production in the Niagara region of Ontario, Canada due to temperature fluctuations. In particular their study attempted to model a temperature variable based on daily observations and subsequent prices of options that could be employed for hedging icewine production. Data limitations and the development of an optimal forecasting model however, mitigated these efforts. Their findings are not unlike previous studies in the application of weather derivatives where the lack of appropriate weather data specific to a region often limits their use.

Cyr and Kusy (2006) later identified a model for estimating optimal icewine hours based upon daily observed temperature variables with fairly high explanatory power. The use of daily temperature variables that are easily measured and observed by both parties to a weather derivatives contract is a critical element to their successful use and aid in the contract's liquidity. Their model was based upon a three year period for which hourly temperature data was available at a critical weather station.

In the current study we employ the model identified in Cyr and Kusy (2006) in order to estimate optimal icewine production hours for the period of 1966 through 2006. Given the time series of estimated icewine hours we then explore its behavior in order to identify a stochastic process. Using Monte Carlo simulation we then estimate the price of put options based on cumulative optimal icewine hours under varying assumptions with regards to the stochastic process.

Section II provides a brief overview of the history and use of weather derivatives and their basic structure. Section III describes the process of icewine production in Canada, the risks inherent in the endeavor and the potential use of weather derivatives to mitigate those risks. In section IV we attempt to define and identify a stochastic process for estimated icewine production hours based upon daily observed temperature variables and in section V we estimate put option values based upon varying assumptions for the stochastic process. Finally section VI summarizes the paper.

II. History and Complexity in the Use of Weather Derivatives

The history of weather derivatives dates back to 1996 and the deregulation of the energy industry in the US with the first weather derivative security issue taking place in August 1996 between Enron and Florida Power and Light for a value of 40 billion US dollars (Geman and Leonardi, 2005). The impetus for growth in these contracts was largely the phenomenon of the El Niño winter of 1997-98. The warm weather conditions during the winter season resulted in significant earnings decline and many energy companies then decided to attempt to hedge their seasonal weather risk. The over-the-counter (OTC) market expanded rapidly driven largely by the energy sector and in September 1999 the Chicago Mercantile Exchange started an electronic market on which standardized weather derivatives could be traded (Alaton et al, 2002).

There are five essential elements to every weather derivative contract, a) the underlying weather index or variable, b) the period over which the index accumulates, typically a season or month, c) the weather station reporting the daily temperatures, d) the dollar value attached to each move of the index value and e) the reference or strike price of the underlying index (Cao and Wei, 2004). In the case of the energy sector these standardized contracts are written on the accumulation of heating degree days (HDD) or cooling degree days (CDD) over a calendar month or season where daily HDD and CDD is calculated as max [18°C – T_i, 0] and max [T_i – 18°C, 0] respectively and where T_i is the daily average temperature defined as the arithmetic average of the daily maximum and minimum temperatures. In Canada and the northern and Midwest city in the United States, an HDD season is typically defined as the winter months from November to March. The basic elements of the contract are the underlying variable HDD, the accumulation period, a specific weather station reporting daily temperatures and the tick size; the dollar amount attached to each HDD. In some cases these contracts specify a cap or maximum payoff. In terms of CDDs the contracts are analogous however the CDD season is defined as the summer months from May through September when temperatures typically rise above 18°C.

It is important at this point to recognize that weather derivatives differ substantially from insurance in that insurance contracts require the filing of a claim and the proof of damages with moral hazard playing a significant role. Insurance is also generally intended to cover damages dues to infrequent high-loss events rather than limited loss, high probability events such as adverse weather conditions. Weather derivatives are simply designed as a "bet" on weather conditions with the only requirement being an observable objective variable agreed upon by both parties. (Richards, Manfredo and Sanders, 2004).

Although the use of weather derivatives has seen much success in applications to the power and energy sectors, their use in other industries where weather is a significant risk factor has not been widespread. In particular exposure in the power and energy markets are almost linear with temperature; power demand increases steadily with both high and low temperatures. Few exposures in other sectors of the economy experience such simple measurement. In addition, alternative uses may involve challenges in terms of non-standardized situations and risks, contingent on illiquid, non-financial assets. This illiquidity issue is unlikely to change, as weather is by its nature a location-specific, non-standardized commodity. As a result the exchange traded instruments such as the degree-day futures and options trading on the CME for major US cities are of little use for many other sectors. The fact that weather is a local phenomenon and can differ dramatically within a small geographic area results in significant "basis" risk for those agricultural producers wishing to use them to hedge as the weather variable defined for a particular large city may differ significant from even a nearby rural area.

A number of applications have however been developed in businesses such as the retail and tourist industries. In a now relatively famous application weather derivatives were used to hedge against low wine consumption in England. In May 2000, Corney & Barrow, a wine bar chain in London England entered into a temperature contract to hedge against low sales on cool summer days. The chain found that wine consumption in their wine bars declines when the temperature fell below 24°C. They purchased a derivative contract for the June-September season which entailed a payoff of 1000 pounds x (24°C – T_i) per day for the days when the average daily temperature was below 24°C (Wei, 2002).

The viticulture industry in general is extremely sensitive to weather. Lack of sunshine exposure and cool temperatures during the stages between pre-bloom and maturation can significantly affect the quality of grapes, and consequently the vintage of the resulting wine. In 1998 for example California's production of wine grapes fell by almost 30% due to a cool and rainy spring, followed by a very hot July and August. Higher than average rainfall during the summer months can also be very expensive for winemakers as this leads to the grapes rotting on the vines and delays the harvest.

In this paper we explore the determination of daily temperature variables that can be employed for the design of weather derivatives for a very specific sector of the viticulture industry - that of icewine production. The production of icewine presents a case in which the benefits from the use of weather derivatives are potentially significant however to date, their consideration has been limited, if at all. This most certainly stems again from the specific nature of production and the lack of non-standardized contracts. In the following section we detail the process of icewine production in the Niagara region of the Province of Ontario, Canada – the largest producing region of icewine in the world.

III. Elements of Icewine Production

Icewine is only produced in a few specific regions in the world where temperature and climate conditions are appropriate. Although Canada remains a relatively small producer of wine world-wide in terms of production and retail value, it is the largest producer of icewine, with the majority of production originating from the Niagara Peninsula region in southern portion of the province of Ontario. The growth of the icewine industry within the Niagara region has been a phenomenal one given that many wine makers in the area did not produce any substantive volume until 1990 (Schreiner, 2001). Although the total volume of icewine produced in the region is relatively small due to its nature, production value is increasing substantially as the market for icewine becomes a global phenomenon. Recently for example, a Saudi Arabian businessman paid $30,000 for a 750 ml bottle of award winning Niagara region icewine (Beech, 2007). As a result, adverse weather conditions can result in substantial production and more importantly value loss to a producer. Although government crop insurance is available to agricultural producers to cover destruction due to severe weather conditions such as hail, it does not offer protection against loss from temperature conditions not optimal for icewine production. Consequently there exists a potential benefit in the use of weather derivatives.

