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Research Note

COMPUTING EXPECTED YIELD LOSSES FOR CROP INSURANCE COVERAGE : APPROPRIATENESS OF A 2-PARAMETER MODEL

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ABSTRACT

This research examined the appropriateness of a 2-parameter model for crop insurance premium ratemaking. Besides conventional way of calculating crop insurance premium using normal curve theory, this study uses empirical crop yield's distribution to measure downside risk in approximating crop insurance premium. Statistical means for all selected crops by country in Ontario with respect to premium calculated under normal yield distribution assumption (NPREM) and premium calculated using empirical yield distribution (EPREM) are presented. With respect to NPREM and EPREM, a significant statistical difference between mean premiums by crops at various coverage levels are found. This study argue that this difference is mainly attributed to the differences in downside risk. This issue is particularly important, because rejecting a null hypothesis that NPREM and EPREM are equivalent, suggest that approximation of the true (i.e., empirical) distribution by a normal distribution may bias insurance premiums. However the key finding is that in determining crop insurance premium, the downside-risk measured relative to a normal yield distribution function does not necessarily violate research which determines crop insurance premium using empirical crop yield's distribution function.

1. INTRODUCION

Crop yield risk in most industrialized and non-industrialized nations is a persistent problem facing agricultural producers.Variability as such can be defined in terms of positive or negative deviations from an expectation based on long-run yield potential. Farmers take actions which are intended to maximize positive yield outcomes (i. e. show a preference for positive skewness) while minimizing downside-risk. Downside-risk generally refers to yield outcomes below a specific target (Rothschild and Stiglitz, 1970).

Farmers can minimize downside-risk through either self-protection or market protection (Ehrlick and Becker, 1973). Self-protection refers to specific operating actions/ strategies

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which minimize or eliminate some perils associated with downside-risk. For example investments in tilling and irrigation are made to minimize weather related risks, and pesticides and herbicides are used to minimize biologically related risk. Self-protection, while minimizing downside-risk does not necessarily eliminate it. Complete elimination of downside-risk can, however, be accomplished through market-protection or crop insurance.

Agricultural insurance (for example, crop insurance and other income or revenue stabilizing policies) is a feasible and well documented method by which farmers can protect and stabilize farm income and investment from' the disastrous effect of crop losses due to natural hazards or low market prices.

Agricultural insurance as a risk reducing and risk sharing measures has long been practised by the developed countries (for example, Canada, U. S, Australia and Japan) and very recently has been started practising in developing agricultural situations. Realizing the importance of crop insurance in terms of yield risk reduction and farm income stabilization, in Bangladesh, the Sadharan Bima Corporation (SBC), a nationalized insurance corporation, undertook a pilot project in 1977.

The main objectives of the scheme are two folds: (i) to protect farmers against crop loss, stabilize farm income and promote agricultural growth, and (ii) undertake research necessary for promoting and developing a comprehensive crop insurance program in Bangladesh (Rahman and Elahi, 1993). Initially, SBC offered insurance only to farmers who belonged to either cooperative societies or similar groups. Under this plan all major crops grown in Bangladesh such as Aus, Aman, Boro, wheat, jute and sugarcane are covered. The crop insurance policy in Bangladesh intends to reduce yield risk and stabilize insureds income by minimizing the uncertainty of crop production caused by natural hazards, such as flood, drought, hailstorms etc.

Under this policy, a farmer can purchase individual coverage yield insurance for 80% of the expected yield. The gross insurance premium is determined by the pure premium plus a loading factor and premium rates are fixed at uniform levels throughout the country for different types of crops. The relevant price of insurance is represented by the premium rate. In the absence of adverse selection, premiums will accurately reflect the likelihood that indemnities will be paid to the insured'. However, if adverse selection exists in premium rates, differences in the returns to insurance will exist for different buyers at the same/fixed premium rate. Adverse selection is usually manifest in premiums that are aggregated in some fashion about average risk levels such that high risk individuals are undercharged while low risk individuals are overcharged (Rothschild and Stiglitz, 1977). Therefore, high risk individuals would like to buy that contract while low risk individuals would opt out from the program. A recent study by Rahman and Elahi (1993) have indicated that the overall performance of the crop insurance programs in Bangladesh both at the national and the farm level was found to be unsatisfactory. Provided that background about the crop insurance programs in Bangladesh, let us briefly summarize the crop insurance programs in Canada.

