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Demand for Private Marketing Expertise by Organic Farmers: A Quantile Analysis Based on Counts

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We study the demand by organic farmers for technical advice using a quantile regression for the demand of organic farmers for consultations with private information providers. There is substantial heterogeneity in the impact of critical explanatory variables on consultations of organic farmer. Larger farm size has a positive effect on contacts, but the effect is absent for the highest number of consultations. Internet use has a positive marginal effect on visits to private information providers across each quantile, suggesting that expanded efforts to deliver programs through web-based resources are a useful investment for information providers.

Key Words: organic farming, technical assistance, quantile regression model, count data, internet access

JEL Classifications: C25, Q12, Q13, Q16

Marketing information is a necessity for organic farmers, but public sector sources are not used extensively by organic farmers for reasons ranging from lack of awareness of availability to lack of relevance of information provided. The U.S. Department of Agriculture (USDA) reported that market access and price issues are primary challenges for 10% of U.S. organic farmers (U.S. Department of Agriculture, 2010). Organic growers, particularly those operating smaller farms, need information on customer trends, prices, and novel market outlets to address market access limitations and pricing power (Kambara and Shelley, 2002; Middendorf, 2007). Interviews and farmer surveys have indicated that marketing is a major challenge for small and midsized organic farms and that lack of marketing and price information is not being addressed by Cooperative Extension and other public sources (Cantor and Strochlic, 2009).

Duram and Larson (2001) found that organic farmers are less likely than other farmers to use public information services, including extension consultants, than to consult private information sources such as talking with other farmers and reading materials provided by nongovernmental organizations. One reason is that government-funded research is not always attuned to the needs of organic farmers. Asked

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about the importance of 30 research topics funded by the USDA Sustainable Agriculture Research and Education (USDA-SARE) program, organic farmers highlighted a need for marketing information, a topic rated as relatively unimportant by researchers funded through the program. Cantor and Strochlic (2009) reported that more than 78% of small organic farmers surveyed in California believe that availability of low-cost private consulting to help with marketing is an important way to overcome marketing barriers.

Proponents of organic farming have decried the lack of organic marketing information and technical support available from government organizations. Organic farmers rely primarily on private sector providers when seeking information about organic markets and marketing issues. The Organic Farming Research Foundation (OFRF) national census of organic farmers indicated that private for-profit and nonprofit agricultural information providers are the most frequently consulted sources for marketing expertise by organic farmers in terms of both number and frequency of consultations (Walz, 2004).

The most frequently consulted market information organizations were organic certification agencies (eight times per user per year), marketing cooperatives (10 times per year), and growers' associations (six times per year) (Walz, 2004). Over one-third of growers used at least one of these information sources. Quality of the marketing information was rated on an integer scale of 1–4 with 1 being "never useful" and 4 being "very useful." Marketing cooperatives rated 3.1 in usefulness of contact, organic certifiers rated 3.0, and growers' associations rated 2.9. Organic growers from the Southern region reported the lowest usefulness ratings for organic certifiers and growers' associations across all the regions.

These results are particularly compelling when compared with percentages of use and ratings of the information provided by the USDA and state agriculture departments. Walz (1999) indicated that 45% of farmers reported using state or federal information sources and the usefulness of these contacts was rated 2.4. Walz (2004) mentioned that only 16% of organic farmers consulted state departments of agriculture (quality rating 2.6) and only 7% sought marketing information from the USDA (quality rating 2.3). Organic farmers have fewer contacts with government agencies than with private information providers. Technical outreach programs may still achieve successful information transfer by delivering the products to private information providers to transfer to farmers.

Duram and Larson (2001) reported that marketing information is particularly important for organic farmers attempting to reduce diversification risk and to find niche markets. In 2008, more than 8% of certified organic farmers were planning to decrease their production, to stop producing organically, or to exit farming altogether in the subsequent 5 years (U.S. Department of Agriculture, 2010). Another 13% of organic farmers were not sure of their future plans, making it possible that as many as 20% of organic farms operating in 2008 would not be certified in 2013. To the extent that marketing information and information access have an effect on retention, attention must be paid to availability and delivery.

In a survey of 77 deregistered California organic farmers, Sierra et al. (2008) discovered that 28% of organic farmers who deregistered (decertified) and shifted to conventional methods named marketing issues as the primary reason for discontinuing organic production compared with 11% of deregistrants who stopped farming and 5% of those who decertified but continued to produce organically. Lack of price information was named by 25% of deregistrants as a serious or severe problem. Inadequate market access was listed as a principal challenge by 17%. Flaten et al. (2010) reported similar results in a survey of 245 Norwegian organic farmers who planned to deregister. Inadequate market access (difficulty finding buyers and having to sell organic as nonorganic) accounted for 9.5% of the variance of the factors influencing the decision to cease organic certification. Inability to obtain premium prices ranked in the top five reasons given for deregistering by all groups and first among farmers who planned to stop farming altogether, whereas difficulty finding buyers ranked in the top 15 reasons.

Marketing information can improve farmers' chances of identifying and accessing the outlets that offer sufficient price premiums to induce industry retention. If organic farmers are less likely to use public/government information sources and providers, or are turning to these sources but not finding the marketing information they need, they are likely to seek out private for-profit and nonprofit sources of advice.

We study the demand by organic farmers for advice from private information providers using the number of contacts with the providers as an indicator of demand. A quantile regression for count data is estimated based on the demand of organic farmers for consultations with private information providers. In the next section, we review the research on the use of extension services by organic and conventional farmers. The quantile regression approach for count data is briefly summarized. The third section outlines the econometric model and is followed by the data and variable descriptions. The interpretation of the results is contained in section 5 and model conclusions and policy implications comprise the final section of the article.

