The Demand for Specialty-Crop Insurance: Adverse Selection and Inefficiency

Timothy J. Richards and Pamela Mischen

Abstract: The twin problems of moral hazard and adverse selection are often blamed for the lack of insurance for many fruits and vegetables. This paper develops an alternative method of testing for adverse selection that uses a two-stage approach to determine the effects of technical inefficiency on the demand for insurance. With this approach, technical inefficiency is interpreted as an indicator of adverse selection. Because there is no active insurance market for many specialty crops, and thin markets for those that are insurable, a contingent valuation approach is used to obtain the data necessary to estimate the demand for three different types of insurance. The results suggest adverse selection may be a deterrent to the viability of extending the breadth of specialty crop insurance products.

Key Words and Phrases: *Adverse selection, contingent valuation, crop insurance, fruits and vegetables, moral hazard, risk, uncertainty.*

Moral hazard and adverse selection are often offered as explanations for both low participation rates and high loss ratios (the ratio of indemnities to premiums) in agricultural crop insurance (Ahsan, Ali and Kurian; Nelson and Loehman; Chambers; Smith and Goodwin). However, there are many definitions of moral hazard and adverse selection in the theoretical literature, and still more employed in empirical studies of the demand for insurance. Arrow, for one, suggests simple and compelling definitions of moral hazard as "hidden action" on the part of an insured agent, and of adverse selection as "hidden knowledge" possessed by the insured as to his probability of loss. With these multiple definitions of moral hazard and adverse selection come as many alternative methods of measuring or detecting their presence in insurance markets. Moreover, as Quiggin et al. suggest, the difference between moral hazard and adverse selection in agricultural crop insurance is unobservable as the decisions to insure and to plant are made simultaneously. Attempts to differentiate between the two largely rest on semantic arguments about the timing of each decision. For our purposes, adverse selection is interpreted as flowing from hidden information about inherent producer characteristics, while moral hazard results from specific input decisions unknown to the insurer. Coble reviews several earlier studies that test for either one or both, while the focus of this study is on adverse selection in specialty crop production.

The existence of adverse selection in specialty crop insurance may mean that insurance markets either do not exist or are extremely thin (Lee, Harwood and Somwaru). Many of the major fruit and vegetable crops were only brought into the Federal Crop Insurance Corporation (FCIC) fold by the 1980 Federal Crop Insurance Act and still suffer from poor participation rates.[1] Because of the absence of insurance markets, price and quantity data that are usually used to estimate the demand for insurance do not exist (Barnett, Skees and Hourigan; Hojjati and Bockstael; Calvin; Goodwin, 1993; Coble et al.). However, the fact that many growers have an interest in fruit and vegetable insurance suggests this is not due to lack of demand, but lack of a mechanism to achieve a market equilibrium (Blank and McDonald).[2] In the absence of an active market, contingent valuation (CV) methods have proven valuable in eliciting potential participants' willingness to pay for a good or amenity, despite the concerns expressed by McFadden. This study employs a CV approach in estimating the potential demand for specialty-crop insurance and in testing for the presence of adverse selection.

Typically, empirical tests of adverse selection using farm-level data rely on estimates of farmers' participation responses to either the returns to insurance (Calvin; Just and Calvin; Coble et al.) or the cost of purchasing insurance (Goodwin, 1993; Goodwin and Kastens; and Smith and Baquet). With this specification, a positive response to returns, or negative response to premiums, is interpreted as evidence of adverse selection. More specifically, Just and Calvin interpret a deviation between aggregate FCIC mean yields and a farmer's own expected yields as evidence of yield heterogeneity the FCIC does not take into account and, hence, a cause of adverse selection. Goodwin and Kastens estimate a model of crop insurance participation that includes both premiums and a premium/yield variability interaction term. They find a positive and significant effect of this interaction term and interpret the result as evidence of adverse selection. Goodwin (1994) calculates actuarially sound premiums for a sample of Kansas wheat farmers and concludes that adverse selection is present because calculated premiums are higher for those who choose to insure compared to those who do not.

If farm-specific measures of yield variability or other measures of the ability to manage yield risk could be included directly in the premium determination process, as Goodwin (1994) suggests, the problem of adverse selection might be dramatically reduced. Current FCIC practice is to use yield averages as indicators of this ability, despite the tenuous nature of this relationship (Goodwin, 1994). Further, standard crop insurance contracts require growers to use "best practice" production methods. Although ensuring that these practices are used is difficult except in cases of flagrant violation, the failure by some growers to use sound farming practices, whether by intent or by nature, may represent a significant cause of their need to insure. Measuring a grower's inability or unwillingness to use best practice techniques is often not directly possible, but estimating this tendency is a simple matter given the appropriate data and indicator of deviation from what is deemed "best."

Farrell's definition of inefficiency, the deviation of a producer from his or her potential level of output, provides one such indicator. Many empirical applications of this notion of inefficiency exist in agricultural economics, including Bravo-Ureta and Rieger in dairy, and Akridge and Hertel in agricultural supply cooperatives, among others.[3] In general, these applications involve the estimation or construction of a stochastic production frontier where the random error about the maximum level of output for a given bundle of inputs includes deviation resulting both from truly random factors and a measure of idiosyncratic inefficiency. Although many other factors can potentially explain farm-specific inefficiency, they are often unobservable or unmeasurable. Given the stringent reporting requirements of the FCIC, the remaining factor most likely to be unobservable to insurance agents is simply the managerial skill or ability of the grower. In fact, Kalaitzandonakes and Dunn use various measures of efficiency as indicators of managerial ability in developing a structural latent variable model of Guatemalan corn production. However, when producers use inputs to increase output and to lower the variance of output (Just and Pope), then it is more plausible to define their objective in terms of both the mean and the variance of output. In this context, efficiency is achieving the optimal tradeoff between risk and return. When insurance is not available when the input decision is made, such as in the case of many specialty crops, then a positive relationship between a farmer's level of inefficiency and his or her willingness to pay for crop insurance provides evidence of adverse selection.

Therefore, the objective of this paper is to develop an empirical test for adverse selection that uses the definition of inefficiency outlined above. The first section presents a simple model of the willingness to pay for insurance in terms of a mean-variance framework. Next, an extension of the mean-variance model incorporates farm-specific inefficiency as a determinant of the value of insurance and as an indicator of adverse selection. This section also explains the stochastic production function method of estimating inefficiency in more detail. Finally, an empirical example of the demand for insurance among U.S. fruit and vegetable growers demonstrates the value of using a CV approach for insurance valuation purposes, and tests hypotheses regarding the presence or absence of adverse selection.

