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Infrequent Shocks and Rating Revenue Insurance: A Contingent Claims Approach

Timothy J. Richards and Mark R. Manfredo

Revenue insurance represents an important new risk management tool for agricultural producers. While there are many farm-level products, Group Risk Income Protection (GRIP) is an area-based alternative. Insurers set premium rates for GRIP on the assumption of a continuous revenue distribution, but discrete events may cause the actual value of insurance to differ by a significant amount. This study develops a contingent claims approach to determining the error inherent in ignoring these infrequent events in rating GRIP insurance. An empirical example from the California grape industry demonstrates the significance of this error and suggests an alternative method of determining revenue insurance premiums.

Key words: Black-Scholes, contingent claim, grapes, insurance, jump-diffusion, option pricing

Introduction

Revenue insurance is becoming an increasingly important risk management tool for U.S. agricultural producers. Insuring gross farm revenue directly addresses the key risk management concern of most growers—providing stable cash flows while minimizing the cost of obtaining insurance. Although many growers choose an individual farm-based yield or revenue insurance product, area-based revenue insurance alternatives, such as Group Risk Income Protection (GRIP), promise advantages for producers and insurance providers alike [U.S. Department of Agriculture/Risk Management Agency (USDA/RMA) 2001].¹ Potentially lower premiums, less stringent data requirements, more complete coverage, and lower administrative costs are all potential benefits from an area-based revenue insurance plan.² Despite these many advantages, participation in GRIP programs remains low (USDA/RMA 2002). Such low participation rates suggest there may be fundamental problems with the GRIP insurance pricing structure.

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¹Crop Revenue Coverage (CRC), a farm-level revenue insurance product allowing growers to take advantage of any price increases between planting and harvest, has become a popular alternative for Midwestern farmers. In 2000, fully 45.9% of all insured corn acreage was represented by CRC contracts (USDA/RMA 2002).

²Some producers' Actual Production History (APH) yields are likely to be much lower than the area-based yields. If this is the case, then the higher implicit premium subsidy under GRIP might encourage producers to buy the GRIP policy, assuming producers are motivated by the absolute dollar value of the premium subsidy, not the subsidy as a percentage of the premium.

Clearly, if premium rates are set too high relative to growers' expected losses, growers will be better off self-insuring or choosing another product. In contrast, if premium rates are set too low, insurance companies and the RMA are less likely to actively market the product for fear of incurring excessive underwriting losses. Rating errors may reflect incorrect distributional assumptions, data problems, or more fundamental issues with the rating methodology. Indeed, a growing number of studies determine the value of insurance through entirely different approaches compared to procedures employed by insurance actuaries—e.g., by using contingent claim, or option pricing techniques.

Several studies demonstrate that a contingent claim approach can be used to determine justifiable premium rates. For example, Turvey, and Turvey and Amanor-Boadu adopt a traditional Black-Scholes approach to investigate the true value of income insurance and price-support programs for Canadian farmers. Stokes, Nayda, and English treat gross revenue as a nontradeable asset in developing an equilibrium pricing approach used to calculate premiums for farm-based revenue insurance products in the United States. Using Monte Carlo simulation methods, Stokes derives an Asian-option pricing analogue for Crop Revenue Coverage (CRC) insurance and shows that existing premiums differ significantly from their true values. Academic research in general has a strong history of contributing to the development of rating methods used in actual practice (Botts and Boles; Skees and Reed; Goodwin; Goodwin and Ker). Therefore, further academic investigation into revenue insurance rating methods will likely have a significant impact on the way in which insurance premiums are determined in the future.

Option pricing techniques have the ability to correct for at least two potential sources of error which may occur in traditional rating methods. First, existing actuarial methods either explicitly or implicitly assume revenue distributions are continuous, despite the fact that crop revenue may follow more of a composite process—i.e., one composed of continuous and discrete-jump elements. While Stokes acknowledges this possibility, he leaves its solution to future research. Second, the value of insurance to growers is twofold. In addition to its intrinsic value, insurance is viewed by growers as akin to an option premium, or the value of having an alternative to selling what yield they are able to harvest for whatever the market will bear. Consequently, if the error caused by ignoring these two sources of value is significant, existing rating methods will understate justifiable premiums for revenue insurance. The implications of such rating errors are of more than notional significance, because mispriced insurance products will likely fail due to either insufficient demand or supply. Moreover, the demand for more accurate pricing techniques promises to grow as innovation extends beyond new products to new markets with unique data constraints and entirely different risk profiles, such as revenue insurance for specialty crops.

In fact, the Agricultural Risk Protection Act (ARPA) of 2000 provides incentives for the extension of insurance to as many growers as possible, including those who grow specialty crops. Given that these growers have limited risk management alternatives, despite research showing a significant latent demand, revenue insurance appears to be a viable option (Blank and McDonald). Pricing revenue insurance for specialty crops, however, requires a method capable of accommodating the idiosyncracies of their price and yield processes. Although the geographic concentration of many specialty crop markets means that discrete events and the natural hedge created by negatively correlated prices and yields are more important than for program crops, most specialty crops are

grown in irrigated or temperate climates. Thus, yields tend to be more stable. Consequently, if rating methods developed for program crops ignore option values and implicit hedges imbedded in revenue insurance, results are likely to (a) understate the true value of insurance due to the existence of discrete events, and (b) overestimate justifiable premiums to the extent negative correlations between price and yield are ignored.

Unlike premiums for CRC, the most popular revenue insurance product, GRIP premiums do take price and yield correlation into account (Goodwin, Roberts, and Coble). However, the GRIP rating method does not explicitly address the likelihood of discrete events. Clearly, as agricultural insurance expands into new products and markets, rating methods must reflect the unique risks involved in each if the performance of the Federal Crop Insurance Corporation (FCIC), measured by both participation rates and loss ratios, is to remain sound.

The primary objective of this analysis is to develop an appropriate methodology for determining area-based revenue insurance premiums, taking into account the possibility that specialty crop revenues experience periodic, discrete shocks to revenue, but also include an implicit hedge due to negatively correlated prices and yields. While the methodology presented here could be applied to any number of crops, the study focuses on rating insurance for specialty crops. Given this focus, data from California grape production (wine grapes, table grapes, and raisin grapes) are used to examine the potential error incurred by ignoring discrete events. California grapes are relevant as a "case study" because they are representative of the types of specialty crops to be insured under GRIP. As such, California grapes may demonstrate the potential shortcomings of the current approach to valuing and administering insurance programs designed for traditional program crops.

