

Direct Marketing and the Structure of Farm Sales: An Unconditional Quantile Regression Approach

Timothy Park

This paper examines the impact of participation in direct marketing on the entire distribution of farm sales using the unconditional quantile regression (UQR) estimator. Our analysis yields unbiased estimates of the unconditional impact of direct marketing on farm sales and reveals the heterogeneous effects that occur across the distribution of farm sales. The impacts of direct marketing efforts are uniformly negative across the UQR results, but declines in sales tend to grow smaller as sales increase. Producers planning to sell more in local outlets should expect sales to decline. Marketing experts and extension professionals can use this information to guide farmers who are considering initiating or expanding direct marketing activities.

Key words: direct marketing, influence functions, unconditional quantile regressions

Introduction

Increased emphasis on the promotion of local food systems that reduce “food miles” and transportation costs while offering consumers the benefits of locally grown food is an emerging issue in agricultural marketing. Agricultural policy makers have suggested that switching to local distribution channels such as direct marketing outlets may allow producers to achieve higher margins and increase their incomes. The “Know Your Farmer, Know Your Food” initiative builds on the 2008 Farm Bill to strengthen USDA programs promoting local foods and includes plans to enhance direct marketing and farmers’ market programs and support local farmers and community food groups in promoting local eating. Whole Foods Market (2014) mentions reasons to buy locally grown and produced food products and suggests that farmers may benefit since “minimizing handling and transportation costs gives farmers, ranchers, growers and producers maximum return on their investment.” Wal-Mart pledged to more than double its local produce sales from 4% in 2010 to over 9% by 2015 by working with large farms to expand their operations closer to Wal-Mart supply centers and by buying more from small farms near its stores (Kirkland, 2010). Wal-Mart offers local food vendors marketing assistance to supply its flagship stores and Sam’s Clubs and presents training sessions to teach prospective suppliers how to win work with Wal-Mart purchasers.

This paper examines the impact of participation in direct marketing on the entire distribution of farm sales using the unconditional quantile regression (UQR) estimator. This approach has rarely been used in current empirical work, but policy makers are generally interested in learning about the influence of a specific program or policy on the unconditional distribution of an outcome. The UQR approach reveals the distributional impacts associated with a policy variable or effects that emerge when producers with specific characteristics and farm features participate in enterprises such as direct marketing. A policy that promotes direct marketing for farmers may have different and more severe impacts on the lower tail of the sales distribution compared to the upper tail, representing

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producers with higher sales. These distributional impacts are masked by looking at shifts in the mean only. The UQR provides the information to assess how the unconditional distribution of sales is changed by expanded involvement in direct marketing. Current efforts to promote direct marketing by farmers do not mention or address the effects of these initiatives on the entire distribution of sales.

The conditional quantile estimator cannot directly assess these effects. The conditional quantile regression (CQR) yields an estimate of the impact of direct marketing on a given quantile of the conditional distribution of sales. Conditional quantile effects measure how sales are conditioned on all other variables in the model, such as the sales of highly experienced male farm operators located in the South operating 100 acres and hiring ten workers. Retail chains aiming to feature local produce in their outlets may want to buy from producers with a minimum scale of operations (sales) but are not typically seeking sales conditioned on demographics and farm characteristics of their suppliers. The conditional quantile regression offers a narrower interpretation of marginal effects, as the effect of the program will explicitly depend on the level of all other conditioning variables in the quantile.

Quantile regressions can be useful in assessing the impact of omitted variables, which reflect idiosyncratic shocks, and identifying areas of the distribution where these factors influence farm sales. Farms operating in the lower tail of the distribution are more adversely impacted by these shocks, and unconditional quantile regression reveals how these shocks lead to differences in the marginal effects across the quantiles.

Our analysis yields unbiased estimates of the impact of direct marketing on farm sales and reveals the heterogeneous effects that occur across the distribution of farm sales. Sales declines associated with direct marketing tend to become smaller as farm sales increase and factors associated with less acute sales declines are identified. This information can assist marketing experts and extension professionals in guiding farmers who are considering initiating or expanding direct marketing activities. Producers who are planning to sell more in local outlets should expect their sales to decline, a finding that has not been uncovered in other current research.

Literature Review

Case studies have provided some evidence of revenue advantages that accrue to farmers selling in local markets, but research is needed to provide a comprehensive assessment of the economic benefits of direct marketing efforts for farmers (Martinez et al., 2010). Current research has not explicitly addressed the impact of direct marketing on farm sales, an essential element in ensuring continued producer involvement in these marketing outlets. We review the marketing science literature regarding direct agricultural marketing by producers and also discuss developments in the applications of unconditional quantile regression models.

Direct marketing may allow producers to receive a better price by selling directly to consumers, who have expanded their demand for fresh and local food due to growing concerns about a healthier diet (Govindasamy, Hossain, and Adelaja, 1999). Darby et al. (2008) suggested that marketing products directly in local markets provides an opportunity for farmers to capture a greater share of consumers' food budgets and confirmed empirically that consumers are willing to pay more for locally grown products. Park and Lohr (2010) assessed farm earnings of organic producers if they commit to various levels of local sales and documented that producers who participate in local direct marketing efforts tend to achieve lower earned income compared to other producers. Estimates of earnings that control for selectivity effects revealed that organic producers who chose to sell the bulk of their product to local markets incurred decreased earnings compared to producers with limited local sales.

Park, Mishra, and Wozniak (2014) developed a multinomial logit model identifying variables that influence the choice of direct marketing outlets by farmers in the United States. Producers with a broader portfolio of management skills—such as more ways to control input costs—are more likely to rely only on intermediated retail outlets or to diversify into both direct-to-consumer and intermediated retail marketing outlets. The results also show that farm operators with a wider set

of marketing skills are more likely to increase farm sales relative to farmers who draw on a more limited set of marketing skills. Detre et al. (2011) and Uematsu and Mishra (2011) reviewed studies that investigate how the adoption of direct marketing strategies are influenced by farm sales, but these studies focus on mean effects only and neglect the distributional impacts uncovered in this research.

The marketing science literature has discussed when manufacturers (here, agricultural producers) can benefit by engaging in direct marketing. Chiang, Chhajed, and Hess (2003) showed that direct marketing indirectly increases the flow of profits through the retail channel and help the manufacturer improve overall profitability by spurring demand in the retail channel. Arya, Mittendorf, and Sappington (2007) discussed how direct marketing (or supplier encroachment) benefits suppliers and retailers by inducing lower wholesale prices and expanded downstream competition. More recent work by Li, Gilbert, and Lai (2015) has incorporated elements of asymmetric information and nonlinear pricing in the decision model and shown that the supplier's ability to encroach (and engage in direct marketing) may either benefit or hurt both the supplier and the reseller. These conflicting theoretical results from marketing science provide support for the empirical work presented here.