The province of Ontario, through the Vitners Quality Alliance (VQA), regulates the nature of icewine production. The VQA is similar to other regulatory systems in countries such as France (AOC), Italy (DOC), and Germany (QmP), and ensures the consumer of high quality standards. The Alliance specifies several conditions for the production of icewine including that grapes must be harvested no earlier than November of each year, must be naturally frozen on the vine, picked while the air temperature is - 8°C or lower for an extended period of time (usually a few hours) and immediately pressed after picking in a continuous process. The finished wine shall be produced from a juice that achieves a computed average of not less than 35° brix – brix being a measure of sugar content. Production is monitored and the producer must report on production quantity and quality as required by regulation.

Although harvesting and production details can differ substantially between wineries depending up the equipment available and quality of product sought, it is generally recognized in the industry that the optimal temperature for harvesting grapes destined for icewine is between -8 and -12°C. In general the juice yield from icewine grape pressing is only 15 to 20% by volume of what the same grapes would have produced if harvested under conditions for the production of table wine. At temperatures below -12°C, although resulting in a product of higher brix level and ultimately sweeter icewine, a greatly reduced quantity of juice derived during the pressing process occurs in most cases. The higher brix level is also not conducive to later fermentation (Schreiner, 2001). Consequently producers would suggest that the optimal weather conditions during the harvest season would result in a significant number of hours when the temperature is between -8 and -12°C occurring sometime during the months of November through January. Generally these conditions occur at night with the grapes usually picked in the early hours of the morning.

The major risk to producers however is that a mild winter with relatively high temperatures could result in the grapes not being harvested at all or more likely, later in the winter months. Harvesting later in the season is usually associated with significant crop loss due to deterioration from wind, rot and other factors, and possibly lower brix levels in terms of the final product. In 1997-98 for example the impact of El Niño produced one of the warmest winters in southern Ontario in 66 years, with temperatures 6°C above normal. Balmy temperatures from December 1997 through February 1998 surpassed those reached during the last strong El Niño winter of 1982-83. Due to this mild weather, losses in the icewine industry were estimated to be in the $10 - $15 million range. Not only was the critical harvesting temperature of -8°C not reached for several consecutive days but in addition a significant proportion of the crop was consumed by starlings who, due to the warm weather, did not migrate south as they usually do.

As noted above, the risks faced by icewine producers are somewhat analogous to those faced by the energy industry during the winter months. For example firms in the energy industry may employ options on cumulative heating degree days over the season to hedge against the possibility of mild winters resulting in reduced energy consumption. The payoff provided by a put option contract for example is then contingent on a specified number of cumulative HDD's over the season. Similarly icewine producers face the risk that the cumulative number of hours when temperatures are between -8°C and –12°C, may not reach a critical level over the months of November through January. Consequently we will consider the modeling and valuation of a put option contingent on a temperature variable reflecting this risk. In this case the payoff of the put option would be contingent on a cumulative number of hours of optimal icewine production hours.

IV. Choice and Estimation of a Temperature Variable for Icewine Production Hedging

Optimally, option contracts designed to mitigate the risk of icewine production would involve an underlying variable, or its transformation, that would closely reflect the cumulative number of hours during the November through January season for which temperatures between -8 and -12 °C were prevalent. Identifying a daily temperature variable or combination of variables that can be measured with reasonable certainty by both parties to the contract is a critical element of a successful weather derivative contract.

As in Cyr and Kusy (2005) we employed temperature data obtained from Environment Canada – a federal government agency which operates a multitude of weather stations nationally and is the primary supplier of weather and temperature data in Canada. Unfortunately analyzing temperature records involves several issues for weather derivative analysts including the movement of measurement sites and misleading trends (Dischel 2001). These issues were also present in terms of acquiring appropriate temperature data for the Niagara region.

Although there are 130 weather stations in the Niagara and neighboring regions for which Environment Canada has recorded weather data, a surprisingly limited number are of value for the proposed application. Firstly the topography of the Niagara region exhibits a significant shift in elevation due to the presence of the Niagara escarpment – an ancient oceanic shoreline above which the elevation increases significantly. The majority of wineries in the Niagara region are located on a relatively narrow strip of land below this escarpment. This area is of relatively lower elevation, close to the Great Lake of Ontario and provides for more temperate conditions conducive to viticulture. As a result only three weather stations within close proximity to each other were appropriate for the study providing daily temperature observations dating back to 1965. Only one (the Vineland Weather station) recorded temperature data on an hourly basis however this dated back only to the year of 2002.

Previous variables defined by Cyr and Kusy

The existence of hourly temperature data dating back only to 2002 provides too short a time period to establish a reasonable stochastic process for the optimal icewine conditions based on actual observed hourly data. Therefore it is it is reasonable to assume that greater liquidity in the over-the-counter market for option contracts would be achieved if the underlying option variable was based upon daily observed data. The length of daily temperature data available would provide for greater certainty for both producers and contract suppliers in determining a reasonable estimate of the stochastic process and ultimately the volatility. Presumably this would increase the probability that the bid and ask differential for such contracts would be minimized.

Cyr and Kusy (2005) focused on two variables based on daily observations of minimum temperature data, somewhat analogous to that of the CDD and HDD measures employed in existing CME traded contracts. The first variable was defined as the number of degrees for which the observed minimum daily temperature is below -8°C. Specifically they defined the number of minimum degree days (MDD_{ij}) as:

$MDD_{ij} = \max(0, -8°C - T_{min})$ for each day i, where T_{min} is the observed minimum daily temperature for day i in year j.

