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ESTIMATING DEMAND FOR PRECISION TECHNOLOGY IN AN EMREGING MARKET: COTTON YIELD MONITORS IN THE SOUTHEASTERN UNITED STATES

Michele C. Marra and Ellen Wu
North Carolina State University
Raleigh, NC
Roland K. Roberts, Burton C. English, James A. Larson, and Rebecca L. Cochran
University of Tennessee
Knoxville, TN
W. Robert Goodman
Auburn University
Auburn, AL
Sherry L. Larkin
University of Florida
Gainesille, FL
Steven W. Martin
Delta Research and Education Center
Stoneville, MS
W. Donald Shurley
University of Georgia
Tifton, GA

Abstract

Survey data from cotton farmers in six southeastern states are used to estimate the willingness-to-pay (WTP) for either retrofitting yield monitors onto cotton pickers or to purchase a yield monitor as an option with a new cotton picker. "Don't Know" responses were either omitted, included as "No" responses, or treated as a separate response in order to compare WTP and price elasticity of demand estimates. Responses to bid price changes, although statistically significant, are very small, indicating a relatively inelastic demand for cotton yield monitors. The low elasticity estimates indicate that factors other than price must be the focus of efforts to increase demand.

Introduction

Practitioners of precision farming gather and analyze information about the variability of crop conditions in order to maximize the efficiency of input use. This is accomplished by tailoring crop management strategies to the distinct needs of each area within a field. The use of precision, or site-specific, farming practices often involves the adoption of a suite of technologies. These technologies can, however, be adopted sequentially with each providing a degree of marginal benefit to the farmer (Khanna; Roberts et al.). Yield monitors fall into the subset of precision farming technologies used to gather information about spatially variability in production yields across a field. Accurate yield monitors for grain have been commercially available since the late 1980s. Many row-crop producers have adopted grain yield monitors as an initial step in the adoption of the complete suite of precision farming technologies.

The adoption of yield monitors for use in precision cotton farming was, until recently, constrained by ineffective equipment (Searcy and Roades; Valco, Nichols and Lalor; Durrence et al.; Sassenrath-Cole et al.). Although yield monitors were first developed for grain and oilseeds in the early 1990s (Mangold), monitors for seed cotton proved unreliable at measuring cotton. Early cotton yield monitors, first introduced in 1997, had many problems including poor accuracy, failure to maintain calibration, and sensors that became blocked by dust and other materials (Wolak et al.; Durrence et al.; Roades, Beck and Searcy). Cotton yield monitor technologies introduced in 2000 are more reliable and may be more readily adopted by cotton growers (Perry et al.). Currently, yield monitors are not standard equipment on cotton pickers. Farmers must either purchase a cotton yield monitor as an option on a new picker or retrofit a monitor on their existing picker. Given that cotton yield monitors are a relatively new technology, there is a lack of information about the factors that may influence the potential demand.

The first precision farming research concerning economics focused mainly on the profitability of applying inputs in variable rates for different crops. The results were mixed. For example, Hammond reported inconclusive results on the profitability of variable rate technology when applying phosphorous and potassium to potatoes. Lowenberg-DeBoer (1994), on the other hand, found variable rate application of phosphorous and potassium on corn to be unprofitable except on fields with previously low levels of these minerals. Fiez, Miller and Pan found that precision farming is potentially profitable for managing nitrogen on wheat, while a study by Malzer and another by Schnitkey, Hopkins and Tweeten found variable rate application of nitrogen profitable on the majority of corn and soybean field trials when phosphorous and potassium were controlled. Overall, Lambert and Lowenberg-DeBoer reported that 73% of the studies they reviewed found precision farming to be profitable. Two recent studies were the first to address the economics of the adoption of a suite of precision farming technologies (Isik, Khanna and Winter-Nelson; Popp and Griffin).

This study differs from previous work in two ways. First, our study examines the economics of one facet of the technology suite for a new crop and region. Second, we also consider the demand for a new technology available to cotton farmers (i.e., an effective cotton yield monitor). To our knowledge, there has been little work on specific technologies for non-Midwestern crops and no studies attempting to estimate the demand for a new precision technology.

Information about the demand for a precision technology, rather than simply studying its profitability or the factors affecting its adoption, gives information of use to several groups. This information is important for sellers of the technology that need to know how farmers will respond to pricing of the technology. It is also important for agricultural engineers and industry managers to have some idea of potential demand and demand elasticities for different user groups so they can optimize the costs of production and target marketing efforts. Government agencies may want to know features of the demand for the technology if they are considering a program to subsidize the purchase of the technology for its potential environmental benefits (Hubbell, Marra and Carlson). Thus, this study has two main objectives: (1) to estimate the demand for a new yield monitoring system for cotton in the Southeastern U.S. using stated preference methods, and (2) to provide estimates of demand elasticities under varying assumptions about uncertain responses. Results will provide a range of price elasticities corresponding to the demand for yield monitors.

This study begins with a review of dichotomous and polychotomous choice models used to estimate probabilities associated with "Yes", "No", and "Don't Know" dependent variables. The models are used to estimate several regressions that provide a range of willingness to pay and price elasticity estimates for cotton yield monitors. Following a description of the survey and empirical models, the regression results are described and compared. The implication of the magnitude of results and model comparisons are included in the final discussion.

Methodology

The contingent valuation method (CVM) has been used extensively to obtain the willingness to pay (WTP) for non-market goods (Mitchell and Carson). Cameron and James were the first to apply the CVM technique to pre-test new market goods. Using that approach, Hubbell, Marra and Carlson examined the potential demand for Bt cotton seed. This research uses CVM to estimate the potential demand for a cotton yield monitoring system with a global positioning system (GPS) receiver. The yield monitor with GPS can be used alone or in combination with other components of the precision technology suite.

