

**PRICING WEATHER INSURANCE WITH A RANDOM STRIKE PRICE:  
AN APPLICATION TO THE ONTARIO ICE WINE HARVEST**

by

Calum G. Turvey  
Professor,  
Department of Agricultural Food and Resource Economics  
Rutgers University  
New Brunswick, NJ  
[turvey@aesop.rutgers.edu](mailto:turvey@aesop.rutgers.edu)

and

Alfons Weersink  
Professor  
Dept of Agricultural Economics and Business  
University of Guelph  
Guelph, ON  
[aweersin@uoguelph.ca](mailto:aweersin@uoguelph.ca)

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**Abstract**

Interest is growing in weather insurance within the agricultural sector but its use has been limited by the difficulty in defining the appropriate weather event and the lack of agreement on how to price the product. In this paper we develop a new insurance pricing method for weather insurance under situations where volume returns depend not only on the occurrence of the weather event, but also its timing. The method is applied to the pricing of weather insurance for ice wine in the Niagara Peninsula of southern Ontario. Because the harvest quantity of grapes for ice wine degrades over time, the strike value on the weather event measured as harvestable hours is random. This random strike, we developed a systematic approach to valuing the insurance using first, the single index model to capture inter-temporal covariance effects, and then a Monte Carlo simulation protocol to estimate the premium. While this study investigated a model unique to ice wine production in particular, the ideas can be extended to a number of other agricultural situations in which weather affects critical timing in the production process.

**Introduction**

The use of weather as the basis for writing insurance to protect against volumetric risk and revenue losses in agriculture has received growing attention in recent years by private and public insurance companies (Turvey 2001). Weather insurance can provide an effective risk management strategy for sectors where there is a significant degree of volume uncertainty attributable to weather (Muller and Grandi). For example, energy generating companies have successfully used weather derivatives to hedge against changes in temperature that affect power demand (Dornier and Queruel, D'Arcy) and Leggio and Lien examine the effectiveness of exchange-traded weather derivatives as a means to hedging exposure to increases in the demand for natural gas. The successful adoption of weather derivatives in other industries and the inherent weather risks faced by the agricultural sector explain the growing interest in their applicability for agriculture and agribusiness.

Weather insurance provides several advantages over conventional crop insurance. First, it is technically free from problems of moral hazard endemic to most crop insurance schemes (Rubinstein and Yaari; Horowitz and Lichtenberg; Smith and Goodwin).<sup>1</sup> Indemnities are based upon measured weather outcomes rather than crop yields directly so there are no opportunities, other than manipulating the weather station/recorder directly, to affect the indemnity amount. Therefore, there is complete independence between the production actions of the insured and the weather insurance payoff and, consequently, no requirement for costly monitoring (Turvey, Hoy and Islam). Second, information about weather is unambiguous and symmetric to both the insurer and the insured. Weather insurance is written on the specific conditions at a local weather station or a secured station on-site. Such data can be easily verified and the resulting transparency eliminates asymmetric information and the problem of adverse selection. Third, when one considers the vast influence of weather on agricultural productivity, weather insurance provides a flexibility that is not normally found in conventional crop insurance and, therefore, increases the number of products that can be offered by insurance companies. This is particularly true for agricultural crops, the variability of which can be tied specifically to weather events.

While interest is growing in weather insurance within the agricultural sector, its use has been limited by the difficulty in defining the appropriate weather event and the lack of agreement on how to price the product (Richards, Manfredo and Sanders). The literature on the theoretical pricing of weather derivative products that are traded and priced to equilibrium (i.e. Richards, Manfredo and Sanders; Cao and Wei; Campbell and Diebold; Alaton, Djehiche and Stillberger;

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<sup>1</sup> Coble *et al* find that Kansas wheat farmers engage in moral hazard when weather conditions are not favorable while operating efficiently when weather conditions are favorable.

Turvey 2002; Froot and Posner; and Muller and Grandi) collectively illustrate the complexities of developing equilibrium models with a variety of assumptions regarding the pricing equation, stochastic processes and the market price of risk. The complexities are further indicated within the few applications that tend to focus primarily on heat-based insurance (i.e. Richards, Manfredo and Sanders; Skees *et al.* 2002; and Turvey 2002) or derivative products with rainfall applications (i.e. Mafoua and Turvey; Skees *et al.* 2001; and Turvey 2001). The mere identification of using weather as an economic instrument for risk management gives rise to innovations and challenges that have not previously been considered. Each innovation comes with a new set of complexity, and rather than common models that can be applied to a broad set of risks such as crop insurance, weather insurance will give rise to a multitude of unique problem-specific solutions. This complexity and uniqueness is the subject matter of this paper.

The purpose of this study is to develop a new insurance pricing method for weather insurance under situations where volume returns depend not only on the occurrence of the weather event, but also its timing. The method is applied to the pricing of weather insurance for ice wine in the Niagara Peninsula of southern Ontario. This particular insurance requires defining a new measure of risk based on a freezing-degree hour. Ice wine is a dessert wine that requires unique winter conditions for proper harvesting of the grapes. The grapes can only be picked in their natural frozen state at air temperatures between  $-8^{\circ}\text{C}$  to  $-12^{\circ}\text{C}$ . Since water in the grapes picked at these temperatures remains partially frozen as ice crystals, the resulting juice is sweet and highly acidic. The juice yield from the frozen grapes is significantly less than the normal yield from grapes harvested in the fall but the resulting vintage sells at a premium of more than four times the price of ordinary table wines. If the specific weather conditions are not met during the winter, the grapes are harvested in early spring and sold for either grape juice or

lower grade “late harvest” wine. Thus, if grapes cannot be harvested for ice wine, the wineries and/or grape growers would have been better off to pick the grapes in the fall for conversion into table wine.

The paper begins by outlining the production of ice wine and the weather events necessary for its success and then develops a method to transform weather risk to a harvest hour basis. An expected utility model is developed to illustrate how specific weather risks affects portfolio choices between harvesting grapes for fresh markets or leaving grapes on vines for an uncertain weather-contingent harvest. It then describes a new insurance pricing method that uses Monte Carlo simulations of a single index model that captures the systematic and unsystematic risks of the weather events. Results are then presented to illustrate how weather variability across space and time affects insurance premiums.

