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Actuarial Impacts of Loss Cost Ratio Ratemaking in U.S. Crop Insurance Programs

Joshua D. Woodard, Bruce J. Sherrick, and Gary D. Schnitkey

This study examines the actuarial implications of the loss cost ratio (LCR) ratemaking methodology employed by the Risk Management Agency as a component of base rates for U.S. crop insurance programs, and identifies specific conditions required for the LCR methodology to result in unbiased rates when liabilities trend. Specifically, constant relative yield risk resulting in growing absolute variance through time and other restrictive requirements are required for the LCR to result in unbiased rates. These requirements are tested against a large farm-level data set for Illinois corn. Our findings indicate that the conditions required for appropriate use of the LCR methodology are violated for this high premium volume market, resulting in large implied rate biases. The process does not correct itself through time with the addition of longer rating periods as sometimes claimed. A simple correction function is suggested and demonstrated.

Key Words: actuarially fair, crop insurance, insurance rating, loss cost ratio, risk growth, Risk Management Agency, yield trends

Introduction

The U.S. crop insurance program has grown consistently since the passage of the Federal Crop Insurance Act of 1980, and is now viewed as the cornerstone of the risk management support system provided by the federal government to the nation's farmers (Glauber, 2004).[1] In 2009, the program insured approximately $80 billion in liabilities on 265 million acres nationwide. The program is delivered by private insurers but is administered by the U.S. Department of Agriculture's (USDA's) Risk Management Agency (RMA). Through a public-private partnership, private insurance companies and the federal government share in the underwriting risk as defined in the Standard Reinsurance Agreement (SRA). Insurance rates are set noncompetitively by the RMA and are heavily subsidized in the form of direct producer premium subsidies, administrative subsidies, and favorable government reinsurance.

The RMA's ratemaking procedures are currently undergoing scrutiny as a result of perceived regional disparities (Glauber, 2004; Babcock, 2008; Woodard et al., 2011), apparent inconsistencies in published rates (Barnaby, 2007), and differences between RMA rates and those implied by different methodologies (Sherrick et al., 2004; *farmdoc*, 2008). Several components of RMA's methodology have received criticism in the past, including biases and inefficiencies in determining guarantees (Skees and Reed, 1986), the equity of state excess

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[1] Crop insurance programs have existed in various forms in the United States since the 1930s, but for practical purposes, the current program essentially follows from the 1980 Act [see Smith and Goodwin (2010) for a more in-depth review].

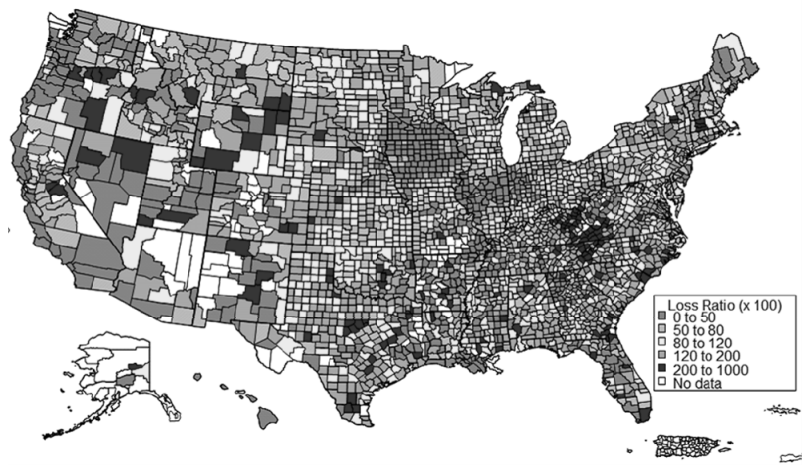


Figure 1. County loss ratios, 1995–2007 (all crops)

loads (Josephson, Lord, and Mitchell, 2000), coverage level differential problems (Babcock, Hart, and Hayes, 2004), and intra-county risk heterogeneity (Goodwin, 1994).

The processes that generate the puzzling divergences in historical loss experience are of particular interest. Figure 1 presents loss ratios for the period 1995–2007, and shows the presence of historically low loss rates throughout the Corn Belt [Federal Crop Insurance Corp. (FCIC), 2008]. What is not apparent from figure 1 is that approximately one-third of the program premium volume is located in this region, virtually all of which is corn and soybeans—representing a combined share of roughly 60% of the total premium in all FCIC programs. Corn and soybeans have also experienced relatively large gains in average yields over the previous decades compared to other crops. Average annual state loss ratios for the period 1995–2007 were also investigated (results are not presented here). Interestingly, from 1995 to 2007, there was not a single year in which the Corn Belt had a higher loss ratio compared to other major regions. This is surprising given the amount of premium in these markets. While not definitive evidence of ratings problems alone, these findings raise questions about which aspects of the rating process may contribute to these patterns.

The backbone of RMA's methodology for determining rates is a technique known as the loss cost ratio (LCR) approach (Josephson, Lord, and Mitchell, 2000; Schnapp et al., 2000). It is crucial for the accuracy of the LCR approach that a specific form of relative risk remain constant through time at each coverage level. More generally, the expected value of the indemnity for any given insurance product must increase proportionally to the product's liability for the LCR approach to provide an unbiased estimate of a forward-looking rate. While it is relatively well known that problems in determining yield guarantees under the program induce bias in coverage levels (Skees and Reed, 1986), the conditions governing the risk growth process of yields through time in the context of LCR methodologies represent a fundamentally different issue that is not theoretically or empirically well understood. The objective of this study is to develop this theory and test key assumptions about risk to assess their effects on premium rates and the performance of existing crop insurance programs.[2]

[2] The intent of the manuscript is not to recreate the entire RMA rating system, but rather to focus on the backbone of the system, the LCR approach, and specific features required for its appropriate use. Woodard et al. (2011) note that the presence of trending liabilities through time may be responsible for much of the observed spatial/regional pattern in historical losses.

We first describe LCR ratemaking concepts and conditions under which the approach will generate unbiased rates. The required conditions imply a fairly straightforward test of, and correction for, cases where violations occur. Tests are devised for both parametric and nonparametric yield representations. Results are presented for the risk evolution tests using a unique and extensive farm-level yield data set for Illinois corn yields. We directly replicate LCR methodology and illustrate that in our data the LCR methodology drastically overstates actuarially fair rates. A practical correction is demonstrated to be appropriate under conditions that appear to be prevalent in actual yield series and that result in no impact in cases where required yield risk characteristics are met. Weather variability impacts are also investigated and found not to affect the analysis.

