Journal of Agricultural and Resource Economics 25(1):177–194

A Two-Stage Model of the Demand for Specialty Crop Insurance

Timothy J. Richards

Recent proposals to reform the federal Multiple-Peril Crop Insurance Program for specialty crops raised concerns that a higher cost for catastrophic-level coverage would significantly reduce program participation. This study estimates the demand for three levels of insurance coverage (50%, 65%, 75%) using aggregate data from grape production in 11 California counties from 1986–96. A discrete/continuous econometric model of the choice of coverage level and the amount of insurance finds that the price-elasticity of demand for 50% coverage is elastic, suggesting that premium increases may indeed reduce participation significantly. Such increases may also cause a significant reallocation of growers among coverage levels.

Key words: California, crop insurance, discrete/continuous choice, grapes, ordered probit

Introduction

Since the creation of "catastrophic" (CAT) multiple-peril crop insurance in the Federal Crop Insurance Reform Act (FCIRA) of 1994, many specialty crop growers have come to rely on this option as an inexpensive safety net in the event of a major crop failure.[1] However, during the summer of 1998, fruit and vegetable growers became concerned that new crop insurance legislation would change the grower cost of CAT insurance from a flat, fully subsidized fee toward a more traditional, actuarially determined, partially subsidized premium.[2] For many growers, this would have meant a dramatic rise in the actual premiums they would have to pay. Grower groups argued that these changes, intended to increase the financial viability of specialty crop insurance, would instead cause many growers to go without multiple-peril crop insurance (Jones), and thus be exposed to significant losses in the event of a poor harvest. Worse, because the premium increases were targeted toward the most basic level of coverage, the affected growers would likely be those on the margin between insuring or not insuring their crop. Given the weight of the existing evidence that shows the demand for crop insurance by growers of program crops to be price-inelastic (Barnett, Skees, and Hourigan; Gardner and

---

Timothy Richards is an associate professor in the Morrison School of Agribusiness and Resource Management, Arizona State University East, Mesa, Arizona. The author is grateful to Richard Anderson of the Federal Crop Insurance Corporation for providing the data, but all findings and conclusions are those of the author and not the FCIC.

[1] Catastrophic insurance provides growers a minimal level of coverage—50% of insured yield at 55% of the expected market price. Premiums for basic CAT insurance are 100% subsidized, but growers may "buy up" to a higher price election with a partial subsidy. Currently, grower costs consist of a nominal registration fee, initially set at $60 per contract and capped at $200 per farm per county, or $600 per farm in total.

[2] The Agricultural Research, Extension, and Education Reform Act of 1998 would have required, prior to its subsequent amendment by the Senate Agricultural Appropriations Subcommittee, growers to pay $50 per policy or 10% of the imputed premium for catastrophic insurance, whichever is greater, plus a $10 fee.

Kramer; Goodwin 1993), such concerns may be unimportant. However, relatively little is known of the demand for crop insurance by specialty crop growers in general, and those that choose only a minimal level of insurance in particular. Further, if there is ever any serious thought of making the delivery of unsubsidized crop insurance viable to private-sector providers, then precise knowledge of the elasticity of demand for insurance is critical to the design of self-sustaining premium rate structures (Barnett, Skees, and Hourigan).

Typically, models of the farm-level demand for crop insurance seek to explain a grower's decision of whether to insure (Calvin; Just and Calvin; Coble et al.) or the joint decisions of whether and how much to insure (Goodwin and Kastens; Smith and Baquet). In aggregate or county-level data, similar to the data used in this study, the goal is more often to explain the proportion of growers who choose to insure or the proportion of their land they choose to cover (Gardner and Kramer; Barnett, Skees, and Hourigan; Goodwin 1993; and many others). Although many of these studies appropriately consider the fact that the decision to insure encompasses two separate but interrelated decisions, they do not consider one aspect of the first-stage decision that appears to be particularly important to specialty crop growers—the choice from among several discrete, yet ordered coverage levels. Participants in the federal Multiple-Peril Crop Insurance (MPCI) Program choose from among three coverage levels: 50%, 65%, and 75%, meaning that they receive indemnities if their actual yield falls below 50%, 65%, or 75% of their insurance yield.[3] Therefore, growers must not only choose a level of coverage, but how much of their land to insure as well.

Hojjati and Bockstael pose a similar type of problem in which farmers choose from among a discrete set of crop and insurance alternatives. They, too, assume only one coverage level. Smith and Baquet use a Heckman two-stage approach and farm-level data to estimate a model of participation and coverage level among a sample of Montana wheat growers.

With the aggregate data available to this study, however, we do not observe nonparticipation, but rather proportions of growers choosing different insurance products and then the amount of land insured under each. With this type of data, considering the discrete nature of the first-stage choice of coverage level not only corrects for sample-selection bias, but also provides a potential source of valuable new information. If it is the case that minimal coverage, catastrophic insurance attracts a different type of grower than the higher coverage levels, then the elasticity of demand for this product may be significantly different. Moreover, because the policy reform proposal focuses specifically on increasing the price of one coverage level, differentiating between the demands for each is necessary to make meaningful comment on the effects of the proposed change. Fortunately, sample-selection bias is easily overcome and the information readily recoverable.

Empirical models of two-stage discrete/continuous demand typically trace their origin to Cragg's analysis of automobile purchases wherein consumers must decide whether to buy before deciding how much to spend. Lee extends this approach to the more general case where a continuous quantity decision for alternative s is only observed if the

[3] Although growers can now select from a greater number of coverage levels, a vast majority (> 95%) of growers in the California grape data set used here chose one of these three levels.

decision maker chooses category *s* from among several mutually exclusive alternatives. Several important variations of this model have appeared in both the theoretical and applied demand literature (Dubin and McFadden; Hanemann; Chintagunta). With respect to the insurance-demand problem, the fundamental logic of this two-stage approach is the same, but the discrete alternatives are inherently ordinal—from a low level of coverage (50%) to a high level (75%).[4]

Consequently, the two-stage model of insurance demand developed here uses an ordered probit specification in the first stage to account for growers' choice of coverage level. A sample-selection correction factor, similar to the inverse Mill's ratio employed in Heckman's procedure, is then taken from the first-stage estimates and is used in censored regression (Tobit), second-stage models of the demand for insurance at each of the three coverage levels. This second-stage model differentiates among the determinants of growers' demand for a minimal level of protection (50% coverage), an intermediate level (65%), or a more comprehensive level (75%).

Typically, county-level field crop data do not contain observations where no insurance is purchased. However, by defining insurance products more narrowly, the data used in this study contain many county/year pairs where no growers buy a particular type of insurance. This censoring of the distribution of insurance demand necessitates a Tobit estimation approach in order to obtain consistent estimates of the second-stage insurance demand parameters. With this approach, the empirical model provides estimates of the factors that determine the probability of purchasing each type of insurance, as well as the factors that drive aggregate participation rates.