They also considered the variable $IWDD_{ij}$ defined as the number of degrees for which the observed minimum daily temperature is equal to or less than -8°C but greater than or equal to -12°C where

$$IWDD_{ij} = \begin{cases} MDD_{ij} & \text{if } 0 \le MDD \le 4 \\ 0 & \text{if otherwise} \end{cases}$$

In 2005 and in a subsequent study (Cyr and Kusy, 2006) they regressed the observed daily number of icewine production hours against both variables for the November through March seasons, for the periods of 2002-03 through 2004-05 and later 2002-03 through 2005-06. Again it is only over these periods that actual hourly data is available and they found similar although mixed results in terms of which daily observed variable provided the greater explanatory power with respect to actual icewine production hours

Cyr and Kusy (2006) however employed regression analysis to identify a multiple regression model of daily observable temperature variables that would provide for the greatest explanatory power in terms of daily icewine production hours (IWH). Although they tested a multitude of daily observed temperature variables and their transformations, their results indicated that ultimately a multiple regression model employing IWDD and MDD along with the maximum daily observed temperature (maxT) had the greatest explanatory power over the four year period of study. In particular Table 1 provides the summary regression results for their model identified as:

$$IWH_i = a_0 + a_1 \max T_i + a_2 MDD_i + a_3 IWDD_i$$

Table 1: Summary of Regression Results of Optimal Icewine Hours on Maximum Temperature (maxT), Minimum Degree Days (MDD) and Icewine Degree Days (IWDD)

Regression Statistics	
Multiple R	0.755145
R Square	0.570244
Adjusted R Square	0.568036
Standard Error	2.797273
Observations	588

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	6063.47	2021.157	258.3035	1.162E-106
Residual	584	4569.646	7.824736		
Total	587	10633.12			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.753218	0.17374	4.335328	1.71E-05
maxT	-0.09895	0.022494	-4.39888	1.29E-05
MDD	0.712034	0.059287	12.00987	7.52E-30
IWDD	2.615868	0.164223	15.92875	1.05E-47

Most other variables considered by Cyr and Kusy (2005) did not exhibit significant explanatory power. Although the daily temperature range was a significant variable in several models tested, the maximum temperature in conjunction with MDD and IWDD provided the greatest adjusted R-squared value of 56.8% representing a significant increase in explanatory value versus MDD and IWDD alone. These results were confirmed using TOBIT analysis given that the independent variable of icewine production hours observed in a day does not represent a continuous variable satisfying the characteristics of a normal distribution. In particular the dependent variable is truncated or censored in both the left and right tail. In the left tail the optimal number of icewine hours observed cannot take a value less than zero and in the right tail, the observed value cannot be greater than 24 hours.

Estimation of Optimal Icewine Hours

In the current study, we employ the regression model identified above to create a time series of estimated optimal icewine production hours, based on the daily observed temperature variables for each day of the winter months of November through March for the 41 seasons of 1965-66 through 2005-2006. Figure 1 below shows the average of the number of estimated icewine hours for each of the 151 days in the 41 seasons observed, with day 1 assigned to the date of November 1st.

Figure 1: Average Number of Estimated Icewine Production Hours from November through March for the Years 1965-66 through 2005-06

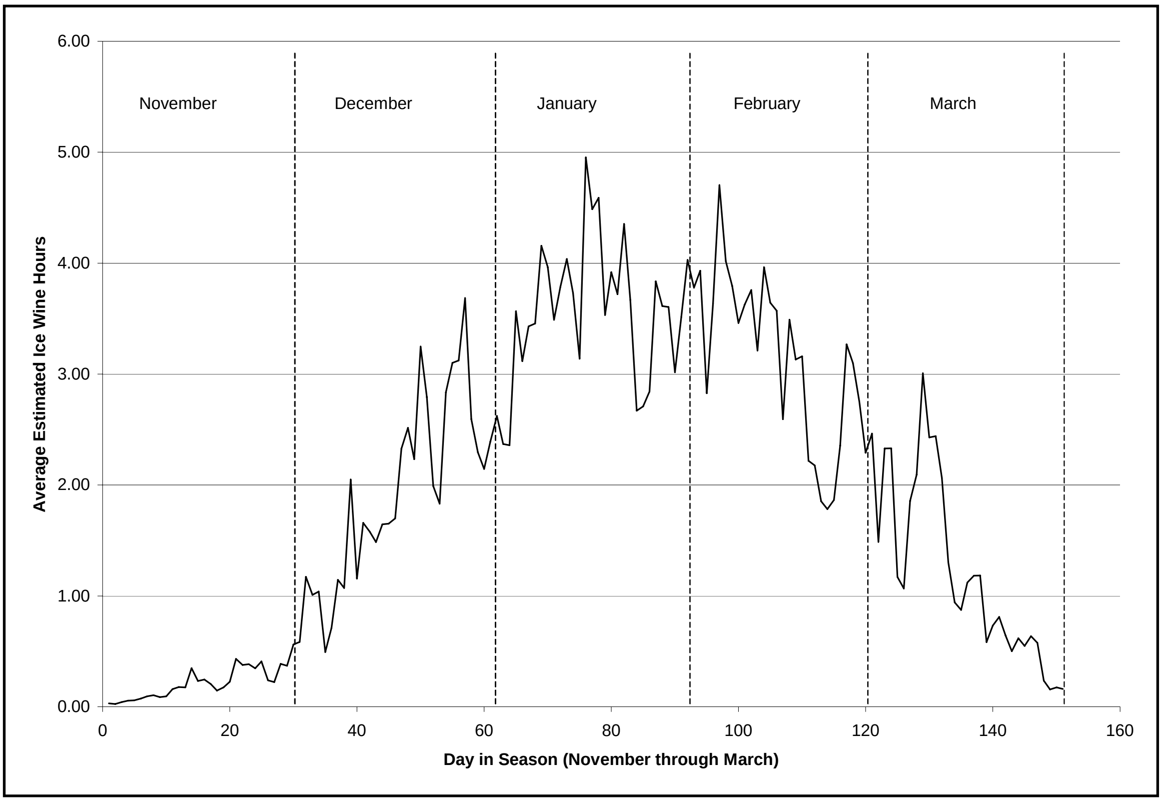
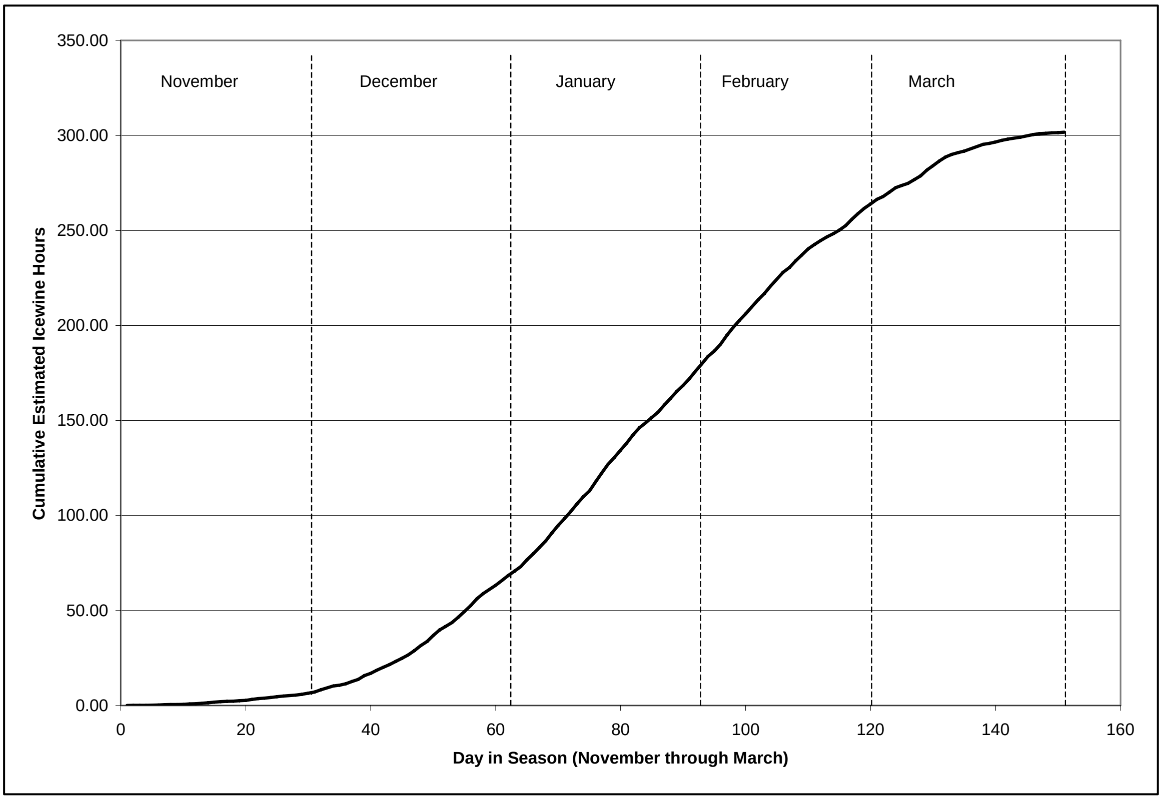