Literature Review

There is very limited research on the use of private extension services by organic producers. Riddle (2002) identified constraints encountered by crop operators and certification applicants in learning about, attaining, and maintaining organic certification and emphasized the value of private organizations in assisting organic farmers. Previous work has instead focused on the provision of public extension services to farmers with an emphasis on conventional producers. Huffman (1978) recognized the potential for extension to enhance the efficiency of production and suggested including extension as an input in the production function. Dinar (1989) examined the demand for and supply of public extension services as simultaneously determined by economic, social, and policy variables and highlighted the role of farm structure, scale, and socioeconomic factors. The variable for the provision of extension services in Dinar's analysis was count data on the number of visits, an indicator with a substantial degree of heterogeneity across the types of farms in the study region. The empirical method we propose explicitly accounts for both the count nature of visits to private information providers and observed heterogeneity in consultations with experts sought by farmers.

Dinar, Karagiannis, and Tzouvelekas (2007) evaluated the impact of extension on farm performance in Crete, Greece, using a non-neutral stochastic production frontier model. An important conclusion was that the demand for extension services is influenced by specific socioeconomic characteristics of the farmer and physical characteristics of the farm operation. This insight provides the motivation for our approach to identify the factors that influence decisions by organic farmers to consult private agricultural information providers.

A quantile regression for the demand by organic farmers for consultations with private information providers is estimated. Quantile regression for count data examines how quantiles of the conditional distribution of a response variable recorded in discrete units (number of visits) depend on a set of explanatory variables. Liu and Peng (2010) noted that the quantile regression model provides a more complete view of how the distribution of the dependent variable (visits) changes with the conditional quantile.

Winkelmann (2006) emphasized that the quantile approach has two advantages. First, the technique models all the conditional quantiles of a probability distribution without imposing the requirement that the conditional probability distribution must be approximated by a few moments of a parametric distribution such as the Poisson or negative binomial forms. Second, restrictions implicit in the parametric specifications of count data models explicitly determine how the explanatory variables are related to the response variables. Winkelmann (2006) showed that the Poisson and negative binomial models imply a single-crossing property on marginal effects. In our context, this restriction means that as the number of visits increases, only a single switch between positive and negative marginal effects is possible. The relative magnitudes of the marginal effects are also fully determined by the count data model.

The quantile model for count data relaxes these restrictions.

Econometric Model

To motivate the approach, Figure 1 plots the number of visits that organic producers make to private information providers as a function of the farmer's organic acreage. The sample of OFRF organic farms was split into four quartiles by farm size and also by income. Visits to private information providers were computed for each farm size and income quartile. Median visits for each farm size and income category are represented by the horizontal lines with the edges of the box revealing the 25th percentile and 75th percentile (the lower and upper quartiles).

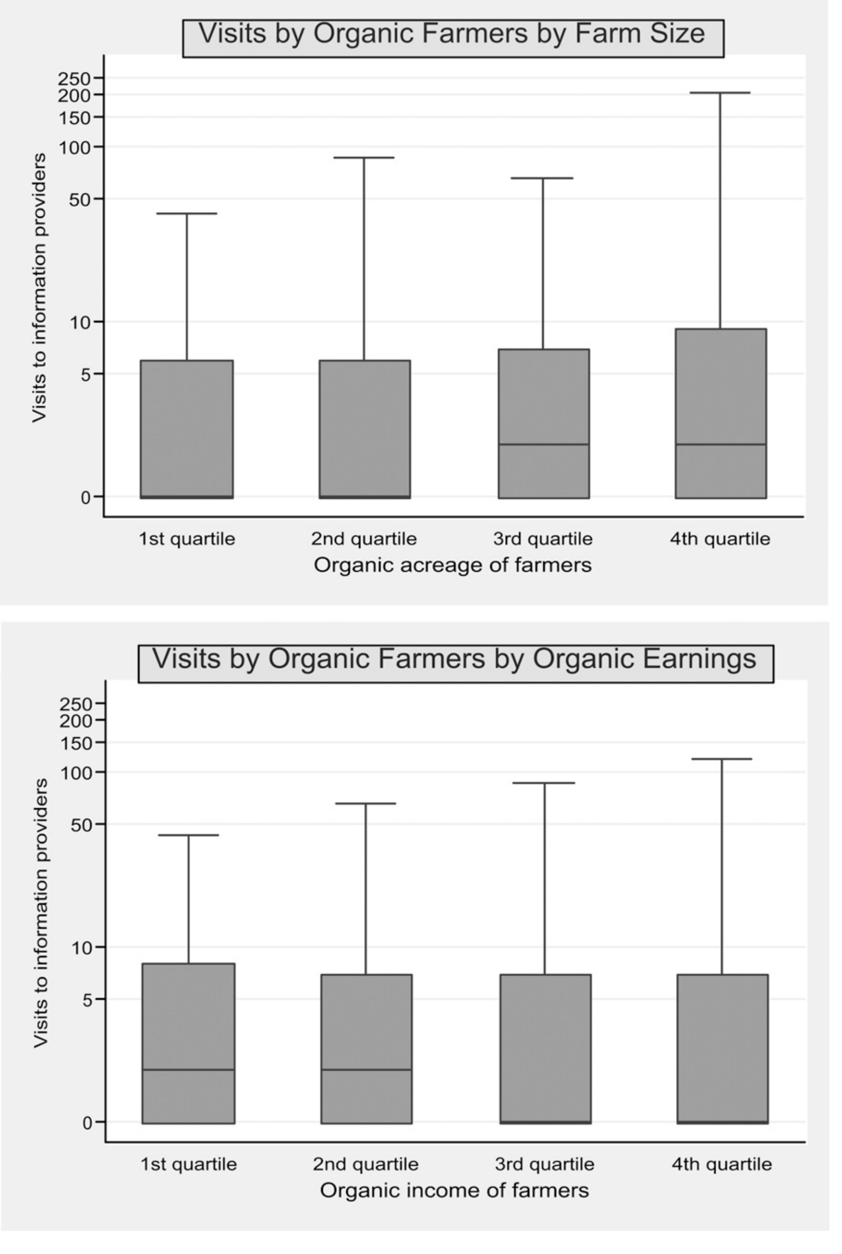

Figure 1. Visits by Organic Farmers by Farm Size

The logarithm of the number of visits made by each organic farmer to a private agricultural organization was plotted showing that visits to information providers increase with farm size. The dispersion of visits, measured by the interquartile range of visits, also increases significantly across farm size. By contrast, the boxplot of visits as a function of organic income shows that the log of the number of visits decreases with organic farm income, whereas dispersion is nearly constant across farm income quartiles.