The current study differs in scope and modeling from previous studies on the use of weather insurance. First, in looking at ice wine we are not examining crop yield per se, but a harvestable quantity that declines through the winter due to wildlife damage. Thus, the key insurable event is not only total harvestable hours but when they occur, which increases the scope of previous studies that focus on the volume impact of weather alone. The unique characteristic of freezing degree hours and its relationship to harvestable hours with a random ‘strike’ illustrates the application of what is termed an ‘exotic’ product to the tool kit of risk managers in the food industry<sup>2</sup>. To complicate the valuation further, harvestable hours is a

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<sup>2</sup> While terms such as ‘strike’ and ‘exotic’ are usually used in conjunction with financial derivatives, we refrain from regarding the insurance product herein as a derivative. The difference between insurance and derivatives is increasingly being blurred. In the past year for example, the National Association of Insurance Commissioners has made the argument that weather derivatives are simply insurance products in disguise to avoid certain regulatory requirement (NAIC 2003). To this, the Weather Risk Management Association (2004) countered that derivatives are not weather insurance since it is not required that any counterparty has an economic or insurable interest in the subject matter of the contract. Furthermore, for insurance the insured must suffer a loss of a pecuniary nature. With weather derivatives, while loss is highly correlated with weather events, proving an economic loss is not

random variable with uncertainty as to when the appropriate temperatures occur and the total number of hours available. Because of this path dependency, the strike price is random and the premium for the insurance product must be obtained through numerical methods rather than through a closed form solution. Finally, the yield decline throughout the winter season gives rise to increasing opportunity costs. The cost of a lost hour of harvest is more valuable earlier in the winter before yields fall than later and thus economic losses depend on the number of harvest hours obtained prior to that point in the season. This paper illustrates how best-available historical data can be used in conjunction with Monte Carlo methods to estimate insurance premiums for an exotic insurance product.

### **Background on Ice Wine Production**

Bordered by Lake Ontario on the north and the Niagara River on the east, the Niagara Peninsula is the largest viticultural area in Ontario and also in Canada (see Figure 1). Lake Ontario cools the summer air so that grapes do not ripen too quickly, and then keeps the fall air comparatively warm so that the first frost is delayed, thus extending the growing season. Approximately 13,000 acres of wine grapes are grown in this area, and this represents about 80% of Canadian grape-growing volume (VQA Ontario). Increasingly, the region is differentiating itself through the production of ice wine which, outside of Canada, is made in Germany and Austria. From a fledging industry over a decade ago, there are now approximately 70 wineries producing 108 ice wines in the region. The 1.72 million litres of ice wine produced in the 2003-04 season is valued at approximately \$3 billion.

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necessary for receiving a payment. The blur in the context of this paper is that the provider is an insured who would not ordinarily sell a contract to an entity without an economic interest in the weather outcome.

In Canada, the production of ice wine is governed by the Vintners Quality Alliance (VQA). Ice wine must be naturally produced using grapes harvested under temperature conditions that ensure the wine has a Brix (sugar level) of 35 or higher, which is obtained when the air temperature is  $-8^{\circ}\text{C}$  or less. If a vintner is found to be using artificial means to “fast-freeze” the grapes or storing grapes in a cold storage, the VQA will penalize the winery by not allowing the VQA label to go on their products.

Although any variety of grapes can produce ice wine, Riesling and Vidal are the two varieties most often chosen for Canadian ice wine. There tends to be a perceived quality difference and thus a price premium in the export market for Riesling ice wines (Speck). However, the majority of ice wine made in Canada is produced from Vidal grapes because it has a relatively thick-skin that offers better protection against winter damage. Vidal, a cross between European and North American white grape varieties, is the only hybrid grape that VQA allows for ice wine. Both varieties can be used for table wine or ice wine and are managed in the same way during the growing season regardless of their end use. The decision on the volume of grapes in the vineyard to set aside for ice wine is made during the growing season. The area set aside will increase with increases in potential export demand and decrease with the volume of ice wine in stock and the severity of the previous winter (Speck).

Once the fall harvest is complete, the grapes left on the vine for potential use in ice wine must be protected against weather and wildlife damage. The longer the grapes remain on the vine, the greater chance they will fall to the ground and be lost or eaten by animals. The vines are netted to help secure grape clusters on the vine and to prevent animals tempted by the high sugar-content grapes, particularly birds, from eating the crop.

Winter harvest of grapes for ice wine is constrained to moments when the air temperature is between  $-8^{\circ}\text{C}$  to  $-12^{\circ}\text{C}$ . At a temperature less than  $-8^{\circ}\text{C}$ , the water crystallizes out of the grapes leaving behind the high concentration of sugars, fruit acids and extracts needed to produce the distinct flavors of ice wines. However, if the temperature drops below  $-12^{\circ}\text{C}$ , the press will be slowed and the quantity of concentrated juice from the frozen grapes will decrease dramatically. The only weather condition required for a successful harvest is the amount of time between the desired temperature band. Other climatic factors such as humidity or wind speed do not affect the quality of the harvested grape.

Warm winter temperatures can significantly limit the winter grape harvest and subsequently the volume of ice wine produced. For example, approximately 60% of Ontario grapes set aside for ice wine were diverted to late harvest wines in 2001 due to insufficient harvest hour temperatures. In addition to the lost opportunity costs of selling the harvested juice in the form of cheaper late vintage table wine or grape juice rather than ice wine, an additional loss is the increased vulnerability of the vines to winter damage. Leaving grapes on the vines after they would normally be harvested does not allow the vines to store extra sugars to help sustain them through harsh winters (Fischer).

The risk of warm winter weather is increasingly borne by the wineries rather than the grape grower. Wineries that do not grow their own grapes, generally contract directly with growers in the summer. Growers are paid 125% of the August price for grapes established by negotiations between the vintners and the Ontario Grape Marketing Board. The volume on which this price is paid is estimated by sampling during the fall harvest. The wine maker pays this pre-determined amount by November 15<sup>th</sup> to the grape grower to ensure the rights to the grapes left on the vine for potential winter harvest. Remaining costs are negotiated on an



individual basis. These costs include netting the grapes which ranges between \$200 to \$300 per acre. Harvest costs are also negotiated.

While most of the juice used for ice wine is from grapes harvested by the vintners in conjunction with the growers, there is a small market for the juice concentrate. Some growers will press their harvested frozen grapes and sell the juice. Current prices are \$15 to \$20 per liter for juice from Vidal grapes, and \$23 to \$32 per liter for Reisling juice (Green, Hope). The price of concentrated juice increases with the Brix degree. There is also a market for late harvest juice, which currently sells for about \$4 per liter. However, the market is thin for ice wine juice as most vintners have contracted directly with growers to ensure a sufficient quantity and quality of juice.