Loss Cost Ratio Ratemaking Concepts

The LCR approach for setting insurance rates is based directly on historical experiences; aggregate rates are created by averaging individual loss rates across individual exposure experiences. RMA's historical loss cost ratio methodology derives rates and premiums by calculating average loss cost ratios at each point in time for insured producers at the county level. First, a liability is calculated for each policy as:

$$Liab_{t,i} = E(y_{t,i}) \times Cover, \tag{1}$$

where $E(y_{t,i})$ is the expected yield in year t for policy/farm i, and $Cover$ is the coverage level (i.e., deductible) election. The indemnity for each policy is then calculated as:

$$I_{t,i} = \text{Max}(0, Liab_{t,i} - y_{t,i}), \tag{2}$$

where $y_{t,i}$ is the realized farm yield. An individual loss cost ratio is calculated for each policy as the ratio of indemnity to liability,[3] $LCR_{t,i} = I_{t,i} / Liab_{t,i}$. Crop insurance risk is subject to extreme catastrophic events, and the same policies do not exist in the experience database from year to year. Thus, an average LCR is calculated for each year as:

$$LCR_t = \frac{\sum_i I_{t,i} / Liab_{t,i}}{N}, \tag{3}$$

where N is the total number of policies/farms. A base rate is then calculated as:

$$E(LCR) = \frac{\sum_t LCR_t}{T}, \tag{4}$$

where T is the total number of years of historical data.

If liabilities and expected indemnities are constant through time, this approach does not present problems other than those endemic to any experience-based rating method. Crop insurance is somewhat different in that it is subject to trending liabilities, because expected yields tend to increase through time. When liabilities trend through time, very specific conditions on the underlying distribution are necessary for the LCR methodology to result in unbiased estimates of forward-looking rates. To illustrate, suppose yields can be modeled as $y_{t,i} = \alpha + \beta t + \varepsilon_{t,i}$, where α is an intercept, β is the trend, $\varepsilon_{t,i}$ is a random innovation,

[3] The RMA also adjusts all policy data to a common coverage level and then uses coverage-level differentials to derive rates for different coverage levels. (For a discussion, see Josephson, Lord, and Mitchell, 2000).

$$\varepsilon_{K,i} \sim \left(0, \sigma_0^2 * \prod_{t=1}^{K-1} (1+g_{t-1}^{\sigma^2})\right) \equiv (0, \sigma_K^2),$$

whose variance grows at an annual rate of $g_t^{\sigma^2}$, and whose distribution function is $F_t(\varepsilon_{t,i})$.[4] The growth rate of the standard deviation can be expressed as:

$$g_t^{\sigma} = \sqrt{(1+g_t^{\sigma^2})} - 1.$$

Expected yield is specified as:

$$E(y_{t,i}) = \int_{-\infty}^{\infty} \left[\alpha + \beta t + \varepsilon_{t,i}\right] dF_t(\varepsilon_{t,i}) = \alpha + \beta t. \tag{5}$$

As a result, $E(y_{t,i})$ has a growth rate of $g_t^{\mu} = \beta / (\alpha + \beta t)$. Notice that the growth rate in the liability is also g_t^{μ}, since $E(y_{t+1,i}) = E(y_{t,i}) \times (1+g_t^{\mu})$, and thus we obtain the following:

$$\frac{Liab_{t+1,i} - Liab_{t,i}}{Liab_{t,i}} = \frac{E(y_{t+1,i}) \times Cover - E(y_{t,i}) \times Cover}{E(y_{t,i}) \times Cover} = g_t^{\mu}. \tag{6}$$

Expected indemnity can be expressed as:

$$E(I_{t,i}) = \int_0^{Liab_{t,i}} \left[E(y_{t,i}) \times Cover - y_{t,i}\right] dF_t(\varepsilon_{t,i}). \tag{7}$$

The growth rate in the indemnity is then given by:

$$\begin{aligned} h_t &= \frac{E(I_{t+1}) - E(I_t)}{E(I_t)} \\ &= \frac{\int_0^{Liab_{t+1}} \left[E(y_{t+1}) \times Cover - y_t\right] dF_{t+1}(\varepsilon_{t+1}) - \int_0^{Liab_t} \left[E(y_t) \times Cover - y_t\right] dF_t(\varepsilon_t)}{\int_0^{Liab_t} \left[E(y_t) \times Cover - y_t\right] dF_t(\varepsilon_t)}. \end{aligned} \tag{8}$$

The expected LCR can be calculated as:

$$E(LCR_t) = \frac{E(I_{t-1}) \times (1+h_{t-1})}{Liab_{t-1} \times (1+g_{t-1}^{\mu})}.$$

Expected LCRs will be constant across years if and only if the growth rate in the liability (or mean) is equal to the growth rate in the indemnity, $h_t = g_t^{\mu}$, at every coverage level. This relationship also implies that forward-looking expected LCRs will be less than historical LCRs if the indemnity growth rate is less than the liability (or mean) growth rate, $h_t < g_t^{\mu}$.

Simply put, if liability growth rate is greater than the growth rate in expected indemnity, the LCR in any year will be an upward-biased estimate of the LCR in any later years and, by implication, the LCR itself will trend down over time. If $h_t \neq g_t^{\mu} \; \forall \, t$, then multiplying each historical $E(LCR_k)$ by a multiplicative adjustment factor equal to:

$$LCR\_Adj_{k,l} = \prod_{t=k}^{l-1} \frac{(1+h_{t-1})}{(1+g_{t-1}^{\mu})} \tag{9}$$

[4] For the exposition here, we adopt a linear trend and arithmetic growth rate risk. Other trend and risk growth rate structures (e.g., constant multiplicative trend, nonlinear trends, etc.) could have been employed, but the specific choice does not change the overall character of the theoretical result or empirical analysis.

results in an unbiased estimate of a forward-looking $E(LCR_l)$, where the subscript k is the year of data being incorporated into the rating structure, and l is the current year for which rates are being generated. To verify the proposed adjustment factor, note that $E(LCR_l) = E(LCR_k) \times LCR\_Adj_{k,l}$.

