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Canadian Ice Wine Production: A Case for the Use of Weather Derivatives*

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Abstract

Weather derivatives are a relatively new form of financial security that can provide firms with the ability to hedge against the impact of weather related risks to their activities. Participants in the energy industry have employed standardized weather contracts trading on organized exchanges since 1999 and the interest in non-standardized contracts for specialized weather related risks is growing at an increasing rate. The purpose of this paper is to examine the potential use of weather derivatives to hedge against temperature related risks in Canadian ice wine production. Specifically we examine historical data for the Niagara region of the province of Ontario, Canada, the largest icewine producing region of the world, to determine an appropriate underlying variable for the design of an option contact that could be employed by icewine producers. Employing monte carlo simulation we derive a range of benchmark option values based upon varying assumptions regarding the stochastic process for an underlying temperature variable. The results show that such option contracts can provide valuable hedging opportunities for producers, given the historical seasonal temperature variations in the region. (JEL Classification: G13, G32, Q14, Q51, Q54)

I. Introduction

Weather derivatives represent a new form of financial security with payoffs contingent on weather related variables, providing firms with the ability to hedge against unforeseen climatic changes that can result in significant variability in revenues and costs. They include various instruments such as swaps, options and option collars with payoffs dependent upon 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 cities in North America, Europe and Asia.

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The importance of weather derivatives to a wide variety of industries is potentially great as approximately one-seventh of the industrialized economy has been estimated to be weather sensitive (Hanley, 1999). Indeed a survey conducted by the U.S. Department of Commerce in 2004 would indicate 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 list of affected sectors includes not only agriculture and utilities but also the entertainment, beverage, construction and apparel industries.

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 survey carried out for the Weather Risk Management Association – an association of firms and participants in the weather risk management business. Much of this growth has occurred in the last few years and recent statistics indicate that the notional value of trading in weather 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 include weather contracts in their investment strategies (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. Although the illiquidity of specialized weather derivative contracts appears to be the main reason for their lack of use, other issues include uncertainties as to their pricing, the identification of an appropriate underlying variable that is the source of uncertainty and the availability of useful historical weather data. These factors all add to the complexity of designing a useful weather derivative contract and perhaps their relatively slow adoption. The over-the-counter (OTC) market for specialized weather contracts has however been growing dramatically as various financial intermediaries have realized their potential. In particular the Weather Risk Management Association's 2006 survey indicates a significant increase in the number of OTC weather derivatives over the past five years with a particular increase in the number of contracts written on specialized "other" weather variables aside from average temperature. In 2007 the value of "other" OTC weather contracts doubled in nominal value from $34.7 million in 2006 to $65.8 million.

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 in the harvest.

In this paper we explore the determination of daily temperature variables that can be employed for the design of a weather derivatives contract for a very specific sector of the viticulture industry – that of Canadian 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.

Section II provides a brief overview of the history and use of weather derivatives, their basic structure and current and potential use. Section III describes the process of icewine production in Canada, the risks inherent in the endeavor and the potential use of a weather derivatives contract to mitigate the major temperature 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 United States with the first weather derivative security issue taking place in August 1996 between Enron and Florida Power and Light (Geman and Leonardi, 2005). The impetus for growth in these contracts was largely the occurrence of the El Niño winter of 1997–98. The warm weather conditions during the winter season resulted in a significant decline in earnings for many energy companies who then decided to attempt to hedge their seasonal weather risk. The market for energy-related weather derivatives expanded rapidly and in September 1999 the Chicago Mercantile Exchange commenced the operation of 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 energy sector 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 are 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 cities in the United States, a HDD season is typically defined as the winter months from November through 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 due 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 exchange traded instruments such as the degree-day futures and options trading on the CME 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.

Aside from the complexities listed above, a growing number of applications have been developed in the OTC market for a wide variety of industries. In a now seminal application weather derivatives were used to hedge against low wine consumption on cool summer days in London, England by the wine bar chain of Corney & Barrow. The chain found that wine consumption in their wine bars declines when the temperature falls below 24°C during the summer months. In May 2000, Corney & Barrow purchased a derivative contract for the June–September season which involved 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).