Crop insurance in Canada and the U. S. is generally offered as all-risk insurance under which all perils from natural hazards are covered. Other plans may not provide full coverage for some perils. For example, some Canadian provincial plans require farmers to purchase additional single-peril crop insurance of which the most common would be hail insurance[2]. One of the more problematic issues facing crop insurance actuarials and farmers is the determination of crop insurance premiums. Typically a coverage level relative to long-run average yields is established and from this base an expected loss is determined. Losses which do occur are then valued at a specific elected price. To compute premiums for a given price which are actuarially fair to both the insurer and the insured therefore depends critically on the expected loss relative to the chosen coverage level. However, determining the expected loss requires, *a priori,* information about the underlying crop yield distribution, an information requirement which is neither generally available or easy to compute.

The purpose of this research is to compute simple linear equations which can be used to describe an estimate expected yield losses. The resulting equations are simple and require input in the form of crop type, coverage level, mean and standard deviation only. Furthermore, the equations require only the assumption of normality in distribution.

The paper proceeds as follows. In the next section a general model of crop insurance is presented. With the focus on the underlying p. d. f. hypotheses regarding empirical versus normal distributions are then established. The data used to compute and assess expected yield losses for the 609 farms in this study are presented. Finally the analytical premiums and specific tests of hypotheses are discussed and the manuscript concluded.

II. THEORETICAL DEVELOPMENT

Crop Insurance Premium Determination

yield losses for crop insurance purposes can be defined in terms of downside-risk. A standard representation is given by

$$(1)\ V(n,f) = P\int_0^Z (Z-Y)^n f(Y)dy$$

Where V is the valuation function, P is the elected price, Z is the elected coverage level (units/acre), Y is actual yield (units/acre), and f (Y) is the crop yield probability distribution function which assigns a probability weight to each of the Z-Y outcomes. The Z-Y outcomes define the yield indemnities; that is equation (1) is defined only over the range of outcomes for which max [Z-Y, 0] > 0, such that if Y < Z an indemnity equal to P (Z-Y) is paid. The index n weights the valuation function : For n = 0 V (0, f) equals the probability of an indemnity being paid n =1 V (1, f) is the expected value of the indemnity which for actuarially-sound insuracne constitutes the premium, and for n = 2, V (2, f) is a measure of target semivariance. This paper will focus primarily on V (1, f) the expected loss/premium function. Focus on V (1, f) is justified because as Porter (1974) has shown assessing distributions in terms of deviations from a target is sufficient for second order stochastic dominance rankings.

In this study we measure downside risk in relation to the crop yield's empirical distribution and test statistically whether or not this mesure of downside-risk is different from down-side-risk as measured by an assumption that yield distribution are defined in terms of the two-parameter (mean and variance) normal distribution. In particular if f(Y) defines the empirical probability distribution function and g(Y) the normal p. d. f. then the null hypothesis is

(2) $H_o : {}_0\int^z (Z-Y)\, f(Y)dy = {}_0\int^z [Z-Y]\, g\,(Y)dy$

Expected losses using the empirical density requires use of a discrete probability model where

$$(3)\ V\,(1, f) = \sum_{k=1}^{K} \max\,[Z-Y_k, 0]\,\theta_{fk}$$

where the index K represents the number of discrete probability outcomes, Y_k is the yield outcome in state K and θ_{fk} is the discrete probability assumed equal to 1/k. In large samples the empirical distribution function will reflect deviations in terms of skewness and higher moments of the distribution.

Expected losses when assuming normality are computed according to the polynomial approximation established by Botts and Boles (1957) and used frequently in crop insurance research (i. e. Skees and Reed, 1986; Skees and Nutt, 1988). Their approach assumes a continuous distribution and thus approximates :

(4) $v\,(1, g) = {}_{-\infty}\int^z (Z-Y)\, g(y)dy$

Failure to reject the null hypothesis defined by equation (2) implies that normal curve theory can be used to compute crop insurance premiums. Note that this does not necessarily imply that crop yield distributions are in fact normal, but that over the range of expected loss outcomes the normality assumption can be used as a first-best two-parameter approximation in the absence of *a priori* information about the true underlying distribution.