Given the observations above, it is reasonable to evaluate the conditions under which $h_t = g_t^{\mu}$. If yields are parametrically represented, the associated distribution's limited expected value (LEV) function can be evaluated to assess this condition. To address potential concerns about the impact of the chosen parametric yield representations, a nonparametric test is also conducted that examines the (distribution-free) quantile behavior directly.

Parametric Yield Restrictions on Loss Cost Ratio Ratemaking

The LCR methodology may be appropriate if the standard deviation grows proportionally to the mean of the distribution, although the general applicability of this proposition has not been thoroughly investigated. Evaluating the growth rate of the standard deviation through time may be sufficient in some cases to ensure the validity of the LCR approach. The underlying yield, y_t, has constant relative risk (CRR) through time if the coefficient of variation (CV) is constant,

$$\frac{\sigma_t}{E(y_t)} = CV_t = CV \; \forall \, t,$$

where σ_t is standard deviation, implying that $g_t^{\sigma} = g_t^{\mu} \; \forall \, t$. If $g_t^{\mu} > 0$ and $g_t^{\sigma} \leq 0$, then CV is strictly decreasing through time; if $g_t^{\sigma} \leq 0$, then absolute risk, σ_t, can be either decreasing or constant through time. Finally, the underlying yield, y_t, exhibits constant absolute risk (CAR) if $g_t^{\sigma} = 0$ or $\sigma_t = \sigma \; \forall \, t$.

Given that h_t is a function of both g_t^{μ} and g_t^{σ}, it may be possible to deduce what conditions must hold between g_t^{μ} and g_t^{σ} for $h_t = g_t^{\mu}$. The required conditions can be expressed in terms of the limited expected value function. The LEV is the expected value of a random variable, X, given that it falls below a certain level, x, and is defined as $LEV[\boldsymbol{\theta}, x] = E[X \mid X < x]$, where X has probability distribution function (pdf) $f(x: \boldsymbol{\theta})$ and $\boldsymbol{\theta}$ is a parameter vector of the distribution function. Suppose the LEV for a given distribution can be expressed in terms of its mean and standard deviation as $LEV(\boldsymbol{\theta}, x) \equiv LEV(\mu, \sigma, x)$. Using standard actuarial notation (Hogg and Klugman, 1984), the expected indemnity and expected LCR are:

$$E(I_t) = E(y_t) \times Cover - LEV\left[E(y_t), \sigma_t, E(y_t) \times Cover\right] \tag{10}$$

and

$$E(LCR_t) = \frac{E(I_t)}{E(y_t) \times Cover} = 1 - \frac{LEV[E(y_t), \sigma_t, E(y_t) \times Cover]}{E(y_t) \times Cover}. \tag{11}$$

For the expected LCR to exhibit no growth under trending liabilities with constant relative risk, the sum of the derivatives of the LCR with respect to proportional changes in mean and standard deviation must equal zero, or

$$\frac{\partial E(LCR)}{\partial \ln(E(y))} + \frac{\partial E(LCR)}{\partial \ln(\sigma)} = 0.$$

Taking the derivative of the expected LCR with respect to $\ln(E(Y_t))$ gives:

$$\frac{\partial E(LCR)}{\partial \ln(E(y))} = -\left[\frac{\frac{\partial LEV[\cdot]}{\partial E(y)} E(y) - LEV[\cdot]}{E(y) \times Cover}\right],$$

and differentiating the LCR with respect to ln(σ) gives:

$$\frac{\partial E(LCR)}{\partial \ln(\sigma)} = -\frac{\sigma}{E(y) \times Cover} \times \frac{\partial LEV[\cdot]}{\partial \sigma}.$$

Thus, if

$$\frac{\partial E(LCR)}{\partial \ln(E(y))} + \frac{\partial E(LCR)}{\partial \ln(\sigma)} = 0,$$

then

$$LEV[\cdot] = \frac{\partial LEV[\cdot]}{\partial E(y)} \times E(y) + \frac{\partial LEV[\cdot]}{\partial \sigma} \times \sigma.$$

That is, if yields exhibit CRR, $g_t^{\sigma} = g_t^{\mu}$, then $h_t = g_t^{\mu}$ if and only if

$$LEV[\cdot] = \frac{\partial LEV[\cdot]}{\partial E(y)} \times E(y) + \frac{\partial LEV[\cdot]}{\partial \sigma} \times \sigma.$$

Standard numeric methods can be used to easily and accurately assess these conditions. For the normal distribution and some other special cases, approximate analytical solutions could be derived. However, doing so has little practical value since these conditions can be easily assessed using simulations for a given distribution over various parameter supports. We were able to validate these conditions for the normal, Weibull, and beta distributions (results are available from the authors on request).

Hence, under reasonable distributional assumptions, the LCR methodology is only appropriate if yields exhibit CRR. If yield risk grows proportionately slower than expected yields (or if expected yields increase through time and also exhibit a constant or declining standard deviation), an LCR approach results in upward-biased rates. Similarly, if expected yields trend through time and exhibit CRR, then a historical LCR will result in an unbiased forward rating structure. Thus, the statistical validity of an LCR system for use with a given set of experience data can be assessed by comparing models of CAR versus CRR in empirical ratings data. If yields do not display CRR, the employment of the adjustment factor, $LCR\_Adj_{k,l}$, can be applied to the LCR methodology to produce unbiased rates.

Nonparametric Yield Restrictions on Loss Cost Ratio Ratemaking

Most generally, indemnities can be related to a given quantile and its distance from an indemnification trigger. On the margin, growth in the level of each quantile relative to the trigger will affect expected indemnities. Analysis of the behavior of quantiles through time allows an assessment of the impact that each quantile has on expected LCRs in a nonparametric fashion. First, define the absolute farm yield deviation as $d_t^A = y_t - y_t^{tr}$, where y_t is the observed yield and y_t^{tr} is the trend yield. Denote the distribution function of d_t^A as $G_t^A(d_t^A)$. The pth quantile of the yield deviation distribution can be found using the inverse distribution function, $Q_t^A(p) = G_t^{A^{-1}}(p)$. The metric of interest is the magnitude of deviation between actual and

expected yields. To simplify notation, a "quantile band" is defined as $B_t^A(p) = \mu_t^A - Q_t^A(p)$, where μ_t^A is the mean of d_t^A. Likewise, relative farm yield deviation is defined as $d_t^R = (y_t - y_t^{tr}) / y_t^{tr}$, with distribution function $G_t^R(d_t^R)$, inverse distribution function $Q_t^R(p)$, and relative quantile band $B_t^R(p)$. For quantiles $Q_t^A(p) \leq \mu_t^A$, given a constant mean, the expected indemnity will increase as the absolute quantile band size increases; i.e.,

$$\frac{\partial E(I_t)}{\partial B_t^A(p)} \geq 0 \text{ since } \frac{\partial I_t}{\partial y_t} \leq 0.^5$$

