Use of Direct Marketing Strategies by Farmers and Their Impact on Farm Business Income

Hiroki Uematsu and Ashok K. Mishra

Direct marketing strategies increasingly have been recognized as a viable business option in U.S. agriculture as they allow producers to receive a better price by selling products directly to consumers. The objective of this study is twofold. Using a national survey, we first estimated a zero-inflated negative binomial model to identify factors affecting the total number of direct marketing strategies adopted by farmers. Then we estimated a quantile regression model to assess the impact of the intensity of adoption of direct marketing strategies on gross cash farm income. The results show that the intensity of adoption has no significant impact on gross cash farm income and that participation in farmers markets is negatively correlated with gross cash farm income at all five quantiles estimated.

Key Words: direct marketing strategies, count data, gross cash income, quantile regression

Direct marketing strategies increasingly have been recognized as a viable business option in U.S. agriculture. According to the 2007 Census of Agriculture, the number of farms that reported sales of agricultural products directly to individuals was 136,817, a 17 percent increase since 2002 (USDA 2007). The value of direct marketing sales has increased by about 50 percent over the same period (USDA 2009). Although the Census of Agriculture accounted only for direct sales to individuals, a direct marketing strategy generally includes a wide spectrum of marketing channels such as farmers markets, you-pick operations, consumer cooperatives, sales to local restaurants and grocery stores, and locally branded meats (Buhr 2004, Kohls and Uhl 1998).

The economic incentives of both producers and consumers have contributed to the recent trend in increasing use of direct marketing strategies by U.S. farmers. Direct marketing strategies allow producers to receive a better price by selling products directly to consumers, who increasingly demand fresh and "local" food due to the growing concern for a healthier diet (Govindasamy, Hossain, and Adelaja 1999, Morgan and Alipoe 2001, Uva 2002). Although there is no clear-cut definition of "local," and although what constitutes "localness" is another ongoing debate in the literature (Hand and Martinez 2010, Martinez et al. 2010), consumers are willing to pay more for locally grown products even after controlling for freshness (Darby et al. 2008). The growing initiative to create a sustainable food supply chain is another important driving force in the implementation of a direct marketing strategy by farm operators (Ilbery and Maye 2005). Since the majority of the food products sold through direct marketing strategies are typically sourced locally instead of transported from national or international sources, direct marketing potentially mitigates the environmental impact of food production by reducing the "food miles" in the food supply chain.

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A broad motivation of this study is to provide a comprehensive picture of the degree to which direct marketing strategies are disseminated in the U.S. farm sector and their impact on the economic well-being of U.S. farmers, using a national survey. Specifically, we first estimate a zero-inflated negative binomial model to identify factors affecting the total number of direct marketing strategies adopted by U.S. farmers. Then we estimate a quantile regression model to assess the impact of the intensity of adoption of direct marketing strategies on gross cash farm income.

The rest of the paper is organized as follows. First, we review existing literature on direct marketing strategies in U.S. agriculture. Then we describe the data used in this study. We then provide an empirical model and estimation strategies, as well as variable descriptions. We follow with estimation results, before making some concluding remarks.

Literature Review

The existing literature on direct marketing strategies has mainly focused on the consumer side from two different perspectives (Brown, Gandee, and D'Souza 2006, Monson, Mainville, and Kuminoff 2008). One is consumer preferences for locally sourced food (Ladzinski and Toensmeyer 1983, Gallons et al. 1997, Lehman et al. 1998, Kuches et al. 1999, Thilmany and Watson 2004), and the other is characteristics of consumers purchasing agricultural products through direct marketing strategies (Eastwood, Brooker, and Orr 1987, Schatzer, Tilley, and Moesel 1989, Govindasamy and Nayga 1997, Wolf 1997, Kezis et al. 1998). In contrast, there are relatively fewer studies on the production side of direct marketing strategies (Govindasamy, Hossain, and Adelaja 1999, Brown, Gandee, and D'Souza 2006, Monson, Mainville, and Kuminoff 2008). This section reviews a limited number of such studies.

Brown, Gandee, and D'Souza (2006) identified demographic and economic factors that influence direct marketing strategy sales in West Virginia counties. Factors such as median housing value, population density, proximity to Washington, D.C., and diverse fruit and vegetable production are found to have a positive impact on county-level direct marketing strategy sales. Brown et al. (2007) surveyed vendors at farmers markets in West Virginia to identify factors affecting the total sales at those markets, among other things. The authors found that retired, part-time, or limited resource farmers generated lower income from farmers markets. Using data from a mail survey of Virginia farmers, Monson, Mainville, and Kuminoff (2008) employed an ordered logit model to explain farmers' reliance on direct marketing strategy sales in terms of the share of those sales in the total farm sales. The authors concluded that smaller farms, farms that typically do not produce many small fruits, farms using organic production methods without USDA certification, and farms with small households are the ones most likely to engage in direct marketing. Factors such as farm size, household size, high-value crop enterprises, and the use of organic production methods without USDA certification are positively correlated with the higher share of direct marketing strategy sales to the total farm sales. An interesting feature of the Monson, Mainville, and Kuminoff (2008) study is that the dependent variable is a proxy for the intensity of adoption of direct marketing strategies, although the authors could not differentiate between the direct marketing strategies that contribute to the share of direct marketing strategy sales in the total farm sales.

In contrast, using a survey from New Jersey farmers, Govindasamy, Hossain, and Adelaja (1999) estimated a binary logit model to examine the impact of adopting a series of what they termed "non-traditional agricultural activities," including direct marketing strategies, on the probability of earning "higher" income per acre.[1] They identified use of agrotourism and direct sales to consumers as factors contributing to higher income per acre. Although this study does not account for the intensity of adoption of direct marketing strategies, it could capture the heterogeneous effects of non-traditional agricultural activities on income.

Finally, Goodsell, Stanton, and McLaughlin (2007) provide a detailed listing of direct marketing opportunities available to livestock and poultry producers, including but not limited to the following: classic farm stands, farm-to-retail,

[1] Govindasamy, Hossain, and Adelaja (1999) estimated two models and set a cut-off point between higher and lower income at the median in one model and at the 75th percentile in another.

farmers markets, farm-to-school, farm-to-restaurant, fundraising dinners, fairs and festivals, and mail orders. They indicate that the process of establishing a direct marketing strategy for a livestock producer can be complex because of regulations, but that it is one of the best methods for livestock producers to capture more of the food dollar.

There are two important aspects missing in the existing literature on the production side of direct marketing strategies. First, most studies are limited to a regional or state-level analysis. An exception is Payne (2002), who reports the summary of national survey on farmers markets conducted by the U.S. Department of Agriculture, but the report does not provide any econometric analysis. Second, few studies examined the intensity at which farms incorporate direct marketing strategies into their businesses and their impact on the farm's economic well-being, while controlling for the impact of adopting different direct marketing strategies. We address these two issues in this study. Our analysis uses a large national survey of U.S. farmers spanning multiple regions and farm sizes. By examining the influence of the intensity of adoption of direct marketing strategies on gross cash farm income, this study can provide significant information to U.S. farmers on whether direct marketing strategies should be part of their farm business management plan, contingent on the type and location of the operation.