We test the null hupothesis in two ways. First we take the ratio V(1, f)/V (1, g) and use a simple two tailed test to see whether or not it is significantly different from 1. Next we regress V (1, f) (labelled here as EPREM) on V (1, g) (labelled NPREM) and crop type and coverage-level dummy variables. The null hypothesis are i) that the regression coefficient on NPREM is not significantly different from 1; and ii) that the crop-type and coverage level dummy variable coefficients are individually and jointly not statistically different from zero. Failure to reject i) implies that expected crop losses from EPREM move in the same direction and relative magnitudes as NPREM. Failure to reject ii) imply that difference between EPREM and NPREM cannot be attributed to crop type or coverage levels. Combined, failure to reject i) and ii) imply that a truncated normal distribution can be used, with confidence, in crop insurance rate making.

Failure to reject the above hypotheses permits the third stage of this research which estimates simple linear regressions which can be used to approximate expected losses. Since the normal distribution is a two-parameter model it is anticipated that expected losses can be approximated using mean and variance, and crop and coverage-level dummy variables. The actual regression equation used are defined explicitly in the results section which follows the next section on data description.

III. DATA DESCRIPTION

The data used in the analyses were drawn from over 96,000 actual farm-yield observations provided by the Ontario Crop Insurance Commission, a statutory corporation which administers and implements crop insurance in Ontario. Crops covered are spring grains, wheat, corn, soybeans and whitebeans. Each of these insured crops had a different number of years under which they were in the program. Hence we elected to use only those observations which defined a crop continuously enroled in the program. Furthermore, in order to make some statement about regional diversity only those counties with a sufficiently large number of observations available were used.

In all, 609 farm specific crop yield series spanning 5 crops and 11 counties were selected. (In some, but not all cases, more than one crop per farm was used. A greater number of series could be defined but only at the expense of shorter time horizons per series.) Summary statistics for crop yields by county used are found in Table 1.

IV. EMPIRICAL RESULTS

Expected losses for each of the 609 series were computed using equations (2) and (3), and each of these were multiplied by the commodity price to obtain actuarially-sound premiums. Coverage levels were specified for 75%, 80%, 85%, 90%, 95% and 100% of long-run average yields.

The means of the premiums for each crop in each county are presented in Table 1 for 75% 80% and 85% coverage level. Casual observation shows the differences between the means of the two distribution types. For example NPREM for winter wheat in Perth county at 80% coverage is $1. 94/acre whereas the equivalent value for EPREM is $2.44/acre. Similarly for 85% coverage of corn in Wellington county NPREM is $8.86/acre with an equivalent EPREM value of $8.56/acre. The bracketed values below these premiums are the sample standard deviations. These are quite high, indicating that there is substantial heterogeneity in farm yield risk across farms.

Perhaps more important to the descriptive aspects of these results are the differences occurring between counties. For example with NPREM actuarial premiums at 80% coverage for winter wheat is \$1.94/acre in Perth county, \$2.60/acre in Middlesex county, S1.42/acre in Lambton county and \$6.04/acre in Norfolk county. These differences reflect differences in mean productivity (yield) and variance between counties. Such heterogeneity in risk profiles requires that insurance premiums be established at the most localized level, preferably by farm, to attain actuarial soundness.

The second stage of this research was to explain the differences, if any, between EPREM. We failed to reject the null hypothesis that the ratio EPREM/NPREM was significantly different from 1 using a simple 2-way t-test. To provide more specific information about differences the following regressions were run for each county.

$$(5)\ EPREM = \alpha_o + \alpha_1\ NPREM + \sum_{i=1}^{4} \alpha_i CD_i + \sum_{i=1}^{5} \alpha_j ZD_j + \epsilon$$

where CDi and ZDj are 0-1 dummy variables for crop type (mixed grain, corn, soybeans, white beans where appropriate) and coverage level (80%, 85%, 90%, 95%, 100%), and $\in$ is the error term. The intercept term is estimated relative to winter wheat at the 75% coverage level.

The results are presented in Table 2. All of the α_1 coefficients were found not to be significantly different from 1 indicating a systematic correspondence between EPREM and NPREM. Of the 15 α_i coefficients estimated, only 4 were significantly different than zero. None of the a_j coefficients were significantly different from zero at the 80% and 85% levels, but 4 were different from zero for each of the 90%, 95% and 100% levels. Despite the possibility of bias at high coverage levels (which incidently are not offered to Ontario producers) over 90% of the variation in EPREM was explained by the model with 10 of the 11 counties having adjusted R^2 values of greater than 94%. Finally the intercept terms which reflect winter wheat and 75% coverage levels (where winter wheat was grown) had 5 of 11 intercepts statistically different from zero.