A Model of Production with Adverse Selection

Adverse Selection and the Willingness to Pay for Insurance. Suppose that growers face a production technology similar to Quiggin et al. where output (Y) is a function of a vector of variable inputs (X), fixed inputs (Z), grower effort (θ), and an additive error term that allows for both the random influences of the environment (ν) and of managerial skill (μ):

$$Y = f(x,z,\theta) + \epsilon \quad \text{where} \quad \epsilon = (\nu,\mu). \tag{1}$$

In their model, Quggin et al. interpret the unobservable effort variable, θ, as an indicator of moral hazard, whereas they include a random "managerial skill" component to a multiplicative error term to represent the effect of adverse selection on output. Although Quiggin et al. define x as consisting of only risk-increasing inputs, a more general definition, such as in the production function of Just and Pope, allows x to contain both risk-increasing and risk-decreasing inputs.

With the technology shown in (1), producer profit becomes:

$$\pi = pf(x,z,\theta) + \epsilon - wx - rz = \bar{\pi} + \epsilon; \tag{2}$$

where w is the vector of variable input prices and r is the vector of rental prices on the quasi fixed inputs. When deciding whether or not to insure their crops in a risky environment, however, risk averse producers consider the expected utility of profit rather than simply its amount.

To determine the amount producers are willing to pay for insurance, begin by expanding the general expression for the utility of profit about its mean:

$$U(\pi) \cong U(\bar{\pi}) + \epsilon U'(\bar{\pi}) + \frac{\epsilon^2}{2}U''(\bar{\pi}) + r_3\epsilon, \tag{3}$$

where the higher order terms go to zero with ϵ. Given the expression for profit in (3), the expected utility of profit is written as:

$$E[U(\tilde{\pi})] = U(\bar{\pi}) + (1/2)\int_{\epsilon_L}^{\epsilon_H} \epsilon^2\phi(\alpha)d\alpha\, U''(\bar{\pi}) + E[r_3\epsilon], \tag{4}$$

where ϕ is the density function of the random error term. In order to determine the "price of risk," or risk premium, Newbery and Stiglitz and compare the mean level of profit to its certainty equivalent, or the certain level of profit that generates a utility level equal to the expected utility of a random profit: $E[U(\tilde{\pi})] = U(\hat{\pi})$. Using this result, the price of risk is then the difference between the mean and certainty equivalent levels of profit: $\rho = \bar{\pi} - \hat{\pi}$. Expanding the utility of the certainty equivalent profit gives an expression in terms of the mean profit and the price of risk:

$$U(\hat{\pi}) = U(\bar{\pi} - \rho) \cong U(\bar{\pi}) - \rho U'(\bar{\pi}) + r_2(\rho), \tag{5}$$

where again the higher order remainder terms go to zero with the price of risk. Setting (5) equal to (4) and solving for the price of risk gives:

$$\rho = -(1/2)\left(\frac{var(\epsilon)U''(\bar{\pi})}{U'(\bar{\pi})}\right), \tag{6}$$

which forms the basis for the empirical inverse demand curve for insurance estimated below.

Several implications can be drawn from this expression. Most important, under the assumption of decreasing absolute risk aversion (DARA), an increase in the variance of output, and, hence, profit, causes the price of risk to rise. Therefore, production inputs that cause the variance of output to rise are likely to cause the willingness to pay for insurance to rise, while risk-reducing inputs reduce the willingness to pay for insurance. Fraser develops a more detailed model of the willingness to pay for crop insurance that includes the covariance of price and yield in determining the variability of farm profit in addition to the coefficients of yield and price variation. His simulation results show that the willingness to pay rises in both yield and price variability, but is relatively insensitive to the covariance between price and yield.[5]

This study focuses on the source of profit variation that is at least partially under control of the farmer (yields), so including price variation is an unnecessary complication. Moreover, it is these individual factors that lead to adverse selection. To the extent that θ measures unobservable producer decisions, a lower value of θ reduces the level of profit. With the DARA assumption, this means that lower θ values result in a higher willingness to pay for insurance, ceteris paribus. This result also suggests that more specific assumptions about the distribution of ϵ can provide insight into the potential factors that influence the willingness to pay for insurance. Furthermore, if two producers are identical in every other observable respect, a difference in willingness to pay that is caused by factors within the distribution of ϵ can suggest an alternative indicator of adverse selection in crop insurance. In particular, many applications consider a composed-error form for ϵ, reflecting both the randomness of production and idiosyncratic inefficiency.

Grower Efficiency and the Stochastic Production Frontier. Specifically, assume that the random error term, ϵ, in the production function given in (1) above consists of two elements: $\epsilon = v - |u|$, where the effect of climate on output is a random normal variable: $v \sim N(0,\sigma^2_v)$, and managerial quality, or the proxy for the effect of adverse selection (u) follows a half normal distribution as specified by Aigner, Lovell and Schmidt. With this assumption, the function (1) becomes a stochastic production frontier. Because this technology defines a frontier along which only the most efficient producers lie, the greater the individual realization of u, the greater is the deviation from the best practice frontier. Assuming that v and u are independently distributed, the standard deviation of the composed error term is: $\sigma = (\sigma_v^2 + \sigma_u^2)^{(1/2)}$. Clearly, the greater the deviation from the frontier, the greater the variance of total production. Therefore, combining this result with (6) above shows that a higher level of inefficiency leads to a greater willingness to pay for insurance.

While this result allows for predictions of aggregate effects, detecting individual cases of adverse selection requires a firm-specific measure of inefficiency. Jondrow et al. derive such a measure from the expectation of u_i, conditional on each firm's realization of ϵ_i. In the composite normal/half normal case described above, the expected value of u_i for each farm is written:

$$E(u_i|\epsilon_i) = \epsilon_i\left(-\sigma_u^2/\sigma^2\right) + \frac{\sigma_u^2\sigma_v^2}{\sigma} f\left(\epsilon\sigma_u/\sigma_v\sigma\right)\left(1 - F\left(\epsilon\sigma_u/\sigma_v\sigma\right)\right)^{-1} \tag{7}$$

where f is the normal density function and F is the normal distribution function. Subtracting the expectation of u_i from the residual ϵ_i gives the value of the random component of the deviation from the best-practice frontier: v_i. Subtracting this random deviation from the predicted level of output and dividing the result by the actual level of output yields an index of efficiency for each observation. Or, equivalently, the technical efficiency (TE) index can be found by direct calculation once the farm-specific error is known: $TE = e^{E[u_i|\epsilon_i]}$.