Dichotomous Choice Model

In this study, the single-bounded dichotomous choice CVM is used to determine the WTP. As pointed out a study by Hanemann and study by Hanemann, Loomis, and Kanninen, the statistical model can be interpreted as a utility-maximization response within a random utility context. The probability of obtaining a "No" or a "Yes" response (i.e., π^n and π^y, respectively) can be represented by:

(1) $$\pi^n(B) = \mathrm{F}(B;\ \theta) = \Pr(B > \text{maximum WTP}) \text{ and}$$

(2) $$\pi^y(B) = 1 - \mathrm{F}(B;\ \theta) = \Pr(B \leq \text{maximum WTP}).$$

Farmers will be willing to pay B dollars to adopt the cotton yield monitoring system if their utility with the purchase of the cotton yield monitoring system is at least as high as their utility without it. That is,

(3) $$U_i(1, y_1;\ \theta_i) \geq U_i(0, y_0;\ \theta_i),$$

where 1 indicates that farmer y_i is willing to pay B dollars for the cotton yield monitoring system and 0 if the farmer is not. Similarly, y_1 and y_0 represent net income with and without the cotton yield monitoring system, respectively. The vector of farm and farmer attributes that may affect a farmer's perceptions about the cotton yield monitoring system and their WTP is represented by Φ. Utility can be divided into an observable portion $V(\bullet)$ and an unobservable, random portion ε that is i.i.d. N(0,1):

(4) $$U = V(d_i, y_i;\ \Phi) + \varepsilon$$

where d_i is the response ("Yes" or "No") of farmer i. Given the distributional assumption on ε, the probability of farmers responding "Yes" to the stated purchase price of the cotton yield monitoring system is specified as a probit model.

Consider N participants in the single-bounded experiment and let B_i be the price offered to the ith farmer. The corresponding log-likelihood function for the set of responses is:

$$\ln L(\theta) = \sum_{i=1}^{N} \left[d_i^y \ln \pi^y \left(B_i\right) + d_i^n \ln \pi^n \left(B_i\right) \right] = \sum_{i=1}^{N} \left[d_i^y \ln\left(1 - F\left(B;\theta\right)\right) + d_i^n \ln\left(F\left(B;\theta\right)\right) \right] \tag{5}$$

where d_i^y is 1 if the ith response is "Yes" and 0 otherwise, and where d_i^n is 1 if the ith response is "No" and 0 otherwise. The maximum likelihood estimator, θ, is the solution to $\partial \ln L(\theta)/\partial\theta = 0$.

Polychotomous Choice Model

Recent literature has considered the interpretation and importance of a response of "Don't Know" to a WTP question (Wang). It is argued that a respondent's ambivalence can be interpreted two ways. First, a "Don't Know" response could be interpreted as a "No" answer since if the respondent wished to answer "Yes" he/she would have; alternatively, due to conservatism on the part of the respondent, he/she would have answered "No" if pressed (Ready, Whitehead and Blomquist). Second, ambivalence could be just that and this response may be a function of the same factors as the "Yes" or "No" answers and should be modeled as a separate response in a polychotomous choice framework (Cameron et al.).

In the polychotomous choice framework, equation (3) becomes:

$$U_i(Y, y_y; \theta_i) \geq U_i(\mathrm{DK}, y_{dk}; \theta_i) \geq U_i(\mathrm{NO}, y_n; \theta_i), \tag{6}$$

where Y indicates farmer i is willing to pay B dollars for the cotton yield monitoring system, DK indicates the farmer's uncertainty about paying B dollars, and NO means the farmer is not willing to pay B dollars. The log-likelihood function (equation 5) then becomes:

$$\ln L(\theta) = \sum_{i=1}^{N} \left[d_i^y \ln \pi^y \left(B_i\right) + d_i^{dk} \ln \pi^{dk} \left(B_i\right) + d_i^n \ln \pi^n \left(B_i\right) \right] \text{ or} \tag{7}$$

$$\ln L(\theta) = \sum_{i=1}^{N} \left[d_i^y \ln\left(1 - F^1\left(B;\theta\right) - F^2\left(B;\theta\right)\right) + d_i^{dk} \ln\left(F^1\left(B;\theta\right)\right) + d_i^n \ln\left(F^2\left(B;\theta\right)\right) \right]$$

where d_i^y is 1 if the ith response is "Yes" and 0 otherwise, d_i^{dk} is 1 if the ith response is "Don't Know" and 0 otherwise, and d_i^n is 1 if the ith response is "No" and 0 otherwise. The first order condition is qualitatively the same as described above in the dichotomous choice case.

Wang, in his study of the value of environmental improvements in the Galveston Bay area of Texas, found (as expected) much lower mean WTP values when the "No" and "Don't Know" responses were combined compared to other frameworks, but found similar mean WTP between the polychotomous choice framework and the dichotomous choice model that ignores the "Don't Know" responses. Cameron et al., in their study of a hypothetical new environmental program in New York, found no significant difference between the dichotomous choice varying bids method and the polychotomous choice model allowing for degrees of preference. We provide additional empirical evidence of both classes of comparisons, that is, among different treatments of "Don't Know" responses and different elicitation approaches.

Survey Data

A mail survey was conducted in January and February of 2001 to establish the current use of precision farming technologies for cotton producers in Alabama, Florida, Georgia, Mississippi, North Carolina, and Tennessee. Of the 5,976 current cotton producers, a total of 1,131 usable responses were received. Of those, 431 answered the WTP questions, which were asked toward the end of the questionnaire.[1]

The survey mailing list was divided randomly into six equal groups, with each group given a hypothetical bid price ($4,500, $6,000, $7,500, $9,000, $10,500, or $12,000). The market price at the time of the survey was $9,500 for a cotton yield monitoring system that included a monitor, a GPS receiver, sensors on two chutes of a four- or five-row cotton picker, and the

[1] Details on the sampling procedures, the survey methods, and the rest of the survey instrument are available from any of the authors upon request.

ability to estimate lint yield within 4% of actual yields. The price of an additional sensor for a six-row picker was $1,500 (Ag Leader Technology). Each respondent was asked two WTP questions as follows:

1. **4 or 5-row cotton pickers owned by farmers** can be equipped with a yield monitoring system that includes a monitor, a GPS receiver, sensors on two chutes, and the ability to estimate yields within 4% of actual yields. Would you purchase the yield monitoring system for your 4 or 5-row picker for $__*B*__ installed? Yes ____ No ____ Don't Know ___Don't own a 4 or 5-row picker ___(Check one).
2. **When a new cotton picker is purchased/leased,** a yield monitoring system can be purchased/leased as an option for an additional cost. Would you purchase an optional yield monitoring system that adds $__**B**__to the purchase price of a new 4 or 5-row picker (or a corresponding increase in the lease rate), or $ *B + 1,285* to the purchase price of a new 6-row picker ($1,285 more for an additional sensor for the larger picker)? Yes ___ No ___ Don't Know ___ Don't intend to purchase/lease a new picker ___ (Check one).