Figure 2 shows the cumulative average estimated icewine hours over the winter season for the 41 year period. As indicated, on average, it is not until January 11th (72nd day of the season) when the cumulative number of estimated icewine hours exceeds 100.

Figure 2: Cumulative Average Estimated Icewine Production Hours for the 151 Days of November through March for the Winter Seasons of 1965-66 through 2005-06.



Given the discussion provided in Section III regarding the risks associated with icewine production we assume producers would be interested in derivative contracts that would allow them to hedge against the possibility of a cumulative number of optimal icewine production hours not occurring during the November through January months of the winter season. This use is somewhat analogous to the uses of HDD and CDD contracts in the energy industry, which trade on the CME.

Identification of a Stochastic Process for Cumulative Estimated Icewine Production Hours

One of the issues in identifying a stochastic process for a weather variable that is the result of the accumulation of a daily observed variable is whether one should attempt to model the daily estimated variable itself. This issue was recently explored by Geman and Leonardi (2005) who explicitly examined alternative approaches to the specification of an underlying variable for weather derivatives. They noted for example that in the case of options written on cumulative degree days, the underlying variable can be specified as either the daily average temperature, the degree days, or thirdly the cumulative degree days themselves. These three approaches require different statistical estimation procedures and ultimately different approaches to option valuation.

In an examination of options written on cumulative degree days for Paris-Le-Bourget they recognized a number of advantages in attempting to model the daily average temperature itself including the capturing of autocorrelation between consecutive day temperatures. However their results show, that of the three possible variables, cumulative degree days exhibit behavior closest to normality. They conclude that if the ultimate goal is to explore the valuation of option contracts written on cumulative degree days, then the optimal underlying variable to model is the cumulative degree days attached to the period for which the weather contract is providing a hedge.

Their results are consistent with those of Campbell and Dieboldt (2005) who found that the effects of small specification errors in modeling daily average temperature cumulate as the forecast horizon lengthens, and has a significant impact on the forecasting of transformed variables such as cumulative HDD. They also suggest that modeling these transformed variables directly may produce more satisfying results.

As a result we examine the behavior of the time series of 41 observations of the November through January, 92 day cumulative estimated icewine production hours defined as $CIWH_j$ where

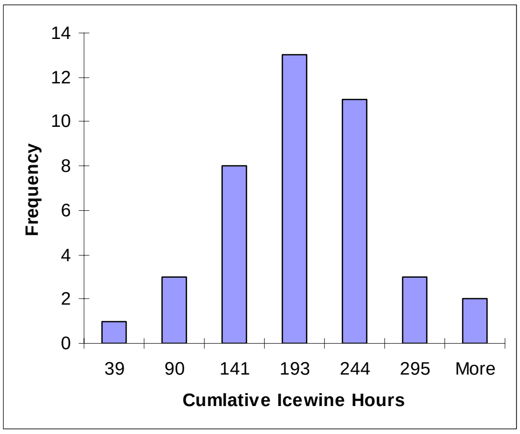
$$\mathrm{CIWH}_j = \sum_{i}^{92} \mathrm{IWH}_i \quad \text{for j = 1 to 41 seasons}$$

Table 2 shows the basic summary statistics for the 41 observations of $CIWH_j$ and Figure 3 shows a plot of the histogram of the data.

Table 2: Summary Statistics of the 41 observations of Cumulative Estimated Icewine Production Hours ($CIWH_j$) over the November through January months.

Summary Statistics	
Mean	176.02
Standard Error	10.47
Median	181.57
Standard Deviation	67.04
Sample Variance	4493.85
Kurtosis	0.23
Skewness	0.35
Range	308.01
Minimum	38.75
Maximum	346.76
Count	41

Figure 3: Histogram of 41 Observations of Cumulative Estimated Icewine Hours Over the November through January Months.



Our goal however is to identify a reasonable stochastic process for the time series of cumulative icewine hours. In order to do so we used standard time series analysis techniques to identify a model that might be applicable to the data. As well, given the possibility of heteroskedasticity in the data caused by the presence of extreme weather seasons such as those resulting from El Niño climate effects, we used intervention analysis to identify potential outliers that may be present given an identified time series model. To carry out the analysis we employed the statistical software ***Freefore*** by Automated Forecasting Systems. This software employs standard time series techniques to automatically identify and estimate a time series model for the data in question while simultaneously identifying any possible outliers characterized as either a pulse intervention (one observation) or level (mean) shift intervention. Any remaining serial correlation is recognized in terms of ARIMA modeling. The results of the final model estimated for the data is provided in Table 3 below along with summary statistics of the analysis.