A Contingent Claims Model of Insurance Premiums

A revenue insurance contract gives a grower the right, but not the obligation, to claim a fixed amount from the insurer in the event of an indemnifiable loss. Because the probability of this loss is known only up to an observed distribution for yields and prices, the value of such an insurance contract can be established in a manner similar to a European call option (Turvey; Gardner 1977, 1988; Fackler; Petzel; Bardsley and Cashin; Marcus and Modest; Stokes, Nayda and English; Stokes). Applying the contingent claim method of option valuation (Black and Scholes 1972, 1973; Black; Merton 1973), the particular value of this option depends upon the parameters of the stochastic processes governing prices and yields, and therefore revenue. Due to the importance of the Black-Scholes (BS) result, both in academia and financial markets, a vast amount of research has been directed toward improving the accuracy of the original BS model.

Several studies document the errors caused by the simplifications made in the original BS pricing model and propose extensions to correct them. Bakshi, Cao, and Chen provide a review of some of these refinements, and demonstrate the relative importance of each using a general option pricing model that nests a number of common submodels. Although many of the crop insurance and price support studies cited above adopt some variant of the original BS model to value protection for program crops, the risks faced by produce growers are somewhat different, requiring an alternative valuation approach.

For produce growers, stochastic processes underlying revenues may not be completely continuous as is commonly assumed, but rather consist of continuous and discrete components. If true, this would mean revenues experience a relatively small amount of year-to-year variation, but possess a probability mass or "fat tail" in the lower end of the distribution, reflecting events such as frosts, floods, or mass pest infestations. Although all crops are adversely affected by these perils, the economic impact on fresh produce growers is often particularly severe as the geographic concentration of produce production and its perishability exacerbate any shock to supply. Historically, yield losses have been covered by ad hoc disaster assistance payments. However, if federally underwritten insurance programs are to be priced correctly, they must reflect the likelihood of these discrete events and the damage such events can cause.

For the arbitrage logic underlying the fundamental valuation equation of the BS model, an investor must be able to create a portfolio consisting of a short position in the derivative security, a long position in the underlying asset, and lending at the risk-free rate such that a zero-risk portfolio is achieved. However, for nontraded assets where derivative securities on the underlying asset do not exist (e.g., grapes), an equilibrium pricing method is more appropriate (Bates 1991; Stokes; Hilliard and Reis).

In a Capital Asset Pricing Model (CAPM) framework, the no-arbitrage condition underlying the contingent claim pricing method requires the periodic returns to holding the asset to be uncorrelated with a market portfolio, so the required rate of return is the risk-free rate. Indeed, if revenues are comprised of both continuous and discrete components, then it is reasonable to assume both the smooth component and the jump component are unrelated to the market portfolio. In the CAPM approach, therefore, both components would have a zero beta, and the required rate of return would again be the risk-free rate (Merton 1976).

Because grapes represent a small portion of the overall economy, it is entirely plausible that grape returns are indeed independent of returns to the market as a whole. Given these simplifying assumptions, an option pricing model is developed for revenue insurance under relatively general distributional assumptions for crop revenue.

Beginning from a specification of the process underlying revenue as the product of price and per acre yield ($R = py$), Black's variation on the BS contingent claim approach to valuing European call options on commodity contracts is used (Black; Cox and Ross; Hull).³ Whereas Black's model relies upon a single stochastic process for the futures price of a commodity, crop revenue is divided into random processes governing both price and yield. The price process is represented as a geometric Brownian motion with drift:

$$(1) \quad dp = \alpha_p p dt + \sigma_p p dz_p,$$

and the yield process in a similar manner:⁴

$$(2) \quad dy = \alpha_y y dt + \sigma_y y dz_y,$$

³ Although Black develops the model assuming the underlying asset is a futures contract, he explains the logic of why this is equivalent to a claim on the spot commodity as well. By transferring risk to those most able to bear it through a corporation, commodity growers are able to establish a zero-beta position in their commodity portfolio, and thus act as if the spot price is equivalent to a futures price.

⁴ Because there is some question as to whether or not yields exhibit trends over time, this assumption is tested in the empirical example below. Contrary to Turvey's findings, a significant drift component is found in these data.

where α_p and α_y are rates of drift, or annual rates of price and yield increase, respectively; σ_p and σ_y are standard deviations of the price and yield processes; and dz is the increment of a standard Wiener process, where $dz^2 \rightarrow 0$, and $dz_p dz_y \rightarrow \rho dt$, and ρ is the correlation between price and quantity. Applying Ito's lemma to R gives:

$$(3) \quad dR = \frac{\partial R}{\partial p} dp + \frac{\partial R}{\partial y} dy + \frac{1}{2} \left[\frac{\partial^2 R}{\partial p^2} dp^2 + \frac{\partial^2 R}{\partial y^2} dy^2 + \frac{\partial^2 R}{\partial p \partial y} dp dy \right],$$

where $\partial R / \partial p = y$, $\partial R / \partial y = p$, $\partial^2 R / \partial p^2 = 0$, $\partial^2 R / \partial y^2 = 0$, and $\partial^2 R / \partial p \partial y = 1$. Substituting these terms and (1) and (2) into (3), and allowing the process to vary by county, gives an expression for the stochastic process for revenue in county i :

$$(4) \quad dR_i = \alpha_{iR} R_i dt + \sigma_{ip} R_i dz_{ip} + \sigma_{iy} R_i dz_{iy},$$

where $\alpha_{iR} = \alpha_{ip} + \alpha_{iy} + \rho \sigma_{ip} \sigma_{iy}$. If revenue in a particular county follows this process, then the value of a guaranteed level of R is equivalent to the value of a call option on the revenue target.

Assume arbitrage so that the value of a call option on a grower's revenue stream in county i , V_{iR}^c , with target revenue Z_{iR} is:

$$(5) \quad V_{iR}^c = e^{-rt} [Z_{iR} \Phi(-d_{i2}) - R_{i0} \Phi(-d_{i1})],$$

where Φ is the normal cumulative distribution function, R_{i0} is the current, pre-contracting farm revenue, r is the discount rate, and the respective values of d_{i1} and d_{i2} are given by:

$$(6) \quad d_{i1} = \left(\frac{\ln(R_{i0}/Z_{iR}) + 1/2(\sigma_{ip}^2 + \sigma_{iy}^2 + 2\rho_{py}\sigma_{ip}\sigma_{iy})\tau}{\sqrt{\sigma_{ip}^2 + \sigma_{iy}^2 + 2\rho_{py}\sigma_{ip}\sigma_{iy}} \sqrt{\tau}} \right)$$

and

$$(7) \quad d_{i2} = \left(\frac{\ln(R_{i0}/Z_{iR}) - 1/2(\sigma_{ip}^2 + \sigma_{iy}^2 + 2\rho_{py}\sigma_{ip}\sigma_{iy})\tau}{\sqrt{\sigma_{ip}^2 + \sigma_{iy}^2 + 2\rho_{py}\sigma_{ip}\sigma_{iy}} \sqrt{\tau}} \right).$$

In (6) and (7), τ is defined as the time to expiry in terms of a proportion of a year (if T is the time to expiry in days, then $\tau = T/365$). For the current example, the time to expiry is assumed to be the average time between contracting for insurance and harvesting grapes, or roughly six months. While this model assumes the revenue process is continuous, shocks to either price or yield can cause the revenue process to differ from that described above.