Because this variable is bound by 0 (perfectly inefficient) and 1 (perfectly efficient), it is expected that the willingness to pay for insurance falls as this measure of efficiency rises. As Coble argues, however, it is necessary to account for a variety of other factors that can affect the decision to insure, and, hence, the willingness to pay, in order to test for the effect of adverse selection. Therefore, this study considers a number of variables describing a grower, his or her operation, and his or her attitudes toward risk. The motivation for including each of these is discussed below, but the variables designed to detect the presence of adverse selection are of primary interest. Specifically, if the willingness to pay falls with efficiency, and the econometric procedure controls for the effect of historic yield variability, then there is evidence of adverse selection. Because none of the farmers in the data set already purchases insurance equivalent to the options presented them in the survey described below, it is not possible to test for the effect of moral hazard. With the contingent valuation method, the ability to insure is purely hypothetical, so farmers do not have the ability to alter their stated input levels in response to each insurance option. The following section describes the survey instrument used to elicit growers' willingness to pay for each of these options, and to gather data on their farming operations, risk attitudes and personal characteristics. It also explains in detail the two-stage estimation procedure.

Data, Variable Definitions and Estimation Methods

The Survey Instrument. A nationwide survey of fruit and vegetable growers provides the data for this study. Specifically, a cluster sample was defined for each of 32 commodities, both insurable and noninsurable, with a target response of at least 20 growers per commodity. The number of growers surveyed per state was selected in order to achieve a representative sample on a grower-number basis, not by production value. With a focus on explaining likely aggregate participation rates, sampling by population rather than value of production provides a better indication of the likely distribution of insurance buyers. The sub-samples selected for this study include potato, apple, grape, onion and watermelon growers.[6] Of the total 132 responses (7.4% of total surveys mailed to growers of these commodities), 76 provided usable input and yield data.[7] The survey was mailed in December, 1995, and the responses used in this study collected by April 30, 1996. Input cost data pertain to the 1995 crop year, while historical yields are provided for the 1991 to 1995 period. The survey instrument consists of three parts: demographic and farm characteristic questions, crop production and input values, and the value of various insurance alternatives. Each section of the survey, and the variables derived from the questions asked, is explained in turn.

To explain the demand for insurance, the first section of the survey includes a number of questions concerning grower characteristics and their farming practices. Other studies that use farm-level data incorporate a variety of proxy variables that attempt to measure either the ability to self insure, or efforts toward that end. These factors include farm size (total acres), debt-to-asset ratio (debt ratio), percentage of income earned off farm (off-farm income), extent of enterprise diversification(number of crops), past participation in government programs (history and program), age, level of education (education), and a subjective measure of the perceived importance of risk (yield risk and price risk), where the terms in parentheses are the exact variable names as they appear in the results tables (Calvin; Just and Calvin; Goodwin, 1993; Goodwin and Kastens; Smith and Baquet; and Coble et al.). This study includes each of these variables in addition to measures of geographic diversification (distance), degree of vertical integration (integration), extent of production-contracting (contract), and the use of irrigation technology (irrigation). Each of the above studies provides a thorough discussion of how these factors is expected to influence the demand for insurance. While self insuring family income through enterprise diversification, off-farm work, investing in irrigation, or equivalent methods may reduce the demand for insurance, farmers who adopt these practices reveal themselves to be relatively risk averse. Therefore, if presented for the first time with the opportunity to insure, there is some question whether these farmers will place a greater or lesser value on insurance than those who do not self insure. It can be said, however, that if two farmers have equivalent attitudes toward risk, the one who chooses to self insure will place a lesser value on additional insurance.

Of the factors unique to this study, geographic diversification and vertical integration are perhaps the most important to fruit and vegetable growers. Many large growers have operations in distinctly different climatic zones and may, in fact, benefit from a catastrophic event occurring in one area if enough of the total crop is removed from the market to cause prices to rise. An example of this occurred during the March, 1995, floods in Monterey County, California. Despite the floods, growers with lettuce fields in both Monterey and Yuma or Imperial counties saw unprecedented levels of revenue and profit. Similarly, many growers are also grower-shippers. Participating in downstream marketing activities allows vertically integrated growers to become less reliant on their own harvests, take advantage of higher and more stable retail-wholesale margins, and exercise some measure of control over market supply. Each of these advantages reduces the need for traditional forms of crop insurance, irrespective of a grower's inherent skill in crop production. In order to calculate the skill indicator, an index of technical efficiency is estimated using farm-level production data.

These data are obtained using a second, or crop production, section of the survey. This section provides information on the number of crops grown, acreage of the primary crop, the distance between parcels of that crop in miles, a five-year history of irrigated and nonirrigated acreage and yields, the average price per pound of 1995 output, and value of fertilizer, chemicals, labor, water, seed, fuels and other variable 1995 costs. This section also asks growers to rank the importance of yield, output price, labor cost, and input cost risk on a Likert scale (1 = high risk, 5 = low risk). The willingness to pay is also hypothesized to be a function of output variability, and various indicators of growers' attitudes toward risk. Using the data from this section, yield variability is calculated as the five-year coefficient of variation (CV[Y]), and the expected price is simply taken to be a naive forecast (E[P]). In other words, growers are assumed to expect last year's price to prevail next period in forming their expectations regarding the value of insurance.

The third section of the survey asks growers to place a subjective value on several insurance alternatives. An open-ended polling technique is used, as opposed to the closed or referendum method, in order to avoid problems with framing or leading the farmers' response. The insurance alternatives include four levels of yield coverage (50%, 65%, 75%, 85%), three levels of cost of production coverage (65%, 75%, 85%)

and three levels of revenue coverage (70%, 80%, 90%). Using the cost of production alternative as an example, growers are asked to submit what they would be willing to pay, on a per-acre basis, for insurance that guarantees them 100% of their variable costs of production if their yield falls below 65%, 75% or 85% of their historical average yield. In order to pool insurance valuations across commodities, the dependent variable (W_i, the willingness to pay) must be expressed in comparable terms for each, and is, therefore, expressed as a percentage of the total cost of production per acre. Approximately 30% of the sample growers, however, would not consider insurance in each case, so entered a "zero" willingness to pay for all options. Consequently, the demand for insurance is assumed to be a censored variable and is estimated using a Tobit procedure.

Two-Stage Estimation Procedure. Independent demand models are estimated for each insurance alternative. Estimating these demand models, however, involves a two-stage procedure. The first stage estimates the efficiency of each grower and the second uses this indicator of managerial skill in testing for adverse selection.