Table 3: Summary Statistics from Automated Time Series Identification and Estimation

```
           MODEL COMPONENT          LAG     COEFF      STANDARD       P        T
 #                                 (BOP)                ERROR       VALUE    VALUE

   1CONSTANT                                168.        8.89        .0000    18.89

 INPUT SERIES X1    I~P00012        12     PULSE

   2Omega (input) -Factor #  1      0    156.        56.2        .0086     2.77

 INPUT SERIES X2    I~P00016        16     PULSE

   3Omega (input) -Factor #  2      0    179.        56.2        .0029     3.18
 LOGARITHM TRANSFORMATION IS NOT NEEDED VIA BOX-COX TEST.
 RESTORING AFTER LOG TEST
 MODEL STAGE:  84    8 EST

  NO STATISTICALLY SIGNIFICANT HETEROGENEITY OF VARIANCE DETECTED.
 MODEL STAGE:  25    9 EST
 MODEL STATISTICS AND EQUATION FOR THE CURRENT EQUATION (DETAILS FOLLOW).

 Estimation/Diagnostic Checking for Variable Y  = IWHoursNovJan
              :  NEWLY IDENTIFIED VARIABLE   X1 = I~P00012       12     PULSE
              :  NEWLY IDENTIFIED VARIABLE   X2 = I~P00016       16     PULSE

              Number of Residuals (R)          =n                41
              Number of Degrees of Freedom     =n-m              38
              Residual Mean                    =Sum R / n       .175493E-08
              Sum of Squares                   =Sum R**2        126258.
              Variance                      var=SOS/(n)         3079.45
              Adjusted Variance                =SOS/(n-m)       3322.57
              Standard Deviation               =SQRT(Adj Var)   57.6417
              Standard Error of the Mean       =Standard Dev/   9.35072
              Mean / its Standard Error        =Mean/SEM        .187679E-09
              Mean Absolute Deviation          =Sum(ABS(R))/n   44.7739
              AIC Value ( Uses var )           =nln  +2m        335.333
              SBC Value ( Uses var )           =nln  +m*lnn     340.474
              BIC Value ( Uses var )           =see Wei p153    148.356
              R Square                     =                    .297609
              Durbin-Watson Statistic      =[A-A(T-1)]**2/A**2  2.42680

          D-W STATISTIC SUGGESTS NO SIGNIFICANT AUTOCORRELATION for lag1.
```

The model identified above after correcting for presence of identified outliers is given by:

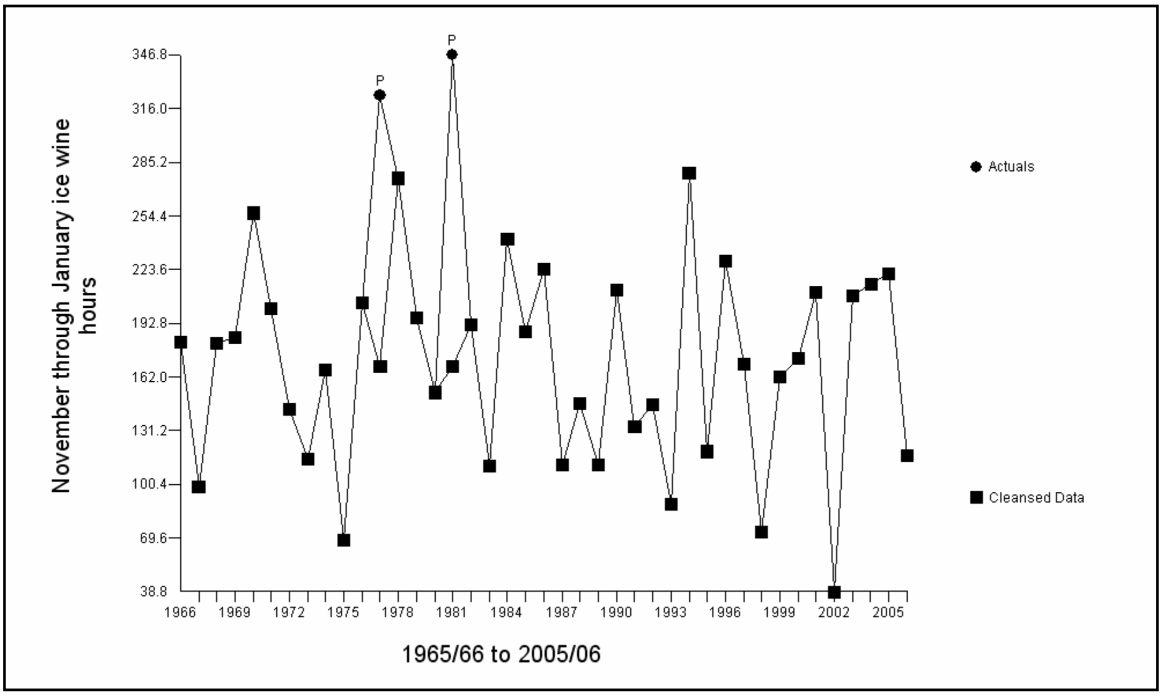
$$CIWH_j = \mu + e_j$$

where μ= 168 hours and $e_j \sim N(0, 57.64 \text{ hours})$

The results of the analysis indicates that CIWH follows a gaussian process where each seasonal observation is independent of the previous one, normally distributed with a mean value of 168 hours and a standard deviation of 57.64 hours. In particular there was no identifiable stochastic trend and the results are somewhat consistent with those of Geman and Leonardi (2005) who found that cumulative CDD and HDD measures were similarly derived from a normal distribution.

There were however significant outliers in the form of pulse interventions that were identified in the analysis. In particular Figure 4 shows the graph of CIWH for the 41 seasons of 1965-66 through 2005-06 as well as the statistically significant outliers. Contrary to general beliefs the outliers identified are not periods of mild winters, but rather those of extreme cold winters. In particular the winters of 1976-77 and 1980-81 have estimated optimal icewine production hours of 323 and 346 respectively compared to an average of 176 hours for the 41 seasons.

Figure 4: Graph of Cumulative Icewine Hours (November through January) for the 1965-66 through 2005-06 Period.



Note: "P" indicates a statistically significant pulse intervention or outlier observation.

It is interesting to consider the historical weather conditions leading to these two winter seasons being statistically identified as outliers in the intervention analysis. An exceptionally cold December of 1976 for example, resulted in neighboring Great Lake Erie achieving an early freezing record of December 14th. On January 28th 1977 what has been described as a winter hurricane (Rossi, 1978) occurred with winds reaching speeds of 60 to 70 miles per hour and wind chill temperatures dropping to as low as –60°C. Indeed this record breaking storm which affected southern portions of the province of Ontario and parts of western and northern New York State, resulted in the declaration of a "state of emergency" by the then US president Jimmy Carter for several New York state counties. The first and only declaration made in the US for a snow emergency. In Ontario, the whole of the Regional Municipality of Niagara was also placed in a state of emergency on January 29th which remained in effect until February 2, 1977. It has been estimated that the blizzard of '77 resulted in a cost of 300 million dollars (Rossi, 1978). Indeed the average daily minimum temperature throughout the months of December 1976 and January 1977 was –10.6°C; the lowest over the 41 year study period, in comparison to average daily minimum temperatures of –6.8°C for the December and January months.