To see that the above expression holds, note that if the guarantee is held constant, then as yield decreases, the indemnity will increase. Similarly,

$$\frac{\partial E(LCR_t)}{\partial B_t^R(p)} \geq 0,$$

since the expected LCR decreases when yields exhibit declining relative risk. When expected LCR is increasing in relative risk, a sufficient condition for the appropriateness of an LCR system is that each relative quantile band, $E[B_t^R(p)]$, be constant through time. Moreover, a sufficient condition to reject an LCR system is that all expected relative quantile bands below the guarantee decrease (or increase) through time. Analyzing quantile band behavior has the advantage of allowing risk evolution to be gauged at different parts of the distribution, and may be more relevant if yields do not follow a well-behaved parametric form.

Testing Risk Evolution Assumptions

Under the assumption of a parameterized distribution, the constancy of yield variance is tested using the Miller jackknife test across a split sample period. Quantile band growth rates are also analyzed to assess yield risk evolution for the nonparametric case. For both the Miller jackknife and the quantile band growth tests, we compare competing models by testing CRR against decreasing relative risk (DRR), CAR against increasing absolute risk (IAR), and CAR against CRR.

Data Used to Test Risk Assumptions

Risk evolution is evaluated for both parametric and nonparametric yield representations using Illinois Farm Business Farm Management (FBFM) corn yield data from 1980–2006. FBFM is a farm-level accounting and record keeping service that uses standardized reporting systems to collect data and assist farmers with record keeping, tax reporting, and management decisions. FBFM has a rich database of farm-level yield data, which is made available to the University of Illinois for specific research purposes through a cooperative agreement. FBFM currently has approximately 5,800 participating farms with an average size of about 1,050 acres.

Miller Jackknife Test

The behavior of the yield *CV* and standard deviation is examined by splitting the 1980–2006 sample period into two subperiods covering 1980–1993 and 1994–2006, and testing for

[5] Note that for this exposition, we drop the farm subscript, *i*, on the indemnity, *I*, since it is clear we are referring to the farm yield and since this can be generalized to the aggregated case without loss of generality.

variance equality using the Miller jackknife test. Farms from the FBFM data set having at least eight years of data for each subperiod were selected for the analysis, with a resulting sample size of 2,067. The Miller jackknife procedure is a test for differences in equality between two sample variances that is not sensitive to normality and does not require equal medians (Hollander and Wolfe, 1999). The Miller jackknife procedure is applied to both absolute and relative yield standard deviations and to each farm series to evaluate whether farm-level relative and absolute yield variance is higher in the first subperiod or the second subperiod.[6] Yield trends are estimated and both absolute and relative deviations from trend calculated for each farm-level observation. Absolute deviation is the observed yield minus the farm's trend yield. The relative deviation is calculated as the absolute deviation divided by the farm's trend yield. The null hypothesis is that risk is equal for the first and second periods. These tests are conducted for both absolute and relative risk measures. Throughout the study, a linear trend at the county level is used for detrending farm yields (Pichon, 2002; Sherrick et al., 2004; and Tannura, 2007).[7]

Quantile Band Growth Tests

The Miller jacknife test could be viewed as overly restrictive since it measures only second-order moment growth (i.e., variance) and splits the data into only two periods. Higher-order moments could also be changing and lower quantiles could be growing in ways inconsistent with constant absolute risk or decreasing relative risk for a specific parameterized distribution, yet through coincidental offsets, result in no changes in the second moment or rate. Thus, quantile growth analyses are also conducted to assess whether risk is increasing through time under a far more general depiction of "risk." To provide further confirmation of the parametric-based analysis, tests of the relative restrictions on quantile band growth trends are compared to a standard Weibull distribution exhibiting constant absolute risk (CAR) and constant relative risk (CRR). Note that the Weibull is not imposed on the empirical data in the tests but used as a baseline comparison.[8]

Finally, we also test how relative and absolute yield variances evolve through time by regressing annual cross-section yield risk on time. The subset of the FBFM data set selected for the analysis included farms with at least 15 years of data. The average number of years of data per farm was approximately 21. Quantile bands are calculated for each year for both absolute and relative deviations from trend for all farms. The analysis is conducted for quantiles of 1%, and 5% through 40%. Linear trends for each quantile band are then fitted and used to represent quantile band growth. This approach allows a test of whether a quantile exhibits increasing/decreasing risk and avoids the possibility that the form of the parameterization chosen somehow restricts the relative coverage measures to be constant. The growth in the quantile bands is then compared to those implied by fitted Weibull distributions exhibiting constant absolute risk (CAR) and a Weibull distribution exhibiting constant relative risk

[6] For the reported analysis, we used only farms which had at least eight observations for both subperiods to ensure adequate coverage. We also evaluated the data using cutoffs of 6–13 years of data and considered different split points around the center of the sample period. The results were not dependent on the cutoffs or division regimes.

[7] Previous research suggests that individual farm detrending may result in excessively high sampling variance when estimating trend (Atwood, Shaik, and Watts, 2003). Also, the econometric properties of an uninterrupted series' independent variable and the level of skewness typical in corn yields may allow OLS to generate better yield trend coefficients than alternative robust estimators (Swinton and King, 1991), although recent research indicates the possibility of small efficiency gains from other methods (Finger, 2010).

[8] Further, past research indicates that yields tend to be negatively skewed (see, e.g., Atwood, Shaik, and Watts, 2003) and that the Weibull distribution is a good candidate for modeling corn and soybean yields in Illinois (Pichon, 2002; Sherrick et al., 2004).