Stochastic Production Frontier. In the first stage, maximum likelihood estimates of a Cobb-Douglas stochastic production frontier provides farm-specific inefficiency estimates (Aigner, Lovell and Schmidt; Jondrow et al.).[9] A stochastic frontier approach is preferred to deterministic alternatives in this case because the latter attribute all deviation from the frontier to inefficiency. Many sources of deviation, however, may be due to factors that are indeed observable to an insurance provider. Such factors may include soil quality, microclimate, or location. Each may cause yield to fall short of the theoretical maximum for a given input bundle, but is not an indicator of truly unobservable managerial skill. A Cobb-Douglas functional form is chosen for this frontier because it is parsimonious representation of the technology, it appears to fit the data well, and is commonly used in the efficiency-estimation literature. In terms of the variables in the survey data set, the frontier is written as:

$$\log Y_i = \alpha + \sum_j \beta_j \log X_j + \gamma_1 C_k + \gamma_2 R_l + \gamma_3 I_m + \epsilon_i, \tag{8}$$

where:

Y = the yield of grower i, in pounds per acre,
X_j = cost of input j, in dollars per acre, j = chemicals, water, labor, other inputs,
C_k = crop k, k = potato, onion, grape, watermelon,
R_l = state l, and
I_m = a binary variable = 1 with irrigation, and = 0 without irrigation.

Recall that in the stochastic production method, $\epsilon_i = u_i + v_i$, u_i is distributed half normal, and v_i is a normally distributed error component reflecting random deviations from the frontier. By pooling across growers of different crops located in different regions, we are able to obtain sufficient degrees of freedom to estimate (8), but at the cost of assuming equal input elasticities across growers. Farm-specific estimates of u are used to calculate a vector of technical efficiency indices using the method of Jondrow et al. This efficiency index is used in the second-stage model to explain growers' willingness to pay for crop insurance.

Empirical Model of Insurance Demand. Linear specifications for the willingness-to-pay relationship shown in equation (6) for each insurance alternative are estimated as functions of grower efficiency, historical yield variability, expected output price, and the other explanatory variables described above. Because of the number of null responses, however, the distribution of the willingness to pay for insurance is assumed to be truncated at zero. Therefore, the empirical insurance demand model uses a Tobit estimation procedure (Maddala). A Tobit approach is required if growers reveal a positive willingness to pay ($W > 0$) only if the latent, or desired, willingness to pay (W^*) exceeds a certain limit value—zero in this case. If the desired amount is below this value, then a grower's true willingness to pay is unobserved. Therefore, the observed willingness to pay is written as:

$$W_i = \begin{bmatrix} W_i^* = \beta X_i + \epsilon^* & \text{if } W_i^* > 0, \\ 0 & \text{if } W_i^* \leq 0 \end{bmatrix}. \tag{9}$$

However, if there are n total observations, m of which are greater than zero, then application of OLS to the problem in (9) yields parameter estimates that are biased and inconsistent. To see this, consider the regression equation in (9) for only the nonlimit observations:

$$W_i = \beta X_i + \epsilon_i, \tag{10}$$

Then, the conditional expectation of W_i given $W_i^* > 0$ is:

$$\begin{aligned} E(W_i | W_i^* > 0) &= \beta X_i + E(\epsilon_i | W_i^* > 0) \\ &= \beta X_i + E(\epsilon_i | \epsilon_i^* > -\beta X_i) \\ &= \sigma \left(\frac{\phi(\beta X_i)}{\Phi(\beta X_i)} \right) = \sigma \lambda_i \end{aligned}, \tag{11}$$

where ϕ is the normal probability density function, Φ the cumulative density function, and their ratio is the inverse Mill's ratio. Given this result, applying OLS to (9) ignores the inverse Mill's ratio, so the estimated parameters suffer from omitted variables bias. Heckman develops a two-stage correction procedure, but the standard errors estimated therein are inconsistent, so it is preferable to use the maximum likelihood method of Amemiya. With this approach, maximum likelihood estimates of the Tobit inverse insurance-demand model are found by maximizing the log-likelihood function:

$$L = \sum_i [(1 - Z_i)\log\Phi(-\beta X_i/\sigma) + Z_i(-(1/2)\log(2\pi\sigma^2) - (1/2\sigma^2)(W_i - \beta X_i)^2)], \tag{12}$$

where $Z_i = 1$ for nonlimit observations, and zero otherwise.

Whereas regression parameters usually are interpreted directly as the marginal response of the dependent variable to changes in any independent variable, the same cannot be said of the Tobit model. This is because there are actually three interpretations of the dependent variable, leading to three different regression models. Interpreted directly, the regression parameters (β) show the change in the expected value of the latent willingness to pay for a change in an explanatory variable. However, the dependent variable of interest may also be the expected value of the observed willingness to pay, or even the expected value of the observed willingness to pay only when it is positive. For the purposes of this study, we are interested in marginal effects on expected values of the observed willingness to pay, so, in order to allow the appropriate interpretation, the Tobit parameter estimates are transformed according to:

$$\frac{\partial E[W_i]}{\partial X_j} = \Phi(\beta X_i)\beta_j. \tag{13}$$

Essentially, (13) means that the expected change in observed willingness to pay for a change in an explanatory variable is simply regression parameter weighted by the probability of observing a non-limit input. The Tobit model is estimated, and the marginal effects recovered, using the maximum likelihood procedure in LIMDEP 7.0. The results from applying this procedure to the survey data are reported in the following section.

Table 1.
Maximum Likelihood Estimates of Cobb-Douglas Production Frontier

Input	Estimate	t-ratio
Constant	10.4520*	3.3992
Labor	0.0028*	2.0307
Chemicals	-0.2278	-1.7756
Water	0.3555*	3.2854
Other Variable	-0.0321	-0.4741
Potato	0.0032	0.5972
Onion	-0.9935	-1.8103
Grape	0.8007*	2.0662
Watermelon	2.0967*	6.4841
σ_u/σ_v	0.4777	1.0850
$\sigma^2_u + \sigma^2_v$	0.8149*	1.7410
L.L.F.	-87.5093	

Notes: A single asterisk indicates significance at a 5% level. Binary state variables are excluded from the table, but parameter estimates are available from the authors.

Results and Discussion

The primary concern of this paper is with the relationship between technical efficiency as a potential indicator of adverse selection and the willingness to pay for specialty crop insurance. Therefore, the presentation of the results focuses on tests for adverse section, but also considers the effect of grower characteristics or business practices on the willingness to pay. Because tests for adverse selection first require the calculation of a measure of technical efficiency for each grower, this section begins with a discussion of the results from estimating a stochastic production frontier.