The winter of 1980-81 was not associated with a natural disaster such as the blizzard of 1977, however with a value of –9.8°C it exhibited the second lowest average daily minimum temperature for the months of December and January over the 41 year period.

Figure 4 indicates that aside from the exceptionally cold winters that there have been fairly warm winter seasons in terms of icewine production hours. In particular the winters of 1974-75, 1997-98 and 2001-02 were associated with fairly low CIWH values which in some cases (1997-98) are believed to be caused by the El Niño effect. The warmest season in terms of icewine hours over the 41 year period was that of 2001-02. During that winter season the mild temperatures resulted in the lack of an ice bridge in the neighboring Niagara river, which typically forms each year. None of these periods however were identified as statistically significant outliers. They fell within reasonable confidence intervals for the identified model.

V. Valuation of a Put Option on Cumulative Estimated Icewine Production Hours

Unfortunately the pricing of weather derivatives involves significant debate in the existing literature over and above the identification of a stochastic process for a fundamental underlying variable. The lack of an agreed approach to pricing is in fact believed to be one of the causes of the lack of liquidity in the weather derivatives market (Richards et al, (2004) and Cao and Wei (2004)).

The major factor giving rise to the debate is that weather derivatives represent a classical case of incomplete markets as the underlying weather variables are not traded. In such cases prices for derivatives cannot be derived from the no-arbitrage condition commonly employed in option pricing, since it is not possible to replicate the payoff of a given contingent claim with a portfolio of the basic securities. Consequently the classic Black-Scholes-Merton methodology cannot theoretically be directly applied.

The literature has seen several approaches to dealing with incomplete markets with one of these being to introduce the "market price of risk" for the particular underlying weather variable The issue then becomes focused on the correlation between temperature for example, and the market index. If the correlation between temperature and the market portfolio is zero then it is theoretically justifiable to value option contracts using risk-neutral valuation approaches. Recent research (Cao and Wei (2004)) indicates however that there is significant correlation between temperature variables and overall consumption, creating market risk. In addition, they indicate that the market price of risk can be a significant factor in the valuation of weather options, particularly when there is correlation between the underlying weather variable and aggregate output processes, coupled with a higher level of risk aversion.

The difficulty exists however in determining this market price of risk, with authors taking various approaches. These have ranged from the search for a traded asset with a high correlation to the underlying weather variable (see Geman and Leonardi (2005) and Jewson and Brix (2005) for a succinct discussion), from which an estimate of market risk can be derived, to models (Davis (2001)) that employ expected utility and marginal values. Other approaches include equilibrium models incorporating weather as an additional fundamental source of uncertainty in the economy (Cao and Wei (2004) and Richards et al (2004)).

In this paper we will forgo the unresolved issue of market price of risk or the level of risk aversion of the producer and will instead simply calculate benchmark prices based upon two approaches. The first approach termed “burn rate” analysis is employed in the industry to provide a calculation of approximate option value. The second approach is to employ Monte Carlo simulation under the assumption of risk neutrality to derive an option price. We will however carry out the simulation approach under different assumptions regarding the stochastic process for the underlying variable given our results above.

Given the discussion outlined above in sections III and IV above we consider the valuation of a put option contract based upon the cumulative estimated icewine production hours for the winter months of November through January. If the actual number of cumulative icewine hours is below a set value K (the strike level) at maturity, the option will pay out a specified value α (the tick size) per hour below the specified strike. Given that this is a put option the maximum payout is achieved if there are zero cumulative icewine hours over the three month winter season. The payout X of the put option at maturity is therefore given as:

$$X = \alpha \max [0, K - CIWH_j]$$

In the OTC market for weather options, the choice of strike level and tick size would be determined by the icewine producer after consideration of their specific operations and needs. In order to simulate results we will base our assumptions upon estimates derived from the 1997-98 season when the El Niño effect is believed to have resulted in a lost of up to $15 million dollars to the icewine industry. The estimated icewine hours for the 1997-98 period was only 72.87 hours. Given the expected value of 168 hours identified in the model, we will assume a linear relationship between the overall industry loss of $15 million and the difference of approximately 95 hours. This results in an assumed overall industry tick size of $157,895 per icewine production hour. Assuming 85 wineries in the region producing icewine, this results in the average producer tick size of almost $2000 per icewine production hour.

Given that a producer may not always wish to hedge completely against the possibility of the icewine hours falling below the mean of 168 hours, we will assume varying strike level values of 170, 150`130, 110, 90 and 70 icewine hours. In actual application the strike and tick size would have to be arrived at by the producer through an analysis of his or her operations and the association between optimal icewine harvesting hours required in a season for their particular vineyard, and that of the weather station employed for the option contract.

In addition we will further assume that the contract is a European option entered into 6 months prior to maturity (the end of January) and that the continuously compounded constant risk free rate over the period is 4% per annum. A summary of the basic assumptions is provided in Table 4 below.

Table 4: Summary of Option Parameters Employed in Analysis

Underlying Variable:	CIWH for Nov. through Jan.
Maturity Date	January 31st
Strike (K)Values :	170, 150, 130. 110, 90 hours
Maturity (months):	6
Riskless rate (r):	4%
Tick Size (α):	$2,000

Burn Rate Analysis

Burn rate analysis refers to a simplified approach to valuing contingent claims often employed in the insurance industry (Geman and Leondardi (2005) and Jewson and Brix (2005)). The method basically consists of pricing the option as the discounted average of the payoffs that would have been observed in past years, based on the historical values of the underlying variable.

It is widely recognized that the burn rate approach is completed disconnected from traditional option pricing and will in general tend to undervalue options due to the fact that it will assign a value of zero for options that are out-of-the-money and more importantly will not necessarily incorporate the true volatility of the underlying asset in the pricing. Nonetheless it represents a simple calculation that if nothing else provides some sense of the order of magnitude of the option value in question. We consider this average value under risk neutrality and discount by the risk free rate for the six-month period to maturity. Table 5 below provides the terminal value (payoff) of the put option for each of the 41 seasons of 1965-66 through 2005-06 given the different strike values. In addition the value of the put option with six months to maturity based upon the burn rate analysis is shown.

Table 5 is interesting from a producer's perspective as it indicates the years in which the theoretical put options would have matured in-the-money, given varying strike values, and consequently the extent of coverage provided by such contracts. By purchasing a put option each year with a strike price of 70 hours, at the theoretical price of $1,570 per year, the producer would have been hedged against the 2001-02 mild season with a payout of $62,496. The number of years for which the option contract would mature in the money, increases as the strike value increases. At a strike value of 170 hours, the option contracts would have matured in-the-money 19 seasons out of the total of 41 with payouts varying from $1,495 to $262,496. Again these values are based upon a contract tick size of $2000 per icewine production hour.