The Empirical Model

Explanatory Variables (X)

The independent variable *price* varied from $4,500 to $12,000 in $1,500 increments. *Price* represents the bid amount, *B*, in the survey. The coefficient on *price* is expected to have a negative sign.

Cotton farmers who have already adopted other precision farming technologies for cotton and any precision farming technology for other crops (*adopter* = 1) are expected to place a higher value on the cotton yield monitor compared to those who had not used precision farming technologies (*adopter* = 0). The coefficient on the dummy variable *adopter* is expected to have a positive sign.

The potential influence of *adopter* on the slope of the estimated demand function is captured by an interactive variable: *price x adopter*. We expect the adopters' demand curve will be more elastic than the non-adopters, therefore, we expect a negative sign on this coefficient.

Education is a discrete variable for farmers' level of education. *Education* equals zero, the base education level, if the respondent didn't finish high school, 1 if the respondent finished high school, and 2 if the respondent spent some time in college. We hypothesize that farmers with more formal education are more likely to adopt precision farming technology (if it is profitable for them to do so), so we expect a positive sign on this coefficient.

Our definition of farm size is the sum of owned, share rented, and cash rented acres. The *farmsize* variable should capture economies of scale factors, if any, as well as serve as a proxy for financial strength (or ability to pay). Therefore, a positive sign on its coefficient is expected.

A dummy variable indicates whether the respondent uses a personal computer for farm management. If so (i.e., *computer* = 1), then the respondent may be more familiar with the value of the site-specific computer output from the yield monitor and be may willing to pay more compared to a farmer who does not use a computer for farm management (*computer* = 0).

Without giving the information on the current market price for a cotton yield monitoring system with GPS (i.e., $9,500), we asked for the producer's best estimate of the current cost of such a system. *Costpercept* is 1 if the respondent's answer was within 20% of the true cost at the time of the survey and equals 0 if their answer differed by more than 20%. A more accurate estimate should be associated with the respondent's familiarity with the technology and would be associated with higher willingness to pay, ceteris paribus.

Table 1 shows the means, standard deviations and number of observations of the variables by state and table 2 reports these statistics by whether the respondents have adopted precision farming technologies to produce other crops or precision farming technologies, other than yield monitors, to produce cotton.[2]

Estimated Models

Several methods can be used to estimate the demand for yield monitors depending on the data collected and the assumptions about the respondents' answers, specifically what to do with "Don't Know" responses. Whether the "Don't Know" re-

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[2] Some farmers responded that they had been using precision farming for many years. Because we are interested in their use of new technologies, we adjusted our definition of an adopter to eliminate those who reported using precision farming before some of the site-specific technologies were available. This study defines "Adopter" as a farmer who has used: (1) a yield monitor on any crop with or without GPS for less than five years, (2) remote sensing aerial photos and satellite images, (3) variable rate lime application for less than eight years in North Carolina and less than seven years in the remaining Southeastern states, or (4) variable rate nitrogen or phosphorous/potassium application for less than ten years.

sponses should be omitted, included with the "No" responses, or included as a separate response is speculative. Consequently, we estimate demand functions under all three assumptions to develop a range of potential elasticities. In addition, because there are two options for having a cotton yield monitor, the three models are estimated for both retrofitting an existing cotton picker with a yield monitor with GPS or adding the yield monitoring system to a new cotton picker.

First, the WTP responses were regressed against the independent variables described previously, which included the bid amounts (B) and socio-economic variables, using the following probit model:

$$\text{(8)} \qquad \mathrm{P}(Y{=}1|X_i) = \varphi(\beta' X),$$

where X_i is the vector of values of the regressors for respondent i, and φ is the standard normal cumulative distribution. Equation (8) was estimated twice for each yield-monitoring alternative. The WTP response, dependent variable, in the first estimation omitted those observations associated with a "Don't Know" response. In the second estimation, the "Don't Know" responses were included as "No" responses, increasing the number of observations. The third equation estimated for each yield-monitoring alternative treated each response as it's own category such that marginal effects could be calculated for the "Don't Know" responses and compared to those from the "Yes" and "No" responses. These assumptions result in three different dependent variables, estimated using two different estimation procedures, for each yield monitoring alternative. In all, the results of six models are presented.

The marginal effect of each explanatory variable is calculated by multiplying the probability density function (pdf) by the estimated coefficient. The pdf is estimated by the sum of the product of each variable mean and its estimated coefficient, plus the estimated intercept term (Greene, 2000). The mean WTPs are estimated using a 'grand constant' approach (Giraud et al.; Hubbell, Marra and Carlson):

$$\text{(9)} \qquad \overline{WTP} = \frac{\beta_0 + \sum (X'\beta)^{np}}{\left|\overline{Adopter} * \beta_{\mathrm{Price\,x\,Adopter}} + \beta_{\mathrm{Price}}\right|}$$

where $\sum (X'\beta)^{np}$ is the sum of the product of the non-price coefficients and the means of the non-price regressors. Finally, the price elasticity of demand is calculated by multiplying the slope of the demand function by the ratio of the average bid price and the average corresponding "Yes" responses.