In applying this method to county-level crop insurance data from California grape growers, this study has two primary objectives. The first is to determine whether there is evidence that elasticities of insurance demand differ by coverage level. Second, this study will also provide some empirical evidence on whether the characteristics of specialty crop insurance demand are similar to those for traditional or program crops. Specifically, this research will test for the tendency of specialty crop growers to self-insure, or for the existence of adverse selection (Arrow; Just, Calvin, and Quiggin; Coble; Knight and Coble).

The first section of the article consists of a brief development of an empirical model that is consistent with growers maximizing expected utility in two stages when their choices are discrete and ordinal. The next section presents an econometric approach that produces consistent parameter estimates of an aggregate insurance participation model while allowing for selection from among various coverage levels. This is followed by a description of how this approach is applied to county-level California grape production data. The remainder of the article presents and discusses the empirical results of this application, including both the immediate implications of proposed changes to catastrophic insurance premiums and to crop insurance in general.

---

[4] As with other studies using county-level data (Gardner and Kramer; Hojjati and Bockstael; Goodwin 1993), this study adopts the convention of regarding each county as a representative grower. Therefore, the dependent variable in question is a continuous measure of the proportion of land insured, rather than the discrete participation choice used by studies with farm-level data (Coble et al.).

An Empirical Model of Insurance Demand

A grower's decision to purchase multiple-peril crop insurance encompasses two related decisions: how much to insure, and the level of coverage.[5] The amount of insurance purchased, however, is only observed if a particular coverage level is chosen. Thus, simple ordinary least squares estimates of insurance demand equations at each coverage level will be biased (Lee). Therefore, this study uses a two-stage discrete/continuous selection approach similar to Lee, but adapted to an ordered probit selection rule by Greene (1997). This method is conceptually identical to the familiar Heckman correction procedure, but because growers face more than two coverage alternatives, and these alternatives are ordinal in nature, the selection process is ordered rather than binomial. Consequently, the growers' first-stage decision among coverage levels is modeled according to an ordered probit specification (Zavoina and McElvey), while the second stage consists of separate, linear models of insurance demand.[6] Although the standard errors at this stage are inconsistent due to the estimated regressor problem, they are corrected using the asymptotic covariance matrix described by Greene (1997).

Formally, the insurance decision consists of a continuous participation equation similar to Goodwin (1993) where the percentage of eligible acres that are insured by a representative grower solves an expected utility-maximization problem. By using a linear approximation to an arbitrary specification of growers' expected utility, we arrive at an expression for grower g's level of utility that consists of a deterministic and random component in a mean/variance framework (Hojjati and Bockstael; Calvin). Solving this problem produces an expression for the optimal amount of insurance. However, we need to recognize the fact that we only observe insured acres by those growers for whom the latent or unobservable value of expected utility exceeds some threshold level:

$$(1)\qquad \begin{aligned} y_k^g &= y_k^{g*} \quad \text{if } y_k^{g*} \geq 0, \\ &= 0 \quad\;\; \text{if } y_k^{g*} < 0, \end{aligned}$$

where $y_k^{g*} = \gamma \mathbf{Z}_k^g + \sigma_k \varepsilon_{1k}^g$, and $\mathbf{Z}_k^g$ is a vector of factors that influence the expected utility of insurance at each coverage level k, including the mean and variance of net revenue, R_k^g, attitudes toward risk, and various self-insurance strategies. In this application, however, the amount of insurance purchased at each coverage level (y_k) is only observed if the particular coverage level k is chosen. A grower's choice of coverage level—the first-stage problem—is determined by the value of an unobserved index of coverage-level expected utility, $E[U(R_k^g)]$, which is also defined over the level of net revenue. In an ordered probit model, the probability that a grower chooses coverage level k (i.e., that y_k is observed) is given by the probability that the expected utility from doing so is greater than a minimum threshold value for that choice, but less than the threshold for moving up to the next coverage level. Formally, the probability of choosing each coverage level is written as:

---

[5] Formally, the multiple-stage decision process also includes a price election as well, but because this price is based on a market price, it is more appropriately thought of as exogenous and included in the measure of total liability. Further, there are often dozens of prices that apply to any one county each year, so it is not practical to include these in the discrete/continuous choice framework developed here.

[6] The logic behind this model is most clear if expressed as a sequential process, but neither the logical nor the statistical consistency of this model requires the actual decision process to be sequential.

$$
\begin{aligned}
(2) \qquad P(k = 0) &= P(E[U(R^g_{k=0})] \le 0),\\
P(k = 1) &= P(0 < E[U(R^g_{k=1})] \le \mu_1),\\
P(k = 2) &= P(\mu_1 < E[U(R^g_{k=2})] \le \mu_2),
\end{aligned}
$$

for the case of three ordered alternatives, and where μ_k are unknown threshold parameters to be estimated.[7] Again using a linear approximation of the expected utility of coverage choice, a grower's expected utility from insuring at a coverage level k can also be written as a function of the mean and variance of net revenue for each k:

$$(3) \qquad E[U^g_k] = \bar{U}^g_k + \varepsilon^g_{2k} = u_k + E[R]^g_k - (\rho^g/2)\mathrm{Var}[R]^g_k + \varepsilon_{2k} = \beta \mathbf{X}^g_k + \varepsilon^g_{2k},$$

where $\mathbf{X}^g_k$ consists of the mean and variance of both expected indemnities and market returns, as well as a time trend.[8] Assuming the ε^g_{2k} are normally distributed, an ordered probit specification results.[9] Although the mean-variance approach is subject to some criticism, primarily due to the assumption of normality and quadratic utility (Newbery and Stiglitz), it nonetheless remains a common maintained hypothesis and has a considerable body of empirical support (Hojjati and Bockstael). Using the sample-selection procedure described by Greene (1998), the expected value of the ordered probit residual, conditional on a grower's choice of coverage level, is then substituted into the insurance participation equation in (1) to obtain both consistent parameter and standard error estimates of the insurance demand equations using maximum likelihood.

Specifically, assuming the marginal distributions of the ε^g_{1k} are $N(0, 1)$, the estimated participation rate equation becomes (Lee; Maddala):

$$(4) \qquad y_k = \gamma \mathbf{Z}^g_k - \sigma_k \tau_k \lambda_k + \varepsilon^g_{2k}$$

for the nonlimit observations, where τ_k is the correlation coefficient between ε^g_{1k} and ε^g_{2k}, and

$$(5) \qquad \lambda_k = \left(\frac{\phi(\mu - \beta \mathbf{X}^g_k) - \phi(-\beta \mathbf{X}^g_k)}{\Phi(\mu - \beta \mathbf{X}^g_k) - \Phi(-\beta \mathbf{X}^g_k)} \right),$$

where ϕ is the standard normal density function, and Φ is the corresponding distribution function. Consistent estimates of (4) are then found with maximum likelihood. Given the choice of coverage level k by a representative grower g in each county and aggregating over all growers in a county, γ can be used to calculate estimates of the marginal effects of county and choice-specific factors on the decision to insure, or the aggregate participation rate. However, the parameter vector β in the ordered probit

[7] For estimation purposes, one of the threshold indices is normalized to zero, so there is only one threshold parameter estimated in the three-coverage level model.