The above results suggest with substantial, but not perfect, confidence that the assumption of normally distributed yields adequately reflects farm yield risks so that a two-moment insurance rate-making model can confidently be applied. This assumption is bolstered by the fact that virtually all crop insurance schemes in Canada and the U. S. provide coverage at less than 85% of long-run average yields. Hence, for the range of downside-risk considered the model provides a near perfect representation of actuarial insurance premiums.

Given this, the following regression was run.

$$(6)\ \ EL = B_o + B_1 E[Y] + B_2\,\sigma_y + \sum_{i=3}^{>} B_i\ CD_i + \sum_{j=8}^{13} B_j\ ZD_j + \epsilon$$

where EL, the expected yield loss is defined as a function of the coverage level, E [Y] is expected yield, σ_y is yield standard deviation, and $\in$ is an error term.

Table 1. Statistical Means for All Selected Crops by County With Respect to Normal (NPREM) and Empirical Premiums.

County/crop	OBS	Mean E (y)	Premium ($/acre)					
			Coverage Level					
			Normal Premium			Empirical Premium		
			75%	80%	85%	75%	80%	85%
Perth								
Winter wheat	16	64.24	1.10	1.84	3.33	1.34	2.44	3.92
		(10.45)	(0.93)	(1.38)	(1.90)	(1.41)	(1.80)	(2.24)
Spring grain	25	65.39	3.56	4.72	6.20	4.06	5.29	6.71
		(17.79)	(2.47)	(2.76)	(2.97)	(2.34)	(2.70)	(3.01)
Corn	32	97.76	4.74	6.87	9.74	6.31	8.18	10.62
		(22.81)	(2.81)	(3.46)	(4.09)	(3.65)	(4.02)	(4.44)
Soybeans	31	36.23	1.48	2.35	3.75	1.73	2.44	3.69
		(5.71)	(1.95)	(2.61)	(3.37)	(2.92)	(3.54)	(4.20)
White beans	28	23.88	10.03	12.68	15.87	11.79	14.02	16.69
		(8.02)	(4.41)	(4.87)	(5.25)	(5.16)	(5.53)	(5.78)
Essex								
Corn	8	102.01	6.47	8.99	12.24	5.35	7.47	10.23
		(26.76)	(2.97)	(3.55)	(4.12)	(3.19)	(3.39)	(3.90)
Soybeans	36	35.42	6.26	8.42	11.19	23.30	8.84	11.85
		(9.68)	(3.46)	(3.87)	(4.19)	(2.33)	(4.39)	(4.71)
Kent								
Corn	19	115.71	3.14	4.77	7.15	3.36	4.94	6.99
		(21.39)	(2.78)	(3.64)	(4.55)	(3.39)	(3.92)	(4.57)
Soybeans	29	38.28	5.05	7.09	9.80	5.54	7.67	10.44
		(9.35)	(3.02)	(3.63)	(4.22)	(3.66)	(4.21)	(4.73)
Wellington								
Spring grain	30	63.67	3.38	4.52	5.98	3.92	5.08	6.51
		(17.28)	(2.30)	(2.59)	(2.86)	(2.64)	(2.91)	(3.19)
Corn	25	82.00	4.48	6.36	8.86	4.38	6.19	8.56
		(19.92)	(2.83)	(3.29)	(3.67)	(3.32)	(3.69)	(3.94)
Middlesex								
Winter wheat	12	60.04	1.61	2.60	4.09	1.69	2.84	4.26
		(10.80)	(1.27)	(1.71)	(2.22)	(1.73)	(1.92)	(2.24)
Corn	21	(103.20)	3.46	5.32	7.76	4.43	6.25	8.59
		(21.33)	(2.57)	(3.21)	(3.84)	(2.95)	(3.37)	(3.89)
Soybeans	19	34.80	1.52	2.52	4.08	1.79	2.83	4.19
		(5.90)	(1.48)	(1.95)	(2.49)	(1.67)	(2.21)	(2.74)

Table 1. (Contd)