Growers and wineries have taken several approaches to reduce the risk of warm winter weather. Many wineries will contract out harvest with several different farmers in different locations within the Niagara Peninsula region. This diversification strategy increases the likelihood that acceptable harvest conditions will be met in at least one region within the Peninsula, which has many micro-climates. In other cases, the wineries have switched to mechanical harvesting to reduce the total number of harvest hours required. Regardless, weather uncertainty remains the major contributor to revenue risk for ice wine vintners and there are presently no risk management strategies available.

### **Effect of Weather Insurance on Production**

One of the critical economic decisions that ice wine producers must make is how much of a crop should be left on the vines to produce harvest or ice-wine, rather than harvested for table wine. Let  $x$  define the percent of grapes to be harvested for ice-wine in the winter and  $1 - x$  as

the percentage harvested for table wine in the fall. In the absence of insurance,  $\pi_i$  are the anticipated profits from ice wine, with variance  $\sigma_i^2$ , and  $\pi_t$  is the expected profits from table wine with variance  $\sigma_t^2$ . Furthermore, let  $\sigma_i^2 - \sigma_t^2 = \Psi(\phi, T) > 0$  so that the spread between the variance of ice and table wine is dictated solely by the existence of the freezing degree-day weather event ( $\phi$ ) and when it occurs ( $T$ ). It is understood that  $\Psi'(\phi) \leq 0$  and  $\Psi'(T) > 0$ . In other words, the spread in variance falls with more ideal weather conditions, but rises with delays in occurrence.

The choice framework is summarized by the following expected utility function,

$$(1) \quad U(\pi) = x\pi_i + (1-x)\pi_t - \frac{\lambda}{2}(x^2\sigma_i^2 + (1-x)^2\sigma_t^2 + 2x(1-x)\sigma_{ii})$$

where  $\lambda$  is the coefficient of absolute risk aversion and  $\sigma_{ii}$  the covariance between the profit streams of the two enterprises. Expected utility is maximized when the proportion of grapes to be kept for ice wine is

$$(2) \quad x^* = \frac{\pi_i - \pi_t + \lambda(\sigma_t - \sigma_{ii})}{\lambda(\sigma_i^2 + \sigma_t^2 - 2\sigma_{ii})}$$

Taking derivatives of the optimal proportion harvested reveals the standard stochastic dominance arguments that the area harvested for ice wine increases with a rise in expected profits of ice wine holding risk constant ( $\partial x / \partial \pi_i > 0$ ), and decreases with an increase in the variability holding expected profits constant ( $\partial x / \partial \sigma_i^2 < 0$ ). If increases in expected profits come at the expense of increased risk, then the area of grapes collected for ice wine will fall as long as

$\partial \sigma_{ii} / \partial \sigma_i^2 < 1/2$ , which will always be true.

The existence of a general contingent claim on the weather event  $\phi(T)$  can influence the management choices of the vintner. For simplicity, define  $\pi_i(\phi, 0) = 0$  when the weather event does not occur and  $\pi_i(\phi, 1) = \pi_{\max}$  when conditions are ideal (i.e. sufficient number of cold days).

We can then state that  $\pi_i(\phi, T) \in [0, \pi_{\max}]$  and that

$$(3) \quad E[\pi_i(\phi, T)] = \int_0^{\pi_{\max}} \pi_i(\phi, T) g(\phi, T) d\phi(T)$$

where  $g(\phi, T)$  is the joint event-time distribution for  $\phi$ . We assume that the insured understands the relationship between the number of cold harvest hours and returns from ice wine production, and that there is a profit floor,  $\pi_f$ , from which the associated weather event,  $\phi_f = \pi_i^{-1}(\pi_f, T)$  can be determined. With  $\pi_f$  and  $\phi_f$  known, an indemnity function can be constructed,

$\omega_f = \omega_f(\pi_f, \phi_f, T)$ . The fair premium to insure the profit floor ( $\nu_f$ ) can be calculated using

$$(4) \quad \nu_f = \int_a^b \omega_f(\pi_f, \phi_f, T) g(\phi, T) d\phi(T)$$

Profits with insurance are thus given by

$$(5) \quad \hat{\pi}_i = \pi(\phi, T) + \omega(\pi, \phi, T) - \nu_f$$

which is designed so that  $\hat{\pi}_i = \text{Max}(\pi_i(\phi, T), \pi_f) - \nu_f$  and  $E[\hat{\pi}_i] = E[\pi(\phi, T)]$  with variance

$\sigma_{if}^2 = E[\text{Max}(\phi, T, \pi_f) - E(\hat{\pi}_i)]^2$ . By design  $\sigma_{if}^2$  is truncated from below with probabilities

stacked at  $\pi_f$ . It will be true that  $\sigma_i^2 > \sigma_{if}^2$  and if  $\nu_f$  is actuarially fair (i.e.  $E[\hat{\pi}_i] = E[\pi(\phi, T)]$ ),

then it is self evident that by  $\partial x / \partial \sigma_i^2$ , the use of weather insurance will lead to an increase in planned ice wine production.

## Pricing Weather Insurance

### *Conventional Pricing of Weather Insurance*

The actuarially fair premium for weather insurance should equal the expected “loss” or “cost” incurred by the buyer if the undesirable weather event occurs. For this premium, the buyer minimizes exposure to adverse weather risk while retaining the ability to capitalize fully on advantageous weather conditions. The price of an insurance contract on weather for ice wine ( $V$ ) can be expressed generally as:

$$(6) \quad V = \theta \int^Z (Z - H) f(H) dH \text{ for } H < Z$$

where:  $\theta$  – is the opportunity cost per hour if grapes are not harvested for ice wine;

$Z$  – is the strike point or number of harvest hours required by the winery;

$H$  – is the actual number of harvest hours during the winter harvest season; and

$f(H)$  – is the probability distribution function of the number of hours of winter temperature between  $-8^{\circ}\text{C}$  and  $-12^{\circ}\text{C}$ .