Data

The study employs data obtained from the nationwide 2008 Agricultural Resource Management Survey (ARMS) conducted by the Economic Research Service (ERS) and the National Agricultural Statistics Service (NASS). The ARMS provides information about the relationships between agricultural production, resources, and the environment, as well as about the characteristics and financial conditions of farm households, management strategies, and off-farm income. Operators associated with farm businesses representing agricultural production in the 48 contiguous states make up the target population of the survey. Data are collected from one operator per farm: the senior farm operator, who makes most of the day-to-day management decisions.

For statistical purposes, the U.S. Department of Agriculture currently defines a farm as an establishment that sold or normally would have sold at least $1,000 of agricultural products during the year (USDA 2005). For the purpose of this study, our sample includes only farms that are classified as family farms that are organized as sole proprietorships, partnerships, or family corporations because they are closely controlled by their operator and the operator's household (USDA 2005). Any operator households organized as nonfamily corporations or cooperatives and farms run by hired managers are excluded from this study because we are interested in farm business decisions made by individual farmers and their family, not by hired managers.

Finally, the fact that the ARMS data has a complex survey design and is cross-sectional raises the possibility that the error terms are heteroscedastic. Using the Breusch-Pagan/Cook-Weisberg test for heteroscedasticity (Judge et al. 1985, p. 446), we rejected the null hypothesis of constant variance of residuals based on $\chi^2_{df=1}$ = 642,263 (p-value = 0.00). Accordingly, all standard errors were adjusted for heteroscedasticity using the Huber-White sandwich robust variance estimator based on algorithms contained in Stata (Huber 1967, White 1980). The robust standard errors were used in all the regression models in lieu of the jackknife variance estimation method, which is a method suitable for estimation of standard errors when the dataset has complex survey design [for further detail in the context of the ARMS, see Kott (1997) and Dubman (2000)], but also for when the dataset is used as a subset rather than in full.

Empirical Model, Estimation Strategy, and Description of Variables

Our econometric analysis consists of two stages. In the first stage, we conduct a count data analysis to estimate the number of direct marketing strategies adopted by farmers. The predicted counts of direct marketing strategies adopted is then used as an instrument in the second stage, to estimate the impact of the intensity of adoption of direct marketing strategies on farm business income using a quantile regression approach.

Factors Affecting the Number of Direct Marketing Strategies Adopted: A Count Data Approach

The count variable is obtained by summing the seven binary variables, each of which represents whether or not a respondent adopts a particular direct marketing strategy. The 2008 ARMS contains specific questions pertaining to the use of direct marketing strategies by farmers. Specifically, the survey queried farmers about whether they have used the following direct marketing outlets or approaches: (i) roadside stores, (ii) on-farm stores, (iii) farmers markets, (iv) regional distributors, (v) state branding programs, (vi) direct sales to local grocery stores, restaurants, or other retailers, and (vii) community-supported agriculture (CSA). Each of the above direct marketing strategies is coded as a binary response variable that takes a value of one when a respondent uses the direct marketing strategy and zero otherwise. Table 1 summarizes these binary response variables. The most frequently used direct marketing strategy in our sample is roadside stores (161 farms), followed by direct sales to local grocery stores, restaurants, or other retailers (153 farms). Although it is often called the most popular direct marketing strategy, only 118 farms reported using farmers markets. Regional distributors, state branding programs, and CSA were used by 57, 27, and 12 farms, respectively.

Table 1. Frequency of Individual Direct Marketing Strategies

Direct Marketing Strategy	Frequency	Percentage
Roadside stores	161	25.39
On-farm stores	106	16.72
Farmers market	118	18.61
Regional distributors	57	8.99
State branding programs	27	4.26
Direct sales to local grocery stores, restaurants, or other retailers	153	24.13
Community-supported agriculture (CSA)	12	1.89
Total	634	100.00

Source: USDA (2008).

In order to construct a variable that represents the intensity of adoption of direct marketing strategies, we count the total number of direct marketing strategies a family farm used in 2008. Table 2 provides descriptive statistics of this variable. Approximately 92 percent of the farms in the sample did not use any direct marketing strategies. Given the fact that 6.2 percent of the total farms reported sales of agricultural products directly to individuals in the 2007 Census of Agriculture (USDA 2007), in terms of use of direct marketing strategies our sample appears to be a good representation of the U.S. farm sector. See Table 2 for the total number of direct marketing strategies adopted.

Table 2. Total Number of Direct Marketing Strategies Adopted

Count	Frequency	Percentage	Cumulative Percentage
0	4,251	91.83	91.83
1	221	4.77	96.61
2	88	1.90	98.51
3	49	1.06	99.57
4	13	0.28	99.85
5	5	0.11	99.96
6	1	0.02	99.98
7	1	0.02	100.00
Total	4,629	100.00	

Source: USDA (2008).

Model selection procedures for a count data analysis involve two issues. The first is to test the distributional assumption of the dependent variable. The basic model for a count data analysis assumes that the count variable has a Poisson distribution in the population. A Poisson distribution assumes that the mean and the variance are equal, but this assumption has to be tested because it does not hold in many empirical applications (Cameron and Trivedi 2005). If this assumption is violated, a common approach is to assume that the dependent variable follows a more flexible negative binomial distribution.

Another issue is the number of observations with zero count. A Poisson or a negative binomial model with a count variable that has a considerable number of observations with zero count results in under-prediction of zero count. If this is a concern, a zero-inflated Poisson (ZIP) or zero-inflated negative binomial (ZINB) model should be used. A zero-inflated counterpart (both ZIP and ZINB) first estimates a binary logit model to determine whether the count is zero or not, after which it conducts a count data analysis (Cameron and Trivedi 2005). The Vuong test can be used to compare a Poisson or a negative binomial model against its zero-inflated counterpart (Cameron and Trivedi 2009).

An important underlying assumption in a zero-inflated model is that it is possible to have a zero count in the second stage. In the context of adoption of direct marketing strategies, the first stage estimates whether or not a particular farm is willing to and capable of adopting any direct marketing strategy, while the second stage estimates the number of direct marketing strategies adopted. A zero count in the second stage indicates that the farmer is willing to adopt and capable of adopting a direct marketing strategy, but the respondent chose not to do so in the 2008 survey period. The farm operator might have adopted direct marketing strategies in the past or may adopt direct marketing strategies in the future, but did not do so at the time of the 2008 survey period. This is an important clarification because, if the possibility of zero count in the second stage is eliminated *a priori*, one would have to estimate a truncated regression model instead of a zero-inflated model.

Our count variable, the total number of direct marketing strategies adopted, has a considerable number of zero counts (92 percent of the sample). Due to the large number of zero counts, the mean number of the total direct marketing strategies adopted is 0.13 with variance equal to 0.28. Because our dependent variable is subject to the two concerns mentioned above, we estimated two models: a negative binomial model and a ZINB model. Results from the negative binomial model[2] show that the test for overdispersion is significant (LR statistic = 135.71, p-value ≤ 0.000), indicating strong evidence in favor of a negative binomial model over a Poisson model.

Next, we estimated the ZINB model to yield the Vuong test statistic that compares the ZINB and negative binomial models. The Vuong test statistic (Z-score of 5.23, p-value ≤ 0.000) suggests significant evidence in favor of the ZINB model. With this result, we decided to maintain the ZINB model to estimate the predicted counts of the total number of direct marketing strategies adopted by farm operators.