Examples of the diversity of other recent applications or contract considerations include hedging against such weather related risks as; losses faced by golf courses due to excessive precipitation (Leggio, 2007), reduced dairy production due to heat stress (Chen et al., 2006), and reduced almond production in California due to temperature variation (Richards et al., 2004). Financial intermediaries such as Evolution Markets and MSI Guaranteed Weather have structured weather contracts for a variety of applications including to hedge against losses associated with delays in construction projects due to weather and low barley quality faced by breweries due to excessive rain.

Icewine production requires relatively low temperatures during the winter season when the grapes employed are harvested in a frozen state. The sensitivity of the harvest to specific temperature levels makes icewine production a good candidate for the application of weather derivatives in hedging production risk. In the following section we provide a description of the process of icewine production in the Niagara region of the province of Ontario, Canada – the largest producing region of icewine in the world and where icewine is a significant contributor to the revenues of most of the approximately 85 wineries in the region.

III. Elements of Icewine Production

Icewine is only produced in a few regions of the world where climate and particularly temperature conditions are appropriate. Although Canada remains a relatively small producer of table wine in terms of total production and retail value, it is the largest producer of icewine worldwide, with the majority of production originating from the Niagara Peninsula in the southern portion of the province of Ontario.

Figure 1 shows a map of the Niagara Peninsula – not a true peninsula but rather a narrow area of land located between the Great Lakes of Ontario and Erie. Due to the presence of these large bodies of water, the micro-climate of the Niagara Peninsula is a relatively unique and mild one compared to the rest of Canada and exhibits conditions favorable to the growing of soft fruit and grapes.

The growth of the Niagara icewine industry has been very rapid given that many wine makers in the area did not produce any substantive volume until 1990 (Schreiner, 2001). In the late 1970's and 1980's the impending 1989 Free Trade Agreement between Canada and the United States, which would ultimately lower trade barriers protecting the Canadian wine industry, resulted in many grape growers and winery owners in the region planting varieties of Vitis vinifera grapes as opposed to the local Vitis labrusca and Vitis riparia varieties. Along with the establishment of a formal appellation system for Canadian wines this strategy resulted in the development of a successful table wine industry in the region. In addition, given the Peninsula's micro-climate the potential for icewine based on the European grape varieties was recognized. Although the total volume of icewine produced is relatively small due to the nature of its production (the juice yield from icewine grape

Figure 1
Niagara Peninsula of Ontario Canada

pressing is only 15 to 20% by volume of what the same grapes would have produced if destined for table wine) the value is increasing substantially as the market for Canadian icewine increases globally. Recently for example, a 750 ml bottle of award winning Niagara region icewine sold for $30,000 CAD (Beech, 2007).

Due to the increasing importance of icewine to Niagara wine producers, adverse weather conditions can result in substantial production and value risk. 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 sub optimal temperatures. Consequently there exists a potential benefit in the use of weather derivatives to hedge against such risks.

The province of Ontario, through the Vintners 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 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 – a measure of sugar content. Production is monitored and the producer must report on production quantity and quality as required by regulation.

Harvesting and production details can differ substantially between wineries depending on the equipment used and quality of product sought but it is generally recognized in the industry that the optimal temperature for harvesting grapes destined for icewine is between –8 and –12°C. At temperatures below −12°C, although resulting in higher brix levels and ultimately sweeter icewine, a greatly reduced quantity of juice derived during the pressing process occurs. 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.

Although a few growers may harvest some of their crop during the first occurrences of temperatures in the –8° to –12°C range, many producers leave the grapes intact with the belief that several "freezings" result in a better quality product. A preference in the industry is for an accumulation of at least 70 hours from the beginning of November during which the temperature is in the range of –8° to –12°C, before the grapes are harvested.

The major risk faced by producers is that a mild winter with relatively high daily temperatures could result in the grapes not being harvested at all or more likely, later in the winter months. Harvesting later in the season after the month of January 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 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.