Indeed, Goodwin, Roberts, and Coble argue that jump processes or jump-diffusion mixtures may be better able to represent the true distribution of revenue. Although they attempt to model nonstandard price distributions as mixtures of normals, shocks may instead be independent, discrete events rather than shifts of the entire distribution. By definition, indemnifiable events are more likely to be discrete in nature, or "abnormal"

(Merton 1976).⁵ As such, these events indicate the stochastic process governing revenue may be a composite of both a continuous part and a jump process, the arrivals of which are assumed to be Poisson distributed and their magnitude lognormal. Because prices and yields are generally assumed to be negatively correlated, the probability of a jump in revenue would seem a priori to be much lower than a shock to either price or yield. Consequently, the premium for revenue insurance is expected to be significantly lower than either price or crop insurance. Although the natural hedge implied by negative price-yield correlation is well understood, the impact of discrete events on the price of insurance is less clear.

In a contingent claim valuation framework, the effect of discrete events is captured by modifying the underlying process governing revenue to incorporate discrete jumps so that:

$$(8) \quad dR_i = (\alpha_{iR} - \lambda\phi)R_i dt + \sigma_{ip}R_i dz_{ip} + \sigma_{iy}R_i dz_{iy} + R_i dq_i,$$

where λ is the mean number of arrivals per unit of time (Merton 1976), dq is the instantaneous change in revenue due to the discrete event, and ϕ is the resulting expected percentage change in revenue. Next, given the dynamics in (8) for returns to the underlying asset, the option price can be expressed as a twice-differentiable function of this value and time: $V_R^J = F(R, \tau)$.

Assuming the CAPM accurately describes the equilibrium to which all asset prices must move, and discrete shocks have a zero beta, Ito's lemma is applied to $F(R, \tau)$ to produce the fundamental partial differential equation describing the equilibrium option value (suppressing the county subscript):

$$(9) \quad \frac{1}{2}\sigma_R^2 R^2 F_{RR} + (r - \lambda\phi)RF_R - F_\tau - rF + \lambda E[F(kR, \tau) - F(R, \tau)] = 0,$$

subject to $F(0, \tau) = 0$ and $F(R, 0) = \max[0, R - Z_R]$. Define k as the realization of an i.i.d. random variable representing the percentage change in the insured variable if the event occurs. Assuming k is lognormally distributed gives (Merton 1976):

$$(10) \quad V_R^J = F(R, \tau) = \sum_{n=0}^{\infty} \left(\frac{e^{-\lambda'\tau} (\lambda'\tau)^n}{n!} \right) f_n(R, \tau).$$

In (10), $f_n(R, \tau)$ is the option value for exactly n realizations of the discrete event which is found by modifying the components of (5) by substituting the variance term ($v_n^2 = \sigma_R^2 + n\delta^2/\tau$) and the interest rate ($r_n = r - \lambda\phi + n\gamma/\tau$), where δ^2 is the variance of the log of k , $\gamma = \log(1 + \phi)$, and $\lambda' = \lambda(1 + \phi)$. Therefore, the value of insurance for revenue following a composite jump-diffusion process is a weighted average of its value under each possible realization of the random number of discrete events, given adjustments to the variance of revenue and the discount rate. Consequently, the difference between the value of insurance calculated assuming a continuous revenue process and the value under a

⁵ More common applications of such jump-diffusion processes consider stock prices, where such abnormal events may be the release of unfavorable information regarding clinical trials of a new drug, the outbreak of a foodborne illness in a restaurant chain, or the recall of a faulty tire. Other examples of jump-diffusion processes in derivative valuation include the likelihood of bankruptcy (Cox and Ross), default on mortgage insurance (Johnson and Stulz), corporate bonds (Hull and White), currency devaluation (Bates 1996), or price movements in equity markets (Jorion; Naik and Lee).

jump-diffusion process is a function of both the probability and magnitude of discrete events. For the purposes of this study, there are two ways of assessing the importance of these two factors.

First, analytical expressions for insurance premiums under competing distributional assumptions are compared in order to predict the direction of the potential error caused by ignoring low-probability catastrophic events. Although option comparative statics (or “Greeks”) are well understood (see Wolf or Hull, for example), this study focuses on comparing the difference between option values calculated under each assumed revenue process. For revenue insurance, the difference in option premiums is given by:

$$(11) \quad V_R^J - V_R^c = \sum_{n=0}^{\infty} \left(\frac{e^{-\lambda'\tau} (\lambda'\tau)^n}{n!} \right) V_{R,n}^c - V_R^c,$$

where $V_{R,n}^c$ is the premium associated with n realizations of the discrete event. Because the first term in (11) necessarily sums to one, it suffices to show that each of the $V_{R,n}^c$ values is greater than the continuous counterpart to determine whether the presence of discrete jumps results in a higher total premium. The impact of discrete events has both an “interest rate” and a “volatility” effect (*vega*), both of which can be shown to be unambiguously positive (details are available from the authors upon request).⁶ Therefore, the empirical question becomes one of whether these analytical differences are indeed economically significant, given the small probability that any adverse event is likely to occur. The larger question remains, however, whether the pricing model in (10) generates estimates of insurance premiums which differ significantly from those calculated using current FCIC methods.

Comparing the insurance premium calculated using (10) with GRIP premiums provides a second basis for evaluating the significance of both discrete events and the option value inherent in a revenue guarantee. The FCIC sets pure premiums for GRIP insurance such that they are actuarially sound, or equal to expected underwriting losses.⁷ First, distributions for price and yield are defined to calculate expected losses. This is necessary because the FCIC defines revenue as the product of these two values, rather than historical realized revenue. Consistent with FCIC practice, an empirical yield distribution for each county is defined, correcting for any trends in yield and scaling the result to represent a common “weather year” based in 1998 (USDA/RMA 2001). Because there is no futures market for grapes, annual county-level prices and historical sample variances are used to describe the price distribution, which is assumed to be lognormal. Lognormality is not only consistent with much of the options-pricing literature, but is also able to account for the positive skewness resulting from the ability to allocate grapes among competing uses (wine, raisins, table) in the event of a poor crop year. Next, because the correlation between prices and yields is likely to be a significant factor in rating county-level revenue insurance, the correlation for each county is estimated and the average correlation is used to help define a distribution for annual revenue.