The zero-inflated negative binomial (ZINB) model is estimated in two steps. For the first-step logit estimation of whether a farmer is willing to adopt and capable of adopting direct marketing strategies, the independent variables included: direct payments received ($) by the farm, whether the farm received Conservation Reserve Program payments, farm type dummy variables (high-value crop farms and other field-crop farms), distance from the farm to the closest city with a population of at least 10,000, and whether there is an animal product processing facility within 50 miles of the farm.

The independent variables in the second step of the ZINB model include years of formal education for the operator and the spouse, the operator's farming experiences, the primary occupation of the operator and the spouse, and the total number of acres in operation. Although females' human capital in the farm household is sometimes cited as a key determinant of adoption of a direct marketing strategy (Monson, Mainville, and Kuminoff 2008), and although the authors' casual observations at farmers markets seem to support this, it is not confirmed as such in this model.[3]

Also included in the ZINB model are the dummy variable for farms that seek advice from the Natural Resource Conservation Service (NRCS) agents, farm tenure dummy variables (tenants and full owners),[4] farm type dummy variables (dairy, other field crops, high-value crops, and livestock),[5] whether there is an animal product processing facility within 50 miles of the farm, distance from the farm to the closest city with a population of at least 10,000, direct payments received ($) by the farm, whether the farm received payments from the Conservation Reserve Program, whether the farm has access to the

[2] Results from the negative binomial model are not provided here, but are available upon request.

[3] In fact, our model initially included the number of female operators in the first three operators in the farm, but it was highly insignificant, perhaps because of little variability in the variable. The variable was dropped from the model accordingly.

[4] Tenants and full owners are compared to the base group of part owners.

[5] Farm type dummy variables are compared to the base group of farms, whose primary enterprise is either cotton or cash grains.

Internet, and dummy variables for production regions defined in the ARMS data (Atlantic, South, Plains, and West regions).[6] See Table 3 for a list of variables and summary statistics.

The Impact of the Intensity of Adoption of Direct Marketing Strategies on Gross Cash Farm Income: A Quantile Regression

In the second stage, we estimate the impact of the intensity of adoption of direct marketing strategies on gross cash farm income, using quantile regression. In the ARMS, gross cash farm income is defined as a sum of the following items: income from crop and livestock operation, livestock grazing, land rented to others, and other farm-related activities such as production and marketing contracts. We use the logarithm of gross cash farm income as the dependent variable. Specifically, the predicted counts of direct marketing strategies adopted obtained in the first-stage ZINB model are used as a proxy for the intensity of adoption of direct marketing strategies in the second stage.

Quantile regression, originally developed by Koenker and Bassett (1978), enables us to focus on the underlying socioeconomic factors influencing extreme values in the conditional distributions of the dependent variable. Quantiles are to percentiles what probabilities are to percentages. For example, the 0.50 quantile is the 50th percentile. Instead of estimating conditional means, $E(y|x)$, as in OLS, quantile regression can estimate any point on the conditional distribution by estimating conditional quantiles, $Q(\beta_q)$. That is, the qth quantile regression estimator is the one that minimizes the following objective function:

$$(1) \qquad Q(\beta_q) = \min_{\beta \in R^p} \left[\sum_{i \in \{i: y_i \geq x_i \beta\}}^{N} q \,|\, y_i - x_i' \beta_q \,| \; + \sum_{i \in \{i: y_i < x_i \beta\}}^{N} (1-q) \,|\, y_i - x_i' \beta_q \,| \right], \quad q \in (0,1),$$

where q is an arbitrarily chosen quantile, p is the number of parameters to be estimated, y_i is the ith observation of the dependent variable, x_i is a $k \times 1$ vector whose each element is the ith observation of k independent variables, β_q is a $k \times 1$ vector of quantile regression parameters to be estimated, and N is the number of observations (Koenker and Bassett 1978, Cameron and Trivedi 2009).

While OLS minimizes the sum of squared errors, quantile regression minimizes a weighted sum of absolute values of errors with different weights being placed on positive and negative errors, as in equation (1) (Kennedy 2008). The major advantage of quantile regression is the robustness to outliers and heteroskedasticity, as quantile regression estimates conditional quantiles instead of conditional means.

Another advantage is that, while OLS estimates the marginal effects of independent variables at the conditional mean of the dependent variable, quantile regression can estimate the marginal effects of the independent variables at any quantile of the conditional distributions of the dependent variable (Koenker and Hallock 2000). Just as the arithmetical average of a variable often gives an incomplete picture of the distribution of the variable, OLS estimates can be misleading when the conditional distributions of the dependent variable are different across different values of the independent variables (Mosteller and Tukey 1977). Despite these restrictive and naïve assumptions, most applied econometric analyses are concerned with the conditional means (Angrist and Pischke 2008). It is these limitations in OLS that quantile regression can overcome. The advantages of using quantile regression over OLS are particularly important in this study considering the fact that its objective is to provide a comprehensive picture of the degree to which direct marketing strategy is disseminated in the U.S. farm sector, and, to the best of our knowledge, this is the first attempt to do so using data from the nationwide survey. For the sake of comparison, we also estimate the same model with OLS.

Explanatory variables in the quantile regression model include the predicted counts of the total number of direct marketing strategies adopted and dummy variables that represent adoption of each of the seven direct marketing strategies (roadside stores; farm stores; farmers markets; regional distributors; state branding programs; direct sales to local grocery stores, restaurants, and other retailers; and CSA), with the intention to measure

[6] These four regions are compared to the base group of the Midwest region. Refer to USDA (2010) for a map of the NASS production regions.