The risk to icewine producers is similar to that faced by the energy industry during the winter season. Energy firms may employ options written on cumulative HDD over the winter season to hedge against the possibility that a mild winter would result 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 with temperatures between –8°C and –12°C may not reach a critical level over the months of November through January. Thus we consider the modeling and valuation of a put option contingent on a temperature variable reflecting this risk.

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

Identifying a daily temperature variable or combination of variables that can be measured with reasonable certainty by both parties to a weather derivative contract is a critical element of its successful design. Given the process of icewine production outlined in section III, option contracts designed to mitigate the risk of production loss would obviously 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 were between –8 and –12 °C.

For this study we employed temperature data obtained from Environment Canada – the federal government agency that operates a multitude of weather stations nationally. As the primary supplier of weather and temperature data in Canada, it provides a source of objective and unbiased weather data upon which a weather contract may be structured. 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 present in terms of acquiring appropriate temperature data for the Niagara Peninsula.

There are 130 weather stations in the Niagara and neighboring regions for which Environment Canada has recorded weather data, however a surprisingly limited number are of value for the proposed application. Firstly the topography of the Niagara Peninsula exhibits a significant shift in elevation due to the presence of the Niagara Escarpment – an ancient oceanic shoreline south of which the elevation increases significantly. The majority

Figure 2
Location of the Major Wine Producing Area in the Niagara Peninsula

of wineries in the Peninsula are located on a relatively narrow strip of land north of the Escarpment. This area is of lower elevation and, moderated by the prevailing winds of Lake Ontario, provides temperate conditions conducive to viticulture. Only three weather stations, within close proximity to each, are located in the prime wine producing area. Between these three weather stations daily temperature observations were available dating back to 1965. However, only the Vineland weather station recorded temperature data on an hourly basis and only from the year 2002 onward. Figure 2 provides aerial photography of the region showing the location of the Niagara Escarpment, the major wine producing region and the Vineland weather station.

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 production conditions based on observed hourly data. Therefore it is reasonable to assume that greater liquidity in the OTC market would be achieved if the proposed derivative contract was based upon an index derived from daily observed temperature data. The length of daily data, available from 1965 onward, would provide for greater certainty for both parties to the contract in terms of establishing a reasonable estimate of the stochastic process and ultimately the volatility of the contract's underlying variable. Presumably this would increase the probability that the bid and ask differential for such contracts would be minimized.

In Cyr and Kusy (2005) we 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 was below –8°C. Specifically we defined the number of minimum degree days (MDD_i) as:

$MDD_i = \max(0, -8°C - minT_i)$ for each day i, where $minT_i$ is the observed minimum daily temperature for day i.

We also considered the variable $IWDD_i$ 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

$$IWDD_i = \begin{cases} MDD_i & \text{if } 0 \le MDD_i \le 4 \\ 0 & \text{if otherwise} \end{cases}$$

In Cyr and Kusy, (2005 and 2006) we defined daily icewine production hours (IWH_i) as the number of hours in a day for which the temperature was between –8 and –12°C and regressed IWH against both of the variables MDD and IWDD for the months of November through March for the periods of 2002–03 through 2004–05 and later the four year period of 2002–03 through 2005–06. Again it is only over these periods that actual hourly data is available. Unfortunately we found that neither the MDD nor IWDD variable exhibited high explanatory power, in terms of the observed daily icewine production hours. Consequently in Cyr and Kusy (2006) we employed stepwise regression analysis to identify a regression model comprised of daily observable temperature variables and providing significant explanatory power in terms of IWH. Although we tested a multitude of daily temperature variables and their transformations, the results (available from the authors) indicated that 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. Table 1 provides the summary regression results for the model identified as:

$$IWH_i = a_0 + a_1 \, maxT_i + a_2 MDD_i + a_3 IWDD_i \qquad (1)$$

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. The model was confirmed using TOBIT analysis given that the independent variable IWH does not represent a continuous variable satisfying the characteristics of a normal distribution. In particular IWH is truncated or censored taking values only between 0 and 24 hours in a day.

A. *Historical Estimation of Icewine Production Hours*

In the current study, we employ the regression model (1) identified and estimated above over the four year period of 2002–03 through 2005–06, to create a time series of *estimated* 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 2005–06. Figure 3 shows the average of the number of estimated daily icewine production hours for each of the 151 days in the 41 seasons observed, with day 1 assigned to the date of November 1^{st}.