Regression Results

Probit Model with only "No" Responses

The estimates of the intercept and the slope coefficients for both WTP questions (i.e., to retrofit a yield monitor or to have a yield monitor installed on a new picker) are presented in Table 3. For each alternative, the estimated coefficient on the bid *price* is negative and significant, but small in absolute value. This indicates some price responsiveness, but the price would have to be lowered by a significant amount to entice the majority of respondents to purchase the technology. The coefficients on the *adopter* dummy, the *computer* use dummy, and cost perception variable (*costpercept*) are all positive and significant, as expected. Coefficients on *farmsize* in the retrofit model and *education* in the new picker model are the expected sign, but not significant at the 5% level.[3] The coefficient on the slope dummy (*price x adopter*) is negative, but not significant for either regression. For this sample, the mean WTP for the retrofit question is \$48.81 and the mean WTP for a yield monitor attached to a new cotton picker is \$3,846.75, quite a large difference.

Probit Model with "No" and "Don't Know" Responses Combined

Table 4 presents the results when the "Don't Know" responses are combined with the "No" responses. As expected, including the "Don't Know" as "No" responses makes the overall price responsiveness much lower in each case. In this set of models, the slope dummy for *adopter* is not statistically significant at the 10% level. All of the marginal effects are smaller in absolute value than their counterparts in the regressions where the "No" responses were omitted. As in the first case with the "Don't No" responses omitted, the differences in the marginal effects between the regression for the retrofitted monitor are smaller in absolute value than those for the monitor installed on a new cotton picker. *Farmsize* is statistically significant in the retrofit model, but quite small. *Education* is not statistically significant in the new picker model. For this sample, the mean WTP for the retrofit question is \$5,024.59 and the mean WTP for a yield monitor attached to a new cotton picker is \$1,965.32. The reversal in relative WTPs compared to the first two models is a little surprising, although lumping the "No" and "Don't Know" responses has been found by others to distort the results (e.g., Wang).

[3] In our initial model estimations we found that *education* was never significant in the retrofit model and *farmsize* was never significant in the new picker model, so they were omitted in the respective models in the final estimations.

Ordered Probit Model

Tables 5 and 6 show the ordered probit regression results for the retrofitted and new-picker models, respectively, when the "Don't Know" responses were considered as a separate response category. All but one of the estimated coefficients are significant in both regressions and have the expected sign. The exception is *farmsize* in the retrofit model, which is positive, but not statistically significant. For this sample, the mean WTP for the retrofit question is $5,153.70 and the mean WTP for a yield monitor attached to a new cotton picker is $9,700.71. This is the only mean WTP that is higher than the market price at the time of the survey. Notice that the coefficients associated with the *price* variable are negative but when the marginal effects are calculated, the price effects for the range of the density function where the WTP response is "No" are positive. This is an artifact (and a shortcoming) of how the marginal effects are calculated in LIMDEP (Greene, 2002).[4] One of the three ranges (the "No" range in this case) is restricted to have marginal effects with opposite signs from the estimated coefficients. Consequently, in the final section, we only report and discuss the price elasticities for the "Don't Know" and "Yes" categories.

Model Comparisons

Price Elasticities

Table 7 reports the estimated price elasticities from the dichotomous choice probit models and the ordered probit model for each yield monitoring system alternative. Considering the dichotomous choice models first, the price elasticity for non-adopters is 3 to 20 times that of adopters (in absolute value) in each case. Including the "Don't Know" responses as "No" lowers the price elasticities considerably, with the elasticites computed from the regressions that ignore the "Don't Know" answers ranging from 115 to 3 times larger when compared to the models where "Don't Know" is included as a "No" response. Adopters are less price responsive if the question is whether to add a yield monitor with GPS to a new picker compared to the retrofit case, but non-adopters show the opposite tendency when the "Don't Know" responses are included as "No". In the other two cases, both adopters' and non-adopters' price elasticities are larger in absolute value for the new picker model compared to the retrofit model.

The model omitting the "Don't Know" answers and the price elasticities for the "Yes" respondents in the ordered probit model are similar, although the elasticities from the ordered probit model are slightly larger. As expected, price elasticities from both of these models are much higher than those from the probit model combining the "No" and "Don't Know" responses. These findings are similar to those reported in Wang and in Cameron et al.

<u>*Mean WTP.*</u> In the first model ("Don't Know" omitted) and third model ("Don't Know" included as a separate response category), the mean WTP is higher for the models of the yield monitor installed on a new cotton picker compared to the same model for the retrofitted yield monitor. This could be because the precision technology, combined with new cotton harvesting technology, may produce a complimentary effect that increases the value of both. If a yield monitor is retrofitted onto an older harvester, that synergy may not exist even though there is some additional value. All models of the yield monitor installed on a new picker have a better fit to the data (a higher likelihood ratio) than the comparable model for the retrofitted monitor, although all models are statistically significant.

We also found, as did Alberini, Boyle and Welsh in their study of uncertain responses in the multiple bid setting, that allowing for the uncertain response as a separate response category resulted in higher mean WTP. In our case, the percentage differences between mean WTP for the polychotomous choice models and the dichotomous choice models ranged from 2.5% to over 10,000% higher in the model where the monitor was retrofitted on the currently-owned picker and from about 150% to almost 4000% in the model where the monitor was assumed to be installed on a new picker.

The WTP for a yield monitor with GPS installed on a new cotton picker seemed to result in better models, in terms of goodness of fit, across the board. It could be that respondents who were not planning to purchase a new cotton picker in the near future had not thought as much about a yield monitor's performance on their farm and, therefore, were unable to give as consistent answers as the group who was planning to purchase a new picker. Or it could be that there is simply a more heterogeneous group among those who are not planning to purchase a new picker in the near future.

Demand for Yield Monitors

Figures 1 through 3 show the estimated demand curves for the cotton yield monitoring system for all the models discussed above. The difference in price responsiveness between adopters and non-adopters is clear in each figure. Adopters are more likely to be willing to adopt than the non-adopters at lower prices. Occasionally, the two demand curves cross at bid prices around the market price. This could indicate that adopters are more certain of the value of the yield monitor with GPS than non-adopters. Also notice that, in every case, the demand curve of those who haven't adopted any kind of precision farming technology shows a lower demand at every bid price than for adopters. This indicates a general propensity to adopt that is

[4] "In at least one case, Prob (cell 0), the partial effects have exactly the opposite signs from the estimated coefficients. Thus, in this model, it is important to consider carefully the interpretation of the coefficient estimates" (Greene, 2002; p. E18-5).

larger among those who are more familiar with the technology. Hubbell, Marra and Carlson found similar results for Bt cotton seed adoption.