The insurance contract provides an indemnity if the actual number of harvest hours ( $H$ ) is less than the amount needed ( $Z$ ). Note that the price of the policy depends on the specific weather event to be insured ( $H$ ), the likelihood of the event ( $f(H)$ ), and the payout ( $\theta$ ) if the actual hours are less than the harvest hours required by the winery ( $Z$ ). For example, assume the weather contract stipulates a payout if cumulative harvest hours are less than 40 hours ( $Z=40$ ) between December 1 and March 15 with a payoff of \$5,000/hour below the strike ( $\theta$ ). If the actual number of harvest hours were 38 ( $H=38$ ), the purchaser of the insurance contract would receive \$10,000 ( $\theta*(Z-H)=\$5,000/\text{hour}*(40\text{hrs}-38\text{hrs})$ ).

### *Pricing of Weather Insurance with a Random Strike Price*

Estimation of the premium for an ice wine weather product is more complicated than the general formula given by equation (6). The major complication arises in the loss of potential yield through the season due (primarily) to wildlife. If the quality of the harvest degrades over time, then so too must  $\theta$  in equation (6). For example, obtaining the strike point (i.e. 40 harvestable hours) may still result in a loss if the desired temperatures occurred late in the season and total harvestable grapes had declined. In our analysis, we determine losses by month,  $\theta_t$  where  $t =$  December, January, February and March. Since the losses vary by month, then the losses attributable to each month are conditioned on the number of harvest hours in the previous month(s). Thus, the strike price is random and the premium for the insurance product cannot be estimated through a simple closed form solution. A numerical approach is ultimately required.

The operational model for this particular weather insurance product is described by the indemnity function

$$(7) \quad V = \sum_{i=1}^4 \theta_i \text{Max}(Z_i - h_i, 0)$$

where  $i = 1, 2, 3, 4$  for the consecutive months of December through March;  $\theta_i$  is the marginal loss for month  $i$  with  $\theta_i \geq \theta_{i-1}$ ;  $h_i$  is the number of harvestable hours in month  $i$  ( $H = \sum_i h_i$ ) and  $Z_i$  is the strike or coverage level. An important aspect, and complication of this model, is that  $Z_i$  is a random variable that is conditional on the accumulation of hours in previous months. More specifically, if  $Z_0$  represents the total number of harvest hours required in a season, then

$$(8a) \quad Z_1 = Z_0$$

$$(8b) \quad Z_2 = Z_1 - h_1$$

$$(8c) \quad Z_3 = Z_2 - h_2$$

$$(8d) \quad Z_4 = Z_3 - h_3$$

For example, if  $Z_0 = 40$  hours and by chance there were no conditions with temperatures between  $-8^\circ\text{C}$  and  $-12^\circ\text{C}$  in December ( $h_1 = 0$ ), then there is a pay out for December associated with the yield decline in that month ( $40 \cdot \theta_1$ ) and the number of required harvest hours remaining in January is 40 ( $Z_2 = Z_1 - h_1 = 40 - 0$ ). On the other hand, if  $h_1 = 30$ , then the payment for December would be  $10 \cdot \theta_1$  and the new coverage for January would be 10 ( $Z_2 = 40 - 30$ ).

Because both the trigger and the hours in January, February and March are dependent respectively on the accumulation of harvestable hours in December, January, and February, the distributions for  $h_i$  must be jointly distributed. In simulation we use a single index model (see Sharpe 1963) to capture the monthly covariance. Defining  $\bar{h}$  as the average number of monthly harvest hours in a given year ( $\bar{h} = 0.25 \sum_i h_i$ ) and  $\bar{\bar{h}}$  as the average of  $\bar{h}$  across all years, we can write

$$(9) \quad \bar{\bar{h}} = \int \bar{h} f(\bar{h}) d\bar{h} .$$

In addition, we express harvestable hours for each month as a function of the single index  $\bar{h}$ .

$$(10) \quad h_i = h_i(\bar{h}), \quad i = 1, 2, 3, 4$$

The expected value of  $V$ , in (7) can now be written as

$$(11) \quad \bar{V} = \int \left[ \sum_{i=1}^4 \theta_i \text{Max}(Z_i - h_i(\bar{h}), 0) \right] f(\bar{h}) d\bar{h}$$

The model is operationalized by defining a linear functional form for (11) and estimating the parameters using the historical data described in section V. Ignoring time subscripts, we define the single index model as

$$(12) \quad h_i = \alpha_i + \beta_i \bar{h} + \varepsilon_i \quad \forall i = 1, 2, 3, 4$$

The single index model has the following properties. First, the sum of the intercepts is equal to zero ( $\sum_i^4 \alpha_i = 0$ ). Second, the sum of the slope coefficients is equal to 4 ( $\sum_i^4 \beta_i = 4$ ) so on average  $\beta=1$ . Third, the variance of harvest hours in month  $i$  ( $\sigma_{h_i}^2$ ) is

$$(13) \quad \sigma_{h_i}^2 = E[h_i - \bar{h}_i]^2 = \beta_i^2 \sigma_{\bar{h}}^2 + \sigma_{\varepsilon_i}^2.$$

Fourth, the covariance in harvest hours between months  $i$  and  $j$  is given by:

$$(14) \quad \text{cov}(h_i, h_j) = E[h_i - \bar{h}_i][h_j - \bar{h}_j] = \beta_i \beta_j \sigma_{\bar{h}}^2$$

Semantically, we can view the average number of monthly harvest hours as a portfolio of the four months distributions and their covariance. Thus

$$(15) \quad \sigma_{\bar{h}}^2 = \sum_{i=1}^4 \sum_{j=1}^4 \beta_i \beta_j \sigma_{\bar{h}}^2 + \sum_{i=1}^4 \sigma_{\varepsilon_i}^2.$$

The variance surrounding monthly harvest hours (equation 8) consists of two components. The first component given by  $\beta_i^2 \sigma_{\bar{h}}^2$  represents the systematic risk, or risk in  $h_i$  that is correlated with the seasonal average. The second component,  $\sigma_{\varepsilon_i}^2$  is the specific or non-systematic risk that is not correlated with the average. Equation (13) allows for common seasonal patterns in monthly harvest hours, as well as independent or idiosyncratic shocks.