Table 1

Regression Results of Icewine Production Hours (IWH) 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 Results

	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 (a_o)	0.753218	0.17374	4.335328	1.71E-05
maxT (a_1)	–0.09895	0.022494	–4.39888	1.29E-05
MDD (a_2)	0.712034	0.059287	12.00987	7.52E-30
IWDD (a_3)	2.615868	0.164223	15.92875	1.05E-47

Figure 4 provides a graph of the cumulative average estimated icewine production hours over the 151 days of the winter season for the 41 year period. As Figure 4 indicates, on average it is not until January 11th (72nd day of the season) when the cumulative number of estimated icewine production hours exceeds a value of 100.

Given the discussion provided in Section III regarding the risks associated with icewine production we assume producers would be interested in a derivative contract that would allow them to hedge against the possibility of a critical *cumulative* number of icewine production hours not occurring during the November through January months. This is again somewhat analogous to the usage in the energy industry of contracts written on cumulative HDD and CDD over a month or season.

B. *Identification of a Stochastic Process for Cumulative Estimated Icewine Production Hours*

One of the issues to be addressed in identifying a stochastic process for a weather variable that is the result of the accumulation of a daily observed variable over a specific time period, is whether one should attempt to model the behavior of the daily variable

Figure 3
Average Number of Estimated Icewine Production Hours for the 151 days of November through March for the Years 1965–66 through 2005–06

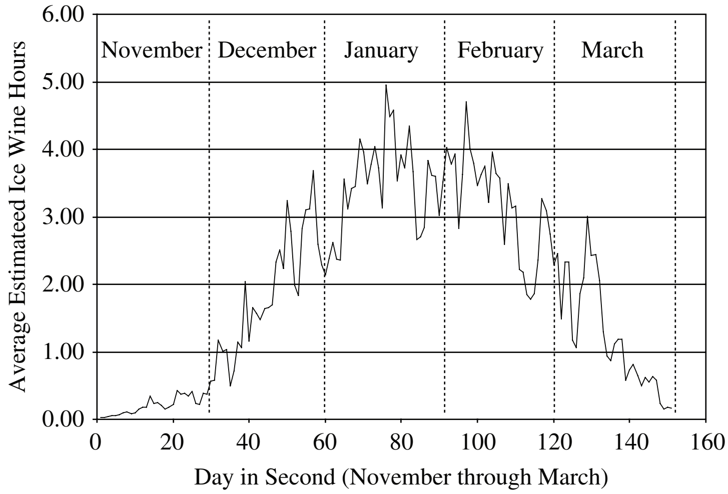
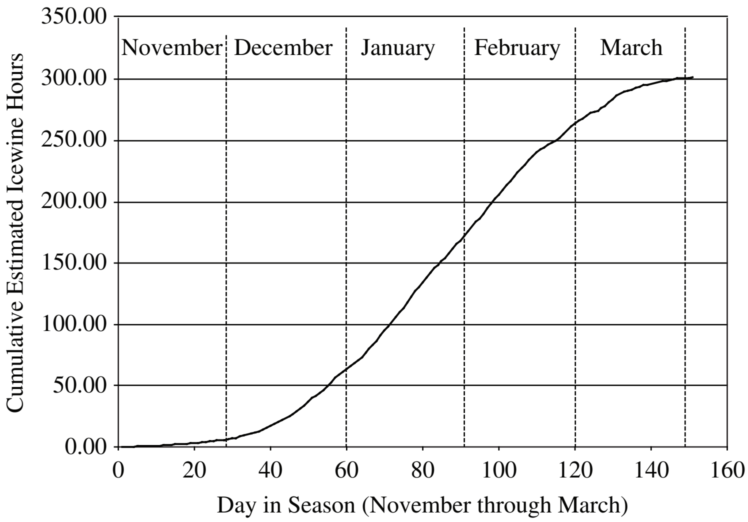


Figure 4
Cumulative Average Estimated Icewine Production Hours for the 151 Days of November through March for the Winter Seasons of 1965–66 through 2005–06.