Conclusions

Southeastern cotton producers are confronted with the decision of whether to adopt a cotton yield monitor with GPS, a technology that has improved accuracy over traditional cotton yield monitoring techniques. This study has examined the demand for these new yield monitors using stated preference methods. Producers were asked if they were willing to pay a certain amount (the bid price) for a new monitor either retrofitted to their existing cotton picker or installed on a new cotton picker they intend to purchase in the near future. Their responses to bid price changes, although statistically significant, are very small, indicating a relatively inelastic demand for this technology. The price elasticities of demand for the cotton yield monitor with GPS ranged from -0.0002 (for a non-adopter and a retrofit yield monitor in the dichotomous-choice probit model where "No" and "Don't Know" answers were combined) to -0.0072 (for an adopter who answered "Don't Know" to the WTP question for a yield monitor installed on the new picker in the ordered probit model). The consistently low price elasticity estimates indicate that, in the absence of increased profit evidence, factors other than price must be the focus of any effort to increase demand. As has been found in other studies, familiarity with the technology and similar technologies and more human capital can have a significant influence on the demand for a new technology.

It is useful to have a method for assessment of the demand for new technologies in the early stages of adoption. Our results support the finding that stated preference methods can prove useful in ex ante demand assessment in an emerging market. The qualitative empirical findings are consistent with other comparative studies that considered the uncertain responses as a separate category as one model for comparison. Since there are still some unknowns about the ordered probit approach, it is difficult to say if the polychotomous choice approach is better than the dichotomous choice approach in this context. At least for now, there is no single accepted way to consider uncertain responses in these types of studies. Further research is needed to understand the underlying nature of these responses. In our judgment, the best approach at this juncture is to report the results of several models to show how the results differ and to provide a range of elasticity estimates for those who will use the information.

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Table 1. Sample Descriptive Statistics by State

Variables (units)	**Alabama (n = 116)**	**Florida (n = 40)**	**Georgia (n = 104)**	**Mississippi (n = 192)**	**North Carolina (n = 195)**	**Tennessee (n = 101)**
Farm size	1,716	609	1,458	2,181	1,162	1,709
(acres)	(1,795)	(466)	(2,304)	(2,078)	(1,379)	(2,535)
Land owned	40	44	54	50	39	39
(%)	(29)	(32)	(33)	(29)	(31)	(32)
Education (0 if not a h.s. graduate,1 if h.s. grad., or 2 if some	1.6	1.5	1.65	1.89	1.61	1.54
college)	(0.49)	(0.51)	(0.48)	(0.31)	(0.49)	(0.50)
Income	149,568	143,750	124,519	143,359	141,154	134,653
($US/year)	(150,722)	(142,859)	(126,183)	(136,828)	(151,693)	(146,798)
Farmer Age	50	49	47	59	49	49
(years)	(11)	(12)	(10)	(11)	(10)	(11)
Average Cotton Yield	642	740	720	791	732	643
(pounds per acre)	(138)	(161)	(167)	(186)	(127)	(114)
Computer Used in Farming (1 if "Yes", 0 if	0.57	0.53	0.57	0.63	0.61	0.58
"No")	(0.50)	(0.51)	(0.50)	(0.48)	(0.49)	(0.50)
Cost Perception of Yield Monitor (1 if within 20%,	0.11	0.10	0.16	0.15	0.12	0.10
0 otherwise)	(0.32)	(0.30)	(0.37)	(0.36)	(0.33)	(0.30)

Notes: Parentheses below mean values contain standard deviations. Fewer observations (*n*) were available for the land owned and yield variables (20% less than total reported in column headings on average).

Table 2. Sample Descriptive Statistics by Adoption Status.

Variables (units)	Non-Adopters (n = 631)	Adopters (n = 117)
Farm size	1,460	2,323
(acres)	(1,780)	(2,691)
Land owned	44.0	45.6
(%)	(31)	(32)
Education		
(0 if not a h.s. graduate, 1 if h.s. grad., or 2 if some college)	1.67	1.77
	(0.47)	(0.42)
Income	136,410	159,188
($US/year)	(141,044)	(152,585)
Farmer Age	49	46
(years)	(11)	(9)
Average Cotton Yield	712	761
(pounds per acre)	(160)	(160)
Computer Used in Farming	0.56	0.79
(1 if "Yes", 0 if "No")	(0.50)	(0.41)
Cost Perception of Yield Monitor		
(1 if within 20%, 0 otherwise)	0.12	0.17
	(0.33)	(0.38)

Notes: Parentheses below mean values contain standard deviations. Fewer observations (*n*) were available for the land owned and yield variables (20% less than total reported in column headings on average except for non-adopter yields, which had 29% fewer observations).

Table 3. Probit Model Results with "Don't Know" Responses Omitted by Yield Monitor Alternative.

	Retrofitted Yield Monitor (n = 331; 12.7% WTP B)			Yield Monitor on New Picker (n = 270; 24.1% WTP B)		
	Estimate (prob[|Z|>z])	Variable Mean	Marginal Effect	Estimate (prob[|Z|>z])	Variable Mean	Marginal Effect
Intercept	-1.009	1.00	-0.153	-0.963	1.00	-0.269
	(0.0154)			(0.0654)		
Price	-0.00013	8,410.88	-0.00002	-0.00010	8,516.67	-0.00004
(*B* = bid price)	(0.0092)			(0.0038)		
Adopter	2.0903	0.1843	0.585	2.2245	0.2037	0.726
(1 if adopter, 0 otherwise)	(0.0104)			(0.0108)		
Price x Adopter	-0.00021	1,567.98	-0.00003	-0.00020	1,672.22	-0.00005
	(0.0541)			(0.1132)		
Farmsize	0.000083	1,942.52	0.00001	Not estimated		
(acres)	(0.1078)					
Education (0 if not h.s. graduate, 1 if h.s. graduate, 2 if college)	Not estimated			0.3788	1.6889	0.106
				(0.0704)		
Computer	0.6114	0.6133	0.085	0.4678	0.6111	0.125
(1 if use for farm, 0 otherwise)	(0.0121)			(0.0278)		
Costpercept	0.737	0.1299	0.158	0.824	0.1519	0.276
(1 if within 20%, 0 otherwise)	(0.0032)			(0.0004)		

Notes: The mean WTP values for the retrofitted and new installs were $48.37 and $3,846.75, respectively. The Likelihood Ratio statistics (χ^2_6) for the retrofitted and new installs were 55.77 and 71.13, respectively, with prob values of less than 0.0001.