County/crop	OBS	Mean E (y)	Premium ($/acre)					
			Coverage Level					
			Normal Premium			Empirical Premium		
			75%	80%	85%	75%	80%	85%
Proescott								
Spring grain	23	53.35	11.51	13.27	15.22	12.32	14.08	16.09
		(27.73)	(2.98)	(3.08)	(3.21)	(3.54)	(3.81)	(4.09)
Corn	43	76.59	14.28	17.34	20.91	16.14	19.26	22.81
		(30.29)	(5.43)	(5.76)	(6.04)	(6.49)	(6.80)	(7.11)
Lambton								
Winter wheat	5	65.96	0.69	1.42	2.70	1.20	2.09	3.43
		(10.00)	(0.31)	(0.54)	(0.83)	(1.08)	(1.20)	(1.53)
Corn	16	106.49	4.53	6.60	9.47	6.01	8.11	10.77
		(23.90)	(3.68)	(4.30)	(4.86)	(3.51)	(4.12)	(4.99)
Soybeans	21	33.71	3.44	5.03	7.21	4.19	5.73	7.84
		(7.54)	(2.31)	(2.81)	(3.29)	(2.68)	(3.28)	(3.89)
Dundas								
Corn	34	82.76	6.16	8.28	11.06	7.28	9.58	12.46
		(21.33)	(5.21)	(5.83)	(6.39)	(5.32)	(5.82)	(6.44)
Ottawa-Carleton								
Spring grain	24	52.60	8.58	10.18	12.01	9.59	11.08	12.73
		(23.46)	(2.02)	(2.09)	(2.15)	(2.19)	(2.30)	(2.48)
Corn	44	84.78	7.34	9.63	12.59	8.52	10.92	13.88
		(23.01)	(5.60)	(6.24)	(6.80)	(6.84)	(7.51)	(7.95)
Russel								
Spring grain	21	43.28	11.34	12.84	14.49	10.72	12.49	14.40
		(25.26)	(4.77)	(5.10)	(5.46)	(4.62)	(5.06)	(5.48)
Corn	33	79.35	12.84	15.85	19.39	14.52	17.35	20.75
		(29.23)	(5.80)	(6.33)	(6.82)	(6.64)	(7.38)	(8.02)
Norfolk								
Winter wheat	14	38.76	4.69	6.04	7.72	4.69	6.15	7.84
		(12.01)	(2.39)	(2.55)	(2.64)	(2.49)	(2.69)	(2.82)

Standard deviations are presented in parenthesis.

Table 2. Cross Sectional Crop Regression for all Farms by County (with respect to winter wheat and 75% cov. level)

County	Variable											R^2	F-Stat
	Intercept	NPPREM	DC2	DC4	DC5	DC6	DCOV80	DCOV85	DCOV90	DCOV95	DCOV100		
Perth	0.94	0.99	0.004	0.14	-0.23	-025	-0.13	-0.36	-0.66	-0.89	-1.11	0.97	2196.26
	(0.197)*	(0.013)*	(0.201)	(0.213)	(0.192)	(0.258)	(0.189)	(0.194)	(0.206)*	(0.231)*	(o.271)*		
Essex	-2.60	0.99	-	-	3.15	-	0.13	0.25	0.32	0.32	0.19	0.94	585.70
	(0.44)*	(0.028)*			(0.31)*		(0.413)	(0.433)	(0.479)	(0.556)	(0.668)		
Kent	0.554	0.97	-	-0.813	0.424	-	0.076	0.036	-0.180	-0.328	-0.456	0.94	593.06
	(0.809)	(0.024)*		(0.799)	(0.803)		(0.383)	(0.396)	(0.428)	(0.490)	(0.592)		
Wellin-	0.596	1.00		0.79	-	-	-0.023	-0.113	-0227	-0.333	-0.418	0.95	960.21
gtion	(0.187)*	(0.020)*		(0.163)*			(0.244)	(0.252)	(0.270)	(0.302)	(0.353)		
Midd-	0.148	0.957	-	0.923	0.244	-	0.124	0.041	0.001	0.041	0.135	0.97	1148.32
lesex	(0.204)	(0.02)*		(0.198)	(0.178)		(0.233)	(0.261)	(0.305)	(0.38)			
Prescott	-0.172	1.13	-	-0.133	-	-	-0314	-0.701	-1.24	-1.86	-2.59	0.07	1800.12
	(0.26)	(0.02)*	-	(0.20)			(0.29)	(0.29)*	(0.32)*	(0.35)*	(0.39)*		
Lambton	0.94	106	-	-0.065	-0.248	-	-0.09	-0.33	-0.67	-1.16	-1.89	0.97	1041.67
	(0.29)*	(0.02)		(0.20)			(0.27)	(0.28)	(0.31)*	(0.36)*	(0.43)*		
Dundas	1.08	1.00	-	-	-	-	0.17	0.25	0.38	0.39	0.48	0.95	796.79
	(0.34)*	(0.02)*					(0.46)	(0.46)	(0.49)	(0.53)	(0.59)		
Ottawa-	0.26	1.08	-	0.27	-	-	-0.14	-0.42	-0.85	-1.42	-2.20	0.95	1145.90
Carleton	(0.27)	(0.02)*		(0.19)			(0.31)	(0.32)	(0.34)*	(0.36)*	(0.40)*		
Russel	-0.52	1.06	-	0.92	-	-	-0.14	-0.30	-0.46	-0.67	-0.83	0.96	1117.41
	(0.33)	(0.01)*		(0.25)*			(0.38)	(0.39)	(0.41)	(0.43)	(0.47)		
Norfolk	0.37	0.92	-	-	-	-	0.19	0.34	0.49	0.61	0.87	0.90	132.24
	(0.46)	(0.06)*					(0.52)	(0.55)	(0.60)	(0.68)	(0.81)		