⁶ The *vega* is usually listed among the group of option-value sensitivities known as “Greeks,” despite the fact that *vega* is not a member of the Greek alphabet.

⁷ Pure premiums are exclusive of administrative costs and are intended to cover underwriting losses only. Gross premiums include the insurance load and are the values quoted to insurance buyers (Vaughn and Vaughn).

The revenue distribution is defined by drawing correlated prices and yields according to the method developed by Johnson and Tenenbein and applied to Midwestern corn production by Babcock and Hennessy. This approach is described in general terms, while readers interested in further details should consult Babcock and Hennessy or the GRIP rating documentation (USDA/RMA 2001).

First, begin by defining marginal distributions for p and y consistent with the assumptions above: $F_1(p)$ and $F_2(y)$. Next, rank all yields from highest to lowest. Define $U' = \Psi^{-1}(F_2(y))$, where Ψ is the standard normal cumulative distribution and $F_2(y)$ is the empirical yield distribution defined as:

$$(12) \quad F_2(y) = (N + 2 - \text{rank}(y)) / (N + 2)$$

for yields that are above county average, and

$$(13) \quad F_2(y) = (N + 1 - \text{rank}(y)) / (N + 1)$$

for those below average. Third, define:

$$(14) \quad V = cU' + (1 - c)V',$$

where V' is a standard normal random variable and c is a constant in the interval $[0, 1]$ selected so as to make the correlation between p and y assume the desired value. Next, define $p' = H_1(V)$, where $H_1(V)$ is the distribution function of V so that $p = F_1^{-1}[1 - H_1(V)]$ provides a variable consisting of price deviates with the required yield correlation. Drawing from this price distribution 1,000 times for each yield value and multiplying the result by the associated yield provides 1,000 revenue deviates for each year in the sample. In the example below, there are 13 years of data for each county, so 13,000 revenue deviates are generated. Finally, expected revenue is multiplied by a fixed coverage level (80%, for example) and the average deviation of actual revenue from this guarantee over all 13,000 possible revenue values for each county is found. This value, as a percentage of total liability, is the expected loss, or the pure GRIP premium. The next section describes the particular application of this approach and the comparison of insurance premiums calculated using each alternative method.

Data and Methods

To assess the premium-valuation error inherent in the current GRIP rating method, this study compares the results from three alternative valuation methods on a pairwise basis. The first set of results compares the difference between insurance premiums calculated using a traditional Brownian motion (BM) contingent claims approach relative to those found with the current GRIP rating methods. For the BM approach, revenue is assumed to be distributed lognormal, with lognormal prices and lognormal yields, while the current GRIP methodology assumes lognormal prices but an empirical yield distribution. Because there is no a priori reason to believe revenues are indeed lognormal, each revenue series is tested for lognormality. To do so, the log of revenue for each different type of grape is regressed against a set of geographic dummy variables

and the residuals are tested for normality using a Jarque-Bera test (the results appear in table 1).⁸

The second comparison examines the difference between insurance premiums using the BM approach relative to premiums calculated under a jump-diffusion (JD) process. The primary hypothesis is that improvements in insurance pricing can result from incorporating a jump-diffusion process for revenue distribution relative to a Brownian motion assumption. Thus, the distribution of revenue is assumed to be lognormal, conditional on no jumps. A growing amount of research suggests that a mixture distribution can explain apparent pricing anomalies among exchange rates (Bates 1996), stock price (Naik and Lee), and commodity options (Hilliard and Reis). Higher insurance premiums are expected to result if revenue follows a JD process as opposed to a BM process.

Because the defining characteristic of the GRIP program is its use of an area trigger, or a "group risk" concept, the data describe grape production and prices on a county level in the state of California. "County Agricultural Commissioner Reports," prepared by the California Department of Food and Agriculture, provide acreage, yield, and price data for wine, table, and raisin grapes.⁹ For wine grapes, the sample counties are Fresno, Kern, Kings, Madera, Mendocino, Merced, Sacramento, San Joaquin, San Luis Obispo, Stanislaus, and Tulare. Raisin and table grapes are grown only in a subset of these counties—raisin grapes in Fresno, Kern, Kings, Madera, Merced, and Tulare counties, and table grapes in Fresno, Kern, Kings, Madera, Merced, San Joaquin, and Tulare counties.

For each county, there are 13 annual observations, from 1986 through 1998. Given the limited number of annual observations per county, all observations are pooled across counties for each type of grape for the purposes of estimating the jump-diffusion parameters. This yields 143 annual observations for wine grapes, 91 for table grapes, and 78 for raisin grapes. Table 1 provides a summary of the price, yield, and revenue data used in each valuation model, while each of the option-value models assumes a risk-free rate of 6%. Although the selection of a risk-free rate is somewhat arbitrary, variation in this value has little effect on calculated option values and does not affect the qualitative conclusions among premiums.

There are two ways of parameterizing the revenue process: implicit estimation, or maximum likelihood. Hilliard and Reis adopt the former approach, arguing that a maximum-likelihood approach requires too many time-series observations to include a sufficient number of low-probability events, and preference parameters must be estimated for use in the risk-neutralized valuation equation. However, an implied parameterization approach requires a series of option prices. Because there are no traded options on grapes, or on many other commodities for which GRIP will eventually

⁸ The assumption of both lognormal prices and yields for the Brownian motion model is a matter of necessity. While lognormal prices are consistent with the literature, as pointed out by a reviewer, it is more difficult to justify lognormal yields. However, the use of the lognormality assumption is standard for contingent claims valuation, and lognormal yields have been used in previous research examining revenue insurance (Turvey). Based on the results reported in table 1, wine and raisin grape revenues appear to be lognormal, but not table grapes. Therefore, the table grape results should be interpreted with the caveat that the BS pricing model is not directly applicable.