Empirical researchers have emphasized the importance of evaluating changes in the quantiles of the unconditional (marginal) distribution. Quantile regressions capture the effects of covariates on the conditional distribution, but this conditional distribution does not reflect the full impact of variability of the covariates in the population. Firpo, Fortin, and Lemieux (2009) developed a regression approach to evaluate impacts on the quantiles of the unconditional distribution. The approach can be generalized to other distributional statistics such as the Gini coefficient or the Theil coefficient. Rothe (2010) extended the Firpo, Fortin, and Lemieux approach to more general models with nonseparable error structures. Frölich and Melly (2013) proposed an unconditional quantile treatment effects model and dealt with the effects of endogenous variables.

Empirical Framework

We begin by documenting the significant degree of heterogeneity in the reported sales of farmers and how this heterogeneity is related to the decision to engage in direct marketing. Based on data from the Agricultural Resource Management Survey, figure 1 shows violin plots of total value of farm sales for producers who participate in direct marketing to consumers or retailers compared to farm operators who do not report any direct marketing efforts. Violin plots combine box plots and density traces in one diagram. The box plot displays the center, spread, asymmetry, and outliers in data while the density traces show the distribution of the data, with the valleys, peaks, and bumps indicating the concentration of observations. The mean value of farm sales for farmers participating in direct marketing is about \$184,000 compared with a mean value of \$323,000 for other operators. The violin plot reveals that the largest share of producers with direct marketing clusters at lower levels of farm sales. Farmers with no involvement in direct marketing have a slightly larger standard deviation for farm sales, suggesting that participation in direct marketing may dampen the volatility of sales. The mean of sales is above the median for both groups (\$38,000 for direct marketers and \$162,000 for the other producers), indicating that the sales distribution is right skewed. A similar pattern of overdispersion is observed for the natural logs of the value of farm sales measure used in the econometric model.

Our formal analysis of sales for the agricultural producer is

$$(1) \quad Y_i = X_i\beta + \delta_i + a_i + \varepsilon_i,$$

where Y_i represent the total value of farm sales for farmer i , X_i is the observed skill characteristics of the operator, a_i denotes the producer's unobserved skills, and ε_i is the stochastic error component. The sales premium (or discount) earned by the farmer is defined by δ_i . We follow Card and de la Rica (2006) by decomposing this component, assuming that it depends on farm-level covariates (Z_i)

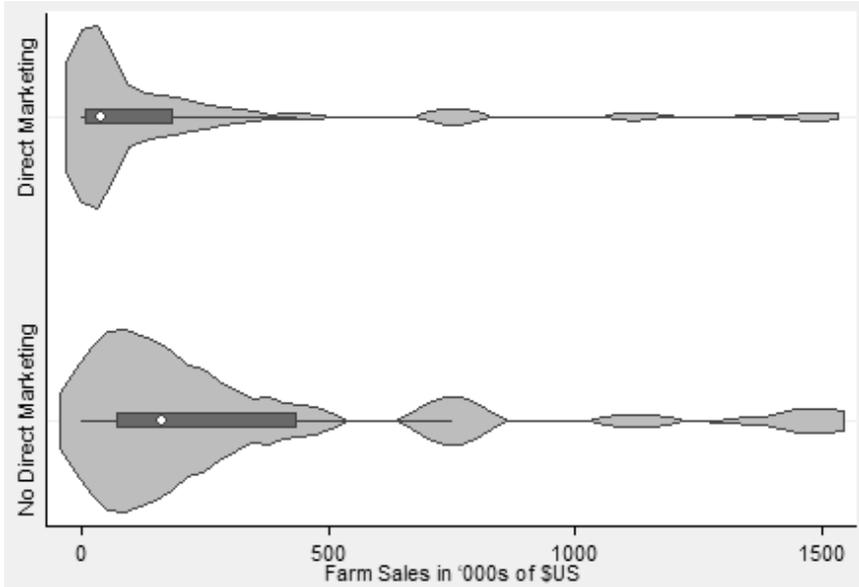


Figure 1. Violin Plot of Farm Sales by Direct Marketing Participation

Notes: Calculations from USDA’s Agricultural Resources Management Survey.

and an indicator of the producer’s participation in direct marketing (DM_i):

$$(2) \quad \delta_i = DM_i\alpha + Z_i\gamma.$$

These assumptions result in a model for farm sales of the form

$$(3) \quad Y_i = X_i\beta + DM_i\alpha + Z_i\gamma + a_i + \varepsilon_i.$$

Random shocks and events that impact farms sales occur after the decision to engage in direct marketing and the producer has committed resources to choosing a direct marketing channel and identified marketing, packaging, and shipping requirements in negotiations with buyers. The idiosyncratic factors that influence the error term are not observed by the producer when the direct marketing decision is implemented, and these factors should also not influence the input choices in the model. Assuming that the unobserved producer has skills that influence participation in direct marketing (after controlling for observed producer, farm, and market area demand characteristics) are uncorrelated with random, short-term shocks that drive the error term, the impact of direct marketing on sales can be estimated by the UQR model. If unobserved operator characteristics are correlated with the error term, the estimates from the UQR are biased and inconsistent.

The approach is consistent with Zellner, Kmenta, and Drèze (1966), who argued that firms maximize expected profits rather than *ex post* profit and that OLS is appropriate to estimate the production function or, in this case, sales. Optimal inputs such as land and different types of labor are derived from the firm’s optimization decision. The error terms for these inputs are due to “human errors” in managerial judgment. By contrast, the error term in the sales equation is due to “random acts of nature” after the optimal choice of inputs has occurred. In this framework, inputs are independent of the error term for the sales equation and OLS estimation yields consistent estimates. In turn, the quantile regression models are not subject to endogeneity from the input choices.

Our strategy for dealing with the potential for any remaining endogeneity has two components. First, the set of operator and farm characteristics is chosen to minimize the correlation between the producer’s unobserved skills and the idiosyncratic shocks to production. We control for a number of unobserved (to the researcher) factors that are known by the producer and could influence input

choice. These variables influence managerial ability and technical skill in marketing and production and include education, experience, and sex. The measure of growth in nonfarm earnings indicates the operator's management expertise. The managerial ability of the operator in developing a strategy to diversify across the production of a portfolio of revenue-producing activities is accounted for by the Herfindahl index based on the revenue share of commodities produced and sold by the farmer. The model also controls for the influence of the local retail environment where the farm is located on the propensity to participate in direct marketing. Second, we implement endogeneity tests to verify that the direct marketing status variable is uncorrelated with the error term. These tests are described in more detail in the appendix.

Econometric Approach and Specification

The unconditional quantile regression (UQR) proposed by Firpo, Fortin, and Lemieux (2009) offers a distinct advantage over the OLS model and the conditional quantile approach. First, the unconditional quantile regression measures the full impact of participation in direct marketing on farmer sales at specific quantiles in the sales distribution. The unconditional quantile is evaluated marginally over the distribution of the vector of explanatory variables and is defined independently of the values of the covariates in the model. The UQR estimates provide a means to isolate specific parameter effects that are not uncovered by the conditional effects. The UQR estimator adopted in this research is implemented using the Recentered Influence Functions (RIF) to evaluate unconditional quantile estimates for the decision to engage in direct marketing.