[8] Although the precise definitions of these variables are given in the text below, it is important to emphasize at this point that the returns to insurance are net of government subsidies, so the price of insurance is defined as a "net premium," that is, premia net of expected indemnities and subsidies.

[9] Although an ordered logit model is also a possibility, Greene (1998, p. 500) states that "... we are unaware of a convenient specification test for distinguishing between the probit and logit models." Further, we could not gain convergence with an ordered logit specification with any reasonable subset of our explanatory variables, so the probit model was maintained throughout.

model does not have a similar intuitive interpretation, so the marginal effect of each regressor on the probability of choosing each coverage level is calculated as described in Greene (1997). The next section describes the determinants of coverage choice and participation at the county level in more detail.

At the coverage-choice stage, the components of $\bar{U}_k$ determine the proportion of growers choosing each coverage level. Specifically, the utility index is given by:

$$(6) \qquad \bar{U}_k = \beta_0 + \sum_j \beta_{1j} E[P_j] + \sum_j \beta_{2j} \mathrm{Var}[I_j] + \beta_3 E[R] + \beta_4 \mathrm{Var}[R] + \beta_5 T,$$

where

$E[P_j]$ = expected premium for coverage level j,
$\mathrm{Var}[I_j]$ = variance of indemnities for coverage level j,
$E[R]$ = expected market revenue,
$\mathrm{Var}[R]$ = variance of market revenue, and
T = a time trend.

The determinants of expected utility at this stage thus reflect the relative desirability of each coverage level, the particular risk history of growers in each county, and their expectations of a profitable return to choosing a particular coverage level. Therefore, the elements of $\bar{U}_k$ include the mean and variance of both market returns and the first and second moments of the returns to insurance (Coble et al.). Specifically, arguments of the choice model (6) include the county-level expected net premiums, or premiums net of expected indemnities and government subsidies.

Expected indemnities are calculated assuming a truncated normal yield distribution for each coverage level and county as described below (Goodwin 1994). By including the expected net premium of each coverage level in each utility index, the results from this stage provide estimates of growers' willingness to substitute between coverage levels due to changes in relative prices. Assuming growers maximize expected utility as described above, coverage choice depends upon the relative variability of the returns to each coverage level as well. Because growers with only CAT-level insurance face constant premiums, the variance in returns to insurance is measured by the historical variance of indemnities. While it is clear that the probability of a coverage choice should also fall in the expected variability of indemnities, the response of coverage choice to the variability of market returns is less obvious.

In fact, both the first and second moments of the distribution of market returns have direct effects on the amount of insurance purchased because they reflect the relative utility of buying versus not buying insurance. However, market returns also have an indirect effect on coverage choice. While the distribution of market returns is the same for each choice of coverage level, it is likely that growers who are relatively certain of their revenue stream may choose only an inexpensive safety-net level of coverage. In contrast, growers who are more uncertain over their market returns may regard a higher coverage level as a necessary alternative source of income in the event of even a moderate loss. This is particularly important in produce markets where individual growers in counties that produce a large proportion of the output of a commodity are often compensated with increases in the market price when significant crop losses occur (Lee, Harwood, and Somwaru). Although the expected market revenues for these growers may be relatively constant, the reduced supply from growers in relatively minor producing regions does not influence the market price, so their revenue loss is proportionate to their yield shortfall.

Finally, we include a time trend in this model intending to capture changes in growers' attitudes toward crop insurance and their experience with the program. At the second stage, or quantity-of-insurance level, however, the determinants of growers' expected utility from insurance include not only variables that reflect the relative return to insuring versus not insuring at each coverage level, but also the extent to which they self-insure through enterprise diversification or other means. This decision is also affected by a grower's subjective attitudes toward risk.

At the county level, aggregating representative growers' insurance decisions for each county means that the insurance-quantity model consists of a participation-rate equation for each coverage level. Knight and Coble review the extensive literature on models of aggregate participation in MPCI among field crop growers. Within this body of work, alternative measures of the aggregate insurance participation rate include either the proportion of eligible acres insured in each county (Gardner and Kramer; Hojjati and Bockstael; Barnett, Skees, and Hourigan; Goodwin 1993), the change in MPCI participation between two sample years (Cannon and Barnett), or liability per acre (Goodwin 1993).

Although Goodwin finds significant differences between parameter estimates for each dependent variable, this study adopts a proportion of acreage measure for the sample of California grape growers.[10] Many argue that the primary weakness of using county-level data for this type of analysis is that it masks the farm-level variability that drives growers' decisions to insure (Goodwin and Kastens).[11] Therefore, using a liability measure of participation is likely to worsen this problem, particularly in a model that differentiates among coverage levels, because it is more likely to be skewed by outlying observations.

Defining participation in this way, the estimated version of equation (4) becomes:

$$
\begin{aligned}
(7) \qquad y_k = {} & \gamma_0 + \gamma_1 E[P_k] + \gamma_2 \mathrm{Var}[I_k] + \gamma_3 E[R] + \gamma_4 \mathrm{Var}[R] + \gamma_5 T \\
& + \gamma_6 T\% + \gamma_7 R\% + \gamma_8 INC + \gamma_9 GR\% + \gamma_{10} LV\% + \gamma_{11} SIZ \\
& + \gamma_{12} y_{k,t-1} + \gamma_{14} \lambda_k + \varepsilon_{1k},
\end{aligned}
$$

where variables unique to this stage include:

$T\%$ = proportion of county grape acreage in table grapes,
$R\%$ = proportion of county grape acreage in raisin grapes,
INC = average income from farming,
$GR\%$ = average proportion of farm enterprise in grape production,
$LV\%$ = average proportion of farm enterprise in livestock,

[10] The second-stage models were also estimated with the dependent variable defined as liability per acre as in Goodwin (1993). We find an elasticity of demand at the 50% level of -1.68, and at the 65% and 75% levels of -0.669 and -0.504, respectively. Both the signs and magnitudes of the estimated price-response elasticities were similar to those estimated with the proportion-insured definition, as described below.

[11] Goodwin's (1993) caveat applies to this analysis as well. Namely, the reduced variability of aggregate relative to farm-level yields is likely to understate the true extent of adverse selection that may be suggested by the empirical results of this study.

SIZ = farm size in harvested acres,
y_{t-1} = lagged proportion of acres insured, and
λ_k = Lee's multinomial correction factor.