⁹ According to the USDA's National Agricultural Statistics Service (NASS), "... these reports [the County Agricultural Commissioner Reports] provide the most detailed annual data available on agricultural production by county. Basic data collected by the Agricultural Commissioners and their staffs are compiled from many sources. Sources vary from county to county. Examples of data sources include grower surveys, regulatory and inspection data, shipment data, industry assessments, etc." [online website, <http://www.nass.usda.gov/ca/bul/agcom/indexcav.htm>]. Given the inconsistency in data collection methods, the quality of these data are of some question, but, as NASS officials state, they remain not only the most detailed, but often the only county-level data available. We assume any errors are random.

Table 1. Summary of Grape Price, Yield, and Revenue Data

Description	Unit	Wine Grapes	Table Grapes	Raisin Grapes
Yield Volatility: σ_y	%	0.029	0.047	0.085
Price Volatility: σ_p	%	0.021	0.034	0.077
Revenue Volatility: σ_R	%	0.052	0.083	0.159
Average Yield: \bar{y}	tons/acre	8.433	8.656	10.541
Average Price: \bar{p}	\$/acre	460.271	939.702	245.312
Price/Yield Correlation: ρ_{py}		-0.046	-0.036	-0.032
χ^2 Value: (H_0 : Lognormal Revenue)		1.400	18.825*	3.436
Critical χ^2 : ($df = 2, \alpha = 5\%$)		5.990	5.990	5.990
Number of Observations (N)		143	91	78

Notes: A single asterisk (*) denotes significance at the 5% level. All volatility and correlation values reported here are sample averages across all counties for each type of grape. Parameters used in the option pricing model are county specific.

be offered, the maximum-likelihood method of Ball and Torous; Jarrow and Rosenfeld; and Das is the only viable alternative. Even with pooling of grape data across counties, there is concern the data series are not sufficiently long to reliably estimate jump parameters. However, the lack of traded options and limited historical data on price and yields are endemic of all produce and specialty crops. Indeed, firms that rate revenue insurance products will be faced with similar obstacles. Fortunately, the use of maximum likelihood imposes little cost. Ball and Torous; Jarrow and Rosenfeld; and Jorion each demonstrate the ability of the maximum-likelihood approach to provide efficient estimates of both the frequency and magnitude of jumps in stock prices, even in relatively small data sets.¹⁰ Adoption of the maximum-likelihood method becomes a matter of necessity, not preference, when estimating jump-diffusion parameters for produce commodities.

Prior to estimating the jump-diffusion parameters, however, specification tests are performed to establish whether a jump-diffusion or continuous Brownian motion process is a better representation of the revenue series. To accomplish this, a maximum-likelihood approach is used to test the Poisson-normal mixture model (Merton 1976; Jarrow and Rosenfeld) against a normal alternative. A Wald chi-square test is used to test the null hypothesis that there are no jumps in the revenue series, or $\lambda = \delta^2 = 0$, based on maximum-likelihood estimates of the unrestricted log-likelihood function:

$$(15) \quad L(r|\Omega) = -T\lambda \frac{T}{2} \ln(2\pi) + \sum_{t=1}^T \ln \left[\sum_{n=0}^N \frac{\lambda^n}{n!} \frac{1}{\sqrt{\sigma_R^2 + \delta^2 n}} \exp \left(-\frac{\left(r_t - \left(\alpha_R + \sigma_R^2/2 + n\delta^2/2 - n\phi \right) \right)^2}{2(\sigma_R^2 + \delta^2 n)} \right) \right],$$

¹⁰ Note, the data sets in each of these studies are considerably larger than the one used here. Therefore, the sampling properties of the maximum-likelihood estimator claimed by Ball and Torous may not be strictly applicable to the current case.

for T observations of annual changes in revenue ($r_i = \ln(R_{i,t}/R_{i,t-1})$) for each i county, where λ is the Poisson intensity parameter, σ_R^2 is the volatility of the continuous part, δ^2 the volatility of the discrete part, and $\mu_R = \alpha_R - \sigma_R^2/2$ is the mean of r . Following Ball and Torous, n is defined as the random realization of a shock to revenue, and N is fixed at a value likely to include all possible occurrences of a shock (three proved to be sufficient).¹¹ The log likelihood (15) is maximized with respect to the remaining parameters after pooling all county data and allowing for fixed county effects for each grape type.

The goal in estimating this model, however, is not only to determine which specification provides a better fit to the data, but also to estimate the revenue process parameters to be used in calculating contingent-claim insurance premia. Therefore, once each of the jump-diffusion parameters has been estimated by maximizing (15), they are used in equation (10) to determine the option value of each insurance premium. Further, it is important to remember that estimates of the jump-diffusion parameters are obtained with the pooled data, but the insurance premiums (option price simulations) use the same 13,000 simulated price and yield values created for the GRIP procedure. Doing this allows for the continuity of market conditions, and permits the examination of differences in the premiums due strictly to the model used.

Results and Discussion

Prior to calculating the premiums implied by a contingent claim approach, it is first necessary to determine the appropriate form of the stochastic process underlying revenue for each type of grape. To do so, we report both results obtained by applying the Wald chi-square test to each revenue process as well as the individual parameter estimates (table 2). For wine grapes, the Wald chi-square test statistic is 68.050. The corresponding value for table grapes is 38.637, and 102.288 for raisin grapes. With two restrictions and a significance level of 5%, the critical χ^2 value is 5.99, so the null hypothesis of simple Brownian motion is rejected in favor of a jump-diffusion specification subject to the caveat raised by Andrews for one-sided hypothesis tests of this type.¹² Further, the majority of individual parameter estimates are significant at a 5% level, so the weight of the available statistical evidence leads, albeit tentatively, to the conclusion that a jump-diffusion process is preferred to a simple Brownian motion for each grape revenue series. Note,

¹¹ Other studies estimate the jump-diffusion model with $N = 10$ (Ball and Torous; Jorion). We adopted the approach suggested by Ball and Torous and first estimated the model as a Bernoulli, or where $N = 1$. With these starting values, the model was subsequently estimated with increasingly higher values of N until the estimated parameters did not change. This occurred at $N = 3$ for each type of grape. This finding is not surprising because the sample used here is considerably smaller than samples used in other studies, so it is expected there will be correspondingly fewer total jumps in the series.