Table 3. Variable Definitions and Summary Statistics

Variable	Mean	Std. Dev.
Gross cash farm income ($)	855,357	2,957,948
Total number of direct marketing strategies adopted	0.14	0.54
Roadside stores as a direct marketing outlet (= 1 if used, 0 otherwise)	0.03	0.18
Farm stores as a direct marketing outlet (=1 if used, 0 otherwise)	0.02	0.15
Farmers markets as a direct marketing outlet (= 1 if used, 0 otherwise)	0.03	0.16
Regional distributors as a direct marketing outlet (= 1 if used, 0 otherwise)	0.01	0.11
State branding programs as a direct marketing outlet (= 1 if used, 0 otherwise)	0.01	0.08
Direct sales to local grocery stores, restaurants, or other retailers as a direct marketing outlet (= 1 if used, 0 otherwise)	0.03	0.18
Community-supported agriculture (CSA) as a direct marketing outlet (= 1 if used, 0 otherwise)	0.00	0.05
Operator's years of education	13.55	1.89
Spouse's years of education	13.74	1.83
Operator's years of farming experience	27.98	14.82
Operator's primary occupation (= 1 if farming, 0 otherwise)	0.72	0.45
Spouse's primary occupation (= 1 if farming, 0 otherwise)	0.28	0.45
Farm size (total acres operated)	1,577.04	7,819.98
Advice from Natural Resource Conservation Service (NRCS) personnel (= 1 if used, 0 otherwise)	0.12	0.33
Farm tenure – tenant (= 1 if tenant, 0 otherwise)	0.10	0.30
Farm tenure – part owner (= 1 if part owner, 0 otherwise)	0.46	0.50
Farm tenure – full owner (= 1 if full owner, 0 otherwise)	0.44	0.50
Entropy index of diversification	0.01	0.03
Average interest rate charged on loans	1.21	1.68
Dairy farm (= 1 if farm is classified as dairy farm, 0 otherwise)	0.08	0.27
Other field crops farm (= 1 if farm is classified as other field crops farm, 0 otherwise)	0.14	0.35
High-value crops farm (= 1 if farm is classified as high-value crops farm, 0 otherwise)	0.12	0.32
Livestock farm (= 1 if farm is classified as livestock farm, 0 otherwise)	0.44	0.50
Cotton or cash grain farm (= 1 if farm is classified as either cash grain or cotton farm, 0 otherwise)	0.22	0.42
Animal product processing facility (= 1 if farm is within 50 miles of an animal product processing facility, 0 otherwise)	0.02	0.15
Distance (miles) from the farm to closest city with 10,000 or more population	23.59	23.80
Government payments (= 1 if farm receives any government payments, 0 otherwise)	0.56	0.50
Conservation Reserve Program (CRP) payments (= 1 if farm receives CRP payments, 0 otherwise)	11,701.85	31,480.29
Direct payments received ($)	0.16	0.36
Internet (= 1 if farm has an Internet connection, 0 otherwise)	0.78	0.41
Atlantic region (= 1 if the farm is located in the Atlantic region, 0 otherwise)	0.20	0.40
South region (= 1 if the farm is located in the South region, 0 otherwise)	0.19	0.39
Plains region (= 1 if the farm is located in the Plains region, 0 otherwise)	0.18	0.39
West region (= 1 if the farm is located in the West region, 0 otherwise)	0.19	0.39
Midwest region (= 1 if the farm is located in the Midwest region, 0 otherwise)	0.24	0.43
Total number of observations	4,629	

the impact of adopting each direct marketing strategy on gross cash farm income after controlling for the intensity of adoption of direct marketing strategies. We expect the predicted counts of the total number of direct marketing strategies adopted (as a proxy for the intensity of adoption of direct marketing strategies) to have a positive effect on gross cash farm income. The intensity of adoption of direct marketing strategies is expected to have a larger impact on gross cash farm income at lower quantiles. On the other hand, we do not have *a priori* expectations about the signs of individual direct marketing strategy variables, partly because little empirical evidence exists on the relationship between the direct marketing strategies and gross cash farm income.

The entropy index is included to assess the effect of diversification across enterprises on gross cash farm income. The entropy index is a measure of diversification that ranges from 0 to 100, with 0 indicating a farm producing only one commodity and 100 indicating a completely diversified farm (Jinkins 1992, Harwood et al. 1999). Since enterprise diversification is a risk management tool, it is ambiguous *a priori* if a higher degree of diversification leads to a higher income. Variables that represent human capital include operator's education, spouse's education, operator's farming experience, and farming experience squared. Highly educated and more experienced farmers are expected to have higher gross cash farm income (Mishra, El-Osta, and Johnson 1999). Dummy variables for the primary occupation of operators and spouses are also included, with the expectation that farming as a primary occupation leads to higher gross cash farm income (Mishra, El-Osta, and Johnson 1999). As a measure of farm size, the total operated acres and the acres squared are used. Following the economies of scale argument, the acres squared is included to capture nonlinearity between farm size and gross cash farm income. Farms with higher acreage are expected to have higher gross cash farm income, but perhaps at a decreasing rate.

To represent financial performance of the farm, the average interest rate charged on loans is included in the model. Its impact is ambiguous. Although a higher average interest rate on loans may be a sign that the farm is in an undesirable financial position, it may be those farms with a solid business plan that are willing to take and capable of taking on a loan with a higher interest rate. We include the dummy variable for farmers seeking advice from the NRCS agents with the expectation that it has a positive impact on gross cash farm income. Farm tenure variables are also included in the model. Specifically, we include two dummy variables for tenants and part owners, leaving full owners as the base category. Compared to the base category of full owners, tenants and part owners tend to operate large farms and are likely to declare farming as their main occupation. Thus, dummy variables for both tenants and part owners are expected to have a positive impact on gross cash farm income. In order to assess the impact of Internet access on gross cash farm income, we include the dummy variable for the Internet. Following Mishra and Park (2005), we expect that access to the Internet would yield higher gross cash farm income. As in the first stage, dummy variables for dairy, other field crops, high-value crops, and livestock farms are included and tested if certain farm types earn higher gross cash farm income relative to the base group of farms specializing in cotton and/or cash grains. Finally, dummy variables for the Atlantic, South, Plains, and West regions are included in the model to assess regional differences in gross cash farm income relative to the Midwest region. See Table 3 for a definition of variables used in this study and summary statistics.

Results and Discussion

Factors Affecting Intensity of Adoption of Direct Marketing Strategies

Parameter estimates of the zero-inflated negative binomial (ZINB) model are presented in Table 4. The coefficient of operator's years of formal education is positive and significant. Considering the fact that a direct marketing strategy requires a special set of skills and abilities (Uva 2002), some of which may not be directly related to agricultural operations, the positive coefficient on the operator's education is expected. The operator's farming experience has a negative and significant effect on the intensity of adoption of direct marketing strategies, indicating that experienced farmers are unlikely to adopt direct marketing strategies. Findings here support Uva's

Table 4. Parameter Estimates from First-Stage Zero Inflated Negative Binomial Model

Variable	Parameter Estimate	95% Confidence Interval	
Operator's education	**0.112**	0.050	0.174
Spouse's years of education	-0.046	-0.106	0.015
Operator's years of farming experience	**-0.012**	-0.019	-0.005
Operator's primary occupation	**0.443**	0.182	0.703
Spouse's primary occupation	**0.175**	-0.022	0.372
Total acres operated	**-0.00001**	0.000	0.000
Advice from Natural Resource Conservation Service (NRCS) personnel	**0.421**	0.099	0.743
Farm tenure – tenant	-0.192	-0.576	0.192
Farm tenure – full owner	-0.075	-0.290	0.140
Dairy farm	0.538	-0.252	1.327
Other field crops farm	**1.109**	0.410	1.808
High-value crops farm	**1.078**	0.413	1.744
Livestock farm	**0.605**	-0.019	1.229
Animal product processing facility	**0.509**	0.153	0.866
Miles to closest city with 10,000 or more population	0.001	-0.005	0.007
Direct payment received ($)	**-0.000003**	0.000	0.000
Conservation Reserve Programs (CRP) payments	**0.619**	0.027	1.211
Internet	**0.242**	-0.040	0.524
Atlantic region	0.218	-0.045	0.482
South region	**-0.366**	-0.699	-0.033
Plains region	**-0.376**	-0.787	0.036
West region	**-0.732**	-1.037	-0.428
Intercept	**-2.241**	-3.377	-1.105
Inflation model = logit			
Direct payment received ($)	**0.00001**	-0.000003	0.00003
Conservation Reserve Program (CRP) payments	**1.685**	0.891	2.479
High-value crops farm	**-3.863**	-4.548	-3.178
Other field crops farm	**-0.739**	-1.284	-0.194
Miles to closest city with 10,000 or more population	**0.005**	-0.006	0.017
Animal product processing facility	**-4.783**	-6.339	-3.227
Intercept	**2.455**	0.020	0.650
alpha	0.113		
Log likelihood = -1249.251 LR χ^2 (22) = **126.26**			
Vuong test of ZINB vs. standard negative binomial: Z = **5.23**			

Note: Bold indicates significance at the 10 percent level.