Stochastic Production Frontier Results. Table 1 presents maximum likelihood parameter estimates of the Cobb-Douglas production frontier. As the data are pooled across all observations, the frontier is allowed to shift neutrally by each commodity and state, defining California as the base state and apples as the base commodity. In general, the model provides an adequate fit of the data as the R^2 between observed and predicted values is 0.8179. It is perhaps surprising, however, to note that agricultural chemicals have a negative effect on yield. For many of the crops considered here, however, many growth regulators, fungicides or pesticides are applied in order to improve or maintain quality as well as improve yield. Residuals from this stage are used to calculate the efficiency index used as a regressor in Tobit models for the willingness to pay for yield insurance, cost of production insurance and revenue insurance, respectively (Table 1).

Willingness to Pay for Yield Insurance Results. The first set of Tobit estimates considers the willingness to pay for yield insurance. Table 2 shows that, when all explanatory variables are held constant, the willingness to pay for yield insurance varies from 2.12% of cost for a 50% coverage level to 2.95% of cost for 85% coverage. Because the production frontier controls for input usage and other random effects, the efficiency index is interpreted as a measure of managerial skill that, at least implicitly, is known to the grower, but unobservable by the insurer. Consequently, tests of the significance of the technical efficiency coefficient in these regressions are tests of the adverse selection hypothesis. Adverse selection is likely to exist if a null hypothesis of a zero coefficient on the efficiency index is rejected in a one-tailed t-test, where the alternative hypothesis is that the coefficient is less than zero. Because higher values of this index are associated with higher levels of efficiency, adverse selection exists if it is found that efficient producers are willing to pay less for yield insurance.

Table 2 shows that this is indeed the case for all coverage levels except the 75% level, where the parameter is marginally insignificant at a 5% level. Because the efficiency index varies from 0.0 to 1.00, these parameters indicate that the willingness to pay differs from between 3.6% of cost (85% coverage) to 4.47% of cost (65% coverage) from perfectly efficient to inefficient growers. In fact, accounting for inefficiency causes historical yield variability, which is typically used to measure the likelihood of a grower making an insurance claim, to become statistically insignificant (Table 2).

Table 2 also shows the marginal effects of many other factors thought to influence the subjective value of yield insurance. Clearly, many of the variables found to be significant by other researchers in other contexts are insignificant here—a result that could be due to their failure to include measures of managerial skill. At a 10% level of significance, only contracting, history of program participation, operator age, distance between parcels of the crop, and a grower's subjective assessment of the importance of price risk are found to be significant. Although contracting growers reduce their exposure to price risk by doing so, they are still subject to the risk that they will not being able to produce their contract amount. This risk is sufficient to cause contracting growers to be willing to pay more for yield insurance than those

Table 2.
Willingness to Pay for Yield Insurance, 50%, 65%, 75%, 85% Coverage

	Coverage Level							
	50%		65%		75%		85%	
Variable	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Constant	2.1184	1.1230	2.3089	0.9390	2.5637	0.9420	2.9542	1.0300
Contract	0.4216*	1.6630	0.5999*	1.8320	0.7028*	1.9710	0.7783*	2.0590
History	0.0223	0.0970	-0.0098	-0.0340	-0.0920	-0.2880	-0.1011	-0.2960
Program	-0.2869	-1.1680	-0.4341	-1.3790	-0.3635	-1.0530	-0.6935*	-1.8870
Off farm Inc	0.0992	0.5570	0.1154	0.5160	-0.0213	-0.0880	-0.1052	-0.4110
Debt Ratio	0.0212	0.4090	0.0236	0.3550	0.0317	0.4330	0.0499	0.6480
Age	0.2245*	1.6920	0.3275*	1.7340	0.4098*	1.9600	0.3853*	1.7250
Education	-0.1178	-0.9650	-0.1431	-0.8950	-0.2597	-1.5110	-0.3486*	-1.8630
Num. Crops	0.0559	0.9020	0.0447	0.0560	0.0465	0.5300	0.0299	0.3220
Distance	0.0081	1.3600	0.0103	1.3210	0.0090	1.0480	0.0061	0.6570
Irrigation	-0.2508	-0.6290	-0.4111	-0.7870	-0.4777	-0.8520	-0.3992	-0.6790
Integration	-0.1036	-1.1720	-0.1045	-0.9110	-0.1435	-1.1710	-0.1436	-1.1060
Total Acres	-0.1350	-0.4770	-0.1251	-0.4360	-0.7561	-0.2680	-0.3321	-0.1080
Yield Risk	0.0623	0.5940	0.0637	0.4740	0.0641	0.4370	-0.0024	-0.0150
Price Risk	-0.1417	-1.5550	-0.1764	-1.4510	-0.1610	-1.2990	-0.1494	-1.0840
Efficiency	-4.0121*	-1.9880	-4.4731*	-1.7120	-4.0902	-1.4290	-3.6433*	-1.9700
CV[Y]	-0.0524	-0.4480	-0.0985	-0.4960	0.0041	0.0660	-0.0213	-0.3130
E[P]	0.1330	0.4860	0.1344	0.3750	0.1910	0.4790	0.2642	0.6110
West	-0.0619	-0.1450	0.0053	0.0100	-0.3022	-0.4910	-0.2335	-0.3540
Southeast	-0.2977	-0.5040	-0.3944	-0.5080	-0.2469	-0.2990	-0.3390	-0.3780
North	-0.0180	-0.0390	0.0291	-0.0480	-0.1307	-0.1940	-0.0789	-0.1090
Apple	0.0300	0.6030	0.3249	0.5010	0.5864	0.8260	0.6362	0.8500
Grape	0.0012	0.3190	0.1497	0.2980	0.2934	0.5270	0.5554	0.9390
Onion	-0.0201	-0.0410	0.3748	0.6150	0.6786	1.0243	1.0641	1.5520
Potato	0.0043	1.0070	0.0025	0.4570	0.0008	0.1390	-0.0028	-0.4460
Watermelon	0.1671	0.3880	0.2494	0.4420	-0.0697	-0.1130	0.1090	0.1640
R^2	25.5554		24.5660		25.0330		24.3700	

Notes: A single asterisk indicates significance at a 5% level. Variable definitions are provided in the text. Note that the parameters have been scaled for presentation purposes: total acres by 10^4, V[Y] by 10^8, and E[P] by 10^4. The marginal effects of each explanatory variable on the willingness to pay is given by: $\partial E[y|x]/\partial x = \Phi(\beta' x/\sigma)\beta$, where Φ is the normal distribution function, y is the vector of willingness' to pay and x is the matrix of explanatory variables.

who sell by some other arrangement. Contracting growers may also be more risk averse than others; the fact that they are willing to sign contracts provides evidence of their degree of risk aversion. Growers who have received benefits under other government programs, however, are less willing to buy crop insurance.