¹² Andrews shows that when the possibility exists for the estimated parameter to lie on the boundary of the null hypothesis (i.e., $\lambda = \delta^2 = 0$), then standard test statistics understate the true critical value of the test. He presents simulated quasi-likelihood ratio (QLR) critical values for a test involving one parameter (in the context of both GARCH and random coefficients models) which he shows to be asymptotically equivalent to those relevant to the Wald chi-square tests used in the current study. Andrews demonstrates they are significantly higher than the values which are typically used. Given that our problem involves two parameters, is fundamentally different from the examples used in Andrews' paper, and is estimated in a relatively small sample, we present the Chebyshev inequality, or upper-bound value for the significance of a test statistic under an unknown distribution. Chebyshev's inequality is calculated as $\Pr[\chi^2 > M] \leq q/M$, where q is the number of parametric restrictions and M is the number of standard deviations defined by the estimated χ^2 value. If the upper bound of this p -value is less than 5%, then the null hypothesis can be rejected under more conservative criteria than is typical when using a Wald chi-square test. As shown in table 2, the significance level is below 5% in both the wine and raisin grape cases, but not table grapes. Therefore, the jump-diffusion estimates for table grapes should be interpreted with some caution.

Table 2. California Wine, Table, and Raisin Grape Revenue Process Maximum-Likelihood Estimates, 1986–2000

Parameters / Counties	Wine Grapes		Table Grapes		Raisin Grapes	
	Coefficient	<i>t</i> -Ratio	Coefficient	<i>t</i> -Ratio	Coefficient	<i>t</i> -Ratio
α	0.091*	4.829	0.026*	2.616	0.161*	9.519
σ^2	0.044*	8.131	0.016*	6.999	0.001	1.122
λ	1.848	1.313	1.313*	2.521	1.755*	7.011
δ^2	0.043*	8.085	0.198*	2.472	0.018*	4.370
ϕ	0.596*	26.884	0.185	1.730	0.050*	2.982
Fresno	0.061	0.920	0.028	0.555	0.012	0.194
Kern	0.067	1.015	0.038	0.751	-0.040	-0.665
Kings	0.054	0.812	0.071	1.388	0.075	1.248
Madera	0.068	1.020	0.055	1.069	0.024	0.399
Mendocino	0.119	1.794	NA	NA	NA	NA
Merced	0.085	1.276	0.031	1.547	0.034	0.565
Sacramento	0.073	1.101	NA	NA	NA	NA
San Joaquin	0.075	1.125	0.098	1.916	NA	NA
San Luis Obispo	0.115	1.735	NA	NA	NA	NA
Stanislaus	0.083	1.254	NA	NA	NA	NA
Tulare	0.057	0.852	0.067	1.305	-0.014	-0.234
No. of Observations	143		91		78	
Log Likelihood	14.540		92.199		12.643	
Wald χ^2	68.050*		38.637*		102.288*	
Chebyshev Upper Bound	0.029		0.052		0.019	

Notes: A single asterisk (*) denotes significance at the 5% level. The parameters are defined as follows: α is the mean drift rate of the series, σ^2 is the variance of the continuous part, λ represents the Poisson intensity parameter, δ^2 is the variance of the discrete part, and ϕ is the conditional shock to the change in revenue, expressed as a multiple of the average revenue value. The null hypothesis for the Wald χ^2 statistic is that $\lambda = \delta^2 = 0$. Because the distribution of the Wald statistic is unknown on the boundary of the null hypothesis, the Chebyshev upper bound provides a maximum value for the probability that the null hypothesis is true. NA indicates no data are available for this type of grape for the associated county.

however, the variance of the jump process for wine grapes is statistically significant on its own, but not the Poisson intensity parameter. This suggests at least two observations: (a) a joint test of both parameters is indeed necessary, and (b) by their very nature, discrete, infrequent jumps are difficult to identify in low-frequency data. Because of the nondefinitive nature of this specification test, insurance premiums are first obtained under a Brownian motion and then a jump-diffusion assumption.

Typically, quoted insurance premiums reflect more than simple expectations of actuarial loss. In this analysis, however, the estimated premiums represent equilibria that are supportable as the outcome of a complete market for agricultural insurance, but do not admit the normal load factors or compensation for moral hazard or adverse selection that may arise. For wine grapes, table 3 compares county-level revenue insurance premiums under three coverage levels (50%, 70%, and 90%) and three rating methods: (a) the current method used by the FCIC, (b) a contingent claims approach under a simple Brownian motion revenue-process assumption, and (c) a more general contingent claims model that assumes revenue follows a composite jump-diffusion process. Tables 4 and 5 provide similar comparisons for table and raisin grapes, respectively.

Table 3. Wine Grape GRIP Premiums: FCIC and Option Value Premium Estimates (\$/acre)

County	RATING METHOD BY COVERAGE LEVEL ^a								
	50%			70%			90%		
	FCIC	BM	JD	FCIC	BM	JD	FCIC	BM	JD
Fresno	0.00	0.36	3.01	0.00	7.58	33.97	10.62	77.21	156.39
Kern	0.00	0.33	5.41	0.00	20.09	52.46	41.58	112.92	196.80
Kings	0.00	0.32	6.09	0.00	22.61	59.65	20.21	131.26	224.62
Madera	0.00	0.55	5.82	0.00	20.80	53.82	52.72	115.45	200.40
Mendocino	0.00	17.64	42.41	17.59	125.34	222.62	153.34	378.73	600.60
Merced	0.00	8.97	28.38	23.69	97.87	176.57	197.44	319.82	490.70
Sacramento	0.00	2.34	18.24	2.67	73.02	153.62	175.64	308.80	499.31
San Joaquin	0.00	5.47	22.58	9.57	84.05	159.32	201.45	298.17	470.32
San Luis Obispo	0.00	13.77	35.71	29.08	111.94	197.10	165.58	322.60	532.14
Stanislaus	0.00	3.15	15.54	7.82	58.88	117.11	149.66	227.83	361.36
Tulare	0.00	0.77	6.24	0.55	23.50	54.57	45.83	105.57	191.58

^a FCIC indicates current Federal Crop Insurance Corporation rating method, BM is option value of insurance with Brownian motion revenue-process assumption, and JD is the option value under the jump-diffusion assumption.

The results in table 3 are used to estimate the magnitude of the difference in premium estimation caused by ignoring the option value implicit in a revenue guarantee. Comparing premiums between the current (FCIC) method and the simplest contingent claim model (BM), it is obvious, at a 50% coverage level, revenue insurance has no value under traditional rating methods, but up to almost \$18 per acre if the similarity between a revenue insurance contract and a financial option is formally taken into account. At the next highest coverage level (70%), the premium suggested by current calculation techniques remains zero for four counties. However, the financial value from a contingent claim perspective is, on average, 7.09 times higher on a per acre basis. At the highest coverage level considered (90%), the average contingent claim estimate, assuming a simple BM process, is 1.97 times the estimate found using conventional rating methods.