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 that in the case of options written on cumulative degree days (HDD or CDD), the underlying variable can be specified as either the daily average temperature, the degree days, or thirdly the cumulative degree days over a month or season. 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 the area of Paris-Le-Bourget, Geman and Leonardi recognized a number of advantages in attempting to model the daily average temperature itself including capturing the 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 goal is to explore the valuation of option contracts written on cumulative degree-days, analogous to the current study of cumulative ice wine production hours, then the optimal underlying variable to model is the cumulative measure itself.

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 produces more satisfying results.

We have examined the estimated daily icewine production hours for the months of November through March, however it is the period of November through January which is most critical to icewine producers. Harvesting later than January is known to be associated with significant losses. Consequently we examine the behavior of the time series of 41 observations of the 92-day (November through January) cumulative estimated icewine production hours defined as $\mathrm{CIWH_j}$ where

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

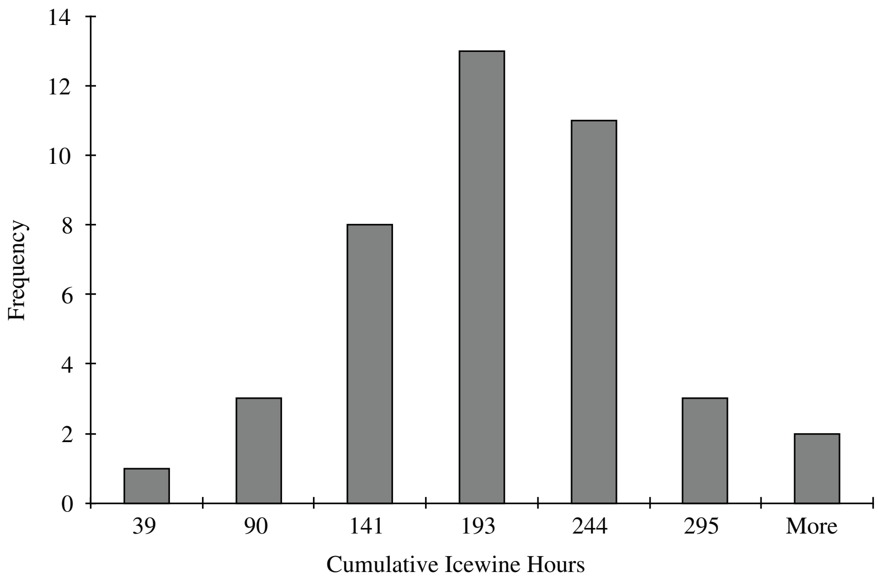
Table 2 shows the basic summary statistics for the 41 observations of CIWH and Figure 5 provides a histogram of the data.

With the goal of identifying a stochastic process for the time series of cumulative icewine hours we used standard time series analysis techniques. Given the possibility of heteroskedasticity, caused by the presence of extreme weather seasons such as those resulting from El Niño, we also employed intervention analysis to simultaneously identify potential outliers that may be present. To carry out the analysis we used the statistical software *Freefore* by Automated Forecasting Systems Inc. This software employs standard time series techniques

Table 2
Summary Statistics of
Cumulative Estimated Icewine Production Hours ($CIWH_j$)
41 observations from November through January

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 5
Histogram of Cumulative Estimated Icewine Production Hours
41 Observations, November through January



to automatically identify and estimate a time series model for the data, while simultaneously identifying any possible outliers or interventions characterized as either a pulse (one observation) or level (mean) shift. Any remaining serial correlation is recognized in terms of ARIMA modeling. The results of the final model estimated for the data using this approach is provided in Table 3 below along with summary statistics of the analysis.

The model identified and estimated, after correcting for the presence of simultaneously identified outliers, is given by:

$$CIWH_j = \mu + e_j$$

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

These results indicates that CIWH follows a Gaussian process where each seasonal observation is independent of the previous one, derived from a normal distribution with a mean value of 168 hours and a standard deviation of 57.64 hours. In particular there was no identifiable trend in the data. These results are consistent with those of Geman and Leonardi (2005) who found that the time series of cumulative CDD and HDD measures in their study were similarly derived from a stationary normal distribution.