The boxplot is limited to examining the distribution of visits with respect to one variable at a time. The quantile regression method is a mechanism for estimating models for the conditional median function along with a full range of other conditional quantile functions, each as a function of a set of explanatory variables.

The quantiles for visits to information providers are the values that divide the distribution such that there is a given proportion of observations below the quantile. A farmer at the pth quantile for the observed sample of visits has made more consultations than the proportion p of the sampled farmers and fewer visits than the proportion (1-p) of the sample. Half of the farmers have more visits than a producer with the median number of visits and half the farmers have fewer visits than this producer. Given a continuous and strictly monotonic cumulative distribution function, $F{:}R \rightarrow (0, 1)$, the quantile function returns the value below, in which random draws from the given distribution would fall $p \times 100\%$ of the time. That is, given a continuous and strictly monotonic distribution function and the random variables Y and X, the quantile function returns the value of x such that

$$(1) \qquad F(x) = Pr(X \leq x) = p$$

For example, the 0.5 quantile is the median so that half the organic farmers make more visits than the median and half make fewer visits. Koenker and Hallock (2001) showed that asymptotically valid inferences on the parameters of the quantile can be made given that the conditional probability density function $f(Y|x)$ is continuous. When the explanatory variable is a count, the random variable Y has a discrete distribution and the quantile cannot be continuous in the parameters.

Machado and Santos Silva (2005) developed a quantile count regression model based on a smoothing algorithm by constructing a continuous variable with conditional quantiles that have a one-to-one relationship with the conditional quantiles of the counts. The discrete count response is represented by y_i and is replaced with a smooth, continuous transformation so that linear quantile regression methods can be applied. An auxiliary variable is created such that $z_i = y_i + U_i(0, 1)$, where U_i is a uniform random variable in the interval (0, 1). Any continuous distribution that has support on (0, 1) can be used in the transformation and standard quantile techniques can be applied to a monotonic transformation of the auxiliary variable z. The estimated quantiles of z are nonnegative and the transformed quantile function is linear in the parameters when a monotonic transformation is used.

Let $Q_y(\tau|X)$ and $Q_x(\tau|X)$ denote the 100th quantiles $(0 \leq \tau \leq 1)$ of the conditional distribution of y and z and define

$$(2) \qquad Q_z(\tau|X) = \tau + \exp[X\beta(\tau)]$$

The transformed y is represented by z, the set of explanatory variables is denoted by X, and β represents the estimated parameters. The predictive equation includes the additive term τ because $Q_z(\tau|X)$ is bounded from below by τ as a result of the additive random variable $U(0, 1)$. The model can be estimated in a linear form using the following logarithmic transformation of z;

$$(3) \qquad \begin{array}{lll} \log(z - r) & \text{if} & z_i > \tau \\ \log(\zeta) & \text{if} & z_i \leq \tau \end{array}$$

and regressing these values on the explanatory variables. The ς term represents a suitably small positive number. The transformation back to the y counts uses the ceiling function:

$$(4) \qquad Q_y(\tau|X) = \lceil Q_y(\tau|X) - 1 \rceil$$

where $[\alpha]$ returns the smallest integer greater than or equal to α. The estimated quantile functions for the z-values (denoted as the jittered y) provide a smooth linear interpolation among the step functions for y. The y are described as "jittered" to signify that uniformly distributed random noise is added to the original data. The result is that $Q_y(\tau|X)$ can be recovered from information on $Q_z(\tau|X)$. The quantile function is not everywhere differentiable because the distribution function has corners. However, when the explanatory variables in the model include at least one continuous variable, the corner points measure zero. Machado and Santos Silva (2005) demonstrated that the estimator is consistent and asymptotically normal.

Winkelmann (2006) addressed the empirical issue of how to choose the quantiles and we use that approach in model specification. In our example, if 51% of organic farmers have not consulted private information providers, the marginal quantiles are zero for all $\alpha < 0.50$. There is limited value in computing conditional quantile functions for very low values of α because the quantiles will not depend on the regressors and each quantile will be flat. In this application, we look at four quantiles, $\tau = 0.25$, 0.50, 0.75, and 0.95.

The impact of a change in any explanatory variable on the conditional quantile of y, given that all other variables remain unchanged, can be calculated following Miranda (2008) as:

$$(5) \qquad \Delta_j = Q_y\left[\tau|x_j^1, X\right] - Q_y\left[\tau|x_j^0, X\right]$$

where x_j is changed from X_j^0 to X_j^1 and all other explanatory variables are unchanged. Machado and Santos Silva (2005) suggest averaging out the noise that was artificially added to the data. The procedure requires that m draws from the $U(0, 1)$ distribution are taken and the average of the QR estimates of the m jittered samples (based on 1,000 draws) is calculated.

Data and Variable Description

Comprehensive data on production and marketing practices, demographic information, and information sources used by U.S. organic farmers were gathered from the Fourth OFRF survey of all certified producers of record as of 2001 (Walz, 2004). A description of the survey and summary results are available from the OFRF (www.ofrf.org). With an 18% response rate, the survey captured data from 1,034 producers. OFRF's analysis indicated that the sampling frame reached 90% of U.S. certified organic farmers with a sample nearly as large as the entire population of interest. The survey does contain missing values for consultations with a private information provider when organic farmers did not respond to the question. These respondents were excluded from the analysis and we acknowledge the potential for some selectivity biases associated with these farmers. The results should be interpreted with caution if selectivity effects are important.

Table 1 shows the variable descriptions and summary statistics for the dependent and independent variables. Sufficient detail was available to use 810 observations from the survey. Natural logs of the continuous variables were used as indicated in the model specification in Table 2.