Although this effect is only significant in the 85% coverage case, the point estimates for each coverage level indicate that growers with experience in other crop programs can be expected to pay between 0.28% and 0.69% of costs less than those with no experience. If crop programs include payments under previous disaster assistance programs, then this result supports allegations that these payments create negative incentive effects on insurance participation, but is counter to the empirical finding by Just and Calvin. Alternatively, these growers may be more knowledgeable about the subsidy that has been implicit in many crop insurance programs, but are also more likely to be aware of the administrative costs associated with participation. Older growers, who are assumed to have more experience in handling administrative work, are likely to be less deterred by such costs.

In each case, growers with more experience are willing to pay more for insurance than younger, less experienced growers. Despite a presumption that more experienced growers should be better managers, they may also be more risk averse than younger, less experienced growers. Besides, including the efficiency index should measure this "managerial ability" effect. More established growers are also likely to have less debt than younger growers who have recently entered the industry. Therefore, the significant effect of age may be causing both the "education" and "debt ratio" variables to become insignificant. Many variables intended to act as indicators of growers' use of commodity diversification to reduce business risk are also insignificant, but only marginally so in many cases.

If crop yields are imperfectly correlated, then growing a portfolio of commodities can reduce the overall yield variability of the farm. Consequently, such crop-diversification can provide a substitute for yield insurance, so diversified growers may be willing to pay less for a given level of coverage than single-crop growers. Calvin finds significant negative effects of farm diversification on participation in multiple-peril crop insurance. In this study, however, the 50% result indicates an opposite effect—growers' willingness to pay for yield insurance rises in the number of crops grown. This suggests either that crop diversification is more an indicator of risk aversion by individual growers, or that among growers of equal skill (efficiency), those with a greater number of crops are less able to manage production risks through other means.

Although diversifying geographically represents a complementary method of reducing business risk, growers' willingness to pay for insurance rises in this variable as well. This result is particulary surprising given recent experience with natural disasters that have paid significant dividends to growers with operations in different counties, regions or states. It is likely that the proxy variable for geographic diversification is highly correlated with another explanatory variable—farm size—so multicollinearity could be deflating the statistical significance of this variable.

In fact, the only form of diversification that appears to represent a viable substitute for yield insurance is vertical integration. By handling other growers' crops, a vertically integrated grower-handler or grower-shipper becomes less dependent upon his or her own crop, so has less of a need for yield insurance to maintain a continuous supply of product. While these methods of self insurance are indirect indicators of a grower's degree of risk aversion, the model includes two more direct measures.

It is expected that the willingness to pay for yield insurance should rise as a grower's subjective assessment of yield risk rises. On the other hand, growers that consider price variability to be the primary source of risk are likely to place less value on yield insurance. In fact, this appears to be the case. Growers who view price risk as "high" tend to be willing to pay less for yield insurance. On the other hand, there is no connection between attitudes toward yield risk and the value of insurance. Although not consistent with expectations, this result does not bode well for the potential of adverse selection. If yield-risk averse growers are not willing to pay more for insurance, then the pool of insured growers may consist disproportionately of those who are unconcerned with yield risk. The next section presents and discusses the results of estimating the demand for cost-of-production (COP) insurance.

Willingness to Pay for COP Insurance Results. Problems with adverse selection may be as likely with cost insurance as with yield insurance, but with less impact on the willingness to pay. Specifically, for every 10% improvement in a grower's level of efficiency, the results in Table 3 show that the value of insurance falls by between 0.06% of costs (65% coverage) to 0.02% of costs (85% coverage), although the latter is not statistically significant. Thus, less efficient growers are likely to be willing to pay more for insurance. Again, this result is consistent with similar farm-level studies for field crop growers that show higher expected returns to insurance have a positive effect on insurance participation (Calvin; Just and Calvin; Coble et al.). Table 3 also shows other factors that are indicators of growers' willingness to pay for COP insurance.

As with yield insurance, Table 3 shows that growers who contract their production are willing to pay more for COP insurance than those who do not. For these two coverage levels, growers with a history of crop insurance participation are also willing to pay an average of 0.04% more for insurance than those who do not. While this background was not found to be important in the case of yield insurance, the results for the two types of insurance agree on the effect of past participation in crop programs. Specifically, growers familiar with government programs are expected to pay an average 0.06% less than those who are not. Although both age and education have significant effects of the same sign as in the yield insurance case, they are an order-of-magnitude smaller. Specifically, a grower who is ten years older than

Table 3.
Willingness to Pay for Cost of Production Insurance: 65%, 75%, 85% Coverage

	Coverage Level					
	65%		75%		85%	
Variable	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Constant	0.2655	1.1320	0.6052*	1.9560	0.0644	0.3350
Contract	0.0730*	2.2990	0.0273	0.6620	0.0679*	2.6660
History	0.0383	1.3160	-0.0203	-0.5560	0.0340	1.4600
Program	-0.0524*	-1.7260	-0.0871*	-2.2280	-0.0441*	-1.7940
Off farm Inc	0.0135	0.6410	-0.0311	-1.1410	0.0044	0.2580
Debt Ratio	0.0018	0.2770	0.0164*	1.9400	0.0009	0.1630
Age	0.0417*	2.3090	0.0351	1.4540	0.0423*	2.8520
Education	-0.0175	-1.1540	-0.0452*	-2.2780	-0.0296*	-2.3820
Num. Crops	0.0088	1.1650	-0.0018	-0.1770	0.0110*	1.7600
Distance	0.0012	1.5630	0.0003	0.3440	0.0009	1.4990
Irrigation	-0.0562	-1.1260	-0.0699	-1.0860	-0.0109	-0.2790
Integration	-0.0111	-1.0060	0.0197	-1.4070	-0.0131	-1.5110
Total Acres	0.0000	-0.2200	0.1355	0.4170	-0.1280	-0.6260
Yield Risk	0.0202	1.5561	0.0046	0.2690	0.0102	1.1060
Price Risk	-0.0165	-1.4490	-0.1804	-1.2150	-0.0090	-0.9830
Efficiency	-0.6160*	-2.4740	-0.6387*	-1.9480	-0.2385*	-1.8130
CV[Y]	-0.0073	-0.5400	-0.0017	-0.2430	-0.0032	0.7020
E[P]	0.0218	0.6320	0.0202	0.4360	0.1316	0.4590
West	-0.0008	-0.0150	0.0020	0.0280	-0.0162	-0.3710
Southeast	-0.0253	-0.3470	-0.0602	-0.6260	-0.0087	-0.1440
North	0.0108	0.1840	-0.0020	-0.0260	0.0220	0.4590
Apple	0.0662	1.0740	0.1077	1.3260	0.0570	1.1500
Grape	-0.0053	-0.0109	0.0485	0.7580	0.0336	0.8570
Onion	0.0483	0.8410	0.1863*	2.5040	0.0371	0.7970
Potato	0.0003	0.6480	0.0006	-0.8610	0.0002	0.4120
Watermelon	0.0070	0.1300	-0.0266	-0.3720	-0.0075	-0.1710
R^2	33.1780		32.6300		35.4310	