Among other insurance demand studies, definitions of the price of insurance are as diverse as those for the participation rate. Gardner and Kramer use an expected returns to insurance variable, defined as the ratio of expected indemnities less premiums to premiums paid. While this variable is expected to have a positive effect on participation, others define the cost of insurance as premiums per acre (Goodwin 1993) or as premiums net of expected indemnities per dollar of liability (Cannon and Barnett). Hojjati and Bockstael use not only the expected profit with insurance, but its variance as well. At the grower level, Coble et al. define a similar, yet more comprehensive set of insurance incentives consisting of the first and second moments of the expected returns to insurance and expected returns to noninsurance, or market participation. As in Hojjati and Bockstael, these variables are derived from a theoretically correct model of grower expected utility maximization, so are consistent with the arguments developed here.

Irrespective of the particular definition, each of these studies interprets a positive relationship between expected indemnities and participation as evidence of adverse selection. Goodwin (1993) extends this "test" by specifying an interaction term between price and measure of county loss-risk, or the relative riskiness of a particular county. A negative interaction effect means that growers in riskier counties are more sensitive to changes in the cost of insurance and are thus more likely to leave the market if faced with higher premiums. In this study, the arguments in (7) suggest a test for adverse selection similar to that found in Coble et al.

Whereas the coverage choice model includes the mean and variance of expected premiums for all coverage levels in each level's set of attributes, at the insurance-quantity level each equation includes only the expected net premium and indemnity variance unique to that coverage level. These expected indemnities are calculated using a method similar to Botts and Boles, as described by Goodwin (1994). With this method, Federal Crop Insurance Corporation (FCIC) premia, and hence expected indemnities if the program is actuarially sound, are the product of an insured price and the expected loss from a normal yield distribution truncated at the chosen coverage level.[12] For each county i and coverage level k, therefore, expected indemnities are calculated as:

$$(8) \qquad E[I_{ik}] = \bar{P}_{ik}\left(\Phi\left(\frac{\alpha\mu_{iky} - \mu_{iky}}{\sigma_{iky}}\right) + \phi\left(\frac{\alpha\mu_{iky} - \mu_{iky}}{\sigma_{iky}}\right)\sigma_{iky}\right) \quad \forall\, i, k,$$

where Φ and ϕ are the normal distribution and density functions, respectively, μ_{iky} is the average yield, and σ_{iky} is the standard deviation of yield for each county and coverage level. These values are calculated using the entire sample history of each county. Because (8) provides indemnities units of yield (i.e., tons per acre), calculating a money premium requires each to be multiplied by a reference price, $\bar{P}_{ik}$, which is the average price election for each county and coverage level. Further, because expected indemnities

[12] The appropriateness of the normal distribution for yields was tested after pooling the county-level yield series and accounting for county-specific effects. Kolmogorov-Smirnov tests for normality failed to reject the null hypothesis at a 5% level of significance. There are alternative ways to measure expected indemnities, such as the beta distribution of Coble et al., the empirical distribution used by Goodwin (1994), or the nonparametric measures used by Goodwin and Ker.

vary only by county and coverage, their variances are found from historical indemnity data. Calculating expected indemnities in this way highlights the necessity of considering each coverage level separately.

Whereas Coble et al. dismiss as inconsequential the fact that they exclude the 11% of growers from their sample who do not choose a 65% coverage level, specialty crop growers tend to choose alternative coverage levels with much greater frequency. However, similar to their study, the model developed here also includes variables measuring expected market returns and the variability of market returns. Assuming naive expectations, $E[R]$ is equal to lagged average grape revenues, while the variability of returns is found by calculating the variance of historical revenues for each county over the entire sample period. If the results show a positive relationship between participation and the variability of market revenue, then this can be interpreted as evidence of adverse selection. Most of the existing research in this area, however, shows that insurance participation depends not only upon relative returns to insurance, but also growers' willingness and ability to self-insure.

The tendency to self-insure is captured by including variables describing a typical grape grower in each county, thereby accounting for unobserved heterogeneity among counties, the effect of size economies on the tendency to insure, and the extent of financial, operational, and geographical diversification. First, there may be inherent differences among raisin, table, and wine grape growers to insure. For example, whereas all growers face similar yield variability at harvest (depending upon variety), raisin growers face the added risk that arises during drying. By excluding the proportion in wine grapes, which is required in order to avoid singularity, the estimated parameters on these variables define the tendency of table and raisin grape growers to insure relative to wine growers.

Second, many studies include a measure of farm size to capture the effect of size economies on the demand for insurance (Barnett, Skees, and Hourigan; Cannon and Barnett; Nieuwoudt et al.; Goodwin 1993) but do not differentiate between physical and economic size. Therefore, this study includes both acreage and total farm income. While growers with operations spread over large areas may benefit from geographic diversification, high-income growers may be more able to afford insurance. On the other hand, growers with a higher level of net income are better able to finance their own contingency fund, so they may also perceive less of a need to insure.[13]

Third, similar to Barnett, Skees, and Hourigan, and Cannon and Barnett, the participation model (7) includes two measures of enterprise diversification: the dominance of a single crop (grapes) and the extent of diversification into livestock. While these two studies confirm a priori expectations by finding a negative relationship between the extent of diversification into livestock and the tendency to insure, Goodwin (1993) does not. Goodwin's result is perhaps not surprising, as diversification may reflect two opposing influences on the demand for insurance. Whereas growers who successfully diversify into other enterprises may require less insurance, many growers who choose to diversify may instead be signaling themselves as inherently more risk averse, and thereby more likely to insure ceteris paribus.

[13] Due to a high degree of multicollinearity between farm income and physical size, however, the latter was dropped from the preferred demand model at each coverage level.

Finally, growers are likely to exhibit significant inertia in their insurance decision simply due to the costs involved in learning new programs and in preparing paperwork for them, so we include a lagged value of insurance demand in (7). Whether growers exhibit this type of habitual behavior, however, is likely to depend on the particular application and data set.

Data and Methods

Data for this analysis are from U.S. Department of Agriculture (USDA)/FCIC, California Department of Food and Agriculture (CDFA), and U.S. Department of Commerce (USDC)/ Bureau of the Census sources. The insurance data include county-level measures of the number of insurance contracts, total premiums, liabilities, and indemnities at each coverage and price-election level for the years 1986–96. Although FCIC records include many more counties than those considered here, the data used in this analysis include the 11 counties for which there are 11 consecutive years of both insurance and grape production data. Data on historical grape production performance were provided by CDFA officials, as compiled from county agricultural commissioners' reports, and include county-level harvested acres, total production, average yield, and average prices disaggregated by intended usage (wine, table, or raisin). Because of changes in the types of grape insurance contracts offered over the sample period, the actual choice of coverage level in recent years goes somewhat beyond the 50/65/75 used here. However, very few growers chose levels other than these standards, and in only one or two counties. For example, in Fresno County in 1996, 15 of 2,400 premiums paid were covered at a 70% level. These growers were therefore included with the 75% coverage group as this option was not available in other years.