The distribution of average monthly harvest hours ( $\bar{h}$ ) through the estimated single index model (equation 12) sufficiently captures the systematic and covariate risks as shown by equation (15). For example, a cold December and the resulting high number of harvest hours are more likely to be followed up by a cold January. Exact covariances can be estimate with knowledge of the single index parameters  $\beta_i$  and  $\varepsilon_i$ . Consequently, we can generate the complete distribution of  $V$  in (11) using the distributions for  $f(\bar{h})$ , and the four distributions for

$\varepsilon_i \sim N(0, \sigma_{\varepsilon_i}^2)$ . As discussed in the background section, areas throughout the Niagara Peninsula differ in microclimates and therefore the distributions for  $f(\bar{h})$  should be expected to differ in their moments, including skewness and higher moments. To capture differences in the distribution of probabilities due to microclimate, the probability distribution functions of harvestable hours for each location was estimated using Palisade Corporations' BestFit computer program. Estimation of (12) does not require normality in the distribution of  $\bar{h}$ , but  $\varepsilon_i$  will still be normally distributed. Regression estimates of the single index model by location are presented in Appendix 1.

### *Numerical Example of Pricing*

To illustrate how the new insurance pricing method is implemented, we provide a step by step example of the procedure using the Beamsville location. With @Risk as the Monte Carlo simulator, the initial step is to draw a value for average monthly harvest hours ( $\bar{h}_j$ ) from its best-fit probability distribution. The distribution of  $\bar{h}$  for Beamsville follows a logistic distribution with a mean of 48.8 hours and a standard deviation of 10.45. Suppose that an initial value for the seasonal average hours per month of 48.08 hours ( $\bar{h}_1$ ) was randomly drawn. Given this value on the average monthly number of hours available throughout the total harvest period, the predicted harvest hours for each month can then be calculated using the Single Index Model. Expected December hours, for example, would be 44.30 found by plugging  $\bar{h}_1$  into the single index regression estimates for Beamsville given in Appendix 1 ( $44.3 = -8.11 + 1.09(48.08)$ ). This represents the systematic component of harvest hour risk. The non-systematic component is



obtained by adding a random draw from a zero-mean normal probability distribution with  $\sigma_{\varepsilon_1}$  of 28.17 for Beamsville. For this example iteration, the value drawn was -17.6 hours, which results in a predicted value of 26.7 hours (44.3-17.6) for the month of December. Using the same process, the predicted monthly harvest hours was 85.91 hours for January, 62.85 hours for February and 12.92 hours for March.

Assuming the value of the harvest is \$10,000 and 250 harvest hours are required, the value per harvest hour is \$40 (\$10,000/250 hours). Given that 26.7 hours of harvest occurred in December, there are 223.3 hours remaining ( $Z_2 = Z_1 - h_1 = 250 - 26.7$ ). The cost to the producer of not being able to harvest the complete crop in December depends on the assumed yield loss. Suppose that grapes not harvested in December incur a 10% loss in yield. Since the value of the unharvested crop at the end of December is \$8,931 (\$40/hr\*223.3 hrs), the 10% fall in harvest quantity implies that the losses from not harvesting in December are \$893.

The losses in successive months are calculated in the same manner. For example, given 85.9 hours of temperatures within the suitable range predicted for January, there would be 137.37 hours required to finish the harvest ( $Z_3 = Z_2 - h_2 = 223.27 - 85.9 = 137.37$ ). Assuming there is a degradation in yield of 20%, the value of the yield loss for January ( $Loss_{Jan,1}$ ) is \$1,099 ( $= .20 * 137.37 \text{ hrs} * \$40/\text{hr}$ ). In February, 62.85 harvest hours occur leaving 74.52 hours remaining. At a 30% degradation the loss is \$894. Finally, in this simulation example 74.5 harvest hours remain going into March but only 12.9 harvest hours occur, leaving 61.6 hours of harvested grapes abandoned for a loss of \$986. The cumulative weather-based loss in the example is \$3,872 ( $= 893 \text{ (Dec)} + 1099 \text{ (Jan)} + 894 \text{ (Feb)} + 986 \text{ (March)}$ ). That is, of an initial expected value of \$10,000 had the crop been harvested in December, degradation due to the lack

of cold temperatures reduced the value to only \$6,128. The simulation process is then repeated 5,000 times so that an average loss (or premium price) can be calculated.

A simple variant of this model is to assume that there is no degradation over time. Consequently, losses depend only on the occurrence of the event and not its timing. For the above example, 188.4 harvest hours were available in the whole season out of the necessary 250 hours. Thus, the losses not accounting for timing of the harvestable hours would have been \$2,464 (61.6 hours \* \$40/hour) as opposed to the \$3,872 cost that does account for yield loss through the season.

## **Weather Data**

The source of meteorological data used in this study is the Ontario Weather Network (OWN). In addition to collecting data from its own weather stations, OWN warehouses meteorological data from co-operating weather networks and government sources such as Environment Canada. OWN can provide custom analysis of this weather data but has also developed a number of weather-based decision models for use within agriculture.<sup>3</sup>

OWN provided data for this study on hourly temperatures since December 1995 through March 2003 for 13 locations in the Niagara Peninsula Region. The specific weather event of concern to ice wine makers is temperature between -8°C and -12°C. However, harvest is generally not done during daylight hours so harvest hours between 10 am and 8 pm are excluded resulting in a maximum of 15 harvest hours per day. The total number of hours within this temperature band for a harvest season is summarized in Table 1 for the 13 locations from the OWN data set.

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<sup>3</sup> Further information on the Ontario Weather Network can be obtained from their website [www.ownweb.ca](http://www.ownweb.ca).

The average harvestable hours over the eight harvest seasons was 171 hours across the 13 locations. However, there are statistically significant differences in the average across both locations and years. The F-stat value from the Two-Way ANOVA testing for differences in means across locations was 5.42 versus the critical F-value of 1.91. On average, the greatest numbers of harvest hours occur in the Grimsby region with the fewest in the Lakeshore region and at Niagara College. Locations further up the escarpment had more hours relative to neighboring sites down the escarpment and closer to Lake Ontario (i.e. Vineland Escarpment (165 hours) vs. Vineland Cherry Ave (156 hours)).

The differences in average harvest hours are greater between years than between locations. While there is a range in mean values of approximately 47 hours between the locations with the most and least average harvest hours (Grimsby and Lakeshore), the average harvest hours across seasons ranges from a high of 282 hours in 1995-95 to a low of 61 hours in 1997-98. The observed value of F is 263.14 from the Two-Way ANOVA and is significantly different from the critical F-value of 2.13 which implies the null hypothesis that the mean acceptable harvest hours is the same across the 8 observed years should be rejected.