Table 5: Burn Rate Analysis – Historical Terminal Value of Put Options Given Varying Strike Values Over the 1965-66 through 2005-06 seasons

Season	Estimated CIWH (Nov-Jan)	Terminal Value (Payoff) of Put Option					
		Strike Value (CIWH)					
		170	150	130	110	90	70
1965-66	182.1	$0	$0	$0	$0	$0	$0
1966-67	98.9	$142,167	$102,167	$62,167	$22,167	$0	$0
1967-68	181.6	$0	$0	$0	$0	$0	$0
1968-69	184.7	$0	$0	$0	$0	$0	$0
1969-70	256.0	$0	$0	$0	$0	$0	$0
1970-71	201.1	$0	$0	$0	$0	$0	$0
1971-72	143.2	$53,599	$13,599	$0	$0	$0	$0
1972-73	115.1	$109,827	$69,827	$29,827	$0	$0	$0
1973-74	166.1	$7,780	$0	$0	$0	$0	$0
1974-75	68.4	$203,190	$163,190	$123,190	$83,190	$43,190	$3,190
1975-76	204.8	$0	$0	$0	$0	$0	$0
1976-77	323.5	$0	$0	$0	$0	$0	$0
1977-78	275.9	$0	$0	$0	$0	$0	$0
1978-79	196.2	$0	$0	$0	$0	$0	$0
1979-80	153.1	$33,761	$0	$0	$0	$0	$0
1980-81	346.8	$0	$0	$0	$0	$0	$0
1981-82	192.0	$0	$0	$0	$0	$0	$0
1982-83	111.0	$117,925	$77,925	$37,925	$0	$0	$0
1983-84	241.0	$0	$0	$0	$0	$0	$0
1984-85	187.8	$0	$0	$0	$0	$0	$0
1985-86	223.9	$0	$0	$0	$0	$0	$0
1986-87	111.3	$117,411	$77,411	$37,411	$0	$0	$0
1987-88	147.0	$46,084	$6,084	$0	$0	$0	$0
1988-89	111.6	$116,892	$76,892	$36,892	$0	$0	$0
1989-90	211.9	$0	$0	$0	$0	$0	$0
1990-91	133.6	$72,828	$32,828	$0	$0	$0	$0
1991-92	145.9	$48,154	$8,154	$0	$0	$0	$0
1992-93	88.7	$162,598	$122,598	$82,598	$42,598	$2,598	$0
1993-94	278.8	$0	$0	$0	$0	$0	$0
1994-95	119.1	$101,762	$61,762	$21,762	$0	$0	$0
1995-96	228.6	$0	$0	$0	$0	$0	$0
1996-97	169.3	$1,495	$0	$0	$0	$0	$0
1997-98	72.9	$194,260	$154,260	$114,260	$74,260	$34,260	$0
1998-99	162.3	$15,393	$0	$0	$0	$0	$0
1999-00	172.5	$0	$0	$0	$0	$0	$0
2000-01	210.3	$0	$0	$0	$0	$0	$0
2001-02	38.8	$262,496	$222,496	$182,496	$142,496	$102,496	$62,496
2002-03	208.4	$0	$0	$0	$0	$0	$0
2003-04	215.0	$0	$0	$0	$0	$0	$0
2004-05	221.0	$0	$0	$0	$0	$0	$0
2005-06	116.7	$106,584	$66,584	$26,584	$0	$0	$0
Average Payout		**$46,687.94**	**$30,628.72**	**$18,417.35**	**$8,895.40**	**$4,452.29**	**$1,602.10**
Put Option Value		**$45,763.46**	**$30,022.23**	**$18,052.66**	**$8,719.26**	**$4,364.13**	**$1,570.37**

Monte Carlo Simulation

Generally the Monte Carlo simulation approach provides for an accurate approximation with a relatively low number of runs (in the order of 10,000, Yoo (2003)). The potential payoffs are simulated given the stochastic process assumed for the underlying variable. Given the analysis in section IV we provide the results of Monte Carlo simulation based upon three different assumptions or cases for the stochastic process of the underlying CIWH variable. In the first case we assume that the CIWH variable is represented by the series adjusted for outliers as identified in section IV, and therefore follows a basic Gaussian process whereby the seasonal observations are independent and normally distributed with a mean of 168 hours and a standard deviation of 58 hours.

However it can be argued that by adjusting the series for outliers we are ignoring some of the sources of risk as the outliers add to the volatility of CIWH, important to option values. We therefore carry out Monte Carlo simulation under a second and third set of assumptions. In the second case we simply assume that the CIWH values can be modeled as independent and normally distributed with the unadjusted mean of 176.02 hours and standard deviation of 67.04 hours as identified by the basic descriptive statistics. This assumption may be viewed as an approximation of the true stochastic process of the CIWH variable. In particular the presence of the pulse outliers may be indicative of a mixed jump diffusion process whereby the usual Brownian motion for the CIWH diffusion is combined with a space-time Poisson process for jumps simulating the presence of outliers. In other similar applications it is usually assumed that the jump amplitudes are independent and identically distributed.

Theoretically parameters of the Brownian noise and jump process should be estimated simultaneously however an optimal methodology remains an area of current research (see for example Ait-Sahalia (2004) and He et al (2006)). In addition simultaneous estimation methods usually require the presence of a significant time series or frequency of data, not present in the current study. As a result, for the third case we will make the simplifying assumption that the jump diffusion parameter is equal to (2/41) = .049 given the identification of two outliers among the forty-one seasons specified in the time series modeling process. In addition, it is assumed that the jump amplitude is normally distributed with a mean of 167.5 hours and standard deviation 11.5 hours derived from the two identified outlier observations.

Table 6 below provides the results of the Monte Carlo simulations given the three cases outlined above, for the stochastic process governing the CIWH variable. Compared to Case 1 based upon the time series of CIWH values adjusted for outliers (μ = 168 hours and σ = 58 hours) the assumptions employed in Case 2 and based upon the unadjusted series (μ = 176.02 hours and σ = 67 hours) result in higher put option values in general. This is consistent with the impact of the higher volatility of 67 hours versus 58, which increases option premiums. Only in the case of a strike value of 170 hours does the assumption of a lower expected outcome of 168 hours in Case 1 result in a higher option value than that of Case 2 with an expected outcome of 176.02 hours.