(2002) argument that a direct marketing strategy requires a set of skills different from those for agricultural operations.

Results in Table 4 show that the coefficients of farming as a primary occupation are positive and significant for both operators and spouses, indicating that farmers and spouses who consider farming as their main occupation are likely to adopt more direct marketing strategies. This is also consistent with the aforementioned skill requirements to adopt a direct marketing strategy. The effect of farm size in terms of the total operated acres on adoption of direct marketing strategies is found to be negative and significant. This is consistent with the general understanding that, compared to large farms, smaller farms tend to rely more on direct marketing strategies. Further, large farms are likely to grow commodity crops and receive government program payments to support farm business income. A positive and significant coefficient of the dummy variable for farmers seeking advice from the NRCS professionals indicates its positive effect on adoption of direct marketing strategies.

Three of the four farm-type variables—other field crops, high-value crops, and livestock farms—have a significant and positive effect on the intensity of adoption of direct marketing strategies, compared to the base category of cash grain farms and cotton farms. This finding is consistent with Figure 1, which shows a breakdown of direct marketing strategy sales by farm type. Other field crop, high-value crop, and livestock farms are more likely to adopt direct marketing strategies at a higher intensity than cash grain farms and cotton farms. The availability of an animal product processing facility within 50 miles of the farm yields a positive coefficient, suggesting that being in close proximity to such a facility helps livestock farms to adopt more direct marketing strategies. Direct payments received by the farm ($) had a negative and significant coefficient, while the dummy variable for CRP payments has a positive and significant effect on the intensity of adoption of direct marketing strategies. This is, however, consistent with the prior discussion about farm types and skill requirements. Just as cash grain farms are less likely to adopt direct marketing strategies, farms that receive more direct payments (regardless of their farm type) are also less likely to adopt direct marketing strategies because direct payments are tied to production of commodity crops like wheat, cotton, corn, soybean, and others. A positive correlation between CRP payments and direct marketing strategies adoption is plausible, as farms with more land retired from production are expected to have higher labor availability, of course, after controlling for primary occupation. Having access to the Internet on the farm is positively correlated with the intensity of adoption of direct marketing strategies. It is likely that Internet access is necessary to set up a successful direct marketing strategy. It may also help farmers to expand the scope of direct marketing opportunities. NASS production regions also yielded significant impact on adoption of direct marketing strategies. Relative to the Midwest region, farms in the Southern, Plains, and West regions are all less likely to adopt direct marketing strategies, whereas farms in the Atlantic region are not significantly different from the Midwest region.

The Impact of the Intensity of Adoption of Direct Marketing Strategies on Gross Cash Farm Income

Results from the second-stage quantile regression are presented in Table 5. The second column in Table 5 presents parameter estimates from the OLS model with robust standard errors. The third through seventh columns are parameter estimates from the quantile regression, evaluated at the 0.10, 0.25, 0.50 (median), 0.75, and 0.90 quantiles. The last column shows the Wald F-test statistics that examine the null hypothesis that all quantile estimates are not significantly different from each other.

Results in Table 5 show that the coefficient of the intensity of adoption of direct marketing strategies obtained from the first-stage ZINB model is not significant at all quantiles, nor in the OLS results. Contrary to our expectation, the intensity of adoption of direct marketing strategies is found to have no significant impact on gross cash farm income. The fact that there are only 20 observations with four or more direct marketing strategies adopted is the potential cause for this insignificance. Another possible explanation is that adopting multiple direct marketing strategies may be a risk management tool rather than a profit-maximizing strategy. Also, if each direct market-

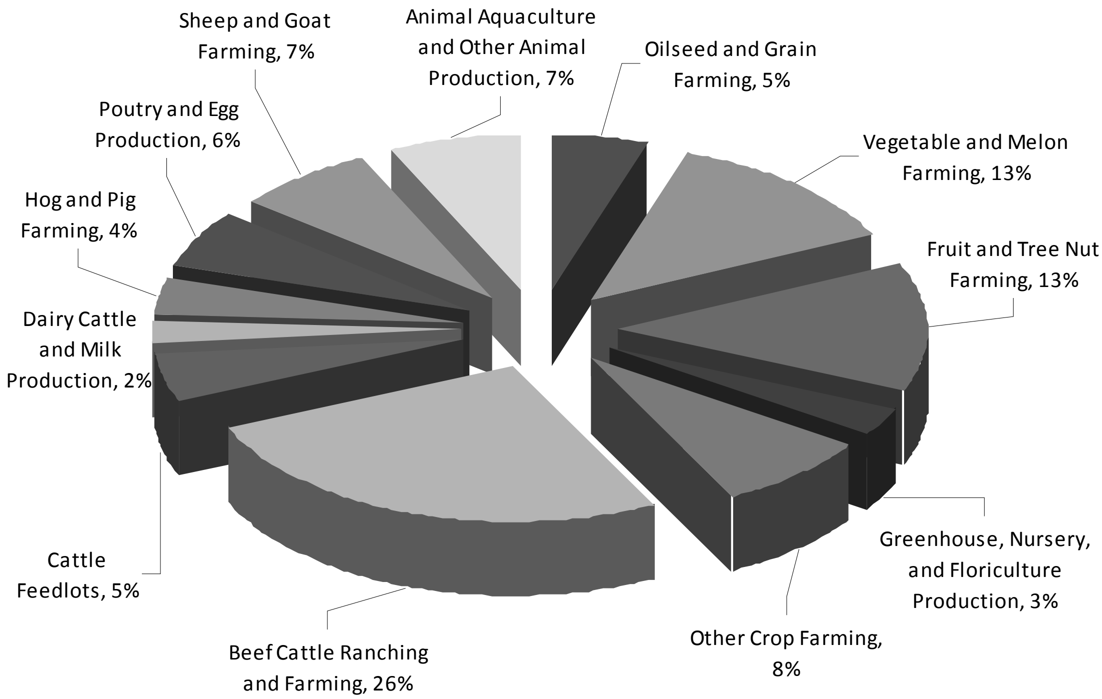

Figure 1. Distribution of Direct Marketing in the United States for 2007
Source: USDA (2007).

ing strategy included in this model requires a different set of skills and abilities, as discussed earlier, the farmers may prefer to concentrate on and expand the direct marketing strategy that is already in place rather than to implement a new strategy, because of the additional labor requirement, learning cost, and other fixed costs associated with adoption.

Even though the intensity of adoption does not seem to have any impact on gross cash farm income, adoption of individual direct marketing strategies showed some significant effect on gross cash farm income. Quantile regression estimates reveal that marketing through roadside stores had a negative and significant effect on gross cash farm income at the 0.25, 0.50, and 0.75 quantiles. However, sales through farm stores had a positive and significant effect on gross cash farm income for all but the 0.90 quantiles. Finally, parameter estimates for farmers markets were unexpectedly negative and significant at all quantiles.