Similarly, other studies of field crop insurance programs report relatively homogeneous price-election levels. For grapes, however, the data typically consist of nearly 20 price-election levels for each county/coverage/year observation. Therefore, insurance prices are averaged across all election levels. Data on farm income, size, and enterprise diversification are from the 1982, 1987, and 1992 editions of the *Census of Agriculture* (USDC/Bureau of the Census). The resulting data set provides 121 panel observations that are used to estimate both the coverage choice and aggregate participation models. Consistent parameter estimates are obtained by sequential estimation of the ordered probit model with maximum likelihood, followed by maximum-likelihood estimation of the participation equation.[14] Both equations are estimated within an annual fixed-effects panel data framework. The following section provides a discussion of the results obtained by estimating both stages of the model in the California grape grower data.

Results and Discussion

In order to address the research objectives outlined above, the key results presented here concern both the elasticities of demand for insurance at each coverage level and the

---

[14] Although this method provides consistent second-stage parameter estimates, their standard errors are not. Consequently, estimates of the correct asymptotic covariance matrix are found using the procedure described by Greene (1998). Breusch-Pagan tests for heteroskedasticity in the first-stage ordered probit model reject the null hypothesis, so the reported estimates have been corrected for additive heteroskedasticity.

Table 1. Ordered Probit Coverage Choice Estimates: California Grape Growers (1986–96)

	Parameter Estimates		Coverage Choice Elasticities		
Variables[a]	Coefficient	*t*-Ratio	50%	65%	75%
Constant	-16.973*	-3.532	—	—	—
$E[P_{50}]$	2.940*	3.392	-4.924	-1.659	3.182
$E[P_{65}]$	1.635*	4.068	-1.919	-0.748	1.423
$E[P_{75}]$	-0.498	-1.447	5.314	-2.058	-3.936
$V[P_{50}]$	7.970*	2.394	-6.232	1.389	4.616
$V[P_{65}]$	1.270*	2.404	-10.848	-3.756	7.154
$V[P_{75}]$	-0.104*	-2.415	3.331	1.349	-2.570
$E[R]$	0.337	1.993	-0.233	0.095	0.175
$V[R]$	-22.903*	-4.775	0.403	0.143	-0.275
Trend	0.176*	3.228	-3.532	1.100	2.096
μ	0.889*	3.503			
χ^2 [b]	52.892				

Note: An asterisk (*) denotes significance at the 5% level.

[a] $E[P_i]$ denotes the expected net premium at coverage level i, $V[P_i]$ is the variance of the net premium for coverage level i, $E[R]$ is the expected level of market revenue, and $V[R]$ is the variance of market revenue.

[b] The χ^2 likelihood-ratio statistic is $LR = 2(LLF_U - LLF_R) \sim \chi^2_q$, which compares the estimated model with a null model, $\beta = 0$. The critical χ^2 value at 5% with 10 degrees of freedom is 18.307.

elasticity of each factor on the probability of coverage choice. Specifically, a comparison of price elasticities among coverage levels indicates whether premium changes are likely to have different effects on the participation rate in each. Further, by including the variability of market returns, we test for the existence of adverse selection in a manner similar to existing studies. Although the coverage and quantity decisions are assumed to be taken simultaneously, this section presents the results of the first stage, or coverage choice model first.

As explained above, the ordered probit parameter estimates convey little information in and of themselves. Consequently, we calculate and interpret the implied elasticity of each regressor on the probability of each coverage choice. First, however, it is necessary to establish the goodness of fit of the entire model. Initial parameter values for this model are obtained by specifying a "null" model where all $\beta = 0$, except for the choice-specific intercept value. This null model also serves as a benchmark against which we compare the fit of the final choice model. Because the null model is nested in the more complete model with nonzero β, a likelihood-ratio test statistic is valid. By this statistic, the coverage model provides a good fit to the data as the χ^2 value of 52.89 is greater than the critical value of 18.31 at 10 degrees of freedom. Consequently, the parameter estimates in table 1 describe a reasonable specification for the coverage choice decision by California grape growers.

The most important result at this stage is the own-price choice elasticity, or the percentage change in the probability of choosing a certain coverage level for a given percentage change in premium. While growers' choice of both the 50% and 75% alternatives is highly elastic, the 65% coverage choice is price-inelastic. This result is very plausible as it suggests that growers at either end of the coverage spectrum are more likely to change their coverage level in response to a change in premium than those who choose a moderate level. Further, combining this result with the estimated cross-elasticities implies that growers move out of both 50% and 65% coverage toward 75% coverage in response to a premium increase at the 50% level. Similarly, growers appear to regard 75% and 65% coverage levels as choice complements, as they move out of both toward 50% coverage when net premiums at the 75% level rise. Although the cross-elasticities with respect to 65% coverage premiums are still elastic, the fact that they are considerably lower than the others suggests that relatively large changes in net premiums are required to induce these growers to change their level of coverage. In summary, targeted premium changes at the 50% level therefore appear likely to drive growers either toward the highest level of coverage, or out of the market.

Perhaps as expected, the probability of choosing each coverage level also falls in the variability of its own net premiums. Interestingly, the elasticities in table 1 show that the impact of variability on choice diminishes with each subsequent coverage level, although all are highly elastic. If growers at the lowest coverage level are indeed on the margin between insuring and not insuring, then we should expect that the aggregate choice probabilities should be particularly sensitive to the degree of risk protection provided by insurance. This is also true with respect to the cross-elasticities—the variability of indemnities at each level has a relatively large impact on the probability of choosing a low level of coverage, but less of an effect on the intermediate level.

Both the own and cross-elasticities suggest that growers who choose either the minimum or maximum levels of insurance are more sensitive to the risk inherent in choosing to insure compared to those at the 65% level. While those at the lower level are likely to question the value of insuring at all when expected returns to insurance are highly variable, those at the highest level are likely more sensitive to the structure of premium subsidies, which tend to favor coverage at lower levels over higher.[15] Although some may interpret these results as implying the existence of adverse selection, this is not necessarily the case in the choice model because the probability of choosing 50% coverage rises in the variability of expected indemnities at a 75% level. This suggests that such changes have significant allocative effects, but does not address the participation question raised by adverse selection.

The variability of market returns, however, has a distinctly different effect at each level. Namely, positive choice elasticities at both the 50% and 65% levels with respect to the variability of market revenue suggest that growers respond to greater market-based uncertainty by, in general, moving away from the highest (75%) level of coverage. This indicates that growers are less interested in being left whole following an indemnifiable event than they are in establishing a floor on their returns (CAT insurance) in an environment of high business risk.