Clearly, if private insurance companies market GRIP to wine-grape growers at “actuarially sound” premium rates, growers would receive a significant amount of economic surplus. Considered another way, these results indicate that existing premium subsidies paid by the federal government are actually a smaller proportion of the true economic benefit of the insurance contract, simply because subsidies are paid as a proportion of the actuarially sound premium rate and not the actual economic value. If the option value ignored in the current method of estimating premium rates is similar for crops now covered by GRIP contracts—such as corn in Illinois, Indiana, or Iowa—this finding may help explain the very low participation rates in GRIP relative to CRC. On the other hand, low participation rates may suggest the problem lies in the supply of GRIP contracts, rather than their demand. If premium rates are set too low, then there is little incentive for insurance companies to actively market the product to growers. Higher premium estimates with a contingent claim approach, however, are not uniform among the empirical examples considered here.

As observed from the results in table 4, three out of seven counties exhibit higher FCIC premiums for table grapes relative to those calculated using the base contingent claim model (BM) at a 90% coverage level. Further, table 5 shows that three of six raisin

Table 4. Table Grape GRIP Premiums: FCIC and Option Value Premium Estimates (\$/acre)

County	RATING METHOD BY COVERAGE LEVEL ^a								
	50%			70%			90%		
	FCIC	BM	JD	FCIC	BM	JD	FCIC	BM	JD
Fresno	0.00	0.00	9.02	0.00	24.36	97.17	90.14	294.78	450.85
Kern	0.00	0.00	11.31	0.00	22.46	49.15	101.17	99.90	234.46
Kings	70.98	0.00	4.28	205.96	23.70	120.12	525.74	434.10	577.52
Madera	0.00	0.00	4.08	0.00	3.19	48.06	25.21	113.23	252.58
Merced	35.09	27.96	28.02	49.03	39.15	39.22	63.04	50.33	50.43
San Joaquin	68.67	97.47	101.70	181.42	221.13	248.82	311.58	412.87	494.65
Tulare	0.00	0.10	18.10	5.69	102.77	176.68	192.88	492.83	622.20

^a FCIC indicates current Federal Crop Insurance Corporation rating method, BM is option value of insurance with Brownian motion revenue-process assumption, and JD is the option value under the jump-diffusion assumption.

Table 5. Raisin Grape GRIP Premiums: FCIC and Option Value Premium Estimates (\$/acre)

County	RATING METHOD BY COVERAGE LEVEL ^a								
	50%			70%			90%		
	FCIC	BM	JD	FCIC	BM	JD	FCIC	BM	JD
Fresno	0.00	0.00	19.42	0.00	9.79	71.17	14.71	48.18	188.97
Kern	0.00	17.38	40.64	159.21	91.77	165.47	431.22	307.71	396.29
Kings	81.01	0.00	12.21	178.25	35.03	44.26	306.60	54.86	123.86
Madera	0.00	0.00	16.74	0.00	15.75	61.32	6.72	47.60	164.15
Merced	11.91	0.80	36.52	52.27	35.87	134.26	210.37	259.53	375.36
Tulare	0.00	7.40	32.55	93.37	51.44	126.84	327.01	226.87	326.06

^a FCIC indicates current Federal Crop Insurance Corporation rating method, BM is option value of insurance with Brownian motion revenue-process assumption, and JD is the option value under the jump-diffusion assumption.

grape counties exhibit similar reversals. Closer inspection of the data reveals FCIC rating methods are likely to overestimate premiums relative to the contingent claims approach when revenue is highly volatile. In the case of table grapes, for example, the average coefficient of variation among counties with the expected pattern of premiums (i.e., higher premiums estimated with a contingent claim approach) is 11.8%, in contrast to the coefficient of variation of 36.7% among counties in which FCIC premiums are higher than those determined using contingent claim methods.

While revenue volatility is a critical parameter for both methods, it is apparent that the static approach used by the FCIC is more sensitive to errors in estimating volatility. This sensitivity, in turn, is due to the distributional assumptions underlying each of the revenue components. Whereas both the FCIC and contingent claim approaches assume lognormality for prices, the FCIC method relies on empirical yield distributions and the contingent claim approach assumes lognormal yields.

Given the relative paucity of data available for this, and any other attempt to rate GRIP insurance (USDA/RMA 2001), empirical yield distributions are likely to better represent data series with nonconforming yield years. Therefore, the "reversals" found in table and raisin grapes reflect instances where the FCIC approach does a better job

Table 6. Percentage Difference Between JD and BM Insurance Premiums for the 50%, 70%, and 90% Coverage Levels: Wine Grapes, Table Grapes, and Raisin Grapes (%)

County	Wine Grapes			Table Grapes			Raisin Grapes		
	50%	70%	90%	50%	70%	90%	50%	70%	90%
Fresno	733.24* (25.27)	348.11* (16.77)	102.55* (11.90)	NA	298.95* (9.54)	52.94* (5.20)	NA	626.98* (72.10)	292.22* (27.90)
Kern	1,554.90* (17.65)	161.09* (10.17)	74.28* (8.42)	NA	406.75* (12.87)	36.18* (4.24)	133.81* (30.11)	80.32* (9.19)	28.79* (4.86)
Kings	1,804.50* (18.46)	163.81* (10.44)	71.13* (8.13)	NA	377.69* (9.89)	134.69* (8.45)	NA	26.35* (23.53)	125.77* (9.60)
Madera	956.85* (13.41)	158.79* (9.37)	73.58* (8.59)	NA	1,406.43* (17.59)	123.07* (9.32)	NA	289.44* (51.30)	244.86* (21.22)
Mendocino	140.46* (5.46)	77.61* (5.20)	58.58* (6.30)	NA	NA	NA	NA	NA	NA
Merced	216.36* (8.37)	80.41* (6.80)	53.43* (7.29)	NA	0.19 (0.06)	0.19 (0.06)	4,458.70* (48.35)	274.35* (19.23)	44.63* (7.77)
Sacramento	678.37* (14.80)	110.39* (8.36)	61.69* (7.68)	NA	NA	NA	NA	NA	NA
San Joaquin	312.86* (9.08)	89.56* (6.71)	57.74* (6.82)	4.34 (0.32)	12.52 (0.96)	19.81 (1.87)	NA	NA	NA
San Luis Obispo	159.35* (5.68)	76.08* (4.81)	64.95* (6.01)	NA	NA	NA	NA	NA	NA
Stanislaus	394.13* (10.78)	98.89* (7.61)	58.61* (7.50)	NA	NA	NA	NA	NA	NA
Tulare	711.09* (11.79)	132.23* (7.49)	81.47* (8.32)	NA	71.92* (4.44)	26.25* (2.89)	339.86* (36.26)	146.58* (12.86)	44.72* (6.91)
Average	696.56	136.09	68.91	0.76	234.04	35.74	616.54	131.27	71.12

Notes: A single asterisk (*) denotes a statistically significant difference in the two premiums at the 5% level using a one-tailed *t*-test. The *t*-ratios in parentheses test the difference in means between JD and BM insurance premiums. Entries labeled NA reflect percentage differences greater than 10,000% which are suppressed for presentation purposes or for counties where no data are available for the particular grape type identified in the column heading.

of capturing the true distribution of revenue. Given this observation, a contingent claim model that more accurately reflects abnormal yield years, such as one based on a jump-diffusion process for the underlying state variable, would likely be an improvement relative to the overly simplistic lognormal or BM revenue distribution. Premiums calculated using a JD assumption are expected to more accurately reflect abnormal yield years in a manner similar to the empirical distribution underlying current FCIC rating methods.