There are many possible explanations for this unexpected result. First, in comparison to other direct marketing strategies, farmers who sell their products at farmers markets may be exposed to greater competition within the confines of those markets. Participation in farmers markets is often cited in the literature as the most popular direct marketing strategy and considered "the historical flagship of local food system" (Brown and Miller 2008, p. 1296). A 91 percent increase in farmers markets from 1998 to 2009 is reported, as the number grew from 2,756 to 5,274 (Martinez et al. 2010). Perhaps for this very reason, farmers market participants are forced to charge prices that are lower than what they would have charged at other direct marketing outlets, such as farm stores and CSA, where they are exposed to a relatively lower degree of competition.

Second, empirical evidence suggests that some farmers markets are failing, despite their increasing popularity. Stephenson, Lev, and Brewer (2008) report that, from 1998 to 2005 in Oregon, 62 new farmers markets opened, while 32 existing farmers markets ceased to operate. They report that unsuccessful farmers markets tend to

Table 5. Parameter Estimates of Second-Stage Quantile Regression Model

		Quantile Regression Parameter Estimates					
		Estimated Quantiles					Wald
Variables	OLS	0.10	0.25	0.50	0.75	0.90	F-Score
Predicted counts of the total number of direct marketing strategies adopted	-0.143	-0.374	-0.004	-0.185	-0.214	-0.143	0.67
Roadside stores	**-0.571**	-0.439	**-0.927**	**-0.508**	**-0.310**	-0.098	**2.10**
Farm stores	**0.740**	**0.979**	**0.890**	**0.733**	**0.362**	0.166	1.82
Farmers markets	**-0.978**	**-0.759**	**-0.882**	**-1.210**	**-1.035**	**-0.954**	0.64
Regional distributors	**0.553**	**1.080**	0.396	0.255	0.439	0.488	1.55
State branding programs	0.078	0.350	0.299	0.344	0.205	0.392	0.07
Direct sales to local grocery stores, restaurants, or other retailers	**0.447**	0.022	0.197	0.281	**0.494**	**0.377**	0.54
Community-supported agriculture (CSA)	-0.228	-0.062	-0.306	0.235	-0.349	**-0.786**	0.58
Entropy index of diversification	**16.988**	**12.134**	**17.486**	**20.556**	**36.327**	**51.237**	**13.80**
Operator's years of education	**0.029**	-0.017	0.032	**0.032**	**0.028**	0.021	1.14
Operator's farming experience	**0.042**	**0.038**	**0.050**	**0.039**	**0.034**	**0.027**	1.38
Operator's farming experience squared	**-0.001**	**-0.001**	**-0.001**	**-0.001**	**-0.001**	**-0.0004**	1.66
Spouse's years of education	**0.029**	**0.054**	0.011	**0.028**	0.027	**0.038**	0.84
Operator's primary occupation	**1.755**	**1.447**	**1.658**	**1.947**	**1.794**	**1.277**	**12.23**
Spouse's primary occupation	**0.321**	**0.415**	**0.354**	**0.281**	**0.133**	0.062	**3.80**
Total acres operated	**0.001**	**0.0001**	**0.0001**	**0.0001**	**0.0001**	**0.0001**	1.00
Total acres operated squared	**-0.000**	-0.000	-0.000	-0.000	-0.000	**-0.000**	0.47
Average interest rate charged on loans	**0.186**	**0.212**	**0.194**	**0.143**	**0.097**	**0.061**	**9.45**
Advice from Natural Resource Conservation Service (NRCS) personnel	**0.118**	0.122	0.068	-0.006	0.022	0.051	0.41
Farm tenure – tenant	**1.010**	**1.530**	**1.177**	**0.910**	**0.733**	**0.461**	**9.33**
Farm tenure – part owner	**0.643**	**1.071**	**0.873**	**0.564**	**0.460**	**0.360**	**8.44**
Internet	**0.472**	**0.306**	**0.353**	**0.435**	**0.568**	**0.500**	1.74
Government payments	**0.644**	**1.003**	**0.949**	**0.652**	**0.454**	**0.269**	**9.83**
Dairy farm	**0.822**	**0.650**	**0.662**	**0.767**	**0.803**	**0.855**	0.45
Other field crops farm	**-0.970**	**-1.604**	**-1.185**	**-0.803**	**-0.311**	-0.032	**19.47**
High-value crops farm	**0.584**	**0.487**	**0.602**	**0.779**	**0.908**	**0.915**	0.76
Livestock farm	**-0.781**	**-1.175**	**-0.985**	**-0.725**	**-0.503**	**-0.338**	**11.14**
Atlantic region	-0.113	**-0.508**	-0.116	-0.125	0.063	-0.048	**4.55**
South region	-0.115	**-0.257**	-0.163	**-0.311**	-0.080	-0.063	**2.46**
Plains region	-0.012	-0.108	0.056	-0.116	-0.041	0.023	1.89
West region	0.054	-0.031	0.055	**-0.150**	**-0.155**	-0.050	1.38
Intercept	7.607	**6.262**	**6.778**	**7.808**	**8.682**	**9.759**	

Note: Bold indicates significance at the 10 percent level. Dependent variable = log(gross cash farm income).

have a small size, less product variety, and inadequate administrative resources, such as low revenue and inexperienced managers because of a high turnover. Again, perhaps because of their popularity, there may exist a considerable competition not only within a farmers market but also among different farmers markets to attract a sufficient number of vendors to generate revenue to keep the market financially viable.

Third, the economic cost of farmers market participation may be substantial, while revenue from them may not be as high as one might expect. For example, in Iowa only 30 percent of participants in farmers markets in 2004 reported sales greater than $5,000 (Varner and Otto 2008). On the other hand, in New Jersey, variable cost of farmers market participation for a 20-week season is estimated at $6,410, excluding production costs (Rutgers Food Innovation Center 2009). Although we cannot simply conclude that farmers markets are not profitable by comparing these two results conducted in different parts of the country, profit margins at farmers markets may be very slim. Because local food markets have relatively shorter supply chains, direct marketing strategies often impose additional labor requirements to producers such as storage, packaging, transportation, and advertising (Martinez et al. 2010). But there are some costs that may be unique to farmers markets. For example, vendors may need to clear the inventory of perishable products even below the marginal cost at the end of the day as farmers markets are typically open only a few days a week.[7]

Despite the negative and significant impact on gross cash farm income, there may be reasons for farmers to continue participating in farmers markets and for policymakers to continue to endorse them as the flagship of local food systems. First, farmers markets can be a risk management tool because they provide producers with additional marketing opportunities (Rutgers Food Innovation Center 2009). Therefore, participation in farmers markets may increase intertemporal utility of risk-averse farmers even if it decreases gross cash farm income in a given year. Second, farmers markets may be used to promote other direct marketing channels such as CSA and to socialize with other farmers and consumers in the community.[8] Third, farmers can develop their entrepreneurial skills through participating in farmers markets (Feenstra et al. 2003). Finally, it is important to note that some portion of producers' lost profit margin induced by competition at farmers markets is shifted to consumers in the form of lower prices, possibly resulting in an increase in the total surplus from a social welfare standpoint.