Selection of demographic variables for inclusion loosely followed Jones, Diekmann, and Batte (2010) who examined the effects of age, years farming, gender, marital status, race, education, gross sales income, type of operation (crop or livestock), region of the country, and consultant use on choice of extension information outlet and satisfaction with extension among Ohio farmers. We included variables describing Internet use, because web distribution is a frequently used method for information-seeking by organic farmers and on locality of market, because farmers selling locally are more likely to be concerned with resource constraints and regulatory costs than information needs (Kambara and Shelley, 2002).

Survey respondents indicated how frequently they met with private organizations on organic marketing issues and evaluated the usefulness of each source. The OFRF survey identified five private, nongovernmental associations or groups providing information: organic certification agencies, growers associations, Appropriate Technology to Rural Areas (ATTRA), nonprofit organizations, and marketing cooperatives. The dependent variable was the number of times these private organizations were consulted (*ConsultPrivate*).

The explanatory variables included in the count data model for information sources include

Table 1. Variable Descriptions and Summary Statistics for Organic Producers

Variable	Description	Mean	Standard Deviation
ConsultPrivate	Consultations with private information sources on organic marketing strategies	6.70	24.32
	Share of consultations by category (percent)		
	0 consultations on marketing	51	
	1–5 consultations on marketing	21	
	6–10 consultations on marketing	11	
	11–20 consultations on marketing	10	
	21–30 consultations on marketing	3	
	31–41 consultations on marketing	2	
	41+ consultations on marketing	2	
OrganicIncome	Total gross organic farming income in thousands of U.S. dollars (US$)	143.03	599.21
OrganicAcres	Acreage farmed organically	190.90	671.93
ConventionalNowMixed	Originally a conventional producer, now farms organic and conventional acres, share	0.16	0.36
SomeHighSchool	Farmer has less than high school education, share	0.05	0.21
HighSchoolGrad	Organic farmer has completed high school, share	0.42	0.49
CollegeGrad	Organic farmer has college, share	0.53	0.50
LocalSales	Sales made within 100 miles of farm location (% of total sales)	57.0	46.0
InternetUses	Use of internet for organic marketing and sales (1–9 of the listed uses)	3.78	3.03
InternetFrequency	Internet activities used monthly or more frequently (% of the nine listed activities)	32.79	32.45
WesternSARE	Farm is in SARE Region 1, share	0.29	0.45
SouthernSARE	Farm is in SARE Region 3, share	0.06	0.24
NortheasternSARE	Farm is in SARE Region 4, share	0.25	0.44
NorthCentralSARE	Farm is in SARE Region 2, share	0.40	0.49
Observations		810	

total gross organic farming income (*OrganicIncome*) and farm size measured as the acreage farmed organically (*OrganicAcres*). The use of private information sources tends to decline slightly across the quartiles of the gross organic farming income variable. Larger farms show a significantly higher demand for advice from information sources. The average number of contacts for farms in the largest acreage quartile (151 acres and above) was 11 and the average contacts across each of the other quartiles was approximately five.

Two dimensions were combined to account for previous and current experience with organic production and marketing methods. Under the U.S. organic regulation, farmers may certify as organic less acreage than they farm, leading to parallel organic and conventional systems being managed by the same operator. Only 18% of the OFRF respondents reported conducting this type of mixed farming. Farmers who were originally conventional producers but transitioned to organic production accounted for 52% of the OFRF respondents compared with 48% who began farming as organic producers. The subset of farmers who transitioned to organic farming but maintained mixed farming operations is fairly stable across the three local selling categories at approximately 16% of operations (*ConventionalNowMixed*). These producers were expected to have more confidence in using extension advisors to locate markets and deal with marketing problems and to be able to better maintain income levels as

Table 2. Quantile Regression Results for Count Data Model of Marketing Consultations[a]

Quantile Variable[b]	0.25	0.50	0.75	0.95	Negative Binomial
Constant	–1.53	0.17	2.31*	3.15*	1.95
	(–1.02)	(0.15)	(3.29)	(4.29)	(2.82)
ln(*OrganicIncome*)	–0.12	–0.28*	–0.15*	–0.06	–0.11*
	(–1.62)	(–2.93)	(–2.89)	(–0.44)	(–1.76)
ln(*OrganicAcres*)	0.15*	0.29*	0.20*	0.11	0.12*
	(2.21)	(2.95)	(3.78)	(1.12)	(2.30)
ConventionalNowMixed	–0.03	–0.20	–0.63	–0.43	–0.11
	(–0.09)	(–0.54)	(–1.29)	(–1.61)	(–0.48)
HighSchoolGrad	0.47	0.57	–0.31	0.10	0.23
	(0.35)	(1.01)	(–0.75)	(0.63)	(0.60)
CollegeGrad	0.63	0.70	–0.23	–0.19	–0.12
	(0.47)	(1.16)	(–0.58)	(–0.74)	(–0.31)
LocalSales	0.35	0.57*	–0.07	–0.11	–0.10
	(1.13)	(1.92)	(–0.20)	(–0.31)	(–0.52)
ln(*InternetUses*)	0.57*	1.13*	0.98*	0.48*	0.72*
	(3.27)	(4.80)	(3.90)	(3.09)	(5.46)
ln(*InternetFrequency*)	–0.12	–0.23*	–0.19*	–0.07	–0.10*
	(–1.59)	(–2.12)	(–1.70)	(–0.92)	(–1.70)
WesternSARE	–0.59*	–1.06*	–0.81*	–0.52*	–0.81*
	(–2.43)	(–3.04)	(–2.73)	(–3.02)	(–3.69)
SouthernSARE	–0.88	–0.94	–0.08	–0.10	0.38
	(–0.99)	(–0.95)	(–0.13)	(–0.27)	(0.98)
NortheasternSARE	0.25	0.41	0.51*	0.53*	0.37*
	(1.05)	(1.20)	(2.75)	(2.69)	(1.74)
η					4.52
					(0.29)

[a] Asterisk indicates asymptotic *t*-values with significance at the $\alpha = 0.10$ level. Values in parentheses are asymptotic t-values.
[b] Dependent variable is consultations with private information sources on organic marketing strategies (*ConsultPrivate*).

they continued to use conventional production techniques.