Table 4. Probit Model Results with "No" and "Don't Know" Responses Combined by Yield Monitor Alternative.

	Retrofitted Yield Monitor (n = 480; 8.8% WTP B)			**Yield Monitor on New Picker (n = 436; 14.9% WTP B)**		
	Estimate (prob[|Z|>z])	**Variable Mean**	**Marginal Effect**	**Estimate (prob[|Z|>z])**	**Variable Mean**	**Marginal Effect**
Intercept	-1.351 (0.0004)	1.00	-0.165	-1.454 (0.0016)	1.00	-0.284
Price (*B* = bid price)	-0.00009 (0.0343)	8,250.00	-0.00001	-0.00009 (0.0164)	8,418.58	-0.00002
Adopter (1if adopter, 0 otherwise)	1.4560 (0.0317)	0.1792	0.329	1.7110 (0.0045)	0.1904	0.511
Price x Adopter	-0.00014 (0.1401)	1,462.50	-0.00002	-0.00012 (0.1066)	1,586.00	-0.00002
Farmsize (acres)	0.000089 (0.0435)	1,912.09	0.00001	Not estimated		
Education (0 if not h.s. graduate,1 if h.s. graduate, 2 if college)	Not estimated			0.3602 (0.0579)	1.6927	0.070
Computer (1 if use for farm, 0 otherwise)	0.4100 (0.0661)	0.6521	0.046	0.3313 (0.0711)	0.6170	0.062
Costpercept (1 if within 20%, 0 otherwise)	0.4817 (0.0219)	0.1542	0.075	0.6111 (0.0022)	0.1514	0.151

Notes: The mean WTP values for the retrofitted and new installs were \$5,024.59 and \$1,965.32, respectively. The Likelihood Ratio statistics (χ^2_6) for the retrofitted and new installs were 41.41 and 61.90, respectively, with prob values of less than 0.0001.

Table 5. Ordered Probit Model Results for Retrofitted Yield Monitors.

	Regression Results (n = 480; 8.8% WTP B, 31% DK, 60.2% not WTP B)		**Marginal Effects**		
	Estimate (prob[|Z|>z])	**Variable Mean**	**Prob[WTP = No]**	**Prob[WTP = DK]**	**Prob[WTP = Yes]**
Intercept	-1.171 (0.4663)	1.00	0.0000	0.0000	0.0000
Price (*B* = bid price)	-0.00007 (0.0096)	8,250.00	0.000020	-0.000017	-0.000009
Adopter (1if adopter, 0 otherwise)	1.5658 (0.0010)	0.1792	-0.5542	0.1752	0.3790
Price x Adopter	-0.00016 (0.0043)	1,462.50	0.00006	-0.00004	-0.00002
Farmsize (acres)	0.000033 (0.3046)	1,912.09	-0.000010	0.000008	0.000004
Computer (1 if use for farm, 0 otherwise)	0.3980 (0.0014)	0.6521	-0.1494	0.1016	0.0478
Costpercept (1 if within 20%, 0 otherwise)	0.4974 (0.0008)	0.1542	-0.1955	0.1122	0.0833

Notes: The mean WTP was \$5,153.70. The Likelihood Ratio statistic (χ^2_6) was 64.30 with a prob value of less than 0.0001. The Threshold parameter MU was estimated to be 1.2242 with a prob value of less than 0.0001.

Table 6. Ordered Probit Model Results for a Yield Monitor Installed on a New Cotton Picker.

	Regression Results (n = 436; 14.9% WTP B, 38% DK, 47.0% not WTP B)		**Marginal Effects**		
	Estimate (prob[|Z|>z])	**Variable Mean**	**Prob[WTP = No]**	**Prob[WTP = DK]**	**Prob[WTP = Yes]**
Intercept	0.0339 (0.9113)	1.00	0.0000	0.0000	0.0000
Price (*B* = bid price)	-0.0001 (0.0010)	8,418.58	0.000030	-0.000020	-0.000020
Adopter (1if adopter, 0 otherwise)	1.6180 (0.0009)	0.1904	-0.5019	0.0100	0.4919
Price x Adopter	-0.0001 (0.0266)	1,586.01	0.00005	-0.00002	-0.00003
Education (0 if not h.s. graduate, 1 if h.s. graduate, 2 if college)	0.2580 (0.0361)	1.6927	-0.1024	0.0490	0.0533
Computer (1 if use for farm, 0 otherwise)	0.2390 (0.0445)	0.6170	-0.0948	0.0470	0.0478
Costpercept (1 if within 20%, 0 otherwise)	0.4726 (0.0023)	0.1514	-0.1802	0.0639	0.1163

Notes: The mean WTP was $9,700.71. The Likelihood Ratio statistic (χ_6^2) was 69.39 with a prob value of less than 0.0001. The Threshold parameter MU was estimated to be 1.2522 with a prob value of less than 0.0001.

Table 7. Price Elasticities by Adoption Status, Yield Monitor Alternative, and Model.