Further, these results provide some (albeit weak) statistical support for a negative effect of higher expected market returns on the choice of 50% coverage. While higher

[15] This somewhat perverse incentive structure has been reversed in virtually all proposals for crop insurance reform currently before Congress. A typical "inverse incentive" premium schedule increases subsidies for higher coverage levels to at least equal those available to growers who choose 50% and 65% coverage.

Table 2. California Grape Growers' Insurance Demand by Coverage Level: 50%, 65%, 75% (1986–96)

	50% Coverage Level			65% Coverage Level			75% Coverage Level		
Variables	β	*t*-Ratio	η	β	*t*-Ratio	η	β	*t*-Ratio	η
Constant	-2.777*	-10.610	—	-0.295*	-3.352	—	0.558*	7.308	—
$E[P_k]$	-0.047*	-5.186	-1.420	-0.110*	-3.360	-0.436	-0.045*	-6.148	-0.408
$V[P_k]$	-0.002*	-3.094	-0.166	-0.001*	-2.155	-4.609	-0.003*	-7.010	-47.884
$E[R]$	-0.027*	-2.767	-1.106	-0.028*	-3.892	-1.116	-0.077*	-3.079	-1.025
$V[R]$	0.872*	2.035	0.931	0.124	0.333	0.161	0.789*	8.224	1.355
Raisin %	0.001*	2.709	0.292	0.003	0.535	0.741	-0.002	-1.266	-1.290
Table %	-0.002	-1.317	-0.126	0.004	0.292	0.263	0.001*	3.499	0.039
Income	-0.016	-0.347	-0.209	0.011	0.148	0.150	-0.020*	-2.890	-0.580
Grape %	-0.061	-0.651	-0.102	-0.262*	-2.722	-0.144	-0.154*	-5.027	-0.162
Livestock %	0.045	0.121	0.230	-0.244	-1.435	-1.004	-0.084*	-2.938	-0.964
Trend	0.032*	10.906	41.886	0.014*	2.125	15.675	-0.005*	-6.177	-6.061
y_{t-1}	0.038*	5.244	0.037	0.399	1.681	0.380	0.462*	6.606	0.451
λ	0.001*	2.346	-0.002	-0.038*	-2.844	-0.512	-0.002*	-3.126	-0.013
σ	0.095*	12.726	—	0.027*	13.871	—	0.021	1.713	—
R^2	0.716			0.762			0.736		
D-W Statistic	1.802			1.887			1.725		

Notes: An asterisk (*) denotes significance at the 5% level. Variable definitions: $E[P_k]$ = premiums net of expected indemnities and subsidies, $V[P_k]$ = variance of expected indemnities, $E[R]$ = expected market revenue, $V[R]$ = variance of market revenue, y_{t-1} = lagged value of the proportion of acreage insured, and σ = standard deviation of the disturbance. Parameter definitions: β_k = coefficient vector for coverage level k, and η_k = elasticity vector for coverage level k.

expected market revenue may allow some growers to be able to afford more comprehensive insurance coverage, it may also cause others to lower their coverage level to achieve a target level of liability. However, the aggregate participation parameters and elasticities provide both a test for adverse selection that is comparable to existing research and a more complete evaluation of the policy implications of a targeted premium increase. These results are shown in table 2.

Legislators and policy analysts' interests likely focus on the implications of these parameters because they reflect the constraints on federally underwritten crop insurance as, ideally, a self-supporting agricultural risk-management tool. In particular, the two criteria by which these programs have been judged in recent years are aggregate participation rates and loss ratios. In the absence of subsidies, if participation is price-inelastic, then financial viability may be improved by a premium increase. However, if participation is price-elastic, then a premium increase will reduce participation proportionately more than the increase in premiums (Barnett, Skees, and Hourigan). As a result, the potential viability of crop insurance as a market-oriented risk-management tool suffers by both measures.

In the case of multiple-peril grape insurance considered here, the price elasticity of participation at the 50% coverage level is -1.420, while the elasticities at 65% and 75%

are -0.436 and -0.408, respectively (table 2).[16] This suggests that an increase in CAT insurance premiums (reduction in subsidies) is likely to cause a relatively large number of growers to leave the program altogether, or to insure a lesser proportion of their acreage. This finding should be of particular concern given California growers' expressed desire for an effective and affordable risk-management tool (Blank and McDonald). However, reducing subsidies (increasing net premiums) at both the 65% and 75% levels may indeed have the desired effect of not only raising program revenue without drastically reducing participation rates, but also of reducing the subsidy burden on the government. This appears to run counter to current reform proposals that, by increasing the subsidy to higher coverage levels, seem to advocate "reverse price discrimination" where markets with lower elasticities of demand are charged lower prices.

More generally, finding that elasticities of demand differ across coverage levels immediately suggests a policy of recognizing heterogeneous groups of growers, rather than charging flat premiums as before, or targeting premium changes as the 1998 Act sought to do. Further, the elasticity structure found here is not unexpected, as growers who choose insurance coverage at a 50% level are likely those who are nearly indifferent between insuring and not insuring. While the elasticities at 65% and 75% are consistent with those found by previous researchers (see Knight and Coble and references therein), none report elastic demand. Our results suggest this discrepancy may be due to the fact that these other studies aggregate all types of insurance into a single product, and thereby do not differentiate between participation at different levels of coverage.[17] Nonetheless, the implications of an elastic demand for insurance are likely to be more severe if participation is also subject to the common problem of adverse selection.

In this model, growers' response to the variability of expected indemnities provides information as to their aversion to risk, while their response to variability in market revenue provides some evidence of adverse selection. In table 2, growers at all coverage levels are less likely to insure the more variable are the returns to insurance, simply because insurance becomes less effective as a risk-management tool the more variable are expected indemnities. Conversely, growers are more likely to insure at their chosen coverage level the more variable are market returns. This result can be interpreted as evidence of adverse selection. Note, however, that the statistical insignificance of the 65% coverage parameter suggests these growers do not exhibit adverse selection.

Perhaps it is the case that adverse selection is not a universal phenomenon for all growers, but arises only with those who tend to view insurance as an alternative to the market (75% coverage) or those who seek only minimal protection at virtually costless premiums. The majority of growers who use insurance as part of an overall risk-management plan therefore tend not to be those who are adversely selected into the insurance market. Such growers may also be more likely to self-insure than growers who tend to rely more on FCIC insurance.

Self-insurance may be achieved through either financial or operating strategies. Whereas many studies use capital structure (debt/equity ratio) as an indicator of a

---

[16] Each of these elasticities is significantly different from -1.0 at the 5% level, but at the 50% coverage choice only when using a one-tailed test (t-ratio = 1.847). Further, the elasticities at 65% and 75% are also significantly different from the 50% elasticity at the 5% level.