Notes: A single asterisk indicates significance at a 5% level. See notes from Table 2 for additional information.

another can be expected to pay 0.04% of costs more for COP insurance. Whereas the willingness to pay rises in experience, it falls in education. Growers' opportunities to limit risk through diversification or other farm practices are less significant determinants of their willingness to pay.

Of this set of variables, irrigation and farm size are never statistically significant influences. However, for an 85% coverage level, growers can be expected to pay 0.01% of costs more for each additional crop grown. As with yield insurance, this result contradicts what we expect if growers use a portfolio of crops to self insure. Distance between parcels of the same crop is again marginally statistically significant for two of three coverage levels, but the sign of the effect is again counter to the portfolio-risk management intuition. Taken together, these results suggest that such behavior is an important signal of risk averse attitudes. As expected, however, growers who are more vertically integrated are willing to pay less for cost insurance than single-function growers.

Growers' attitudes toward risk also have effects on the willingness to pay for cost insurance that are consistent with those found in the yield insurance case. For a 65% coverage level, growers who place less importance on yield risk are willing to pay more for cost insurance (0.02%), while growers who regard price risk as important are willing to pay more (0.02%). Again, this is consistent with Blank and McDonald's findings that fruit and vegetable growers face more uncertainty from market sources than from agronomic. Despite this attention to price risk, heterogeneity among growers' yield risk is likely to determine the pool of insured growers—a result Coble et al. also interpret as an indicator of adverse selection. The next section presents the results of applying the Tobit model to growers' demand for revenue insurance.

Willingness to Pay for Revenue Insurance Results. In a qualitative sense, the results for revenue insurance are consistent with those found for both yield and COP insurance. While not as severe in absolute value as in the yield insurance case, willingness to pay for revenue insurance is significantly higher among inefficient growers than efficient growers. The fact that this variable is both statistically and economically significant for virtually all insurance products and coverage levels lends considerable support to the belief that adverse selection will be a problem for specialty crop insurance, as it has been for traditional crops. The primary implication of this result is clear—to eliminate the effect of adverse selection on the viability of specialty crop insurance, insurance providers (or the FCIC) need to develop a procedure for assessing the adherence of growers to statistically-verifiable best practice technologies. Many of the other variables are consistent with findings for the previous insurance alternatives (Table 4).

On average, across coverage levels, growers who contract are willing to pay 0.52% of costs more for revenue insurance than those who sell into the open market, while growers with crop program experience will pay between 0.26% (80% coverage) and 0.43% (90% coverage) less than those who have not. Consistent with each of the

Table 4.
Willingness to Pay for Revenue Insurance: 70%, 80%, 90% Coverage Level

	Coverage Level					
	70%		80%		90%	
Variable	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Constant	1.2619	0.8290	1.0687	0.6590	1.8572	1.0830
Contract	0.4407*	2.2100	0.5264*	2.3660	0.5897*	2.6210
History	-0.0414	-0.2250	-0.0338	-0.1750	-0.1090	-0.5250
Program	-0.3162	-1.6240	-0.2631	-1.2850	-0.4247*	-1.9390
Off farm Inc	-0.0253	-0.1820	-0.0348	-0.2360	-0.0782	-0.5020
Debt Ratio	0.0086	0.2070	0.0208	0.4770	0.0411	0.8890
Age	0.3046*	2.4930	0.3752*	2.9270	0.3806*	2.7500
Education	-0.1288	-1.2610	-0.1363	-1.2730	-0.2315*	-2.0186
Num. Crops	0.0465	0.9310	0.0414	0.7870	0.0219	0.3860
Distance	0.0057	1.2010	0.0060	1.1190	0.0042	0.7620
Irrigation	-0.1262	-0.4000	-0.1941	-0.5830	-0.2120	-0.6100
Integration	-0.0866	-1.2530	-0.0867	-1.2020	-0.1145	-1.4770
Total Acres	-0.1219	-0.0770	-0.2755	-0.1650	-0.2344	-0.1290
Yield Risk	0.1100	1.3140	0.0575	0.6650	0.0187	0.2040
Price Risk	-0.0941	-1.3157	-0.0937	-1.2260	-0.0947	-1.1780
Efficiency	-2.8422*	-1.7920	-2.6898*	-1.6910	-2.7837	-1.5630
CV[Y]	-0.1287	-0.3560	-0.2976	-0.7890	-0.1744	-0.4460
E[P]	0.6951	0.3130	0.1221	0.5190	0.1513	0.5960
West	-0.1595	-0.4600	-0.2750	-0.7520	-0.2450	-0.6240
Southeast	-0.6282	-1.1380	-0.5005	-0.9930	-0.4976	-0.8690
North	-0.0254	-0.0680	-0.1836	-0.4660	-0.1950	-0.4580
Apple	0.2849	0.7100	0.4452	1.0600	0.4686	1.0520
Grape	0.2007	0.6400	0.3494	1.0580	0.2808	0.7920
Onion	0.2859	0.7810	0.3894	0.9990	0.6353	1.5910
Potato	0.0023	0.7080	0.0022	0.6520	-0.0002	-0.0060
Watermelon	-0.0173	-0.0470	0.0721	0.1890	-0.0291	-0.0700
R^2	32.1300		30.8020		31.7449	

Notes: A single asterisk indicates significance at a 5% level. See Table 2 for additional information.

other insurance options, age has a significant and positive effect on willingness to pay, while education has an opposite effect that is only statistically significant at a 90% coverage level. For both variables, the size of the effect is similar between yield and revenue insurance, with both effects considerably larger than for the COP option. Among self-insurance practices, vertical integration is perhaps the most relevant to the value of revenue insurance as stabilizing revenue is often the reason why growers move downstream. Although significant only at relatively low levels of confidence, the negative effect of greater integration on willingness to pay is consistent with a priori expectations.