Model Yield Monitor Alternative	**Adopters**	**Non-Adopters**
Dichotomous Choice Probit: “Yes” vs. “No”		
Retrofit Used Cotton Picker	-0.0051	-0.0006
Install on New Cotton Picker	-0.0050	-0.0016
Dichotomous Choice Probit: “Yes” vs. “No”/“Don’t Know”		
Retrofit Used Cotton Picker	-0.0034	-0.0002
Install on New Cotton Picker	-0.0022	-0.0005
Polychotomous Choice Ordered Probit: “Don’t Know” Respondents		
Retrofit Used Cotton Picker	-0.0059	-0.0006
Install on New Cotton Picker	-0.0072	-0.0009
Polychotomous Choice Ordered Probit: “Yes” Respondents		
Retrofit Used Cotton Picker	-0.0039	-0.0012
Install on New Cotton Picker	-0.0062	-0.0035

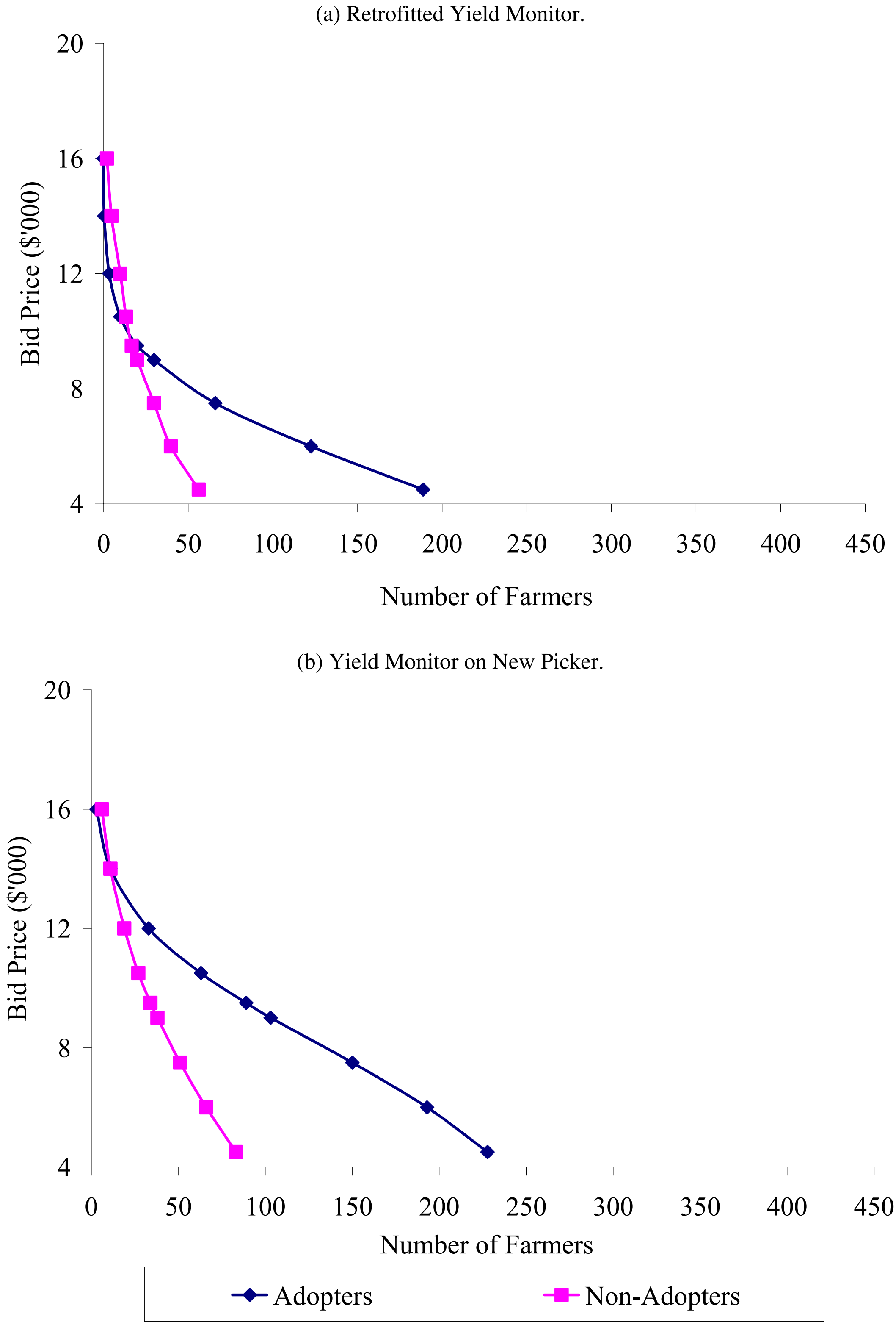

Figure 1. Probit Model Demand Results with "Don't Know" Responses Omitted by Yield Monitor Alternative (Table 3).