Based on the properties of the ordinary least squares (OLS) regression model, the conditional mean $E(Y|X) = X\beta$ is equal to $E(Y) = E(X)\beta$. The OLS model conveniently yields consistent estimates of marginal effects for both the conditional and unconditional mean of the explanatory variable. The linearity of the expectation operator does not apply to cases with nonlinear operators such as quantiles and other measures of distributional change. The conditional quantile regression (CQR) model developed by Koenker and Hallock (2001) cannot address policy issues that depend on the unconditional statistical properties of the response variable.

Both quantile regression models allow the explanatory variables to have different impacts across the distribution of the outcome variable. The parameter estimate from the UQR measures the change in sales at the τ th quantile while the CQR measures the change in conditional sales at τ th quantile. These measures are not equal:

$$(4) \quad \frac{\partial Y_{Sales}(\tau|DM, X)}{\partial DM} \neq \frac{\partial Y_{Sales}(\tau)}{\partial DM}.$$

The impact of farmer experience on sales may be quite different for farmers who are at the twentieth quantile of the distribution compared to farmers at the ninetieth quantile. The CQR model assesses the impact of a covariate on a quantile, conditional on specific values of the other explanatory variables included in the model.

The unconditional quantile approach is based on the concept of the RIF developed from the field of robust statistics and summarized in Hampel (2005). The influence function (IF) assesses the impact of an individual observation on a distributional statistic, $v(F)$, such as the median, interquartile range, or any quantile without having to recalculate that statistic. The IF is defined as

$$(5) \quad IF(y; v(F)) = \lim_{\varepsilon \rightarrow \infty} \left[\frac{v((1 - \varepsilon) \times F + \varepsilon \delta_y) - v(F)}{\varepsilon} \right], \quad 0 \leq \varepsilon \leq 1,$$

where F represents the cumulative distribution function for Y and δ_y is a distribution that puts mass at the value y . The influence function for the τ th quantile of Y is

$$(6) \quad IF(y; F) = \left[\frac{\tau - I[Y \leq q_\tau]}{f_Y(q_\tau)} \right],$$

where q_τ refers to the τ th quantile of the unconditional distribution of Y , the probability density function of Y evaluated at q_τ is represented by $f_Y(q_\tau)$, and $I[Y < q_\tau]$ is an indicator variable denoting whether the observed value is less than or equal to q_τ . The RIF is obtained by adding the relevant statistic (here, the quantile) to its IF:

$$(7) \quad RIF(y; q_\tau) = q_\tau + IF(y; q_\tau),$$

The conditional expectation of the RIF ($y; q_\tau$) can be modeled as function of explanatory variables, that is, $E[RIF(y; \tau)|X = x] = \xi(X'\beta_\tau)$; Firpo, Fortin, and Lemieux (2009) demonstrated that this RIF regression can be viewed as an unconditional quantile regression.

The steps for implementing the UQR are similar to those for an OLS regression. The RIF of the τ th quantile of Y is estimated following equation (8), and q_τ is estimated using the sample estimate of the unconditional τ th quantile. The probability density function $f_Y(q_\tau)$ can be estimated non-parametrically (using a kernel density estimator). The RIF is computed for each observation $R\hat{I}F(y_i; q_\tau)$, and this value is regressed on the observed explanatory variables, X . Firpo, Fortin, and Lemieux (2009) outline the steps to compute the unconditional quantile partial effects on the dependent variable.

The linear RIF regression for the producer is specified as

$$(8) \quad E[RIF(y_i; q_\tau)|X, Z] = X_i\beta + DM_i\alpha + Z_i\gamma + a_i + \varepsilon_i,$$

where α represents the marginal effect of direct marketing activities on the relevant distributional statistic, here the quantile q_τ . The RIF regression results have a similar interpretation as coefficients from an OLS regression and are estimates of unconditional quantile marginal effects. We estimate the marginal effect on farmer sales at the τ th quantile associated with a small change in a given explanatory variable. Frölich and Melly (2013) summarized additional advantages of the unconditional quantile regression approach, showing that the estimator is \sqrt{n} consistent, asymptotically normal, and efficient. They noted that the unconditional effects are averages of the conditional effects and are more precisely estimated than conditional effects. Quantile effects are also robust to noisy data outliers that may be prevalent in reported sales measures. The quantiles are defined even if the outcome variable does not have finite moments due to fat tails. These features are observed in the value of the variable of farm sales for producers, supporting the application of a conditional quantile regression approach.

Variable Description and Model Interpretation

We use data from the nationwide 2008, 2009, and 2010 Agricultural Resource Management Survey (ARMS) collected by the Economic Research Service (ERS) and the National Agricultural Statistics Service (NASS). The ARMS provides information about agricultural production, resources, and the environment as well as characteristics and financial conditions of farm households, marketing strategies, input management strategies, and off-farm income. Data are collected from the senior operator making the management decisions on each farm.

The survey instrument elicits information on farmer participation in producing, raising, or growing any commodities sold or provided directly to individual consumers for human consumption, directly to retail outlets, directly to regional distributors (including food hubs, CSAs, and other local foods aggregators), or directly to institutions. This information defines participation in direct marketing efforts or local sales by producers, but information about the amount of sales in direct marketing efforts is not available in the ARMS. Table 1 shows the variable descriptions and summary statistics for the total value of farm sales reported in each year of the ARMS, the dependent variables in the model, and the complete set of explanatory variables, discussed in more detail below. Natural logs of the continuous variables were used, as indicated in the model specification in table 3.