From the simulation results in tables 3, 4, and 5, the difference in premium estimates between the BM and JD models is not inconsequential. Table 6 summarizes the extent of the difference for three coverage levels for each type of grape. Focusing on wine grapes, and excluding counties where the premium estimate is virtually zero, the average difference under 50% coverage is almost 700%, falling to 136% at a 70% coverage level for all counties, and 69% for 90% coverage. Each of these differences is statistically significant based on a one-tailed *t*-test for the difference in two means. At lower coverage levels, the likelihood that "normal" volatility will cause revenue to fall below the trigger diminishes, so discrete events assume a greater proportionate share of the total risk of a loss. Nonetheless, even at the highest coverage level, a 69% error can

mean the difference between financial viability and failure when normal load factors average approximately 12% (Vaughn and Vaughn).

The differences in premiums are slightly less compelling for table and raisin grapes, but are still significant both economically and statistically. Perhaps more important, if insurance companies ignore the impact of discrete events on the value of revenue insurance, they will not only fail to price their coverage correctly, but will likely miss the opportunity to market a potentially beneficial product to their clients. If premiums are actuarially sound, insurance companies participating in the federal crop insurance program should not stand to make abnormal economic profits over the long run, but growers will definitely benefit from having access to a powerful risk management tool.

Given the events of 2001, companies beyond agriculture now realize the importance of risks which were previously thought to be of such low probability they could safely be ignored. Indeed, the most pressing problem facing the insurance and risk management industry is the pricing of such low probability events. This analysis represents an example of how existing methods can be brought to bear in helping to solve this problem, but future research may address the breadth of the problem in other insurance markets. Although the rating error found is relatively small in some cases, the degree of underestimation varies widely from county to county, as it is highly dependent upon a particular county's price and yield history. Such rating errors can have a significant impact on a grower's decision to insure or not, potentially exacerbating adverse-selection problems shown to plague many forms of crop insurance (Turvey). Moreover, the use of county-level data is likely to lead to an underestimate of the Poisson parameter that would be relevant for a farm-level product such as CRC. Because the JD option value is a weighted average of the value under each realization of the Poisson variable, higher values of λ would lead to dramatically higher premiums.

Conclusions and Implications

With passage of the Agricultural Risk Protection Act of 2000 and subsequent discussion regarding risk management components of future farm legislation, federally subsidized insurance is expected to play a significant role in future farm policy and, consequently, farm management as well. Moreover, with the success of revenue insurance products such as CRC and the inherent cost advantages of revenue insurance relative to combinations of price and yield insurance (Hennessy, Babcock, and Hayes; Richards 2000a, b), future offerings likely will target farm income rather than just price or output individually. Efforts to develop new insurance products have targeted an expanded range and number of covered crops, particularly "specialty crops." Given these trends, it is therefore critical to develop an accurate method for determining the financial value of these new insurance products to growers. Such a method would not only help growers assess the economic value of competing insurance products, but also would assist the government in determining their likely cost.

This study presents a method of estimating revenue insurance premiums using a contingent claims, or option pricing, approach and compares them to premiums calculated using current FCIC methods. Unlike previous applications of options-pricing techniques to rating insurance, this analysis allows for the possibility that revenue processes contain both continuous and discrete elements. An empirical example using county-level wine, table, and raisin grape data from the state of California demonstrates the magnitude of

the difference in insurance premiums caused by ignoring both the option value inherent in a revenue guarantee and the effect of abnormal events.

The results show that current FCIC rating methods significantly understate the economic value of revenue insurance relative to a simple option-pricing model in most cases. This discrepancy occurs because the FCIC uses a static approach and, as such, does not consider the "option value" component of a revenue guarantee. Yet, in cases of extreme volatility, or where revenue is distinctly not lognormal, the opposite may occur and FCIC premiums can be greater than those obtained through an option-pricing technique. Permitting revenue to follow a Poisson-normal mixture, however, accounts for these seemingly anomalous cases and provides premium estimates that are higher than either FCIC or simple option value estimates.

If revenues do indeed follow a Poisson-normal process, then growers and regulators alike must use a rating technique which accounts for both the option value inherent in insurance and the composite discrete-continuous nature of the revenue distribution. Given increased Congressional scrutiny of RMA operations and its budgetary impact, accurate pricing is necessary to minimize the impact of problems such as moral hazard and adverse selection that may doom the program to financial ruin (Turvey). Further, production contracting in wine grapes is a common price-risk management practice (Heien).

Contracting between small growers (at least relative to their bargaining partners) and increasingly large and concentrated wineries gives rise to the potential for opportunistic behavior on the part of the wineries, and hence adverse bargaining outcomes for growers. If small growers are presented with a viable alternative risk-management technique, then perhaps they would not need to sacrifice price levels for price stability to the same extent they do now.

This study provides an important point of departure for future research, not only for the pricing of revenue insurance, but also for the further examination of alternative distributions of specialty crop revenue. Foremost, further research in this area will benefit from more extensive price and yield data. Truly accurate estimates of yield and price volatility require far more data than those available to this investigation. Nevertheless, paucity of data is a common problem faced when dealing with specialty crops. While our example focuses on GRIP, which is a county-level (or group-risk) product, farm-level price and yield data would permit a more accurate valuation of individual-risk revenue products like the CRC or the "new generation" whole-farm income products. However, because payment prices under the CRC are determined as the higher of that prevailing during planting or harvest, Marcus and Modest's endogenous-exercise price approach would be the appropriate method in the farm-level case. Future research with more detailed data would also benefit from considering some of the other extensions to Black's model in the finance literature, namely stochastic volatility and asynchronous trading data.

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