Table 3

Summary Statistics from Automated Time Series Identification and Estimation

Identified and Estimated Time Series Model

$$CIWH_t = a + \beta_1 P_1 + \beta_2 P_2 + \varepsilon_t$$

P_1 = intervention variable having a value of 1 for t = 1977, 0 otherwise.
P_2 = intervention variable having a value of 1 for t = 1981, 0 otherwise.

	Coeff.	*S.E.*	*F*	*t*
A	168.00*	8.89	0.0000	18.89
β_1	156.00*	56.20	0.0086	2.77
β_2	179.00*	56.20	0.0029	3.18

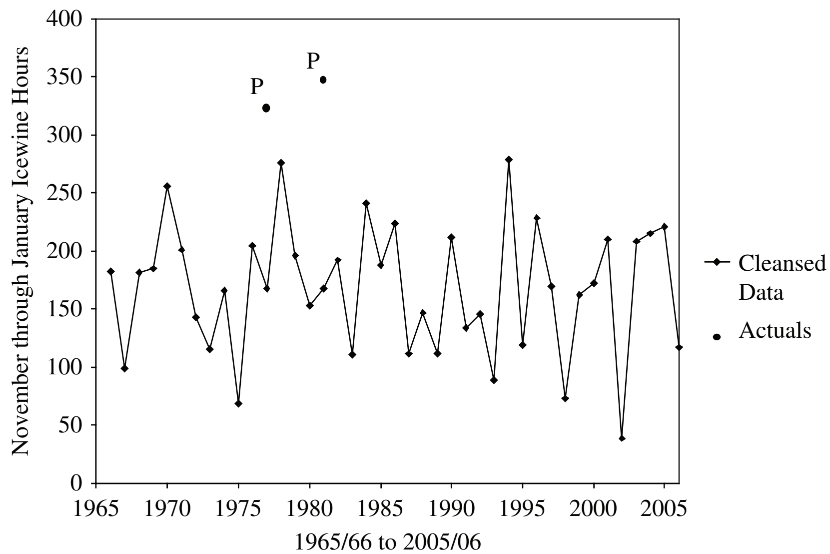
Summary Model Statistics	
Number of Residuals	41
Number of Degrees of Freedom	38
Residual Mean	1.75E-09
Standard Deviation	57.6417
Standard Error of the Mean	9.35072
AIC Value	335.333
SBC Value	340.474
BIC Value	148.356
R Square	0.297609
DW Statistic	2.4268

*Statistically significant at the 0.05 level.

There were however significant outliers in the form of pulse interventions that were identified in the analysis. In particular Figure 6 shows the graph of the CIWH variable for the 41 seasons of 1965–66 through 2005–06 and identifies the statistically significant outlier periods. Contrary to general industry beliefs that abnormal winters are typically mild seasons caused by such factors as El Niño or global warming, the outliers identified are actually associated with extreme cold seasons. In particular the winters of 1976–77 and 1980–81 have estimated icewine production hours of 323 and 346 respectively – almost double the average of 176 hours for the 41 seasons.

It is interesting to consider the historical weather conditions resulting in these two particular seasons being identified as significant outliers in the intervention analysis. The exceptionally cold December of 1976 resulted in neighboring 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. 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. This was 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,

Figure 6
Cumulative Icewine Production Hours (November through January)
1965/66 to 2005/06



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

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 period of study, 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 that of 1976–77, however with a value of –9.8°C it was the second lowest average daily minimum temperature for the months of December and January over the 41-year period.

Figure 6 indicates that aside from the exceptionally cold winters there have been fairly warm seasons measured 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 that in some cases (1997–98) are believed to be caused by the El Niño effect. The warmest season in terms of cumulative 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. They fell within reasonable confidence intervals for the identified model.

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

In addition to the identification of a stochastic process for a fundamental underlying variable the pricing of weather derivatives is the subject of significant debate in the existing literature. 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. The classic Black-Scholes-Merton methodology cannot theoretically be applied.