Table 1. Variable Descriptions and Summary Statistics

Variable	Description	Direct Marketing	No Direct Marketing
Sales	Total value of farm sales (thousands of dollars)	183.78 (340.50)	323.29 (394.30)
Experience	Number of years the farmer has operated	26.28 (14.80)	28.49 (14.82)
Education	Education completed by the farmer (%)		
	Less than High School	8	10
	High School Graduate	41	27
	Some College	28	28
	College Graduate	23	35
Male	Farm operator is male (1 = male, %)	91	95
Growth in Off-Farm Income	Growth in off-farm income over previous year (% , ranges between -200 and +200)	54.87 (97.63)	62.97 (102.55)
Acres	Total acres farmed	233.63 (360.58)	517.10 (513.59)
Operator Labor	Hours of paid labor by operator (hours/week over the year)	13.91 (69.66)	15.43 (80.29)
Hired Labor	Hours of paid labor by hired worker (hours/week over the year)	320.38 (867.83)	234.47 (676.89)
Diversification in Commodities	Number component of Herfindahl index for commodities sold	0.11 (0.21)	0.04 (0.13)
Diversification in Distribution	Distribution component of Herfindahl index for commodities sold	-0.05 (0.13)	-0.02 (0.08)
Grain Share	Share of sales accounted for by major grains	18.43 (37.46)	46.44 (48.96)
Fruit Share	Share of sales accounted for by fruits and nuts	25.53 (41.52)	4.07 (19.61)
Vegetable Share	Share of sales accounted for by vegetables	28.49 (42.46)	1.71 (12.14)
Dairy Share	Share of sales accounted for by dairy products	2.65 (15.47)	9.11 (27.96)
Grocery Growth	Growth rate in grocery stores in FIPS location of farm (1997-2010, in %)	-4.38 (19.63)	-5.72 (24.20)
Supercenter Growth	Growth rate in supercenters in FIPS location of farm (1997-2010, in %)	30.23 (59.30)	38.59 (71.60)
Convenience Store Growth	Growth rate in convenience stores in FIPS location of farm (1997-2010, in %)	-4.21 (13.05)	-4.79 (18.77)
Farmers' Market Growth	Growth rate in farmers' markets in FIPS location of farm (1997-2010, in %)	40.17 (75.56)	37.06 (80.77)
Mountain	Farm is located in a Mountain state, (1 = Yes, in %)	7	4
Midwest	Farm is located in a Midwestern state (1 = Yes, in %)	27	45
Northeast	Farm is located in a Northeastern state (1 = Yes, in %)	31	13
South	Farm is located in a Southern state (1 = Yes, in %)	22	29
Pacific	Farm is located in a Pacific state (1 = Yes, in %)	13	9
N		646	4,537

Notes: Descriptive statistics of raw data reported while model is estimated using total value of farm sales (in logarithms) as the dependent variable. Data are from USDA's Agricultural Resource Management Survey. Standard deviations appear in parentheses.

Description of Variables

Demographic variables that are plausibly related to participation in direct marketing include the operator's experience, education, and gender. Experience and education are included to control for management ability and technical expertise. The total value of farm sales tends to increase across the quantiles of the farm experience variable but shows a decline in the fourth quartile of the farm experience measure where operators have more than thirty-eight years of experience.

More experienced farmers face greater risk in their operations. The standard deviation of farm sales increases with experience and declines for operators in the fourth quartile of the experience measure. The same pattern in total farm sales is shown across quantiles of operator's education.

About 21% of female farmers participate in direct marketing compared to 12% of male farmers; female farmers comprise about 5% of the overall sample. Both female and male farmers experience decreased sales when they participate in direct marketing, but the drop is higher for women (a sales decline of about 79%) compared to men (about 36%). Another interesting effect is a decrease in the variability of sales for both males and females associated with participation in direct marketing. The effect is higher for females than for males, with female farmers reporting a 66% lower standard deviation in farm sales when participating in direct marketing compared to a 5% drop for male farmers.

To account for the impact of economic performance, we include the growth of off-farm income, a measure that is readily available from farm financial record keeping systems and in the ARMS. The measure is drawn directly from the ARMS and represents the off-farm wages, salaries, and tips before taxes and withholdings that accrue to the household, principal operator, and spouse. This question appears frequently over the various years and types of the survey, so respondents should be familiar with it. The growth variable was defined following Davis, Faberman, and Haltiwanger (2006) by measuring the change in off-farm income over the year divided by the average income based on beginning and end of the year values. This measure of growth is standard in the labor literature and results in growth rates from -200 to $+200\%$.

The descriptive statistics (table 1) show that the growth rate is lower for farmers engaged in direct marketing compared to the farmers who do not use these markets. The growth rate of income from off-farm occupations is fairly high for both sets of farmers: 55% for farmers who use direct marketing and about 63% farmers who do not.

The model includes controls for the impact of farm specialization and cropping choices using shares of income from the categories of commodities: cash grains (Grain Share), vegetable (Vegetable Share), fruits (Fruit Share), and dairy products (Dairy Share). The managerial ability of the operator to develop a strategy to diversify across the production of a portfolio of revenue-producing activities is accounted for by the Herfindahl index based on the revenue shares reported by the farmer.

Similarly, the Herfindahl index accounts for the impact of farm diversification decisions on sales based on the revenue shares for the operation. The Herfindahl index is defined as $d = 1 - \sum_i s_i^2$, where s_i is the share of gross sales from the i th activity of the producer. We use five groupings of activities from the ARMS survey including major grains, other grains (combining oilseeds, dry beans, and dry peas), fruits (including tree nuts and berries), vegetables (with melons, potatoes, and sweet potatoes), and dairy products.

A decomposition of the Herfindahl index proposed by Gollop and Monahan (1991) is used to provide insight into two components of the diversification decision:

$$(9) \quad d = \left[1 - \frac{1}{y} \right] + \sum_i \left[\frac{1}{y^2} - s_i^2 \right],$$

where y is a count of the number of commodities marketed by the farmer. The first term in brackets is the number component (diversification in commodities), reflecting the number of different commodities produced by the operation. The diversification index increases as the number of different commodities marketed grows. A producer who markets in each of the five categories has a number component of 0.80 while a producer who markets one commodity has the minimum value of 0 for the number component (no diversification). Higher values of the number component indicate higher degrees of diversification in choosing to produce a variety of commodities.

The second bracketed term in the equation is the distribution component (diversification in distribution), accounting for the shares of different commodities that are marketed. Consider two different farmers who are each marketing two commodities in a given year. One farmer

Table 2. Total Value of Farm Sales by ERS Region

Category	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile
United States	17.75	96.51	198.06	748.03
Midwest	13.24	89.23	206.25	680.15
Mountain	6.60	55.00	212.50	979.17
Northeast	9.14	96.50	198.21	892.86
South	15.38	98.29	189.88	541.67
Pacific	13.87	84.30	196.59	982.14

Notes: Data are from the USDA's Agricultural Resource Management Survey. Farm sales are in thousands of dollars.

reported equal sales for the two commodities for a distribution component of -0.25 , or $\frac{1}{2^2} - (0.5^2 + 0.5^2) = -0.25$. The second farmer reported 90% of farm sales from the first commodity and the remaining 10% of the sales from the second commodity, for a distribution component of -0.57 , or $\frac{1}{2^2} - (0.9^2 + 0.1^2) = -0.57$. Larger negative values indicate an increasingly unequal distribution of sales across the marketed commodities. The distribution component has its maximum value (0) for a farmer with sales from one commodity.

Decomposition of the Herfindahl diversification index into its number and distribution components yields values of 0.11 and -0.05 , respectively, for producers engaged in direct marketing, as shown in table 1. These values indicate that producers involved in direct marketing have more diversified set of products (higher positive value for the diversification measure). These producers also rely on a less diversified distribution of earnings from those commodities (higher negative value for the share diversification component). For farmers not involved in direct marketing, the values of the components are 0.04 (diversification in commodities) and -0.02 (diversification in distribution).