Table 1. Miller Jackknife Tests: 1980–1993, 1994–2006 (*N* = 2,067)

	Absolute Deviations		Relative Deviations	
α Level of Significance	Farms Exhibiting Variance Growth	Farms Exhibiting Variance Reduction	Farms Exhibiting Variance Growth	Farms Exhibiting Variance Reduction
α = 20%	6%	50%	3%	68%
α = 10%	3%	32%	1%	49%
α = 5%	2%	18%	0%	33%
α = 1%	0%	5%	0%	12%

Notes: Overall, 19% of farms exhibited absolute variance growth, while 81% exhibited decreasing absolute variance; 10% of farms exhibited relative variance growth, while 90% exhibited decreasing relative variance.

(CRR). To determine if the quantile growth in farm yields is more characteristic of CAR or CRR, we also test whether the trends in quantile band growth are statistically different from those implied by the Weibull. Specifically, for each quantile band, three hypotheses are tested corresponding to: (*a*) slope equal to zero, (*b*) slope equal to that implied by a Weibull with CAR, and (*c*) slope equal to that implied by a Weibull with CRR.

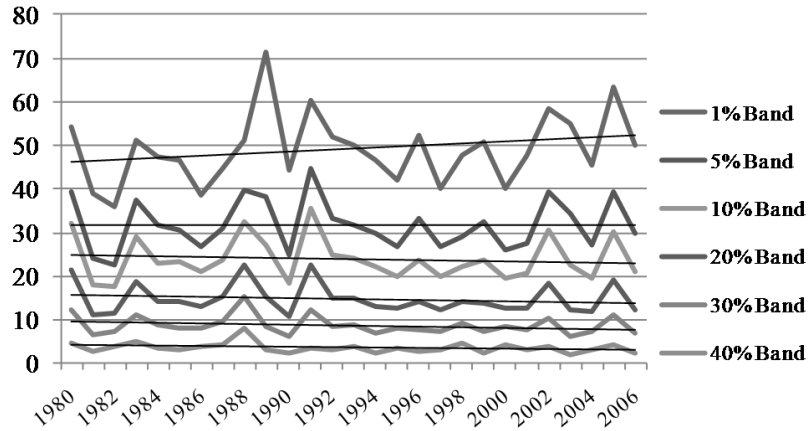
Miller Jackknife Results

Table 1 presents the Miller jackknife variance equality test results for both absolute and relative yield deviations. We test whether, during the second period, the variance for each farm was higher (increasing variance growth) or lower (decreasing variance growth) for both absolute and relative risk at four different significance levels: 20%, 10%, 5%, and 1%. The table reports the percentage of farms exhibiting yield risk growth or reduction for each significance level. Results indicate that increasing absolute risk is not reflected in the data. In this data set, 81% of farms had lower absolute yield variance for the second subperiod (1994–2006), while 19% had lower variance for the first subperiod (1980–1993). At the 10% significance level, only 3% of farms exhibited increasing absolute risk. In contrast, 32% of farms showed decreasing absolute risk at the 10% significance level, which could easily result from improving technologies through time. The findings for relative risk also indicate that the use of an LCR approach may be inappropriate because 90% of farms exhibited decreasing relative risk. Nearly 70% displayed decreasing risk at the 20% significance level, while 49% displayed decreasing relative risk at the 10% significance level.

Quantile Band Growth Test Results

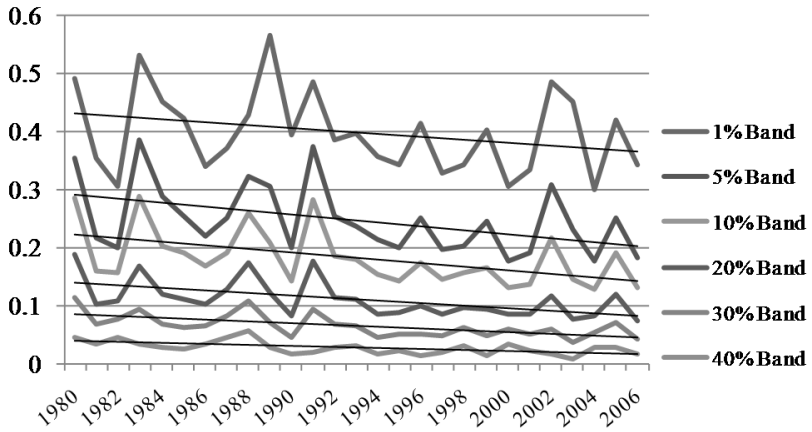
Results of the quantile band tests are provided in figures 2 and 3, which display quantiles of FBFM farm absolute and relative yield deviations from trend for 1980–2006. A visual inspection reveals the data most closely correspond to those implied by a distribution with CAR. The correspondence appears to be most obvious at the 1% and 5% quantile bands. The absolute risk implied by a Weibull with CRR is much greater than that embodied in the data, while the absolute risk implied by the Weibull with CAR is consistent with the observed data, suggesting the FBFM farm data exhibit CAR, or decreasing relative risk.

Table 2 presents results for the growth tests in standard deviation, semi-standard deviation, and quantile bands (absolute only, relative risk results not reported). For completeness, we also test whether they are different from those implied by the theoretical Weibull distributions



Note: Series labels are vertically sequential (contact authors for original color versions).

Figure 2. FBFM absolute risk quantile band growth



Note: Series labels are vertically sequential (contact authors for original color versions).

Figure 3. FBFM relative risk quantile band growth

exhibiting CAR and CRR. The expected values of the statistics (i.e., the quantile band at each point in time, the cross-section variance at each point in time, etc.) are estimated by fitting linear time trends on the annual cross-section statistics to provide a fitted estimate of the statistic at each point in time. The changes in standard deviation and semi-standard deviation are not statistically different from zero, which is consistent with CAR. Furthermore, the lack of growth in both standard deviation and semi-standard deviation implies CRR is not appropriate. The same is true in all cases for the quantile band growth. For all bands, the slopes are consistent with a distribution with CAR, and the CRR hypothesis is rejected. The results indicate that the generating process for the observed data does not embody CRR, but is more likely CAR, and therefore not appropriate for an LCR ratemaking approach.