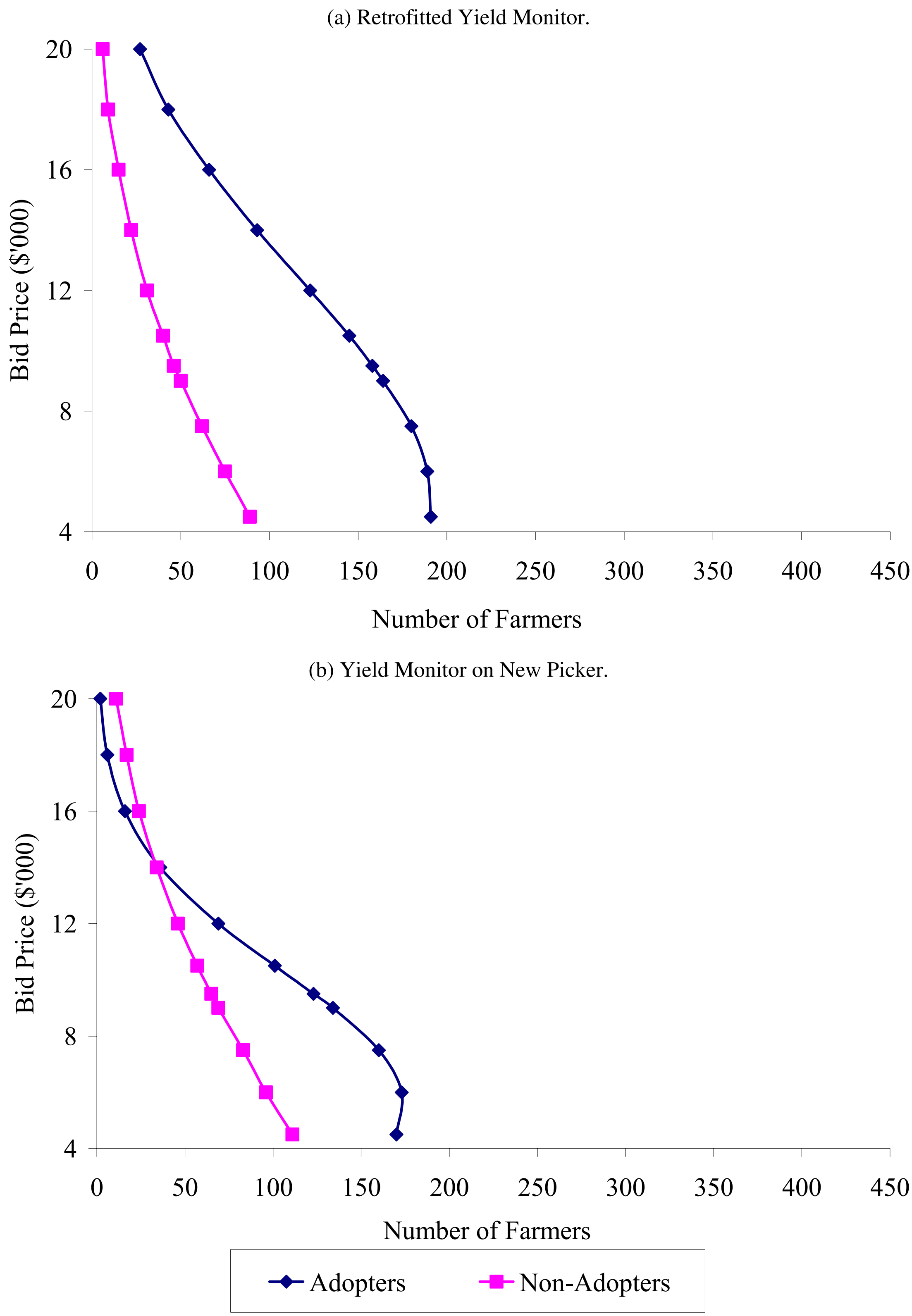

Figure 2. Probit Model Demand Results with "No" and "Don't Know" Responses Combined by Yield Monitor Alternative (Table 4).

(a) Retrofitted Yield Monitor.

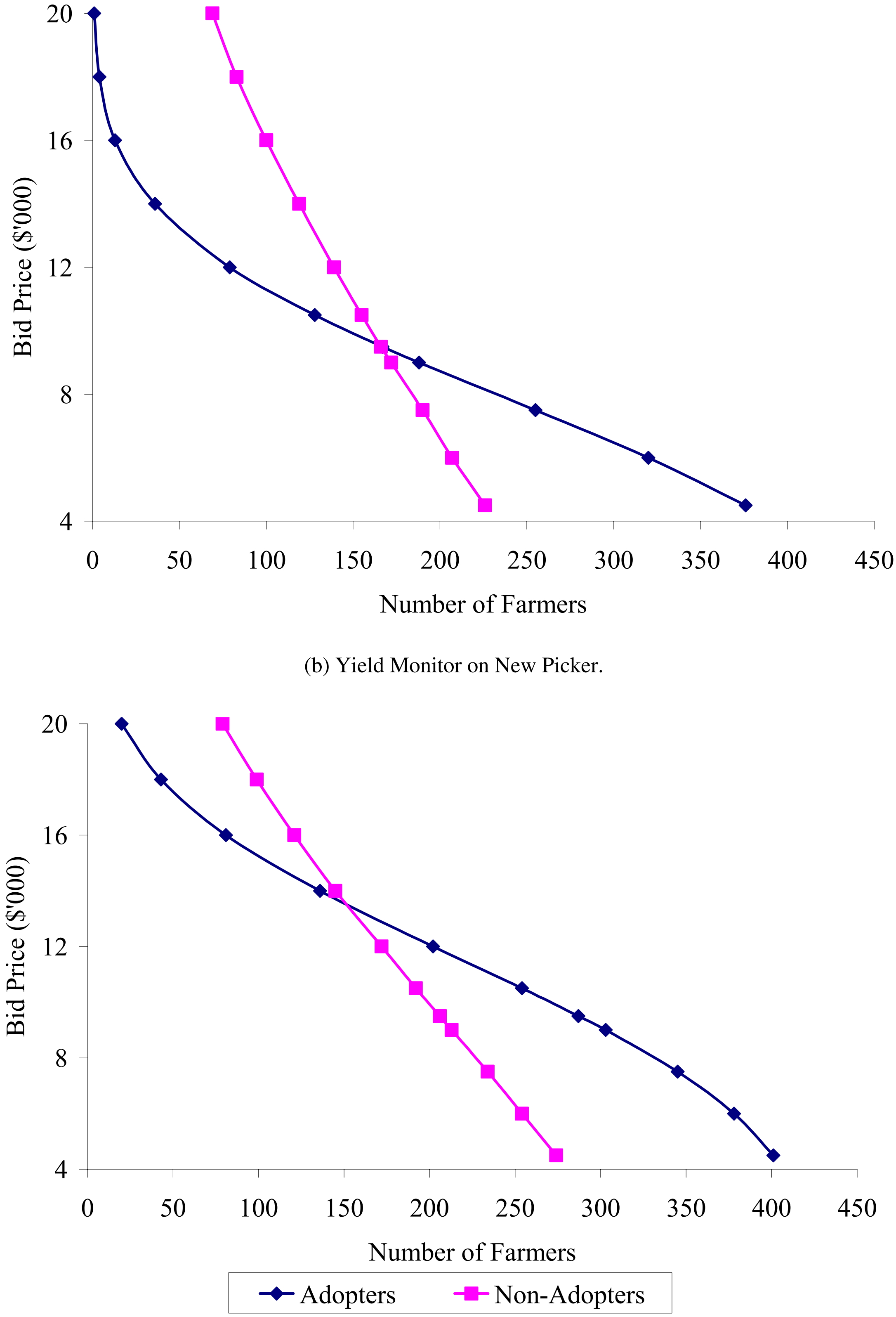

Figure 3. Ordered Probit Model Demand Results by Yield Monitor Alternative (Tables 5 and 6).