We control for regional effects by using the five geographic production regions identified by Low and Vogel (2011), which account for regional differences in farm structure, marketing constraints, and agronomic conditions. A dichotomous variable was created for each region, equal to 1 if the respondent's farm was in that region and 0 otherwise. In the sample, the highest rate of participation in direct marketing was for farmers in the Northeast at 25% and Midwestern farmers showing the lowest level of direct marketing at 7.9%. Producers in the Mountain region reported the highest mean level of sales given direct marketing efforts (\$236,391) and Southern farmers the lowest at \$140,829. The risk involved in direct marketing (as measured by the coefficient of variation) also reveals the same pattern, with the Mountain region the second-lowest risk level (1.76) and the South the highest (2.05).

We account for the influence of the local retail environment in which the farm is located on the propensity to participate in direct marketing. The model includes information on the availability of grocery stores, supercenters and club stores, convenience stores, and farmers' markets in the county where the farm operation is located. The number of each store type operating in each county was gathered from the Census of Business Patterns, and the growth rate in each type of store over the period was calculated.

Interpretation of Unconditional Quantile Results

Before discussing the results in detail, we provide a concrete example of the difference between the UQR and CQR using our data on direct marketing. Table 2 reports the sales for the United States and the five geographic production regions (described in detail in a later section) across the quartiles. If we include the region effects in a regression model, the CQR would show the impact of direct marketing on sales at the fourth quartile of the five region-specific farmer sales distributions. But the region-specific distributions may deviate substantially from the national sales distribution for farmers.

For example, the fourth quartile of farm sales in the Pacific region is substantially above the fourth quartile of national farm sales. The fourth quartile of farm sales in the Southern region is substantially below the fourth quartile for the nation. The CQR at the fourth quartile produces an estimate of direct marketing on earnings for farmers who earn \$982,000 in the Pacific region, for farmers who earn \$541,00 in the South region, and for values in between for the other regions. By contrast, the UQR yields an estimate of the impact of direct marketing on farm sales at the fourth quartile, regardless of the region.

This simple example includes only the regional effects in the interpretation. The estimated model includes variables for experience, education, gender, and a set of farm-specific measures. Interpretation of the CQR coefficients is conditioned on all these variables simultaneously.

Results from the Estimated Model

We apply the RIF regression model to provide estimates of the unconditional quantile marginal effects. Table 3 reports the unconditional quantile regression estimators of the logarithm of total sales on participation in direct marketing for the twenty-fifth, fiftieth, seventy-fifth, and ninety-fifth quantiles with controls for operator demographics, farm characteristics, geographic location, and retail market conditions where the farm is located. Following Thornton and Innes (1989), the proportional impact of the discrete direct selling indicator on total sales is measured as $p_i = [\exp(\alpha_i) - 1]$ where α_i is the coefficient of the direct selling variable. We view these estimates as providing a descriptive comparison of the sales distribution for the farmers and do not claim that the estimates have a causal interpretation.

Figure 2 shows that the impacts of direct marketing efforts are uniformly negative across the unconditional quantile regressions, indicating that involvement in direct marketing is associated with a decrease in farm sales. The direct marketing penalty remains even after controlling for important demographic factors, education, farming experience, characteristics of the farm operation (such as crop choices and diversification across commodities), and geographic effects. The estimates at the low quantiles are substantially larger (more negative) than at higher quantiles, and the estimates decline across the quantiles. The findings show that the sales declines associated with direct marketing tend to grow smaller as farm sales increase. For operators involved in direct marketing, the drop at the twenty-fifth quantile is about 63.69% ($\exp[-1.013] - 1$) compared to operators with no involvement, while the drop at the ninety-fifth quantile is only about 5.59%. Because the confidence intervals for the direct marketing effects do not overlap at the twenty-fifth and ninety-fifth quantiles, the null hypothesis that the effects of directing marketing are equal at these two quantiles is rejected.

Another implication is that operations with lower levels of farm sales are more severely impacted when participating in direct marketing compared to operations with high farm sales. The unconditional quantile marginal effects are statistically significant across all the quantiles except for the ninety-fifth quantile. Hoppe, MacDonald, and Korb (2010) confirm that, in general, "large-scale farms are more viable businesses than small family farms." Most types of small farms report average operating profit margin and negative rates of return on assets and equity. These financial measures are generally positive for large farms (annual sales of \$250,000 to \$499,999) and very large farms (annual sales of \$500,000 or more). MacDonald, Korb, and Hoppe (2013) reiterate that larger farms utilize labor and capital more intensively, which is the primary source of their financial advantage. The earnings penalties tend to get smaller across the quantiles as farm sales increase, but we do not see a constant decline in the penalty. Farmer involvement in direct marketing is actually associated with more severe penalties, as penalties increase by about 12% and 10% when moving across operations at the tenth to twentieth sales quantiles. After that the sales penalty gets smaller farm sales increase. The penalty then tends to decline across the remaining quantiles.

Figure 2 also illustrates the differences between the conditional and unconditional quantile regressions and confirms the value of the unconditional quantile approach proposed in this research. The negative association between direct marketing and sales is 26% larger on average for all