Standard errors are presented just beneath the estimated coefficient.

* All the coefficients are highly significant at 1% level.

Table 3. Expected Loss (EL) Regression for All Farms by County (with respect to winter wheat and 75% cov. level)

County	Variable												R^2	F-Stat
	Intercept	EY	Std	DC2	DC4	DC5	DC 6	DCOV80	DCOV85	DCOV 90	DCOV 95	DCOV 100		
Perth	-1.45	-0.02	0.32	-0.01	-0.00	-0.06	-0.14	0.43	1.03	1.82	2.84	4.14	0.90	640.74
	(0.29)*	(0.004)*	(0.008)*	(0.12)	(0.19)	(0.15)	(0.19)	(0.19)*	(0.09)*	(0.09)*	(0.09)*	(0.09)*		
Essex	-1.798	-0.03	0.34	-	-	0.12	-	0.46	1.05	1.81	2.72	3.82	0.90	276.20
	(0.74)	(0.006)*	(0.02)*			(0.49)		(0.15)	(0.15)*	(0.15)*	(0.15)*	(0.15)*		
Kent	1.63	-0.02	0.29	-	0.03	-0.03	-	0.45	1.08	1.95	3.13	4.67	0.88	229.96
	(0.60)*	(0.004)*	(0.01)*		(0.43)	(0.41)		(0.17)*	(0.17)	(0.17)*	(0.17)*	(0.17)*		
Wellington	-2.31	-0.03	0.34	-	-0.01	-	-	0.65	1.50	2.60	3.97	5.62	0.98	1918.30
	(0.17)*	(0.002)*	(.004)		(0.057)			(0.067)*	(0.067)*	(0.067)*	(0.067)*	(0.067)*		
Middlesex	-1.83	-0.02	0.30	-	-0.04	0.01	-	0.41	1.01	1.85	3.02	4.54	0.89	264.31
	(0.32)*	(0.004)*	(0.01)*		(0.26)	(0.17)		(0.16)*	(0.16)*	(0.16)*	(0.16)*	(0.16)*		
Prescott	-2.89	-0.04	0.34	-	0.009	-	-	0.99	2.14	3.43	4.89	6.52	0.97	1625.47
	(0.16)*	(0.001)*	(0.005)*		(0.07)			(0.09)*	(0.09)*	(0.09)*	(0.09)*	(0.09)*		
Lambton	-1.71	-0.03	0.33	-	-0.01	-0.15	-	0.46	1.11	1.99	3.16	4.63	0.89	224.05
	(0.53)*	(0.007)*	(0.02)*		(0.41)	(0.29)		(0.19)*	(0.19)*	(0.19)*	(0.19)*	(0.19)*		
Dundas	-2.49	-0.03	0.34	-	-	-	-	0.73	1.69	2.92	4.48	6.38	0.98	1292.08
	(0.21)	(0.002)*	(.005)					(0.11)*	(0.11)*	(0.11)*	(0.11)*	(0.11)*		
Ottawa Carleton	-2.28	-0.03	0.34	-	0.01	-	-	0.79	1.77	2.96	4.40	6.10	0.98	2060.48
	(0.18)*	(0.002)*	(.005)*		(.07)			(0.07)*	(0.07)*	(0.07)*	(0.07)*	(0.07)*		
Russel	-2.74	-0.03	0.37	-	-0.07	-	-	0.92	1.99	3.21	4.59	6.14	0.96	1044.91
	(0.17)*	(0.003)*	(.005)*		(0.13)			(0.12)*	(0.12)*	(0.12)*	(0.12)*	(0.12)*		
Norfolk	-1.53	-0.03	0.36	-	-	-	-	0.43	0.97	1.61	2.39	3.29	0.98	691.69
	90.15)*	(0.002)*						(0.07)*	(0.07)*	(0.07)*	(0.07)*	(0.07)*		