The highest level of formal education of the farm operator was available from the OFRF survey. Three categorical variables were formed to indicate whether the organic producer completed some high school (*SomeHighSchool*), had a high school diploma (*HighSchoolGrad*), or had graduated from college (*CollegeGrad*).

Emphasis on selling to local markets can reduce the need for extension marketing information services. Selling locally allows farmers to more easily monitor prices and market conditions. Face-to-face interactions with consumers enable farmers to obtain valuable feedback that allows them to meet preferences more easily while finding a niche in the market (Kambara and Shelley, 2002). We developed an indicator for local sales (*LocalSales*) and examined how this variable influenced the demand for information from private agricultural organizations. In the OFRF survey producers indicated the volume of organic products delivered to product buyers within 100 miles of the farm for three commodity categories: 1) vegetable, herb, and floriculture products; 2) fruit, nut, and tree products; and 3) grain and field crops across three types of marketing outlets: direct-to-consumer, direct-to-retail, and wholesale.

Producers who did not sell to the local market made slightly more visits compared with farmers who made any level of commitment to local sales. Over 60% of the producers focused intensively on sales to local markets, selling more than 75% of their total output through these channels. These producers made an average of five visits, the least of any selling group.

A variable representing the producer's use of the Internet for marketing and sales (*InternetUseIndex*) was constructed based on activities defined in the OFRF survey. We defined U_i as 1 if the Internet was used for an activity and 0 otherwise. FR_i is 1 if the source was used once per month or more frequently and 0 otherwise. Information from nine different Internet activities was available. The activities were checking the weather, accessing conventional market information, selling organic products, purchasing seed, purchasing other inputs, reading or searching for farm news, looking for organic production information, looking for organic marketing information, and communicating with other farmers.

The composite index of Internet use is:

$$\begin{aligned} InternetUseIndex &= \sum\nolimits_{i=1}^{9} U_i FR_i \\ &= U \sum\nolimits_{i=1}^{9} \frac{U_i FR_i}{U} = UFR_p \end{aligned} \tag{6}$$

where U is the total number of sources consulted. The term FR_p is the proportions of Internet activities that are used at least once per month. The Internet use index accounts for both the number of activities for which organic producers access the Internet and how frequently the Internet was used for that activity. The components of the Internet use index are included in the count data model in log-linear form as

$$\begin{aligned} InternetUseIndex &= UFR_p \\ &= InternetUses \cdot InternetFrequency \\ \mathrm{Ln}(Internet\ Use\ Index) &= \mathrm{Ln}(Internet\ Uses) \\ &\quad + \mathrm{Ln}(InternetFrequency) \end{aligned} \tag{7}$$

Organic producers reported an average of approximately two separate uses (*InternetUses*), although 37% of producers did not use the Internet at all or lacked access. The frequency of Internet use on at least a monthly basis for the set of chosen activities (*InternetFrequency*) averaged 53%. The *InternetFrequency* variable shows the proportion of activities that are performed at least monthly. The variables measuring the frequency of Internet use and the total number of Internet applications capture different channels for how the Internet influences marketing decisions and show only a moderate degree of correlation (correlation coefficient of 0.48).

To assess regional differences in institutional support and information availability for organic production and marketing systems, we used the four USDA SARE regions (see www.sare.org/about/regions.htm for a listing of states in each region). These regions reflect the U.S. government's demarcation for sustainable agriculture extension–research support. A dichotomous variable was created for each region, equal to one if the respondent's farm was in that region and zero otherwise. In the sample, farmers relying on one marketing outlet are concentrated most heavily in the North Central region with 45% and the West region at 30%. Farmers with a diversified marketing plan are more likely to be located in the West (44%) or the Northeast (26%).

The West region has historically received the strongest institutional support for organic agriculture and is home for two of the nation's oldest organic farm and certifying organizations, California Certified Organic Farmers and Oregon Tilth. The locality-specific research needed for successful organic farming emerged earlier in the West than in the other regions. Estimation results are expected to show more visits in the West region.

Model Interpretation

In the count data regression model, the dependent variable y_j ($j = 1, \ldots, N$) is the number of consultations by an organic farmer with a private information provider. We estimated selected conditional quantiles of the continuity-corrected counts by using the specification:

$$\begin{aligned} Q_z(\tau|X) &= \tau + \exp[X\beta(\tau)] \quad \text{for} \\ \tau &= 0.25, 0.50, 0.75, 0.95. \end{aligned} \tag{8}$$

The dependent variable shows considerable overdispersion because the conditional variance (24.32) is greater than the conditional mean (6.70). A negative binomial II model was also estimated incorporating unobserved heterogeneity in an underlying Poisson model. The unobserved heterogeneity is indicated by $c_j > 0$ and

$$y_i | X_j, c_j \sim \mathrm{Poisson}\left[c_j \exp[X\beta(\tau)]\right]. \tag{9}$$

The distribution of y_j given X_j is negative binomial with conditional mean and variance:

$$(10) \quad \begin{aligned} E[y_j|X_j] &= \exp[X\beta(\tau)] \\ \mathrm{Var}[y_j|X_j] &= \exp[X\beta(\tau)] + \eta^2 \exp[X\beta(\tau)]^2 \end{aligned}$$

where c_j is independent of the explanatory variables and follows a gamma distribution with unit mean and Var $(c_j) = \eta^2$.

We examined the potential endogeneity of the variables organic farming income, acres farmed organically, and the percent of sales made within 100 miles of the farm location applying the procedures outlined by Wooldridge (2002) developed from an omitted variables perspective. A set of instruments was identified that is highly correlated with each of the variables. Variables that are related to organic earnings are based on the farmer's human capital and experience in farming and expertise with organic production methods. These variables include the number of years in organic farming, the number of years certified organic, and the age of the farmer.