Table 2. Absolute Risk Quantile Band Growth Tests, 1980–2006

Band	Average	Slope	Standard Error	Theoretical Slopes: Weibull CAR	Theoretical Slopes: Weibull CRR	*p*-Value for Slope Hypotheses: Equal to Zero	*p*-Value for Slope Hypotheses: Equal to Weibull CAR	*p*-Value for Slope Hypotheses: Equal to Weibull CRR	Conclusion of DGP
40% Band	3.6577	−0.0435	0.0303	−0.0225	0.0610	0.1639	0.4952	0.0020	CAR
30% Band	8.7755	−0.0653	0.0523	−0.0231	0.1565	0.2232	0.4272	0.0002	CAR
20% Band	14.8642	−0.0803	0.0845	−0.0189	0.2731	0.3508	0.4742	0.0003	CAR
15% Band	18.8193	−0.0718	0.1016	−0.0132	0.3472	0.4859	0.5687	0.0003	CAR
10% Band	23.9127	−0.0613	0.1207	−0.0019	0.4423	0.6160	0.6271	0.0003	CAR
5% Band	31.8071	0.0077	0.1431	0.0244	0.5859	0.9574	0.9084	0.0004	CAR
1% Band	49.1363	0.2330	0.1973	0.1111	0.8554	0.2483	0.5419	0.0040	CAR
Std. Dev.	19.2176	0.0317	0.0756	0.0000	0.3306	0.6789	0.6792	0.0005	CAR
Semi-Std. Deviation	13.8964	0.0201	0.0578	0.0110	0.2461	0.7315	0.8770	0.0006	CAR

FBFM Implied LCR Rates, RMA Rates, and Empirical Rates

To evaluate the overall magnitude of the effect and economic importance that violations in implicit LCR risk evolution assumptions have on rates, a direct LCR methodology is replicated using FBFM corn yield data, and the proposed associated adjustment factor estimated. FBFM-implied LCR rates are compared to RMA published rates, as well as to direct empirical experience rates.[9]

The following procedures are employed to estimate FBFM-implied LCR rates. First, actual production history (APH) is estimated for each year for each farm with at least 15 years of data. Standard RMA rules specify that a farm's APH should be calculated using an average of between four and ten years of data. Next, an LCR is calculated for each farm observation for three coverage levels—65%, 75%, and 85%—as follows:

$$LCR_{t,i} = \max\left\{0, (APH_{t,i} \times Cover - y_{t,i})\right\} \Big/ (APH_{t,i} \times Cover). \tag{12}$$

The LCRs for each farm observation are then averaged together for each year to obtain an average annual LCR. The annual LCRs are then averaged to arrive at a base rate.[10] The process is conducted for each coverage level, and average implied premiums are then calculated by multiplying the rate by the farm APH and the coverage level. To obtain the proposed adjustment factors for the rate analysis, $LCR\_Adj_{k,l}$, a simulation is conducted to estimate h_t for each t using a "typical" characterization of Illinois farm yields. Specifically, a farm with a 2006 expected yield of 162.8 bu./acre, constant standard deviation of 25 bu./acre, and trend of 1.55 bu./acre is used.[11] To provide a conservative estimate, the growth in absolute

[9] Note that the Biotech Yield Endorsement also exists under the Federal Crop Insurance Program, but is not central to this work, as it was initiated after the primary sample period used. The BE is applied after rate calculation and may be viewed as an ad hoc adjustment factor reflecting decreased risk and the failure of the LCR to reflect such.

[10] In practice, the RMA estimates a base rate for each county, applies a spatially smoothing procedure, caps and cups rate changes, and applies a state excess load. We pool at the state level to analyze aggregate rate levels. While conducting the analysis on a county-by-county basis would likely produce variations across counties, on average the results of a county analysis in sum would be similar to the state analysis.

[11] These figures correspond to the average for all farms.

Table 3. Illinois Rates and Premiums: RMA Published, FBFM Implied LCR, and FBFM Empirical Detrended

		Coverage Level		
Description		85%	75%	65%
RMA, 2008 Published Rates (Panel 1)				
Average Rate		0.0477	0.0331	0.0217
Average Premium ($/acre)		$30.13	$18.43	$10.49
FBFM Implied LCR Rate (RMA method – Panel 2)				
Average Rate		0.0338	0.0216	0.0130
Average Premium ($/acre)		$21.32	$12.03	$6.29
Implied RMA Load		41.32%	53.12%	66.76%
FBFM Implied LCR Rate (with LCR adjustment – Panel 3)				
Average Rate		0.0192	0.0098	0.0046
Average Premium ($/acre)		$12.10	$5.45	$2.22
FBFM Empirical Detrended Rate (Panel 4)				
Average Rate		0.0160	0.0080	0.0037
Average Premium ($/acre)		$10.12	$4.44	$1.79
Base Price ($/bu.)	$4.75			
Average Farm Expected Yield (bu./acre)	164.32			
Average Farm Standard Deviation	25.35			
No. of Observations	2,222			

risk is assumed to be zero. Numerical integration is used to calculate h_t and the adjustment $LCR\_Adj_{k,l}$ calculated for each year. The adjustment factor is then multiplied by each historical LCR to obtain an adjusted LCR. RMA published rates are then recovered for each farm in the data set.[12] For comparison, detrended empirical cost estimates are also calculated. The empirical premium is estimated for each farm as the average payout. A base price of $4.75/bu. is used for all analyses.

Results for Rate Analysis

Table 3 presents results for the premium comparisons. The average RMA premium is consistently higher than the FBFM-implied premium calculated using an LCR methodology. The average RMA premiums at the 85%, 75%, and 65% coverage levels are, respectively, $30.13, $18.43, and $10.49. In contrast, the corresponding FBFM-implied LCR premiums are $21.32, $12.03, and $6.29. Table 3 also reports the implied RMA loads (representing the mark-up in the premium above the expected indemnity to equal the actual premium) that would be required to account for the difference. The implied RMA load is expressed as a percentage of the estimated actuarially fair LCR premium, to cover other costs and provide for

[12] The FBFM data are for enterprise units; although the RMA does not offer the APH policy on enterprise units, it does offer them on Revenue Assurance and Crop Revenue Coverage. While the enterprise adjustment factors differ by acreage and/or number of sections, an enterprise adjustment factor of about 0.75 is typical in terms of magnitude for our data, and thus is used to obtain an estimated RMA APH enterprise rate. This approach reflects RMA's own unit adjustment loads and enables a direct comparison of calculated rates with RMA rates.

higher likelihoods of premiums covering random claims. In table 3, the implied loads average about 46%, ranging from about 41% to 67%, and are higher at lower coverage levels.[13]

Next, the adjusted FBFM implied LCR rates are examined to assess the impact that the LCR-required assumption of constant relative risk can have on rates charged. In all cases, the resulting rate bias is substantial. At the 85% (75% and 65%) coverage level, the adjusted rate is $12.10 ($5.45 and $2.22). The results imply actuarially fair premium biases of 76.2% (120.73% and 183.33%). Further, the results suggest RMA premiums exceed actuarially fair premiums by 149.01%, 238.17%, and 372.52%, respectively, at the 85%, 75%, and 65% coverage levels, yielding expected loss ratios on these products of 0.4, 0.29, and 0.21.