## **Results**

The actuarial pricing of ice wine insurance is based upon the number of hours required, the likelihood that the harvestable hours will become available, the sequence in which the hours become available, and the opportunity costs of lost or delayed harvest. This section summarizes the Monte Carlo results of our analysis by examining the sensitivity of the premiums to changes in each of the variables.

This first simulation examines how the premiums respond to changes in the number of hours required. Each of the 12 locations represent different probabilities for harvest hours, so the analysis examines the issue in two dimensions. The assumption is that the harvest quantity decays by 10% in each month and any crop remaining in the field in March is lost. The premiums presented assume the value of harvest is \$10,000. The average value of icewine production across all 70 wineries in the regions is approximately \$30 million but there are significant differences in size as the market is dominated by several large wineries. A typical vintner may have sales in the \$1 million range so the premiums for a weather contract should be multiplied by 100. On an hourly basis a \$10,000 value assigns \$400/hour for a 25 hour harvest and \$100/hour for 100 hour harvest. The values also assume initially that there is a maximum of 15 harvest hours per day and that there is no monthly yield loss until March 15 when any remaining grapes are left on the vine.<sup>4</sup> Most vintners confine their harvest to the non-daylight hours so that the skin of the grape does not thaw in the sun despite the cool temperatures, which implies a maximum of 15 hours per day for harvest.

The estimated premiums (or average losses to winery) are presented in Table 2 for the 12 locations. Premiums increase at an increasing rate with the number of harvest hours required. For example, the premium to ensure at least 50 hours of temperatures between -8 and -12 is \$122.53 in Beamsville and this premium increases to \$371.28 if required hours ( $Z$ ) rise to 100 hours. As  $Z$  rises, the need for a colder winter increases and thus so does the likelihood of losses.

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<sup>4</sup> Another restriction for some vintners is that their labor crew can only pick for a maximum of 8 hours per day. Premiums are inversely related to the amount of time available in a day to harvest. Less time in a day to harvest means that there will be times during the winter when the temperature is appropriate to harvest but picking cannot occur because the daily time limit on picking has been reached. Thus, the likelihood of insufficient harvest time increases, as does the probability of loss. Premiums under the different labor hours per day assumption are available from the authors upon request.

An important observation is that premiums are not only affected by the number of required harvest hours but also by the location of the winery (see Table 2). The premium for Grimsby would be \$70.26 per \$10,000 of loss but this would rise to \$555.38 for a winery in the Lakeshore region. The differences reflect the differences in micro-climates within the Niagara Peninsula region. Locations with cooler climates and greater likelihood of temperatures between  $-8^{\circ}\text{C}$  and  $-12^{\circ}\text{C}$  have lower premiums than the locations with warmer climates by Lake Ontario. From Table 1, Grimsby has an average 194.63 harvest hours with a standard deviation of 64.06 hours, while Lakeshore has a lower average of 152 harvest hours with a much wider standard deviation of 94.45 hours. These results strongly suggest that the feasibility of a weather insurance product requires dealing with a significant basis risk. Without acknowledging the existence of the micro-climates and measuring weather data at alternative sites, adverse selection problems will confront the insurer.

The premiums presented in Table 2 assume a simple 10% decline in harvestable yield until March 15<sup>th</sup> when any available grapes left on the vine cannot be harvested. However, damages can reduce yield through the season in variable amounts and the effects of the decline in alternative yield loss assumptions are listed in Table 3. The premiums required increase significantly with monthly yield loss. For example, at a Beamsville location and with 100 harvestable hours required, the premium is \$371.28 with no monthly yield loss through the winter. This premium provides only a payout from losses of unharvested crop in March and would be reflective of an insurance product that only accounts for if adequate harvest hours had occurred and not when they happened. If there is a constant 10% decline in unharvested crops in December, January and February the premium rises to \$984.91 and to \$1,905.36 if there is a 25% monthly reduction in grape yield. The 10%, 20%, 30% loss row illustrates, perhaps more

reasonably, that losses increase by month, with a small loss in January and increasing through March. The relative difference between premiums under different yield loss assumptions is directly related to the number of harvest hours required. The higher the number of harvest hours required, the higher the premiums.

Estimated premiums (or expected losses) are decomposed into the monthly estimates in Table 4 for the Beamsville site. If required harvest hours over the season are low, most losses are due to not being able to harvest the full crop in the month of December before there is a decline in harvestable quantity. For example, approximately 72% of the \$250 premium for a vintner insuring for at least 25 hours of harvest time is due to the reduction in grape volume by not getting the crop off by the end of December. In contrast, most of the premiums for a contract requiring a high number of harvest hours is associated with having to leave some of the crop in the field at the end of the winter. For example, 45% of the approximately \$2,500 expected loss associated with a 200 harvest hour requirement is due to the complete yield loss at the end of the season whereas it is only 15% (\$38) of the \$250 premium for a 25 hour harvest requirement. The decomposition again illustrates the effect of when the weather event occurs (and not only if it occurs) on the expected loss or premium

## **Summary**

The greatest risk faced by ice wine vintners is insufficient winter hours between  $-8^{\circ}\text{C}$  to  $-12^{\circ}\text{C}$  necessary for harvesting the grapes. To mitigate this risk, this paper developed an exotic approach to insuring unharvested hours. The key features of the model presented are that: a) the probability distribution of harvestable hours is not constant across time, and b) when the harvest quality degrades over time, the strike value, measured in harvestable hours, becomes random.

Because of this random strike, we developed a systematic approach to valuing the insurance using first, the single index model to capture inter-temporal covariance effects, and then a Monte Carlo simulation protocol to estimate the premium. While this study investigated a model unique to ice wine production in particular, the ideas can be extended to a number of other agricultural situations in which weather affects critical timing in the production process. An example would be the harvest of vegetables and tender fruit for which the quantity and quality of product depend not only on the length of harvest period but also when the harvest occurs.

Applying the model to twelve different locations in the Niagara Peninsula showed clearly that different microclimates require flexibility in product design, and a one-product-fits-all philosophy will not work. The variation in premiums across locations suggests the existence of significant basis risk that will require the use of weather stations located in sites reflective of the local situation of the insured. Furthermore, in discussions with the vintners and other wine specialists, it is also clear that any product has to be adaptable to the specific requirements of the vintner. For example, the insurable risks of a vintner with machine harvesting capabilities will surely be different than one with manual harvesting capabilities.