The diversity of the crops managed by the farmer as measured by the farm's concentration in the production of field crops, vegetable, and fruits, nuts, or tree crops along with the acres rented serve as instruments for the organic acreage variable. These measures reflect long-term planning decisions for the farm operation and are influenced by the agronomic characteristics of the region along with the expertise of the farmer. These instruments are strongly correlated with the organic acreage variable. Cropping and rental decisions represent commitments made at the beginning of the growing season and would not be adjusted in response to contacts with information providers that occurred after the planting decision.

Producers in the OFRF survey indicated the sales outlets through which they have expanded the volume sold. The producers chose from direct-to-consumer markets, direct-to-retailers, sales through marketing cooperatives, and sales to wholesalers. Over 54% of producers confirmed plans to increase sales volumes in at least one market. Direct-to-consumer outlets were the dominant choice, listed by 34% of respondents. The organic growers also provided information on the change in average price received for organic products during the previous production year. Organic farmers who report an increase in average prices received exhibit the highest commitment to local sales. These variables serve as instruments for the local sales decision because they reflect the marketing expertise and entrepreneurial skill of the producer in finding markets for their products and are highly correlated with the local sales commitments.

We follow the procedures outlined by Wooldridge (pp. 663–665). Assume that a subset of the explanatory variables in the model, say x_2, are potentially endogenous with coefficients denoted by ρ_2. The remaining explanatory variables x_1 are considered to be exogenous. The suspect variables have a linear reduced form, written as $x_2 = z\Pi_2 + \nu_2$ where Π_2 is a matrix of reduced form parameters and the reduced form error is ν_2.

To implement the procedure to test for endogeneity, estimate the reduced form by ordinary least squares (OLS) to obtain the OLS estimates. Define $\hat{\nu}_2 = y_2 - z\hat{\Pi}_2$ as the residuals from the OLS model. Estimate the negative binomial model with regressors x_1, x_2, and $\hat{\nu}_2$. The resulting coefficients provide consistent estimates following standard arguments from two-step estimation methods. The test for endogeneity is straightforward. A test of the null hypothesis that $\rho_2 = 0$ uses a Wald or Lagrange Multiplier test. The test statistic follows a chi-square distribution with degrees of freedom equal to the number of potentially endogenous variables. A failure to reject the null hypothesis is evidence that the variables are exogenous. Wooldridge notes the procedure is very robust and can be applied when the y_2 contains binary, count, or other discrete variables.

The Hausman test for the endogeneity of the organic farming income, acres farmed organically, and the local sales variables did not reject the exogeneity of these variables. The calculated chi-square statistic (4.52 with 3 degrees of freedom) was well below the critical value at any conventional significance level.

Organic farmers must make acreage commitments and sales decisions in tandem, typically 1 year or more in advance of deciding to seek advice on marketing and production specifics. To be certified, organic farmers must submit an Organic Systems Management Plan, also called an Organic Farm Plan (Tourte et al., 2006). The plan requires farmers to provide an audit registry detailing current and future cropping practices and input use and to document a long-term program for soil building, natural resource protection, and pest management. It is also strongly recommended that organic farmers develop a marketing plan because they are making these farm management decisions to ensure revenue maximizing allocations of outputs among contract and direct markets. The Organic Farm Plan is part of the certification process and is submitted along with other documentation at the beginning of the 3-year statutory transition period to organic agriculture and is maintained and updated in accordance with the National Organic Program throughout the period that the farm retains certified status. Consultations with technical sources are usually in response to a specific problem such as an insect outbreak that occurs during the growing season rather than in support of long-term planning.

Results

The results for the quantile regression and the negative binomial model are shown in Table 2. The variables that are significant in the negative binomial also tend to be significant in the quantile regressions, but there are important differences in the signs of the coefficients across the quantiles. For example, heterogeneity in the relationship between the income of the farmer and the demand for consultations cannot be captured by the negative binomial model.

Organic farming income has a significant negative effect on consultations with information providers only at the 50% z_α- and 75% z_α-quantiles. At the other quantiles, higher organic income does not reduce the demand for consultations. Organic income does not have an impact on visits for organic farmers who are both the least frequent and most frequent users of marketing information from private agricultural organizations. The income coefficient from the negative binomial model does not provide information on demand across the quantiles of information consultations. The negative binomial model incorrectly implies that income has a uniformly negative impact on the demand for visits for private associations. The quantile regression model provides more complete information to assess the impact of income on visits to information providers compared with the negative binomial model.

These findings have management implications for predicting visits to private information providers. Based on results from the negative binomial model, increases in organic farmer incomes would lead the private association to incorrectly predict a decline in consultations. The quantile effects show that this decline would occur in two quantiles and not in the portion of the distribution with the highest number of visits.

Farm size has a positive effect on demand for information by private providers except at the 95% z_α-quantile. Farm size does not influence the demand for visits from organic producers with the highest level of consultations. For both the income and farm size variables, the coefficients tend to increase with α, reaching a maximum at $\alpha = 0.50$ and declining across the remaining quantiles. Our results here are consistent with research on the use of private extension by conventional farmers. Hanson and Just (2001) reported that larger farmers are more likely to rely on private extension services to formulate nutrient management plans for conventional crop producers in Maryland. The quantile regression model for count data suggests that the impact of farm size has different effects across the distribution of demand for technical information.