[17] A more fundamental cause, but not addressed by this research, may be the difference in yield distribution between field and specialty crops. Specialty crops tend to be irrigated, grown in mild climates, and intensively managed, thereby creating a lower probability of below-average yields (negative skew).

grower's degree of financial risk, these data are not available on the current sample of California grape growers. Net income, however, may serve as a measure of the financial strength of a grower's operation. As such, a higher level of net income may have competing effects on the tendency to insure. More profitable growers may be better able to afford insurance, but these growers may also be less likely to perceive a need to insure. The results in table 2 provide some support for the latter effect, although only in the case of the demand for 75% coverage insurance. On the other hand, net income is also highly correlated with the physical size of the farm. Consequently, higher levels of net income tend to be associated with growers who have a greater ability to reduce the variability of their returns by farming geographically disperse land holdings and thus face less than perfectly correlated weather patterns. As such, this effect may constitute an alternative explanation for the parameter estimate for $V[R]$ at the 75% level in table 2. The difference between this result and that of Goodwin (1993), who reports a significant positive effect of average farm size on participation, may be due as much to differences between grape and wheat growers' risk attitudes as it is to their ability to diversify geographically. From an operational standpoint, perhaps a more viable method of smoothing earnings is through enterprise diversification.

By this reasoning, if a grower focuses on only one commodity, then he or she is more likely to insure as a means of preventing the loss of an entire year's revenue. In fact, this study finds the opposite for growers choosing either the 65% or the 75% coverage level. It may be the case that, by growing only one crop, these growers are signaling their relative lack of aversion to risk.

This result could also be due to the relative expertise of growers who specialize in one crop, believing that insurance is only valuable to those who are less skilled in growing grapes. A common measure of diversification among studies of the demand for insurance by Midwestern farmers is the percentage of farm production value due to livestock (Cannon and Barnett). Although this represents a natural portfolio choice for these growers, as their grain output can be used as an input to their livestock enterprise, livestock diversification among grape growers is less common. Nonetheless, counties with a higher percentage of farm production in livestock have significantly lower insurance participation rates at the 75% coverage level compared to other counties. This finding is consistent both with a priori expectations and the empirical results of Barnett, Skees, and Hourigan, and Cannon and Barnett for wheat and corn growers, respectively. Other variables in the participation rate model are intended to capture the impact of heterogeneity among growers in different counties that is otherwise unexplained.

Because the cultural practices associated with growing grapes for alternative end uses differ somewhat, it is likely that their demand for insurance will differ as well. Using wine-grape growers as a benchmark, raisin-grape growers are less likely to insure at the 75% level, but significantly more likely to insure at a 50%, or catastrophic level. Given the price elasticity results above, this means that a targeted premium increase is likely to have distributional effects among growers, impacting raisin growers proportionately more than others. On the other hand, table-grape growers are significantly more likely to insure at a 75% level, suggesting that they would be relatively indifferent to the proposed premium increase.

Growers as a whole, however, are not likely to support such a proposal given the overall trend toward choosing a minimal coverage level. In fact, the inertia toward 50% coverage is the most significant determinant of the demand for coverage at each level.

If growers feel the government's commitment to abandon the business of disaster support is credible, this result is to be expected as growers begin to take greater responsibility for their own risks, however small the probability of an indemnifiable loss may be.

Finally, these results show that growers choosing each coverage level exhibit a significant amount of inertia in the amount of insurance they buy. This suggests that the administrative burden may be a significant impediment to bringing new products successfully to market, even if demanded by growers.

Conclusions and Implications

Legislation passed in 1998, and subsequently amended, promised to dramatically increase the cost (net of subsidies) of catastrophic-level insurance to specialty crop growers. Growers and grower organizations feared that this would dramatically reduce participation in the federal crop insurance program by growers of high-valued, specialty crops. This concern is particularly acute among produce growers who, facing relatively low probabilities of indemnifiable losses, tend to prefer coverage at a minimal, safety-net, or catastrophic (CAT) level of insurance. Whether their concern is well founded depends upon the elasticity of demand for insurance, particularly for those at the margin between insuring and not insuring their crop.

Existing studies of the demand for crop insurance by growers of nonspecialty crops do not differentiate between the demand for different coverage levels, because a large majority of these growers choose a 65% coverage level. Consequently, it is not known whether there is indeed a difference in the price elasticity of demand for insurance at each coverage level. Because the majority of these studies find the demand for crop insurance to be price-inelastic, the policy recommendations that follow would be quite different from those suggested by a finding of elastic insurance demand.

In order to account for differences in the structure of demand among coverage levels, this study applies a two-stage empirical method that accounts for the selection of a discrete, ordinal level of coverage, followed by a model of the demand for insurance at each coverage level. With this approach, the coverage-choice and insurance-quantity decisions are assumed to be two separate but interrelated decisions. Formally, a grower's purchase of insurance is only observed once a choice of coverage level is made, so the coverage choice serves as a sample-selection mechanism for a set of insurance demand models. Further, the amount of insurance purchased is itself only observed if the value of insurance to a grower exceeds some minimum value, so the method used to estimate the demand for insurance explicitly takes into account the existence of several year/county pairs in which insurance at a particular coverage level was not purchased at all.

By controlling for both the ordered selection and truncated demand problems, the participation elasticities for each coverage level estimated at the quantity stage are not only consistent in a statistical sense, but more relevant for policy analysis than single-coverage elasticities. We demonstrate an application of this method to a county-level sample of insurance choice and participation rates by California grape growers over the period 1986–96.

Determinants of both the demand for insurance at each level and the choice of coverage level include the mean and variance of the returns to insurance as well as the mean and variance of market returns. The study finds empirical support for including each of these variables in the demand model for each coverage level. More importantly, however, the results show the demand for insurance at a 50% coverage level to be elastic, while higher coverage levels are inelastic in demand. Thus, the proposed premium changes would have potentially serious negative effects on grower participation at the 50% level, but less impact on growers at higher levels of coverage. Growers at both the 50% and 75% levels are also more likely to insure the greater the variability of their market-based returns. This suggests that adverse selection is likely to exacerbate the participation problems caused by a premium increase. Because the least adversely selected growers are the first to drop out, the remaining growers will tend to be the worse risks, so indemnities will likely rise due to this indirect, unintended side effect as well.

The most obvious implication of this research concerns the design of subsidy schedules across different levels of coverage. Many of the proposed specialty crop insurance bills contain provisions for an "inverted subsidy" scheme whereby growers who buy up to higher levels of coverage would receive higher subsidies than is currently the case, whereas growers who choose a low level, or CAT insurance, would see their subsidies fall. If this scheme were to be implemented, the results here suggest that it would almost certainly fail to generate high participation rates. Moreover, although the reduction in subsidies would reduce the total cost of providing specialty crop insurance, elastic demand implies that the level of theoretical premium revenues would fall. It is this loss-ratio measure that is of greatest interest to a potential privately sustainable crop insurance market. Following policies implied by studies using coverage-aggregated data and Midwestern field-crop growers is likely to worsen, rather than improve, the performance of multiple-peril crop insurance for produce growers.