Table 6: Monte Carlo Simulation of Put Option Prices for Different Strike Values

	Strike Values					
Diffusion Assumptions	**170**	**150**	**130**	**110**	**90**	**70**
Normal (μ = 168, σ = 58)	$46,745.77	$29,323.03	$17,003.98	$9,021.80	$4,315.77	$1,814.47
Normal (μ = 176.02, σ = 67.04)	$45,318.70	$29,505.06	$18,011.16	$10,205.04	$5,284.30	$2,430.57
Mixed Normal and Poission Jump (μ = 168, σ = 58, λ = .049, $\mu 2$ = 167.5, $\sigma 2$ = 11.5)	$44,473.78	$27,832.01	$16,272.41	$8,680.78	$4,116.81	$1,726.19

Finally Case 3 provides the results of the simulation under the assumption of a mixed diffusion process that includes the possibility of positive jumps. Case 3 indicates that modeling the jump process has value resulting in lower estimated option premiums in general. This is of course due to the fact that the jump process has been modeled upon the assumption of positive jumps in the CIWH value. In particular Case 3 results in option values significantly lower than Case 2 and shows that approximating the mixed diffusion process with an assumed Gaussian process based on the unadjusted data can result in significant estimation error. This is true even with the relative infrequency of the jumps.

VI Conclusion

As the size and scope of the viticulture industry grows, there is an increased focus on the application of science and technology to the endeavor. In the case of business applications this entails the use of the latest technology and approaches to modeling of inherent problems and risk.

The potential application of weather derivatives to hedging of temperature risk in icewine production in the Niagara region of Canada represent a significant potential benefit however, it is fraught with many technical issues similar to those found by other researchers in analogous applications. Firstly the lack of appropriate hourly temperature data of a sufficient historical time period requires the use of a estimated variables based upon daily temperature observations. Secondly, the choice of an underlying set of daily observable variables or their transformations is critical to the modeling of a time series process for forecasting of future values and a successful market for weather derivatives.

This paper has extended the work of Cyr and Kusy (2005 and 2006) by creating a time series of estimated optimal icewine production hours over a 41 year period, based upon temperature variables measured on a daily basis. The time series of cumulative icewine production hours for the months of November through January of each season was then analyzed in order to identify a potential stochastic process for an underlying variable that could be employed in option contracts. Although the time series of cumulative icewine production hours appears to follow a simple Gaussian process, statistically significant outliers were found in the data through the use of intervention analysis. Contrary to common beliefs these outliers were due to seasons of extreme cold as opposed to exceptionally warm winters. More importantly, preliminary analysis indicates that such outliers may be representative of a mixed diffusion process with infrequent jumps governing the behavior of cumulative icewine production hours. Although the jumps in seasonal values of such hours are relatively infrequent, their impact upon simulated option prices was significant.

Further research would require extending the study to areas of icewine production which may have a longer history of recorded temperature data. Although contributing a smaller level of icewine production volume than the Niagara region, such areas exist in other parts of southern Ontario. The efficient and simultaneous estimation of the parameters of the mixed diffusion process would be facilitated with a greater number of observations

In this paper we have also considered the risks solely due to temperature in icewine production however other climatic variables also introduce risk. Variables such as rainfall during the growing season summer months affects the overall grape production including those destined for icewine. In addition decay in the icewine grapes due to wind destruction over the winter months is also a potentially important factor. To hedge against these additional variables adds complexity, as correlations between variables must be considered. Dishel (2001) provides an example of the issues that arise in formulating a weather hedge that includes more than one weather variable.

References

He, C., J. S. Kennedy, T. F. Coleman, and P. A. Forsyth, et al. "Calibration and Hedging Under Jump Diffusion" *Review of Derivatives Research*, Vol. 9, Iss. 1; p. 1-36

Ait-Sahalia, Y. 2004, "Disentangling Diffusion from Jumps," Journal of Financial Economics, vol 74, p.487-528

Alaton, P., B. Djehiche and D. Stillberger, 2002, "On Modelling and Pricing Weather Derivatives," *Applied Mathematical Finance*, Vol. 9, No. 1, pp. 1-20

Beech, M., 2007, "Icewine Fetchs a Cool $30,000", *St. Catharines Standard*, Friday January 12th, 2007, Page A1.

Cao, M. and J. Wei, 2004, "Weather Derivatives Valuation and Market Price of Risk", *The Journal of Futures Markets* Vol. 24, No. 11, p. 1065-1089

Campbell, S. and Diebold, F.X. 2005, "Weather Forecasting for Weather Derivatives", *Journal of the American Statistical Association*, March 2005, vol. 100, no. 469 p.6 – 16.

Ceniceros, R., 2006, "Weather Derivatives Running Hot, *Business Insurance*. Chicago: Aug 7, 2006.Vol.40, Iss. 32; pg. 11

Cyr, D. and M. Kusy, 2005, "Weather Derivatives and their Potential use for Hedging Canadian Ice Wine Production: A Case Study and Simulation", *Bacchus in Bourgogne 2nd International Conference*, Conference Proceedings, Dijon, France, November, 2005.

Cyr, D. and M. Kusy, 2006, "Identification of Daily Temperature Variables for use in Hedging Ice Wine Production with Weather Derivatives"*Wine in the World: Markets, Tourism and Globalisation*, Second International Conference on Economics, Management Sciences, Florence, Italy, June, 2006.

Davis, M. 2001, "Pricing Weather Derivatives by Marginal Value", *Quantitative Finance* May 2001, v. 1, iss. 3, pp. 305-08

Dischel, B., 2001," Double Trouble: Hedging", *Risk, Weather Risk Special Report,* s24-s26

Finnegan, J., 2005, "Weather or Not to Hedge", *Financial Engineering News*, Issue 44, p. 1-3.

Geman, H. and M. Leonardi, 2005, "Alternative Approaches to Weather Derivatives Pricing", *Managerial Finance*, Vol. 31 No. 6, p. 46-72

Hanley, M. 1999, "Hedging the Force of Nature", *Risk Professional*, Issue 1, p. 21-25.

He, C., J. S. Kennedy, T. F. Coleman, and P. A. Forsyth, et al. "Calibration and Hedging Under Jump Diffusion" *Review of Derivatives Research*, Vol. 9, Iss. 1; p. 1-36

Jewson, S and A. Brix, 2005, *Weather Derivative Valuation: The Meteorological, Statistical, Financial and Mathematical Foundations*, Cambridge University Press.

Maillet B. and T. Michel, 2005, "Extreme Distribution of Realized and Range-based Risk Measures", working paper.

Richards, T.J., M.R. Manfredo and D.R. Sanders, 2004, "Pricing Weather Derivatives", *American Journal of Agricultural Economics*, Vol 86, no. 4. p. 1005-1017

Rossi, E, 1978, White Death – The Blizzard of '77, Seventy-seven Publishing, Ontario Canada

Schreiner, J., 2001, ***Icewine, The Complete Story***, Warwick Publishing, Toronto

Wei, 2002, "Weather Derivatives; A Truly Alternative Asset Class for Investors", *Canadian Investment Review*, Spring 2002.

Yoo, S. 2003, "Weather Derivatives and Seasonal Forecast", Working Paper, Cornell University