As indicated in the introduction, designing weather insurance to manage agricultural risks will require unique solutions. This paper illustrated how unique these designs can be. While previous research has examined continuous data for a specific coverage level (or strike price), this paper illustrated how exotic insurance products can be designed when the coverage level changes over time depending on whether specific weather events do or do not occur. We have shown how historical probabilities, inter-temporal correlations, and inter-temporal degradation could be combined into a single Monte Carlo simulation framework to set the premiums for a product with a random strike price.

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Department of Agricultural Economics and Business, University of Guelph

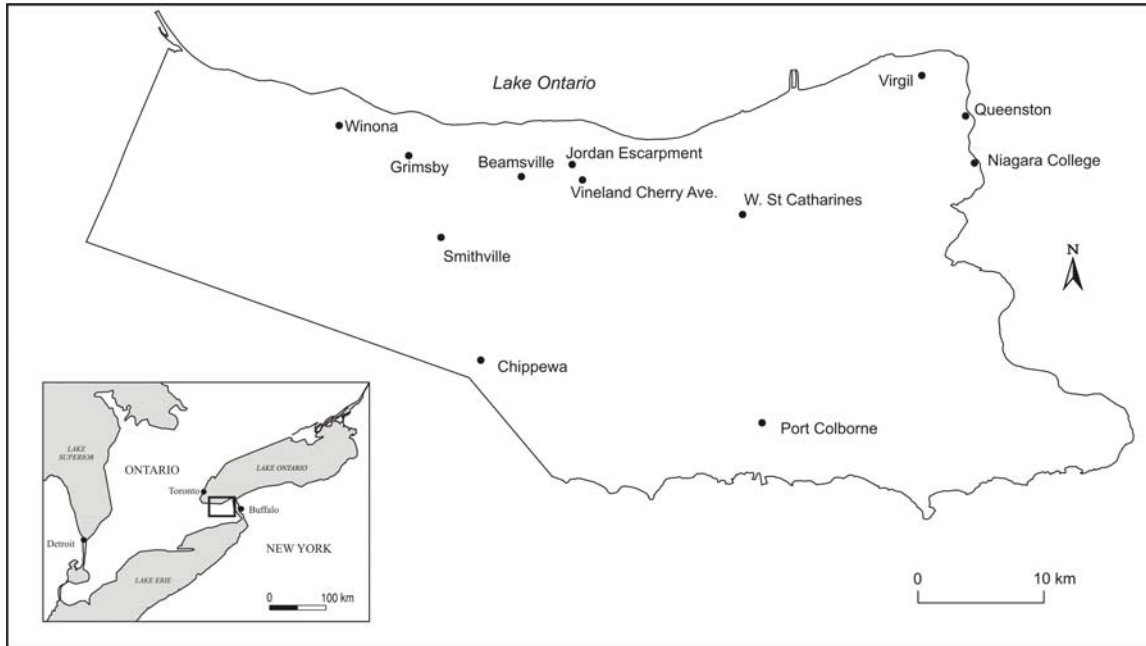
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**Figure 1. Location of Sites in the Niagara Peninsula Region of Ontario**



**Table 1. Total Harvest Hours\* by Season and Location**

Location	Harvest Season								Avg (Std Dev)
	95-96**	96-97	97-98	98-99	99-00	00-10	01-02	02-03	
Beamsville	312	223	82	182	187	237	88	223	191.75 (76.89)
Grimsby	279	216	122	173	161	250	105	251	194.63 (64.06)
Jordan Escarpment	297	214	90	170	168	243	96	226	188.00 (71.53)
Jordan Highway 8	308	198	64	158	176	192	62	201	169.88 (79.60)
Lakeshore	323	172	28	157	137	150	36	213	152.00 (94.45)
Niagara College	NA	NA	NA	NA	NA	202	44	197	147.67 (89.81)
Niagara Parkway	319	184	29	171	153	148	39	207	156.25 (92.64)
Queenston	303	190	50	167	138	185	37	199	158.63 (85.56)
Vineland Cherry Ave	320	209	68	183	166	199	42	215	175.25 (87.54)
Vineland Escarpment	308	219	70	166	168	220	82	215	181.00 (78.16)
Virgil	301	198	35	192	159	177	49	201	164.00 (86.30)
West St Catherines	308	212	82	152	170	212	77	194	175.88 (75.20)
Winona	289	216	77	191	160	204	62	188	173.38 (74.18)
<b>Average (Std Dev)</b>	282.08 (85.65)	188.54 (58.64)	61.31 (32.23)	158.62 (49.27)	149.46 (46.97)	201.46 (31.99)	63.00 (24.18)	210.00 (16.75)	171.41

\*- Harvest hours is the total number of hours in the harvest season between -8 and -12 Celsius but not including those between 10 am and 8 pm (daylight hours).

\*\* - The harvest season from December 1995 to March 1996 refers to the 1995 harvest season

**Table 2. Estimated Premiums by Location (Max. of 15 harvest hours per day)**

Loss of \$10,000 with no yield loss for each month								
Target Harvest Hours								
Location	25	50	75	100	125	150	175	200
Beamsville	54.43	122.53	222.94	371.28	581.89	853.04	1198.83	1612.04
Grimsby	24.78	70.26	153.98	289.68	493.51	759.29	1104.86	1527.34
Jordan Escarpment	45.66	109.36	207.56	366.46	591.09	881.91	1254.30	1694.74
Jordan Highway 8	104.48	208.59	364.55	593.51	889.96	1268.47	1719.52	2214.95
Lakeshore	328.27	555.38	839.14	1172.60	1577.04	2030.64	2523.22	3026.58
Niagara Parkway	271.18	466.78	727.70	1034.82	1409.78	1842.33	2318.31	2812.99
Queenston	204.15	375.42	606.89	899.78	1255.70	1681.57	2159.42	2660.88
Vineland Cherry Ave	144.19	257.78	416.81	637.18	913.61	1258.97	1668.58	2124.73
Vineland Escarpment	89.79	180.50	316.48	509.30	765.97	1088.12	1485.77	1939.11
Virgil	163.31	304.34	497.92	756.32	1070.34	1459.63	1908.08	2391.10
West St Catherines	80.36	171.53	315.33	527.78	806.00	1165.68	1604.03	2090.71
Winona	78.78	167.68	307.19	510.21	779.67	1126.79	1556.60	2037.90