[Received July 1999; final revision received January 2000.]

References

Arrow, K. "The Economics of Agency." In *Principals and Agents: The Structure of Business*, eds., J. Pratt and R. Zeckhauser. Boston: Harvard Business School Press, 1984.

Barnett, B. J., J. R. Skees, and J. D. Hourigan. "Examining Participation in Federal Crop Insurance." Staff Pap. No. 275, Dept. of Agr. Econ., University of Kentucky, 1990.

Blank, S. C., and J. McDonald. "Crop Insurance as a Risk Management Tool in California: The Untapped Market." Research report prepared for the Federal Crop Insurance Corporation, Project No. 92-EXCA-3-0208. Dept. of Agr. Econ., University of California-Davis, August 1993.

Botts, R. R., and J. N. Boles. "Use of the Normal Curve Theory in Crop Insurance Ratemaking." *J. Farm Econ.* 40(1958):733–40.

California Department of Food and Agriculture. *County Agricultural Commissioners' Reports: Summary.* CDFA, Sacramento. Various issues, 1986–96.

Calvin, L. "Participation in Federal Crop Insurance." Paper presented at SAEA annual meetings, Little Rock AR, 1990.

Cannon, D. L., and B. J. Barnett. "Modeling Changes in the Federal Multiple Peril Crop Insurance Program Between 1982 and 1987." Paper presented at AAEA annual meetings, Indianapolis IN, August 1995.

Chintagunta, P. K. "Investigating Purchase Incidence, Brand Choice, and Purchase Quantity Decisions of Households." *Marketing Sci.* 12(Spring 1993):184–208.

Coble, K. H. "Asymmetric Information and Crop Insurance: An Assessment of Our Current Knowledge." Paper presented at AAEA annual meetings, San Diego CA, August 1994.

Coble, K. H., T. O. Knight, R. D. Pope, and J. R Williams. "Modeling Farm-Level Crop Insurance Demand with Panel Data." *Amer. J. Agr. Econ.* 78(May 1996):439–47.

Cragg, J. G. "Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods." *Econometrica* 39(1971):829–44.

Dubin, J. A., and D. L. McFadden. "An Econometric Analysis of Residential Electric Appliance Holdings and Consumption." *Econometrica* 52(March 1984):345–62.

Gardner, B. L., and R. A. Kramer. "Experience with Crop Insurance Programs in the United States." In *Crop Insurance for Agricultural Development: Issues and Experience*, eds., P. Hazzell, C. Pomereda, and A. Valdez, pp. 195–222. Baltimore: Johns Hopkins University Press, 1986.

Goodwin, B. K. "An Empirical Analysis of the Demand for Crop Insurance." *Amer. J. Agr. Econ.* 75(May 1993):425–34.

———. "Premium Rate Determination in the Federal Crop Insurance Program: What Do Averages Have to Say About Risk?" *J. Agr. and Resour. Econ.* 19(December 1994):382–95.

Goodwin, B. K., and T. L. Kastens. "Adverse Selection, Disaster Relief, and the Demand for Multiple-Peril Crop Insurance." Unpub. manu., Dept. of Agr. Econ., Kansas State University, May 1993.

Goodwin, B. K., and A. Ker. "Nonparametric Estimation of Crop Yield Distributions: Implications for Rating Group-Risk Crop Insurance Contracts." *Amer. J. Agr. Econ.* 80(February 1998):139–53.

Greene, W. *Econometric Methods*, 3rd ed. Englewood Cliffs NJ: Prentice-Hall, 1997.

———. *LIMDEP: Version 7.0 User's Manual.* Plainview NY: Econometric Software, Inc., 1998.

Hanemann, W. M. "Discrete/Continuous Models of Consumer Demand." *Econometrica* 52(May 1984): 541–61.

Heckman, J. J. "Sample Selection Bias as a Specification Error." *Econometrica* 47(January 1979): 153–61.

Hojjati, B., and N. E. Bockstael. "Modeling the Demand for Crop Insurance." In *Multiple Peril Crop Insurance: A Collection of Empirical Studies*, ed., H. Mapp, pp. 153–76. Southern Cooperative Series No. 334, Dept. of Agr. Econ., Oklahoma State University, Stillwater, May 1988.

Jones, R. "Coming Up Short." *Amer. Vegetable Grower* 46(September 1998):9–12.

Just, R., and L. Calvin. "An Empirical Analysis of U.S. Participation in Crop Insurance." In *Economics of Agricultural Crop Insurance: Theory and Evidence*, eds., D. L. Hueth and W. H. Furtan, pp. 205–52. Boston: Kluwer Academic Publishers, 1994.

Just, R., L. Calvin, and J. Quiggin. "Adverse Selection in Crop Insurance: Actuarial and Asymmetric Information Incentives." Unpub. manu., Dept. of Agr. Econ., University of Maryland, October 1993.

Knight, T. O., and K. H. Coble. "Survey of U.S. Multiple Peril Crop Insurance Literature Since 1980." *Rev. Agr. Econ.* 19(Spring/Summer 1997):128–57.

Lee, H., J. Harwood, and A. Somwaru. "Implications of Disaster Assistance Reform for Non-insurable Crops." Paper presented at AAEA annual meetings, Indianapolis IN, August 1995.

Lee, L.-F. "Generalized Econometric Models with Selectivity." *Econometrica* 51(March 1983):507–12.

Maddala, G. S. *Limited Dependent and Qualitative Variables in Econometrics.* Cambridge, UK: Cambridge University Press, 1983.

Newbery, D. M. G., and J. Stiglitz. *The Theory of Commodity Price Stabilization: A Study in the Economics of Risk.* London/New York: Oxford University Press/Clarendon, 1981.

Nieuwoudt, W. L., S. R. Johnson, A. W. Womack, and J. B. Bullock. "The Demand for Crop Insurance." Agr. Econ. Rep. No. 1985-16, Dept. of Agr. Econ., University of Missouri-Columbia, 1985.

Smith, V. H., and A. Baquet. "The Demand for Multiple Peril Crop Insurance: Evidence from Montana Wheat Farms." *Amer. J. Agr. Econ.* 78(Februrary 1996):189–210.

U.S. Department of Agriculture, Federal Crop Insurance Corporation. *Annual Summary: Price and Coverage Level.* Kansas City MO. Annual issues, 1986–96.

U.S. Department of Commerce, Bureau of the Census. *Census of Agriculture.* Washington DC, 1982, 1987, 1992.

Zavoina, R., and W. McElvey. "A Statistical Model for the Analysis of Ordinal-Level Dependent Variables." *J. Mathematical Sociol.* (Summer 1975):103–20.