Table 3. Unconditional Quantile Regression Results for Farm Sales Model

Variable	Quantile				Ordinary Least Squares ^a
	25th	50th	75th	95th	
Constant	7.84* (36.27)	9.93* (89.75)	11.46* (169.77)	13.47* (139.79)	8.20* (48.93)
Direct Marketing	-1.01* (-9.75)	-0.30* (-6.67)	-0.16* (-5.20)	-0.06 (-1.16)	-0.91* (-11.22)
Experience	0.02 (0.41)	-0.03 (-1.42)	-0.04* (-2.96)	-0.04 (-1.92)	0.01 (0.28)
High School Graduate	0.10 (0.89)	0.03 (0.53)	0.03 (0.87)	0.01 (0.14)	0.02 (0.53)
Some College	0.06 (0.56)	0.09 (1.50)	0.08 (1.98)	-0.04 (-0.63)	0.09 (1.50)
College Graduate	-0.05 (-0.55)	0.03 (0.55)	0.09* (2.36)	0.01 (0.15)	0.03 (0.55)
Male	0.20 (1.58)	0.07 (1.00)	0.07 (1.89)	0.06 (1.20)	0.28* (2.93)
Growth in Off Farm Income	0.04 (1.77)	0.05* (3.38)	0.03* (2.98)	0.02 (1.11)	0.04* (2.20)
ln(Acres)	0.60* (24.18)	0.35* (28.52)	0.18* (21.45)	0.08* (5.88)	0.54* (28.59)
ln(Operator Labor)	0.04* (2.35)	0.06* (5.64)	0.07* (8.70)	0.11* (5.01)	0.10* (6.32)
ln(Hired Labor)	0.17* (15.55)	0.14* (22.13)	0.11* (24.71)	0.11* (14.56)	0.20* (23.09)
Diversification in Commodities	-0.17 (-0.66)	-0.07 (-0.48)	-0.06 (-0.53)	-0.40* (-2.06)	-0.25 (-1.33)
Diversification in Distribution	-0.81 (-1.81)	-0.28 (-1.12)	0.06 (0.32)	-0.12 (-0.31)	-0.68* (-2.17)
Grain Share	-0.56* (-7.02)	-0.28* (-7.02)	-0.14* (-4.96)	-0.24* (-6.32)	-0.36* (-6.59)
Fruit Share	-0.63* (-4.77)	-0.09 (-1.48)	0.07 (1.65)	-0.16* (-2.27)	-0.29* (-2.75)
Vegetable Share	-0.60* (-4.01)	-0.09 (-1.40)	0.08 (1.82)	0.09 (0.93)	-0.02 (-0.13)
Dairy Share	-0.14 (-1.34)	0.01 (0.19)	0.08 (1.79)	0.38* (3.85)	0.17* (2.25)
Grocery Growth	0.18 (1.47)	0.01 (0.17)	0.09* (2.18)	0.10 (1.61)	0.17* (2.09)
Supercenter Growth	-0.09* (-2.26)	-0.02 (-1.13)	0.00 (0.11)	-0.02 (-0.82)	-0.04 (-1.49)
Convenience Store Growth	-0.08 (-0.54)	0.08 (0.91)	0.07 (1.35)	0.26* (2.85)	0.13 (1.27)
Farmers' Markets Growth	0.01 (0.76)	0.03 (1.58)	0.01 (1.00)	0.03 (1.50)	0.00 (0.12)
Midwest	-0.22* (-2.92)	0.04 (0.99)	0.16* (6.07)	0.18* (5.08)	0.06 (1.08)
Mountain	-0.68* (-4.99)	-0.14* (-2.01)	0.16* (3.40)	0.48* (4.88)	-0.24 (-1.96)
Northeast	-0.18* (-2.12)	0.00 (0.01)	0.04 (1.24)	0.01 (0.14)	-0.02 (-0.36)
Pacific	-0.22* (-2.09)	0.04 (0.83)	0.15* (4.11)	0.46* (6.25)	0.14 (1.66)
Pseudo R-Squared	0.32	0.37	0.35	0.19	0.46

Notes: A single asterisk (*) indicates asymptotic t-values with significance at $\hat{\alpha} = 0.05$ level. Values in parentheses are asymptotic t-values. Specification includes geographic production regions identified by Low and Vogel (2011). Dependent variable is total value of farm sales (in logarithms). Data are from USDA's Agricultural Resource Management Survey.

^a Robust standard errors are used.

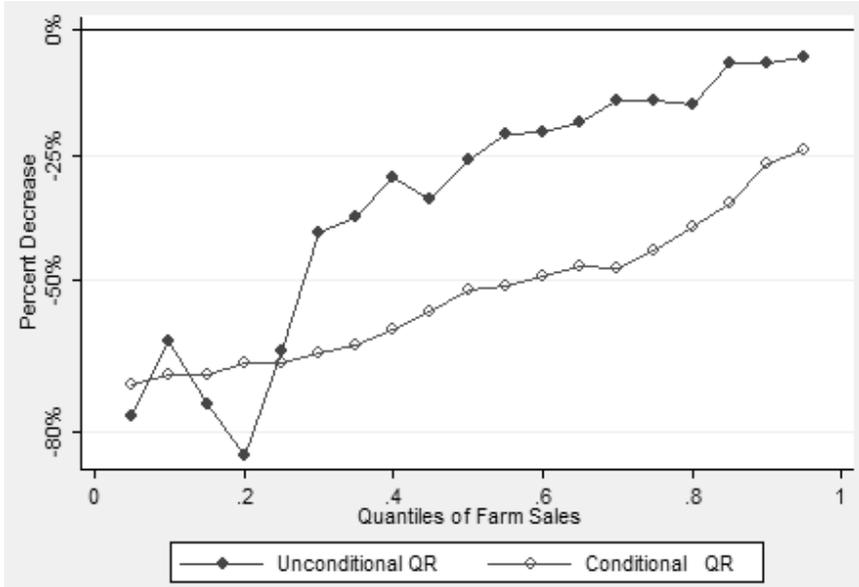


Figure 2. Unconditional Quantile Effects for Direct Marketing Participation and Farm Sales

Notes: Calculations from USDA’s Agricultural Resources Management Survey.

quantiles at or above the thirtieth quantile when using the conditional estimator as opposed to the unconditional estimator. The implication is that the conditional quantile approach results in estimates of direct earning declines that may be too high and that may discourage farmers from participating in these markets.

Farmer Demographics and Financial Indicators

The coefficients from the unconditional quantile regressions indicate that experienced farmers involved in direct marketing are faced with larger sales declines compared to farmers who are not involved in direct marketing. A farmer’s experience does not appear to mitigate the sales declines observed when farmers adopt direct marketing techniques. The farm experience variable does not generally have a positive effect on sales across the quantiles. Male farmers earn more than female farmers, but the unconditional quantile regression show that this sales advantage is generally not significant after controlling for farm structure and location. The sales equation estimated by OLS (neglecting a quantile approach) shows a positive and significant coefficient for males.

Growth in off-farm income is positively related to farm sales in two quantiles (fiftieth and seventy-fifth) in the unconditional quantile model. We calculate marginal effects across the quantiles for farmers who are involved in direct marketing for each of the quantiles. At each quantile the marginal effects evaluate the impact on farm sales when growth in off-farm income is higher by one standard deviation. Conditioning on the change in off-farm income, farmers participating in direct marketing are able to mitigate the drop in sales associated with direct marketing by 1.48% at the twenty-fifth quantile, 3.47% at the fiftieth quantile, and 2.64% at the seventy-fifth quantile. These marginal effects are statistically significant for the fiftieth and seventy-fifth quantiles but disappear for farmers in the ninety-fifth quantile.

Participation in direct marketing is associated with a decline in farm sales, but farmers who experience growth in off-farm income are better able to withstand these sales declines. We can translate these percentages into the dollar amounts that farm sales are projected to recover as off-farm income grows. At the twenty-fifth quantile the dollar amount is about \$815, and farm sales rise to about \$8,242 at the seventy-fifth quantile, suggesting that farm operations experiencing growth in

their off-farm income have management and marketing skills that contribute to reducing declines in farm sales associated with direct marketing operations.

To provide more insight into the factors that could be influencing these findings, we looked more closely at indicators of demographics and business expertise for farmers engaged in direct selling. We gathered information from the ARMS on the off-farm businesses from which the principal operator and spouse received wages or salaries. The respondents could identify eleven different businesses, including agriculture, construction, manufacturing, and various retail, wholesale, and service industries. On farms involved in direct selling, neither the operator nor the spouse is likely to be involved in an off-farm business.

When an operator does become involved in an off-farm business, direct marketing participants tend to take second jobs in retail. By contrast, operators who do not participate in direct marketing gravitate primarily toward jobs in agriculture enterprises (along with forestry, fishing, hunting, or mining) to generate additional off-farm income.