Table 3 also presents FBFM empirical detrended premiums. As expected, the empirical detrended premiums are very close to the adjusted FBFM implied LCR rate because the empirical detrended premiums were also derived from FBFM data.[14] The implication of these results is that LCR rates are biased upward and an adjustment factor can be created to reverse the bias created through use of the LCR methodology. In general, this framework can accommodate several types of underlying distribution and evolving risk with little loss in generality.

Sensitivity Analysis: Estimation Efficiency in the Presence of Non-Constant Weather

A common perception is that the framework proposed above to evaluate yield risk evolution is invalid under non-constant weather (Yu and Babcock, 2010; Coble et al., 2010). While it is clear that the framework and estimators employed above would provide unbiased estimates of the yield risk process through time in a statistical sense, sampling variability in observed weather could cause efficiency problems with such estimators in small samples or thin panels. Thus, it is sometimes argued that insurance loss experience patterns, such as those observed in figure 1 in the Midwest, are caused simply by the fact that there was a drought early in the period (1988), or that the sample is "too short" (see, e.g., Lanclose, 2010; Coble et al., 2010; Smith and Goodwin, 2010).

To address this issue, a direct regression approach is employed with a sample of 6,018 yield observations from a major corn production county, McLean County, Illinois, in a framework where weather effects are controlled as broadly as possible.[15] Temperature and precipitation data from June–August were collected from the National Climatic Data Center for a weather station in McLean County for the period 1980–2007. The temperature data were transformed to cooling degree days (CDD) and cumulated over the growing season to construct a *CDD* index, as some have argued this provides a better representation of the nonlinear impacts of weather on yields (Woodard and Garcia, 2008).

A precipitation index (*PRCP*) was constructed as the sum of daily precipitation. The farm-level yield observations also contain acreage (*ACRE*) and soil productivity rating (*SPR*)

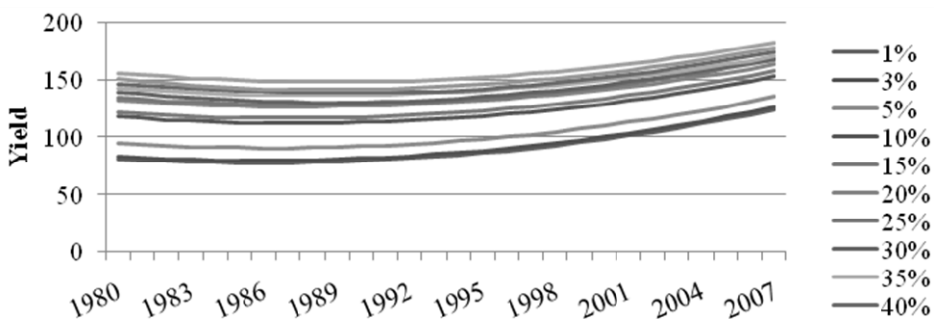
[13] RMA rates contain loads for expected losses due to quality losses, as well as replant and prevented planting provisions. The FBFM data may not embody these losses, and thus these loadings may account for a portion of the wedge observed between FBFM and RMA rates. Under an agreement with RMA on a related but separate project, we calculated prevented planting and replant loss rates (1998–2008) and found the expected cost to be approximately 0.5% of liability for this region (0.2% for replant, and 0.3% for prevented planting), or roughly $2.10/acre ($0.80 for replant and $1.30 for prevented planting) at the price and liability levels reported for 2008. Thus, including these factors does not account for the differences between RMA rates and expected costs implied by the data we use in this study.

[14] However, as discussed above, the process used to generate the premium was different than the method used to obtain the adjusted FBFM-implied LCR premium.

[15] McLean County is the single largest corn-producing county in the United States and a location for which we have an exceptionally complete set of farm-level yields covering more acres than enrolled in Federal Crop Insurance programs.

Table 4. Sensitivity Analysis Regressions of Yields on Weather and Controls

Variable	Coefficient	Std. Error	*t*-Statistic	*p*-Value
Intercept	29.377	20.366	1.442	0.149
TIME	−4.540	0.527	−8.613	0.000
PRCP	5.153	0.951	5.416	0.000
CDD	0.200	0.027	7.502	0.000
ACRE	0.013	0.001	9.890	0.000
SPR	0.925	0.041	22.476	0.000
TIME × *PRCP*	−0.016	0.013	−1.217	0.224
TIME × *CDD*	0.001	0.000	4.521	0.000
$PRCP^2$	−0.140	0.011	−12.282	0.000
CDD^2	0.000	0.000	−17.851	0.000
PRCP × *CDD*	−0.002	0.001	−2.465	0.014
$TIME^2$	0.105	0.006	17.108	0.000
R^2	0.656			
Adjusted R^2	0.655			
Standard Error	19.098			
No. of Observations	6,018			



Note: Series labels are vertically sequential (contact authors for original color versions).

Figure 4. Estimated yields under various weather stresses, McLean County

information, which were used to control for size and soil productivity differences among farms. A time trend (*TIME*) was included to control for technology changes. A specification with quadratic time and weather terms was employed to investigate the potential for differential impacts of weather on yields through time (via time trend and weather variable interactions). The quadratic specification also allows for nonlinear weather impacts and permits weather deviations from ideal conditions to result in yield losses.[16] A standard regression of yields on the above variables is estimated to obtain initial parameter estimates using the quadratic specification outlined above.

[16] Several alternative approaches were also investigated, including various regression estimators and panel data models, several different weather variables, counties/regions, and data subsets. In all cases, similar qualitative results arose. While it is not the central point of this manuscript, interested readers may contact the authors for further results.