As shown in Table 3, the 75% z_α-quantile of the jittered data evaluated at the mean of the continuous variables and the mode of the dummy variables is $Q_z = (0.75|X) = [5.584]$. Using the ceiling function, this implies that $Q_z = (0.75|X) = [5.584–1] =$ five visits. For farmers who transitioned to organic production and operate mixed operation (*ConventionalNowMixed* = 1), the 75% z_α-quantile is reduced to 5.584–2.494 = 3.090. This result is $Q_z = (0.75|X) = [3.090–1] =$ three visits. The marginal effect of comparing original organic farmers with all organic operations to the transitioned, mixed organic farmers is to reduce

Table 3. Quantile Regression Results for Count Data Model of Marketing Consultations[a]: Marginal Effects[b]

Quantile Variable[c]	0.25	0.50	0.75	0.95	Negative Binomial
ln(*OrganicIncome*)	–0.033	–0.191*	–0.721*	–1.282	–0.110*
	(–1.47)	(–2.74)	(–2.57)	(–0.46)	(–1.76)
ln(*OrganicAcres*)	0.039*	0.196*	0.956*	2.257	0.121*
	(1.89)	(2.74)	(3.65)	(1.19)	(2.30)
ConventionalNowMixed	–0.007	–0.128	–2.494	–7.940	–0.111
	(–0.09)	(–0.57)	(–1.62)	(–1.59)	(–0.48)
HighSchoolGrad	0.130	0.411	–1.446	2.249	0.232
	(0.34)	(0.927)	(–0.81)	(0.61)	(0.60)
CollegeGrad	0.166	0.480	–1.097	–4.080	–0.122
	(0.47)	(1.12)	(–0.59)	(–0.69)	(–0.31)
LocalSales	0.067	0.383*	–0.316	–2.315	–0.103
	(1.20)	(1.89)	(–0.19)	(–0.30)	(–0.52)
ln(*InternetUses*)	0.098*	0.423*	2.786*	7.845*	0.715*
	(2.78)	(5.83)	(6.02)	(3.17)	(5.46)
ln(*InternetFrequency*)	–0.044	–0.252	–1.367	–1.673	–0.103*
	(–1.29)	(–1.46)	(–1.26)	(–0.77)	(–1.70)
WesternSARE	–0.140*	–0.607*	–3.392*	–9.950*	–0.806*
	(–2.16)	(–3.01)	(–3.29)	(–2.56)	(–3.69)
SouthernSARE	–0.163	–0.441	–0.392	–2.052	0.382
	(–1.43)	(–1.47)	(–0.14)	(–0.28)	(0.98)
NortheasternSARE	0.069	0.310	2.837*	13.090*	0.372*
	(0.095)	(1.09)	(2.45)	(2.67)	(1.74)
η					4.52
					(0.29)
Predicted quantile	0.239	0.514	1.184	5.584	22.277

[a] Asterisk indicates asymptotic *t*-values with significance at an $\alpha = 0.10$ level. Values in parentheses are asymptotic t-values.
[b] Marginal effects are calculated by setting all continuous variables to their means and all dummy variables to their modes.
[c] Dependent variable is consultations with private information sources on organic marketing strategies (*ConsultPrivate*).

consultation with private information providers by two visits.

The producer's level of local sales within 100 miles of the farm increases the visits to private information providers at the 50% z_α-quantile. By contrast, the results from the negative binomial model suggest that local sales uniformly reduce visits to these agricultural organizations. Farmers involved in local sales have a variety of market channels that they consider when deciding on techniques to most effectively boost sales. Data from the OFRF survey indicate that organic producers market through direct-to-consumer sales, directly to retailers, through grower or marketing cooperatives, and other wholesale market channels. The quantile regression model indicates that information providers could expand demand for their services by understanding the marketing channels used by producers involved in local sales.

Internet use has a positive marginal effect on visits to private information providers across each quantile and the estimated coefficients increase with α. Organic producers who use the Internet for a wider set of marketing activities tend to consult more frequently with agricultural information providers. Producers who use the Internet for three or fewer uses report an average of three contacts with information providers. For producers conducting more than three farm-related activities online, the average number of consultations with the agricultural associations increases to nine contacts.

The implication is that Internet use is a positive indicator of the demand for visits to private agricultural associations and can be used to predict future demand for services from the associations. Internet use can be readily assessed in surveys and informal discussions with producers and is tracked in the USDA Agricultural Resource Management Surveys of farmers.

The frequency of Internet access has a negative marginal impact on consultations but these effects are not statistically significant across any of the quantiles. Demand for consultations with private agencies can be stimulated by inducing producers to begin using the Internet for marketing-related tasks. The frequency of Internet use does not play a significant role in expanding visits to private information providers.

The significant negative coefficient for the West SARE region implies that the private associations receive lower visits across most of the quantiles from farmers in the West relative to the omitted category of North Central farmers. The West region historically has made greater commitments to organic research and education. University extension advisors are highly visible and their effectiveness rankings reported in the OFRF survey are higher than the U.S. average. The West is home to the nation's oldest organic farm and certifying organizations, California Certified Organic Farmers and Oregon Tilth, which have had more than 20 years to develop a research and education agenda and develop positive relations with state and local extension advisors. California and Washington were among the first extension services to conduct outreach and applied research on organic agricultural systems using extension teams rather than individuals. The Northeast SARE region offers a potential growth area for expanding services to organic farmers because both the 50% z_α-quantile and 75% z_α-quantile of visits are positively related to the regional indicator.

Conclusions and Policy Implications

Private agricultural organizations are the primary sources for organic farmers' agronomic, production, and marketing information. Organic certification agencies, marketing cooperatives, and growers' associations are the organizations most frequently visited and consulted by organic farmers. Government agencies have experienced a decline in visits by farmers seeking technical expertise over the same period that private sector organizations have seen an increase in demand. We study factors influencing the demand for advice from private organic information providers.

We apply a technique for estimating quantile regressions for count data, represented here by the number of visits that organic farmers make to private information providers. Quantile regression techniques have an advantage in their ability to describe the differential impact of an explanatory variable across the response distribution. Higher organic incomes are shown to reduce visits to information providers in two specific quantiles (the 50% and 75% quantiles) but have no effect for the most frequent (95% quantile) and least frequent private sector information users (25% quantile). Private information providers will need to monitor the growth of the organic sector in their service area along with the overall size distribution of farms to predict future demand for their services. The negative binomial model incorrectly suggests that higher incomes uniformly reduce the demand for access to these organizations.