Standard errors are presented just beneath the estimated coefficient.

* All the cefficients are highly significant at 1% level.

As in equation (5), equation (6) is a cross sectional regression with EL obtained for each crop-yield series according to equation (3). The results of these regressions for each county are presented in Table 3.

As one would expect the *ceteris paribus* effects of an increased mean yield decreases expected loss, whereas increased dispersion as measured by σ_y increases decreases expected loss, whereas increased dispersion as measured by σ_y increases expected loss. We find that crop type does not affect the EL prediction. Finally we find, as anticipated, that expected losses increase with increased coverage levels. The fit of the regressions are good with the lowest adjusted R^2 being 88% and 6 of the 11 regressions having R^2 greater than 96%.

Equation (6) can be used as a simplified approach to expected loss estimation. Note that just like normal curve rate making expected loss measures require knowledge of only expected yields, standard deviation and coverage level. In fact since equation (6) is in essence a step-function, expected losses can be assessed for a number of different coverage levels. Finally with a robust estimate of expected loss, crop insurance premiums can easily be determined by multiplying the expected loss value by the elected commodity price.

As an example assume that an Ottawa-Carlton county farmer had a long-run corn yield average equal to 80.28 bu./acre with σ_y of 14.47 bu./acre and an elected price of $2.89/bu. The estimated premium for 80% coverage is $3.67/acre and for 85% coverage $6.06/acre. Suppose that another farm had a similar yield equal to 80.61 bu./acre and σ_y equal to 21.51 bu./acre. The corn yield insurance premiums would be $8.14/acre and $11.13/acre for 80% and 85% coverage, respectively.

V. CONCLUSIONS

This research examined the appropriatess of a 2-parameter model for crop insurance premium rate-making. The key results indicate that over the conventional nature of downside-risk applicable to problems of crop insurance a normal distribution is meaningful. In this sense the normal curve theory approach used by Skees and Reed and others does provide meaningful results. In addition, using estimates of expected loss, a loss factor was estimated which is easy to use and simple to apply. Providing farmers with such equations would enable them to assess yield losses. It has been shown in a vast literature that an expected deviation from a target can be used to rank crop selections according to stochastic dominance criteria. A useful extension of this work would be to present equation (6) to farmers in various counties to determine whether or not they can rank crop choices by their mean absolute deviations. Even so, farmers may wish to use equation (6) to estimate premiums and compare those with premiums offered on equivalent coverage by crop insurance agencies. Crop insurance agencies can use the equations to estimate premiums for their own programs.

This study was not limited by data, however in some instances the crop yield series were not long, so that it is unlikely that true population measures of moments were captured. This can be remedied as new data become available.

Finally, a finding that downside-risk can be measured relative to a normal distribution does not and should not violate research which examines crop yield distributions. Rather, our conclusions relate only to the relevant range of downside-risk assessed by a normal distribution as an approximation to the downside-risk of a true but unknown probability distribution function.

Footnote :

1 Determination of actuarially sound insurance premium is very important for the financial performance of an insurance plan and program participation as well. If insurance premiums are not actuarially sound, such mispricing insurance can lead to adverse selection which may results in gearing up the program costs of the insurance plans. Therefore, adverse selection occurs if premium rates do not accurately reflect loss risk. If rates are actuarially fair, expected indemnities will be equal to the total premium paid in, and by definition program costs will be zero. In an actuarially sound insurance market, premiums will slightly exceed expected indemnities in order to cover administrative costs.

2 E. g. most all-risk plans provide some but only limited protection for hail damage.

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