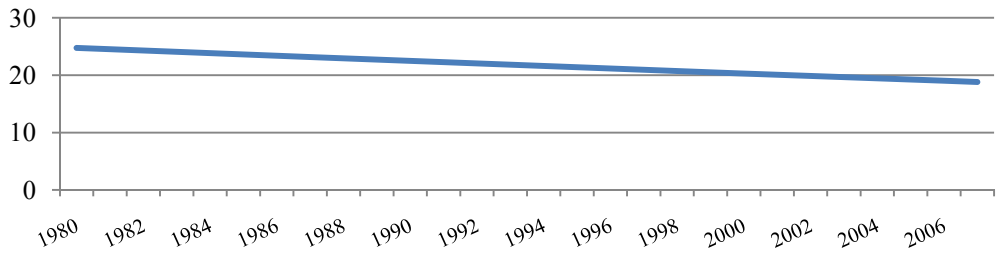


Figure 5. Estimated yield standard deviation (weather unconditional), McLean County

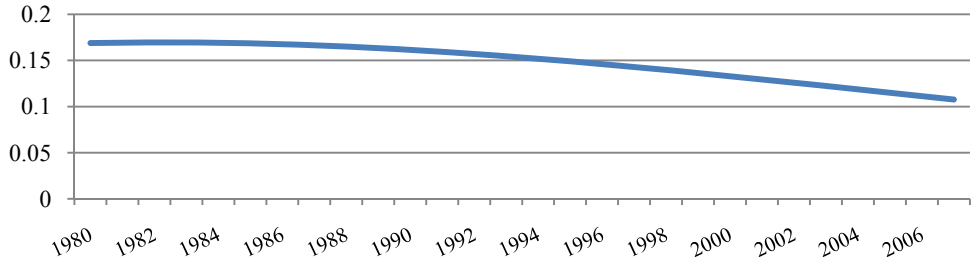


Figure 6. Estimated relative yield risk (weather unconditional), McLean County

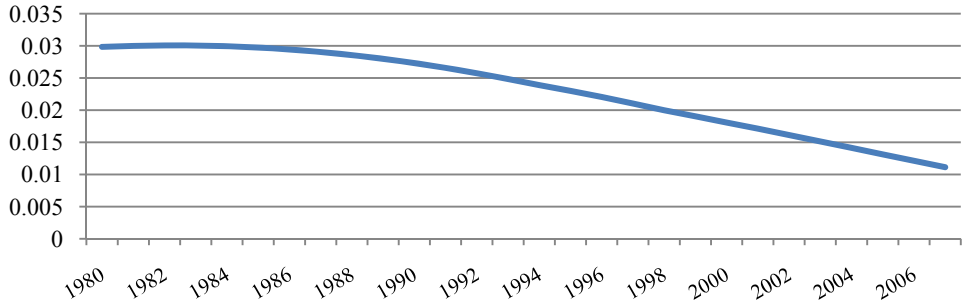


Figure 7. Estimated *E*(*LCR*), 85% coverage (weather unconditional), McLean County

Next, to construct weather unconditional estimates of yields under varying levels of technology through time, the model is used to integrate out the weather variables using the empirical joint distribution of *CDD* and *PRCP*. Regression results are reported in table 4. Figure 4 displays yields at various weather stresses as estimated from the model by yield percentile at the average of *SPR* and *ACRE*. As is evident from figure 4, not only do yields trend through time, but the deviations from trends also decrease through time under all levels of adverse weather stress, perhaps because of changes in management and the increased use of drought-resistant varieties. Figure 5 provides estimates of (weather unconditional) standard deviations through time, and figure 6 gives estimates of relative risk. Figures 5 and 6 indicate that the conditions necessary for an unbiased LCR system are violated. Figure 7 graphically illustrates the estimated (weather unconditional) expected loss cost ratio through time at 85% coverage, $E(LCR)$, which also decreases through time.

Conclusions and Discussion

This study examines the actuarial implications of the loss cost ratio (LCR) ratemaking methodology employed by RMA for setting base rates, and identifies specific conditions required for the LCR method to result in accurate estimates of forward rates. Implicit in the LCR methodology is a specific form of yield risk evolution through time. Using a unique farm-level data set, empirical evidence concerning the conditions necessary for an LCR system to generate accurate rates is presented. Results from both parametric and nonparametric representations of yields demonstrate that the LCR methodology will likely result in upwardly biased rates for Illinois corn—a high premium volume market. An adjustment method is developed and illustrated that would be applicable to very general departures (e.g., upward- or downward-trending yields, increasing or decreasing risk, alternative distributional forms, etc.), and cause no harm if LCR requirements were satisfied. Rates implied from FBFM data are generated and compared to both actual rates and associated empirical rates.

For Illinois corn, estimated LCR premium biases range from 75% to 180% in excess of actuarially fair premiums. These biases appear to be attributable to violations in the relative risk requirements that are necessary for accurate forward rates. These levels are at odds with the program's mandated objectives of regional equity and a target loss ratio of approximately 1.0. Further, the pattern highlights the dissimilar differences across coverage levels resulting from methods that do not reflect correct treatment of the changing liability structure through time. This result is consistent with Sherrick et al. (2004), who find that RMA rates are much higher than those implied from estimated farm-level distributions in Illinois. This result is also consistent with the historical observation of Glauber (2004) and the recent suggestion of Babcock (2008), as well as the recent findings of Woodard et al. (2011). These differences are economically important given that the LCR methodology directly or indirectly affected rates on approximately $579 million in 2008 for Illinois crop insurance premiums, approximately $3.3 billion in national corn premiums, and over $8.5 billion dollars for the entire program (FCIC, 2008).

Failure to account for crucial risk evolution processes appears to result in substantial rate estimation bias. As an implication, areas with increasing relative risk will have rates that are too low under an LCR system, while areas exhibiting decreasing relative risk will have rates that are too high. Further, it is worth noting that the results suggest farmers in Illinois and, most likely, some other Corn Belt states, may have been willing to pay amounts at or in excess of actuarially fair rates, which may or may not be in the interest of taxpayers. While

this situation is at odds with currently legislated loss levels, it could be interpreted as consistent with original legislation dating back to the 1930s. The current ratemaking procedures used by RMA could also be significantly contributing to the regional disparities which have been observed over the past 20 years. Moreover, the results presented here indicate that an LCR methodology will continue to produce biased rates under these conditions rather than self-correct through time.

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