**Table 3. Estimated Premiums by Location under Alternative Monthly Yield Losses**

Location	Yield Loss Assumption	Harvest Hours					
		25	50	75	100	125	150
Beamsville	No yield loss	54.43	122.53	222.94	371.28	581.89	853.04
	10% decline	249.87	449.08	698.70	984.91	1305.49	1659.46
	25% decline	543.03	938.89	1412.34	1905.36	2390.89	2869.08
	10%, 20%, 30%	275.48	495.79	778.47	1107.81	1479.84	1891.63
Grimsby	No yield loss	24.78	70.26	153.98	289.68	493.51	759.29
	10% decline	214.82	380.32	603.43	873.61	1189.66	1541.77
	25% decline	499.87	845.40	1277.59	1749.50	2233.89	2715.49
	10%, 20%, 30%	239.45	427.17	684.35	997.88	1365.07	1773.88
Lakeshore	No yield loss	328.27	555.38	839.14	1172.60	1577.04	2030.64
	10% decline	596.37	997.90	1437.48	1883.08	2355.43	2846.47
	25% decline	998.53	1661.67	2334.99	2948.81	3523.03	4070.23
	10%, 20%, 30%	642.11	1076.05	1555.18	2052.87	2577.33	3116.70
Queenston	No yield loss	204.15	375.42	606.89	899.78	1255.70	1681.57
	10% decline	441.86	770.27	1158.10	1575.98	2017.89	2493.70
	25% decline	798.42	1362.55	1984.91	2590.28	3161.17	3711.90
	10%, 20%, 30%	488.66	851.70	1280.51	1748.92	2246.80	2772.97
Virgil	No yield loss	163.31	304.34	497.92	756.32	1070.34	1459.63
	10% decline	388.01	689.01	1043.10	1426.43	1829.11	2272.91
	25% decline	725.05	1266.00	1860.88	2431.60	2967.26	3492.82
	10%, 20%, 30%	422.69	752.01	1142.83	1570.36	2026.55	2521.75

**Table 4. Estimated Premiums for Beamsville Location Broken Down by Month\***

<b>Month</b>	<b>Required Harvest Hours</b>							
	<b>25</b>	<b>50</b>	<b>75</b>	<b>100</b>	<b>125</b>	<b>150</b>	<b>175</b>	<b>200</b>
December	178.55	297.99	427.92	542.55	628.32	689.33	733.56	766.86
January	24.49	47.15	82.80	130.64	190.77	257.92	327.37	394.13
February	8.72	18.16	31.93	51.82	79.07	115.09	158.87	208.76
March	38.10	85.77	156.06	259.90	407.32	597.13	839.18	1128.43
Total	249.87	449.08	698.70	984.91	1305.49	1659.46	2058.97	2498.18

\*- Loss of \$10,000 with loss of 10% for December and additional 10% for each month following

**Appendix 1. Regression Estimates of Single Index Model of Monthly Harvest Hours ( $h_i$ ) as a Function of Seasonal Monthly Average ( $\bar{h}$ ) by Location**

Location	December			January			February			March		
	Intercept	Slope	R <sup>2</sup>	Intercept	Slope	R <sup>2</sup>	Intercept	Slope	R <sup>2</sup>	Intercept	Slope	R <sup>2</sup>
Beamsville	-8.11 (0.80)*	1.09 (0.12)	0.35	-1.48 (0.95)	1.62 (0.01)	0.65	8.40 (0.61)	0.94 (0.02)	0.61	1.19 (0.96)	0.36 (0.48)	0.09
Grimsby	-24.37 (0.54)	1.50 (0.09)	0.40	12.26 (0.74)	1.34 (0.10)	0.38	-4.15 (0.85)	1.13 (0.03)	0.57	16.26 (0.55)	0.03 (0.95)	0.00
Jordan Escarpment	-17.78 (0.59)	1.30 (0.08)	0.42	16.92 (0.55)	1.27 (0.06)	0.48	-2.81 (0.85)	1.13 (0.01)	0.72	3.67 (0.89)	0.30 (0.56)	0.06
Jordan Highway 8	-0.19 (0.99)	0.90 (0.14)	0.32	8.41 (0.71))	1.37 (0.03)	0.59	7.02 (0.58)	0.95 (0.01)	0.69	-15.24 (0.52)	0.78 (0.15)	0.31
Lakeshore	1.60 (0.92)	0.77 (0.08)	0.43	1.70 (0.92)	1.59 (0.00)	0.77	7.08 (0.47)	0.97 (0.00)	0.78	-10.38 (0.49)	0.67 (0.09)	0.41
Niagara Parkway	3.50 (0.85)	0.75 (0.10)	0.39	-0.60 (0.97)	1.70 (0.00)	0.77	6.29 (0.60)	0.90 (0.01)	0.67	-9.19 (0.59)	0.65 (0.12)	0.35
Queenston	-0.28 (0.99)	0.93 (0.09)	0.41	-3.64 (0.85)	1.64 (0.01)	0.74	7.98 (0.54)	0.90 (0.02)	0.64	-4.06 (0.81)	0.54 (0.18)	0.27
Vineland Cherry Ave	0.93 (0.97)	0.83 (0.12)	0.36	2.48 (0.91)	1.64 (0.01)	0.71	6.74 (0.61)	0.90 (0.01)	0.68	-10.14 (0.63)	0.62 (0.19)	0.27
Vineland Escarpment	-2.79 (0.92)	0.97 (0.14)	0.33	-1.79 (0.94)	1.62 (0.02)	0.64	6.64 (0.62)	0.97 (0.01)	0.70	-2.05 (0.93)	0.45 (0.38)	0.13
Virgil	-0.27 (0.99)	0.88 (0.09)	0.40	-0.45 (0.98)	1.68 (0.01)	0.70	9.75 (0.42)	0.83 (0.02)	0.65	-9.03 (0.63)	0.61 (0.16)	0.29
West St Catherines	-3.72 (0.90)	1.00 (0.14)	0.32	4.06 (0.88)	1.45 (0.04)	0.55	10.63 (0.49)	0.88 (0.03)	0.58	-10.97 (0.64)	0.67 (0.20)	0.26
Winona	-1.25 (0.96)	0.90 (0.17)	0.28	-1.39 (0.96)	1.70 (0.02)	0.61	10.18 (0.52)	0.84 (0.04)	0.53	-7.54 (0.73)	0.56 (0.25)	0.21

\*-  $p$ -values are in parentheses.