There are several approaches in the literature to dealing with incomplete markets with one being the introduction of the "market price of risk" for the particular underlying weather variable. The issue then becomes focused on the correlation between temperature and the market index for example. 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 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 determining this market price of risk has resulted in a number of 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 the current study 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, referred to as "burn rate" analysis is frequently employed in the insurance 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 again derive a benchmark option price. We will however carry out the Monte Carlo simulation under varying assumptions with respect to the stochastic process for the underlying variable, given the presence of outliers in the CIWH data.

In light of the discussion outlined in sections III and IV 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 dollar value α (the tick size) per hour below the strike. With a put option, the maximum payout is achieved if there are zero cumulative icewine hours over the three-month period. The payout (X) of the put option at maturity is therefore given as:

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

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

A producer may not always wish to hedge completely against the possibility of the icewine hours falling below the mean of 168 hours, so we will consider the strike values

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

of 170, 150, 130, 110, 90 and 70 hours for the simulation. In actual application the strike and tick size would have to be determined by the producer through an analysis of their operations and the relationship between optimal icewine harvesting hours required in a season for their particular vineyard, and that of the Vineland weather station employed for the option contract.

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.

A. *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 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 disconnected from traditional option pricing and will tend to undervalue options as it will assign a value of zero for options that mature out-of-the-money and will not necessarily incorporate the true volatility of the underlying asset in the pricing. Nonetheless it represents a simple calculation that 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 to arrive at the put option value. Table 5 provides the terminal payoffs of the put option for each of the 41 seasons of 1965–66 through 2005–06 assuming various strike values and the burn rate analysis option values.

Table 5 is interesting from a producer's perspective as it shows the years in which the theoretical put options would have matured in-the-money, under 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

Table 5
Burn Rate Analysis
Historical Terminal Value of Put Options Given Varying Strike Values
1965/66 to 2005/06

	Estimated CIWH	*Terminal Value (Payoff) of Put Option Strike Value (CIWH)*					
Season	*(Nov-Jan)*	*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**

$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 a 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.

B. *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.

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 (λ) is equal to (2/41) = .049 given the identification of 2 outliers among the 41 seasons. In addition, it is assumed that the jump amplitude is normally distributed with a mean (μ_2) of 167.5 hours and standard deviation (σ_2) of 11.5 hours derived from the average of the two identified outlier observations.

Table 6 provides the results of the Monte Carlo simulations for the three sets of assumptions outlined 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

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

	Strike Values					
Diffusion Assumptions	*170*	*150*	*130*	*110*	*90*	*70*
Case 1: Normal ($\mu = 168$, $\sigma = 58$)	\$46,745.77	\$29,323.03	\$17,003.98	\$9,021.80	\$4,315.77	\$1,814.47
Case 2: Normal ($\mu = 176.02$, $\sigma = 67.04$)	\$45,318.70	\$29,505.08	\$18,011.16	\$10,205.04	\$5,284.30	\$2,430.57
Case 3: Mixed Normal and Poission Jump ($\mu = 168$, $\sigma = 58$, $\lambda = .049$ ($\mu_1 = 167.5$, $\sigma_2 = 11.5$)	\$44,473.78	\$27,832.01	\$16,272.41	\$8,680.78	\$4,116.81	\$1,726.19

$\sigma = 58$ hours) the assumptions employed in Case 2 and based upon the unadjusted series ($\mu = 176.02$ hours and $\sigma = 67$ 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.

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 significant value, resulting in lower estimated option premiums in general. This is due to the assumption of positive jump values in the CIWH variable resulting in lower put option values. 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. 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 ice-wine production in the Niagara region of Canada represents a significant potential benefit however, it is fraught with many technical issues similar to those found by other researchers in similar 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.

In this paper we have estimated a time series of icewine production hours over a 41 year period, based upon temperature variables measured on a daily basis. A time series of cumulative icewine production hours for the months of November through January for the 41 seasons was derived season in order to identify a potential stochastic process for an underlying variable to 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 addition, other areas in the world where icewine is produced may face greater risk of adverse temperature conditions than does the Niagara region resulting in a greater benefit from the use of weather derivatives. This will also be true for the Niagara region if global warming begins to have significant impact.

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.

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