The coefficient of marketing farm products through regional distributors is positive and significant at the 0.10 quantile. The coefficient of direct sales to local grocery stores, restaurants, and other retailers has a positive and significant effect on gross cash farm income at the 0.75 and 0.90 quantiles. This may be an indication that sales through regional distributors are more suitable for farms with smaller gross cash farm income, while farms with larger gross cash farm income can profit from direct sales to local grocery stores and restaurants, which tend to be a higher volume transaction. Finally, the coefficient of direct marketing strategy through community-supported agriculture is negative and significant at the 0.90 quantile, suggesting that at the higher gross cash farm income farmers are not profiting from CSA, perhaps due to commodity specialization or the fact that farms may not be producing commodities that are being demanded by consumers through direct sales. It is important to note, however, that the Wald test statistic for all but one of the seven direct marketing strategies as well as the intensity of adoption of direct marketing strategies are insignificant, indicating that estimated coefficients are not significantly different at different quantiles. The exception is roadside stores; the impact on gross cash farm income of selling products at roadside stores is different across different quantiles. Nonetheless, considering the paucity of empirical research on the impact of direct marketing strategies on the economic well-being of farmers, the finding that the effect of direct marketing strategies adoption on gross cash farm income is mostly not statistically different across different quantiles on a national scale is an important addition to the existing lit-

[7] This may not be the case if there are multiple farmers markets within a reasonable proximity, allowing a farm to sell at farmers markets more often. We thank the reviewer for this comment.

[8] We thank the reviewer for this comment.

erature on the use of direct marketing strategies in the U.S. farm sector.

The entropy index of diversification has a positive and significant coefficient at all quantiles, and the magnitude of the coefficient increases with quantiles. The Wald test statistic ($F = 12.83$, p-value = 0.000) confirms that the impact of diversification on gross cash farm income differs across quantiles. The operator's years of education has a positive and significant effect on gross cash farm income only at the 0.50 and 0.75 quantiles. The spouse's educational attainment also has a positive and significant effect on gross cash farm income at the lowest quantile (0.10), the median (0.50), and the highest quantile (0.90).

While the operator's farming experience has a positive and significant effect on gross cash farm income at all quantiles, experience squared has a negative and significant impact on gross cash farm income at all quantiles, confirming the expectation that the marginal impact of farming experience on gross cash farm income is increasing at a decreasing rate. However, the Wald test statistic shows that this trend is not significantly different across quantiles. Farming as a primary occupation is positively correlated with gross cash farm income for operators and spouses, and its impacts are different across quantiles for both operators and spouses.

Farm size in terms of the total number of acres in operation has a positive and significant effect on gross cash farm income at all quantiles. The average interest rate charged on loans has a positive and significant impact on gross cash farm income at all quantiles, and the positive impact is larger at smaller quantiles. This is perhaps due to the fact that smaller farms may tend to be more financially constrained, and thus that small farms that are willing to take on a higher interest rate are likely to have a solid business plan. Higher interest payments may reflect the debt-repaying capacity of the farm. Higher interest rates on borrowed capital may be associated with energetic and dynamic farmers, or entrepreneurs and innovators (Bowler 1992). Another possible explanation is that higher interest rates might also be indicative of the farm business having borrowed in order to upgrade the commitment to agriculture (Goodwin and Mishra 2000, Mishra, El-Osta, and Sandretto 2006).

Two dummy variables for farm tenure (tenants and part owners) both have positive and significant impact on gross cash farm income at all quantiles, indicating that, compared to full owners, tenant and part owners have higher gross cash farm income. This is consistent with the fact that part owners and tenants tend to operate larger farms and have larger sales than full owners (USDA 1998). Further, the Wald test statistics are significant for both tenants and part owners, indicating that the impact of farm tenure on gross cash farm income differs across quantiles. The coefficient of having Internet access is positive and significant at all quantiles, but the estimates are not significantly different across quantiles. The dummy variable for government payments has a positive impact on gross cash farm income across all quantiles. The Wald test statistic of 9.83 confirms that the impact of government payments is statistically different across various quantiles.

Farm type dummy variables yielded mostly significant estimates. Again, the base group consists of a combination of cotton farms and cash grain farmers. The coefficients of dairy farms and high-value crop farms are positive and significant at all quantiles. Quantile regression coefficients are negative and significant at all quantiles in the case of livestock farms, and are negative and significant at all but the 0.90 quantile for other field-crop farms. For both variables, the negative magnitude of the coefficient is larger for smaller quantiles, confirmed by the large Wald statistics ($F = 11.14$ for livestock farms and $F = 19.47$ for other field-crop farms). This may be evidence of economies of scale in these enterprises.

Because the dependent variable is in a log form, coefficient estimates are not marginal effects. Tables 6a and 6b provide marginal effect estimates of discrete regressors and elasticity estimates of continuous regressors, respectively, from the quantile regression model. Cameron and Trivedi (2009) recommend using the average marginal effects (AME) by multiplying the estimated coefficients and the exponentiated linear predictions of the dependent variable at each quantile. However, we opted to use sample quantiles of the dependent variable because the exponentiated linear predictions over-predicted the quantiles by a large margin with a wide confidence interval.[9]

A caveat to these marginal effects and elasticity estimates is that the confidence intervals of the

[9] Confidence interval estimates are available upon request.

Table 6a. Marginal Effect Estimates of Discrete Regressors from Quantile Regression Model

	Marginal Effect Estimates ($)				
	Estimated Quantiles				
Variables	0.10	0.25	0.50	0.75	0.90
Predicted counts of the total number of direct marketing strategies adopted	-1,172	-67	-30,302	-160,131	-291,594
Roadside stores	-1,375	**-16,121**	**-83,187**	**-232,540**	-198,425
Farm stores	**3,067**	**15,473**	**120,097**	**271,783**	338,140
Farmers markets	**-2,379**	**-15,342**	**-198,174**	**-776,282**	**-1,940,909**
Regional distributors	**3,385**	6,885	41,735	329,244	992,494
State branding programs	1,097	5,197	56,310	153,917	796,523
Direct sales to local grocery stores, restaurants, or other retailers	68	3,432	45,995	**370,637**	**767,174**
Community-supported agriculture (CSA)	-196	-5,328	38,431	-261,701	**-1,598,375**
Operator's years of education	-52	550	**5,219**	**20,672**	43,299
Spouse's years of education	**170**	188	**4,514**	20,111	**77,111**
Operator's primary occupation	**4,534**	**28,849**	**318,872**	**1,345,214**	**2,597,449**
Spouse's primary occupation	**1,302**	**6,160**	**46,062**	**99,754**	126,877
Average interest rate charged on loans	**665**	**3,373**	**23,340**	**72,994**	**123,795**
Advice from Natural Resource Conservation Service (NRCS) personnel	384	118	-929	16,380	104,224
Farm tenure – tenant	**4,795**	**20,471**	**148,948**	**549,623**	**938,332**
Farm tenure – part owner	**3,356**	**15,181**	**92,339**	**344,896**	**731,465**
Internet	**960**	**6,146**	**71,280**	**425,750**	**1,016,701**
Government payments	**3,143**	**16,514**	**106,844**	**340,216**	**547,859**
Dairy farm	**2,038**	**11,524**	**125,565**	**602,210**	**1,739,033**
Other field crops farm	**-5,027**	**-20,619**	**-131,506**	**-232,889**	-66,036
High-value crops farm	**1,525**	**10,465**	**127,578**	**681,016**	**1,860,784**
Livestock farm	**-3,683**	**-17,135**	**-118,755**	**-377,381**	**-688,074**
Atlantic region	**-1,593**	-2,020	-20,498	47,076	-96,807
South region	**-805**	-2,829	**-51,002**	-60,091	-127,781
Plains region	-339	974	-19,054	-30,754	46,101
West region	-99	952	**-24,604**	**-116,515**	-101,723

Note: Bold indicates significance at the 10 percent level. Marginal effects are estimated using sample quantiles of regressors.