The 2010 ARMS also collected data on the types of occupations chosen by farm operators when working off the farm. Respondents could choose from six occupation categories, including management, services, sales, natural resources and construction, production and transportation, and military. Farm operators with direct marketing efforts were less likely to be involved in management and professional occupations and more frequently employed in service occupations than farm operators who were not involved in direct marketing.

This study provides suggestive evidence that producers with direct marketing could benefit by obtaining off-farm income. This additional source of household revenues could potentially decrease producers' exposure to market risks while providing other benefits that enhance direct marketing—such as increased networking with potential clients or accumulation of human capital—that could be transferable to the agricultural operation.

Production Elasticities and Farm Diversification Effects

The coefficients on the acreage and labor variables in the log-linear model for value of farm sales represent elasticities. The output elasticities measure the change in producers' sales as inputs change, indicating that a 10% increase in acreage is associated with expanded sales of 5.96% at the twenty-fifth quantile and expanded sales of 0.75% at the ninety-fifth quantile. The output elasticity for acreage is positive and significant across all quantiles and is highest at the lowest quantile. The differences in the elasticities across the twenty-fifth and ninety-fifth quantiles are statistically significant. The output elasticities suggest that producers using direct marketing who also expand their acreage by 10% can mitigate the sales drop associated with direct marketing; these effects are highest for the smallest farms. The sales effect at the twenty-fifth quantile moves from a decline of 63.69% to a decline of about 57.73%. The evidence here is consistent with findings presented by MacDonald, Korb, and Hoppe (p. 50 2013), which highlighted that “localized knowledge, quick and flexible adjustments to changed circumstances, and the incentives to act on each of those” remain necessary to crop production” for small and family organizations.

The output elasticities for labor (both operator and hired labor) suggest that a 10% increase in labor is associated with expanded sales of 2.01% at the twenty-fifth quantile and 2.21% at the ninety-fifth quantile. The differences in the labor elasticities are not statistically significant. The labor output elasticities are fairly constant across the quantiles. At the lower quantiles (the twenty-fifth and fiftieth), acreage elasticities are higher than labor elasticities, with the managerial implication that revenues are most responsive to an expansion of acreage for smaller operations shifting to direct marketing.

Conclusions and Additional Research

The unconditional quantile regression provides the information that allows us to assess how the unconditional distribution of sales is changed by expanded involvement in direct marketing. The definition of the unconditional effect does not depend on the level of the explanatory variables in the model. As Frölich and Melly (2013) noted, this means that the UQR model estimates the same object, even when different explanatory variables are considered, enhancing the value of the model in examining the robustness of the results as alternative control measures are used. Policy makers who promote direct marketing by farmers are interested in assessing how the unconditional distribution of sales is changed by expanded involvement in direct marketing, and the UQR clearly measures this effect. The UQR approach also reveals the distributional impacts associated with a policy variable.

The UQR is easy to estimate and can be estimated precisely, even without functional form restrictions. Future work can consider alternative variables and more recent ARMS data yet still estimate the same effect and assess the robustness and validity of these findings. By contrast, Borah and Basu (2013) emphasized that the conditional quantile regression “may generate results that are often not generalizable or interpretable in a policy or population context.” The conditional quantile results depend explicitly on the full set of covariates in the model.

Our results assess how farmers’ sales are influenced by their involvement in direct marketing. Gilg and Battershill (2000) noted that evaluating the economic effects associated with specific marketing practices could enhance the sustainability of farm systems. The impacts of direct marketing efforts are uniformly negative across the unconditional quantile regressions, indicating that involvement in direct marketing is associated with a decrease in farm sales. The direct marketing penalty remains even after controlling for important demographic factors, farm experience, characteristics of the farm operation such as crop choices and diversification across commodities, and geographic effects.

The UQR reveals that the impact of direct marketing involvement on the unconditional distribution of farm sales varies across the quantiles. Smaller operations are more severely impacted when farmers participate in direct marketing compared to larger operations. These impacts are completely masked by the traditional linear model. The unconditional quantile marginal effects are statistically significant across all the quantiles, except at the ninety-fifth quantile.

One surprising finding is that farm experience plays little role in mitigating declines in sales. The unconditional quantile regressions indicate that experienced farmers involved in direct marketing are faced with larger sales declines compared to farmers who are not involved in direct marketing. More generally, the results support the use of unconditional quantile regressions. The conditional quantile yields estimates for the impact of direct marketing efforts that are more negative than the unconditional quantile results and this evidence would provide a stronger deterrent to farmers considering participating in these markets.

Although participation in direct marketing is associated with a decline in farm sales, farmers who experience growth in off-farm income are better able to withstand these sales declines. Growth in off-farm income is positively related to farm sales across the lower quantiles (twenty-fifth, fiftieth, and seventy-fifth) in the unconditional quantile model. We calculate marginal effects across the quantiles for farmers who are involved in direct marketing for each of the quantiles. These findings indicate that farm operations experiencing growth in off-farm income have management and marketing skills that contribute to reducing declines in farm sales associated with direct marketing operations.

Additional research could be directed at extracting a consistent set of indicators from ARMS and identifying management and marketing skills that may contribute to reducing declines in farm sales associated with direct marketing operations. One indicator is the number of hours that a farmer accesses the Internet each week to gather information in two categories: farm-related news (including weather, farm, local and other news, along with stock market and agricultural market information) and farm input pricing and other farm-related information. A second category is farm-related commerce, which is defined as making purchases and sales, banking, on-line record-keeping

or accounting, operating a proprietary website, and working with the local farm cooperative. We plan to investigate these variables as additional years of the ARMS are made available and the direct marketing variable is maintained in the survey.

Retailers promoting local foods, such as Whole Foods Markets and Wal-Mart, are interested in understanding how participation in direct marketing is related to farm sales, since significant sales declines may deter farmers from joining these efforts. Wal-Mart has set goal to support farmers engaged in direct marketing efforts by selling \$1 billion in food sourced from one million small and medium-sized farmers and increasing the income of the small and medium-size farmers from whom it sources by 10–15%. Whole Foods Markets promotes a “Local Producer Loan Program” of low-interest loans to farmers, ranchers, and artisan producers; the chain may favor providing these loans to farms below a specific sales level. We estimate unconditional impacts of direct marketing efforts on farm sales of agricultural producers directly from the UQR. The UQR provides the most relevant information for understanding how producers in a lower sales quantile are affected by participation in direct marketing and could provide information to target these loans more effectively.

The “Know Your Farmer, Know Your Food” website lists opportunities for farm loan programs such as direct and guaranteed ownership loans for beginning farmers and socially disadvantaged groups, farm storage facility loans, value-added producer grants, beginning farmer and rancher development programs, and technical assistance and marketing services for farmers engaged in local selling.¹ Extension agents, crop consultants, and agricultural marketing groups can use these results to predict the sales a farmer can expect if a direct marketing program were initiated or to identify farmers who may be less susceptible to declines in sales. This information could be used to target farmer participation in the “Know Your Farmer, Know Your Food” programs.