USDA rural development programs featured at the 2011 USDA Agricultural Outlook Forum highlight modern broadband infrastructure as a fundamental building block of sustainable economic development, job growth, and promoting entrepreneur and business expansion. These results confirm the benefits of broadband access and indicate effects on the provision of extension services. Internet use has a positive marginal effect on visits to private information providers and this impact is increasing across each quantile. Linking to government web sites through private sector information providers may be a way to deliver additional technical information to producers, sidestepping the problem of low levels of direct government contact.

The USDA Know Your Farmer, Know Your Food (KYF2) initiative builds on the 2008 Farm Bill to strengthen federal programs promoting local foods and includes plans to enhance direct marketing and farmers' promotion programs, to support local farmers and community food groups, to strengthen rural communities, and to promote consumption of locally grown products. The results relate to the KYF2 program by showing that the producer's level of local sales within 100 miles of the farm increases the visits to private information providers at the 50% z_{α}-quantile. By contrast, the results from the negative binomial model suggest that local sales uniformly reduce visits to these agricultural organizations.

These results reinforce the findings reported by Dinar, Karagiannis, and Tzouvelekas (2007) that the provision of information services should be targeted based on socioeconomic characteristics of farmers and physical characteristics of the farm operation. The quantile regression model reveals substantial heterogeneity in factors influencing demand for the technical expertise related to organic farming. Farmers who consult extensively with information providers (farmers at the high quantiles) are clearly influenced by different factors than farmers who make few requests (farmers at the low quantiles). The quantile regression model provides essential information that allows private-sector agricultural organizations to more accurately predict demands for their services.

The presence of missing values for consultations with a private information provider when organic farmers did not respond to some of the questions may lead to some selectivity biases associated with these farmers. The results should be interpreted with caution if selectivity effects are important. Future research can investigate additional instruments and controls (such as lagged income) to account for potential endogeneity, but these lagged values may require panel survey data or the addition of new questions to the OFRF survey. Researchers implementing this technique using data from the Agricultural Resource Management Survey can exploit information about farmers' earnings in the previous year. Research on econometric methods to deal with endogeneity in quantile regressions for count data is a topic that remains unaddressed.

References

Cantor, A., and R. Strochlic. *Breaking Down Market Barriers for Small and Mid-sized Organic Growers*. Davis, CA: California Institute for Rural Studies, 2009.

Dinar, A. "Provision of and Request for Agricultural Extension Services." *American Journal of Agricultural Economics* 71(1989):375–93.

Dinar, A., G. Karagiannis, and V. Tzouvelekas. "Evaluating the Impact of Agricultural Extension on Farms' Performance in Crete: A Nonneutral Stochastic Frontier Approach." *Agricultural Economics* 36(2007):135–46.

Duram, L.A., and K.L. Larson. "Agricultural Research and Alternative Farmers' Information Needs." *The Professional Geographer* 53(2001): 84–96.

Flaten, O., G. Lien, M. Koesling, and A.K. Løes. "Norwegian Farmers Ceasing Certified Organic Production: Characteristics and Reasons." *Journal of Environmental Management* 91(2010):2717–26.

Hanson, J.C., and R.E. Just. "The Potential for Transition to Paid Extension: Some Guiding Economic Principles." *American Journal of Agricultural Economics* 83(2001):777–84.

Huffman, W.E. "Assessing Returns to Agricultural Extension." *American Journal of Agricultural Economics* 60(1978):969–75.

Jones, L.E., F. Diekmann, and M.F. Batte. "Staying in Touch Through Extension: An Analysis of Farmers' Use of Alternative Extension Information Production." *Journal of Agricultural and Applied Economics* 42(2010): 229–46.

Kambara, K.M., and C.L. Shelley. *The California Agricultural Direct Marketing Study*. Davis, CA: California Institute of Rural Studies, 2002.

Koenker, R., and K.F. Hallock. "Regression Quantiles." *The Journal of Economic Perspectives* 15(2001):143–56.

Liu, C., and A. Peng. "A Reinvestigation of Contract Duration Using Quantile Regression for Counts Analysis." *Economics Letters* 106(2010): 184–87.

Machado, J.A.F., and J.M.C. Santos Silva. "Quantiles for Counts." *Journal of the American Statistical Association* 100(2005):1226–37.

Middendorf, G. 2007. "Challenges and Information Needs of Organic Growers and Retailers." *Journal of Extension* 45(4) Article 4FEA7. Internet site: http://www.joe.org/joe/2007august/a7.php (Accessed January 2012).

Miranda, A. "Planned Fertility and Family Background: A Quantile Regression for Counts Analysis." *Journal of Population Economics* 21(2008):67–81.

Riddle, J. 2002. "Most Common Mistakes Made by Certified Crop Operators and/or Certification Applicants." Internet site: http://www.onecert.net/mistakes.htm (Accessed January 2012).

Sierra, L., K. Klonsky, R. Srochlich, S. Brodt, and R. Molinar. *Factors Associated with Deregistration among Organic Farmers in California*. Davis, CA: California Institute for Rural Studies, 2008.

Tourte, L., M. Gaskell, R. Smith, C. Fouche, S.T. Koike, and J. Mitchell. *Publication 7247. University of California Small Farms Center*. Davis, CA: Organic Certification, Farm Planning, Management, and Marketing, 2006

U.S. Department of Agriculture. *Organic Production Survey, (2008)*. Volume 3, Special Studies, Part 2 AC-07-SS-2. Washington, DC: U.S. Department of Agriculture, National Agricultural Statistics Service, 2010.

Walz, E. "Final Results of the Third Biennial National Organic Farmers' Survey." Santa Cruz, CA: Organic Farming Research Foundation, 1999. Internet site: http://ofrf.org/publications/survey.html (Accessed January 2012).

———. "Final Results of the Fourth National Organic Farmers' Survey." Santa Cruz, CA: Organic Farming Research Foundation, 2004. Internet site: http://ofrf.org/publications/survey.html (Accessed January 2012).

Winkelmann, R. "Reforming Health Care: Evidence from Quantiles for Counts." *Journal of Health Economics* 25(2006):131–45.

Wooldridge, J.W. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: The MIT Press, 2002.