Table 6b. Elasticity Estimates of Continuous Regressors from Quantile Regression Model

Variable	Estimated Quantiles				
	0.10	0.25	0.50	0.75	0.90
Entropy index of diversification	**0.12**	**0.17**	**0.20**	**0.36**	**0.50**
Operator's farming experiences	**1.07**	**1.40**	**1.09**	**0.94**	**0.76**
Operator's farming experiences squared	**-0.50**	**-0.72**	**-0.61**	**-0.48**	**-0.37**
Total acres operated	**0.21**	**0.17**	**0.18**	**0.21**	**0.23**
Total acres operated squared	**-0.06**	-0.04	-0.03	-0.03	**-0.03**

Note: Bold indicates significance at the 10 percent level. Elasticities are estimated at the sample means of regressors.

estimates tend to become very large at the higher quantiles, especially for direct marketing strategy variables. This could be due to the fact that only about 8 percent of farms in the sample adopted at least one direct marketing strategy, and it is those farms with lower gross cash farm income that are more likely to adopt a direct marketing strategy. Therefore, we limit literal interpretation of the marginal effects and elasticity estimates of direct marketing strategy variables at the lower quantiles (0.10 and 0.25), as it may not carry practical meaning at the higher quantiles because of the wide confidence intervals.

Given the unexpected finding that participation in farmers markets has a negative impact on gross cash farm income, the degree to which it affects gross cash farm income is of interest. Marginal effect estimates (Table 6a) show that participation in farmers markets could decrease gross cash farm income by $2,379 and $15,342 at 0.10 and 0.25 quantiles, respectively, *ceteris paribus*. The marginal effect of selling products at roadside stores is also found to be negative; at the 0.25 quantile of the conditional distribution of gross cash farm income, selling products at a roadside store decreases gross cash farm income by $16,121. The marginal effect of using farm stores is positive; it increases gross cash farm income by $3,067 at the 0.10 quantile and by $15,473 at the 0.25 quantile. The marginal effect of selling products through regional distributors increases gross cash farm income by $3,385 at the 0.10 quantile, but it is not significant at the higher quantiles.

An additional year of education increases gross cash farm income by $5,219 for the operator and $4,514 for the spouse at the 0.50 quantile, suggesting the relative importance of the operator's human capital over that of the spouse's. The marginal effect of having Internet access is $960 at the 0.10 quantile, but about $1 million at the 0.90 quantile. Although these estimates are vastly different, they are both about half of the gross cash farm income at the respective quantiles.

Elasticity estimates (Table 6b) show that a 1 percent increase in the entropy index leads to a 0.12 percent increase in gross cash farm income at the 0.10 quantile and about 0.50 percent at the 0.90 quantile, suggesting an increasing positive impact of enterprise diversification on gross cash farm income, which is consistent with Mishra, El-Osta, and Sandretto (2006). The estimated elasticity for the operator's farming experience is positive at all the quantiles and ranges from 0.76 (at the 0.90 quantile) to 1.40 (at the 0.25 quantile). On the other hand, the operator's farming experience squared has a negative elasticity estimate at all quantiles. The percentage change in gross cash farm income with respect to a 1 percent increase in farming experience ranges from 0.39 (at the 0.90 quantile) to 0.68 (at the 0.25 quantile). The elasticity of gross cash farm income with respect to farming experience is positive but inelastic at all the quantiles.

The analogous elasticity estimates for the total acres in operation and the total acres squared range from 0.15 percent (at the 0.10 quantile) to 0.20 percent (at the 0.90 quantile). The elasticity of gross cash farm income with respect to the total operated acres is also positive, but inelastic at all the quantiles.

Conclusions

The objective of this study was to estimate the relationship between the intensity of adoption of direct marketing strategies and the economic well-being of U.S. farmers. We employed quantile regression to estimate the relationship at various points in the conditional distributions of the dependent variable, which is gross cash farm income. In doing so, we first conducted a count data analysis and estimated a zero-inflated negative binomial model (ZINB) to obtain the predicted counts of the total number of direct marketing strategies adopted. The predicted counts were used as a proxy for the intensity of adoption of direct marketing strategies in the second-stage quantile regression, in which we obtained two unexpected results. One was that the intensity of adoption of direct marketing strategies was not found to be significant at any quantile. We posited several explanations for this unexpected result. First and foremost, the small number of observations with four or more direct marketing strategies adopted is the likely cause of the insignificant estimate. Second, this may indicate that a direct marketing strategy is a risk management tool rather than a profit-maximizing strategy. Third, it may be due to additional labor requirements necessary to implement a new direct marketing strategy, as each direct marketing strategy may demand a unique set of skills and abilities.

The other unexpected finding was the negative impact of participation in farmers markets on gross cash farm income at all quantiles. We proposed that this unexpected result can be attributed to several factors, such as competition among producers in a farmers market, competition among farmers markets, inadequate management resources, a low profit margin, and intermittent operation. We also discussed why farmers may continue to participate in farmers markets despite such participation's negative impact on their economic well-being from economic and sociological perspectives. An important question that remains but that is beyond the scope of this study is: What lies ahead for farmers markets if there are few economic incentives for participation? Despite these unexpected results, this study fulfilled our primary motivation to provide a comprehensive picture of the degree to which direct marketing strategies are disseminated in the U.S. farm sector and their impact on the economic well-being of the U.S. farmers as of 2008.

Finally, some of the challenges that we experienced in this study are noted here. First and foremost, the 2008 ARMS data has a small number of observations of farms that implemented direct marketing strategies. In our sample, only 378 out of 4,629 farms implemented at least one direct marketing strategy, and only 20 farms implemented 4 or more (Table 2). It is likely that this sample reflects the actual status of direct marketing strategies in U.S. agriculture, as direct marketing strategy sales account for a growing but small share of the farm sector sales (Martinez et al. 2010), but it may have caused the wide confidence intervals for coefficients, marginal effects, and elasticity estimates, especially at the higher quantiles, possibly causing some estimates to be statistically insignificant. Another challenge we faced was that our model could not capture the intensity of adoption of each direct marketing strategy and possibly heterogeneous skill requirements for different direct marketing strategies. Delineating the relationship between skill requirements and the intensity of adoption of different direct marketing strategies and their impact on gross cash farm income would be an exciting topic for another study. Future research will address these challenges and build on our first attempt to explore the impact of the intensity of adoption of direct marketing strategies on the economic well-being of U.S. farms, using a national survey.

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