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¹ <http://www.usda.gov/knowyourfarmer>

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Appendix A: Endogeneity Tests for the Direct Marketing Measure

We examined the potential endogeneity of the direct marketing measure by applying the procedures outlined by Wooldridge (2010), which were developed from an omitted variables perspective. A set of instruments was identified that are highly correlated with the direct marketing variable but have no direct impact on the farm sales. The variables that are related to direct marketing measure both farmers' knowledge about input availability in local markets and the structure of local markets, representing the buyers that could purchase farmers' output.

The ease with which farmers can conveniently purchase inputs from local markets is derived from information in the ARMS. An initial question asked about the distance of the operation from the nearest town with a population of 10,000 or more. Farmers also indicated the main reason that four key inputs—fuel, fertilizer, chemicals, and machinery and implements (including repairs and supplies)—were not purchased in the nearest town. For these four inputs we recorded when the farmer noted that the availability of the input was the critical factor in constraining purchases from local markets.

The purchasing constraint variable is highly correlated with the decision to participate in direct marketing but has little direct influence on total sales from the farm operation. The farmer's ability to adjust to problems in locating needed inputs reflects the long-term planning and management skills needed to identify and participate in direct marketing markets. Farmers engaged in direct marketing more frequently report problems in acquiring inputs from local markets and are more likely to report availability constraints for fertilizer, feeds, and machinery (three of the four inputs) compared to the other farmers. Forty-five percent of direct marketing farmers report difficulty locating at least one of the inputs compared to about 40% of other farmers.

The structure and vitality of the local retail environment are indicators of potential consumer demand for local food and are used as a second instrumental variable. We gather information on the availability of grocery stores, supercenters and club stores, convenience stores, and farmers' markets in the county where the farm operation was located. The numbers of each store type present in each county were used to form a Herfindahl index measuring the variety of retail outlets. Higher values of the Herfindahl indicate that the market is less concentrated and offers a greater variety of outlets for consumers to purchase food.

The data confirm a positive correlation between the Herfindahl index of food outlets and the probability that a farmer participates in direct marketing. Farmers participating in direct marketing operate in counties that have a greater probability of having access to each of the food outlets (grocery stores, supercenters and club stores, convenience stores, and farmers' markets) compared to farmers who do not participate in direct marketing. The outlet variety measure is not directly related to reported farm sales and shows a very low positive correlation with farm sales.

We follow the procedures outlined by Wooldridge (2010, pp. 126–127). Assume that an explanatory variable in the model, say DM_i , is potentially endogenous with a coefficient denoted by β . The remaining explanatory variables, X_i and Z_i , are considered to be exogenous. The suspect variable has a linear reduced form, written as $DM_i = \alpha\mathbf{\Pi}_2 + v_2$, where $\mathbf{\Pi}_2$ is a matrix of reduced form parameters and the reduced form error is v_2 .

To test for endogeneity, estimate the reduced form by ordinary least squares (OLS) to obtain the OLS estimates. Define $\hat{v}_2 = DM_i - \hat{\alpha}\hat{\mathbf{\Pi}}_2$ as the residuals from the OLS model. Estimate the linear model for farm sales with regressors X_i , Z_i , and \hat{v}_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 the estimated coefficient on $\hat{v}_2 = 0$ 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 (2010) noted that the procedure is very robust and can be applied when the endogenous variable under consideration (here, DM_i) is a binary, count, or other discrete variable type.

The Hausman test did not reject the exogeneity of the direct marketing variable. The calculated chi-square statistic (0.939, with 1 degree of freedom) was well below the critical value at any conventional significance level. The underidentification test that the excluded instruments are correlated with the (potentially) endogenous regressor confirms that the model is identified. The calculated value of the test statistic is 10.52 and is distributed as a chi-squared statistic with two degrees of freedom. The calculated value exceeds the critical value of 5.99 at the 0.05 confidence level. The null hypothesis that the equation is not identified is rejected.

Appendix B: Computing Marginal Effects and Estimated Elasticities

The output elasticities measure the change in the producer's sales as the input changes. Using a simplified model to illustrate the calculations (for convenience, we omit other explanatory variables along with the error term), we consider a change in the dependent variable when X is in log form. We write acreage as $\ln X$ so that the output elasticity for a 1% change acreage at the twenty-fifth quantile is:

$$(B1) \quad \ln Y + \ln X_j \beta_j \quad \text{so that} \quad \frac{\partial \ln Y}{\partial \ln X_j} = \frac{\% \Delta \text{Sales}}{\% \Delta \text{Acreage}} = \beta_j = 0.596\%.$$

A 10% change in acreage at the twenty-fifth quantile would result in a 5.96% increase in sales. Similar effects can be read off from the acreage estimates the different quantiles.

The calculations for marginal effects from a log-linear model follow Thornton and Innes (1989) to evaluate the proportional impact of a discrete variable (such as the direct marketing indicator) on the logarithm of the dependent variable. The farm sales variable is specified in logarithms and the percentage change in sales associated with direct marketing participation is measured as $[\exp(\beta_i) - 1] \times 100$, where β_i is the coefficient of the direct marketing variable.

Using a simplified model to illustrate the calculations (omitting other explanatory variables along with the error term), we consider a unit change in the independent variable X_j and β_j is the estimated coefficient associated with that variable:

$$(B2) \quad \ln Y_1 = X_j \beta_j \quad \text{and} \quad \ln Y_2 = (X_j + 1) \beta_j \quad \text{so that} \quad \beta_j = \ln \left(\frac{Y_2}{Y_1} \right) = e^{\beta_j} - 1 = \frac{Y_2 - Y_1}{Y_1} - 1.$$

The percentage change in Y equals $(e^{\beta_j} - 1) \times 100$, and we can compute the change in sales (at a given point, say the twenty-fifth quantile) by $Y_2 - Y_1 = (e^{\beta_j} - 1) \times Y_1'$, where Y_1' is the value of sales at the twenty-fifth quantile. The result is the same if we consider a change in a dummy variable, such as direct marketing participation or the impact of gender, on farm sales. The change in the explanatory variable can be an increase in a specific number of years of experience or a change equal to one standard deviation of the explanatory variable.

The standard deviation of the off-farm income variable at the twenty-fifth quantile is 0.917 with a mean of 0.471. The coefficient on the off-farm income variable at the twenty-fifth quantile from the table of unconditional quantile results is 0.044. The coefficient for farmers participating in direct marketing is -1.013 at the twenty-fifth quantile. The percentage change in farm sales for a one-standard-deviation change in off-farm income when the producer is participating has initiated a direct marketing effort equals $(e^{[0.917 \times 0.044 + (-1.013)]} - 1) \times 100 = -62.21\%$. The percentage change in farm sales when the producer has initiated a direct marketing program yet does not experience an increase in off-farm income equals $(e^{[-1.013]} - 1) \times 100 = -63.69\%$. The difference is 1.48%, so that farm sales do not decline as much in this situation.