Table 4 also shows that growers who are more concerned about yield risk (have a lower value of this variable) are willing to pay less for insurance, whereas the opposite is true for price insurance. Although this pattern was also found for other insurance products, the explanation is more intuitive in this case. This option gives growers their only protection against market-borne, as opposed to agronomic, risk. In the absence of futures markets for most fruits and vegetables, growers have more options to manage yield risk than price risk. Consequently, they are likely to place a greater value on a product with few substitutes. This value is evident in comparing contract terms for fruits and vegetables for processing with open market prices. Although highly variable from season to season, potato growers estimate that such contract arrangements cause them to give up $400 to $500 per acre in gross revenue to ensure a market for their product. Whereas risk aversion may lead to a viable market for revenue insurance for many commodities, adverse selection again presents a problem.

Conclusions

Low participation rates and high loss ratios in agricultural crop insurance are typically blamed on the problems of moral hazard and adverse selection. Existing empirical measures of adverse selection in crop insurance consider a positive association of the expected returns to insurance and the decision to insure as evidence. This study contends that the relationship between a grower's idiosyncratic measure of inefficiency and his or her willingness to pay for insurance constitutes a better measure. Where markets for insurance either do not exist or are not widely used, a contingent valuation (CV) approach is required to examine this relationship. Consequently, this paper uses a CV approach to test the hypothesis that producers' technical efficiency helps to explain fruit and vegetable growers' willingness to pay for crop insurance. Specifically, it is believed that a more inefficient producer is likely to have a higher willingness to pay for insurance for two reasons: first, a higher level of inefficiency causes the variance of output to rise, ceteris paribus, and second, a more inefficient grower is likely to find it more costly to reduce risk through his or her own behavior.

Empirical results from a survey of U.S. fruit and vegetable growers support the hypothesized effect for three different insurance products: yield, COP and revenue insurance. Furthermore, for yield insurance, older growers, growers who contract their production and those with large distances between parts of their farm are willing to pay a greater amount for insurance, while more efficient growers, those who have participated in farm programs in the past and those who feel price risk is severe are willing to pay less. A similar pattern of results is shown for COP insurance, but growers with a more diversified crop portfolio and greater regard for yield risk will pay more for COP insurance while more educated growers will pay less. Vertical integration appears to cause grower-packers to place a lower value on the opportunity to buy revenue insurance.

Several implications follow from these results. First, many of the methods of self-insurance that other studies show to be important (Calvin; Just and Calvin; Goodwin, 1993) are not necessarily viewed as substitutes for insurance by specialty-crop growers. Second, growers' appear to regard price risk as a greater threat than yield risk, perhaps reflecting the fact that few growers have the ability to use futures markets to manage price risk for fruits or vegetables. Third, it appears likely that adverse selection will be problematic, perhaps limiting the ability of the FCIC to privatize the widespread delivery of specialty crop insurance, or requiring costly monitoring and data gathering services for crop insurance participants. Future research into this problem could entail an ex post analysis of adverse selection among crops that are just now becoming insured. Further, the methodology used here could be extended by investigating the effect of alternative efficiency estimation techniques on the test for adverse selection.

Notes

Timothy J. Richards is Assistant Professor, School of Agribusiness, Arizona State University, and Pamela Mischen is Project Director, National Food and Agricultural Policy Project, Arizona State University. *The authors gratefully acknowledge the assistance of Joy Harwood, Glenn Zepp and Keith Coble.*

1. This list includes almonds, cranberries, grapes, onions, peppers, popcorn and walnuts, or "...any agricultural commodity grown in the United States (Gardner and Kramer). Insurance for potatoes, tomatoes, peaches and citrus was available prior to the Act. Participation exceeded 25% for only almonds (31), citrus trees (91) and peaches (44) in 1993. An anonymous reviewer, however, provides newer information indicating that participation rates have risen to more than 50% for

grapes, about 50% for apples and potatoes, and 25% for onion growers. Despite these increases, participation rates remain below the goals of the 1994 Federal Crop Insurance Reform Act.

2. Using a survey of California farmers, Blank and McDonald find that 39% of those who cannot insure rank crop insurance either first or second among a group of desired risk management tools that includes crop insurance, government programs, forward contracting, diversification or hedging. Further, the primary reason why 28% of growers who do not insure do not buy insurance is simply because it is not available for their crop. A majority of the rest cite excessive premiums as the reason, suggesting that a positive reservation price exists, albeit below current levels.

3. Much of this literature prior to 1992 is reviewed by Battese, and more recent literature by Coelli.

4. Ramaswami provides a similar result in a multi-input model that takes into account both the output and risk effects of additional input use.

5. Additionally, Fraser finds in his "base case" scenario for Australian wheat farmers that willingness to pay is roughtly 10% greater than actuarial costs. This result supports Patrick's survey results showing that participation in a hypothetical insurance scheme is likely to be limited.

6. This procedure produces a sample that is broadly representative of the population of growers of each commodity on a regional basis. The largest sampling errors occur in Southwest watermelons (sample understates population share by 21.5%), Southwest potatoes (sample understates population share by 16.7%), and Western potatoes (sample overstates population share by 14.7%). For all commodities and regions, the average sampling error is 6.55%.

7. As a reviewer suggests, this low response rate may be a source of nonresponse bias. If growers perceive crop insurance as an incursion of the government into their business, then growers may be less inclined to respond to the survey. Therefore, nonrespondents may indeed have a lower willingness to pay than those who do respond. This caveat should be kept in mind when interpreting the results.

8. In estimating the production frontier, fertilizer and chemicals are combined in a "chemicals" variable, while seed and fuels are included with "other variable costs."

9. As noted by a reviewer, estimates of efficiency are typically sensitive to the estimation method used. Bravo-Ureta and Rieger, however, show correlation coefficients typically over 0.95 in comparing linear programming, statistical production function and stochastic production function methods in a sample of Northeastern dairy farms. Other studies show greater sensitivity. Hjalmarsson et al. report correlation coefficients typically less than 70% with 11% of the cases showing negative correlation in comparing efficiency indexes derived from data envelopment analysis, deterministic parametric frontier and stochastic frontier methods. Neff et al. find the correlation between stochastic production frontier and nonparametric estimates of efficiency to be less than 50%. A comparison of these fundamentally different methods is beyond the scope of this study, but the efficiency estimates reported here are highly correlated (0.85) with those found assuming an exponential error structure. Moreover, the choice of error distribution has no qualitative impact on the efficiency–willingness-to-pay relationship.

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