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**Farm Operator Benefits from Direct Marketing Strategies:  
How Does Local Food Impact Farm Financial Performance?**

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## **Farm Operator Benefits from Direct Marketing Strategies: How Does Local Food Impact Farm Financial Performance?**

### *Abstract*

In the era of a global economy, farmers face increasing pressure in developing a portfolio of various marketing channels. However, the literature on direct marketing strategies has mainly focused on consumers. Using farm-level data this study investigates factors associated with the choice of three direct marketing strategies. We apply a selectivity based approach for the multinomial logit model to assess the relationship between the choice of direct sales marketing strategy on the financial performance of the business. Findings from this study suggest that obtaining an Internet connection and accessing the Internet for farm commerce increases the likelihood of using intermediated marketing outlets. Using the Internet for farm commerce and operating diversified farms (more enterprises) is associated with increases in the likelihood that the farmer relies on direct to consumer marketing outlets. The gender of the operator, the portfolio of input acquisition and management practices, and participation in Federal, State, or local farm program payments is positively associated with total farm sales in all three direct marketing strategies. Finally, an accurate evaluation of the projected earnings from the direct-to-consumer marketing outlet must account for selectivity effects.

**Key words:** direct marketing outlets, multinomial logit, farm sales, selectivity correction

## **Farm Operator Benefits from Direct Marketing Strategies: How Does Local Food Impact Farm Financial Performance?**

### **1. Introduction**

According to the 2007 Census of Agriculture, 136,817 farms implemented a form of direct marketing strategy (DMS). Moreover, the number of farm operators incorporating direct marketing into their farm business model increased by 17 percent from 2002 to 2007 (Detre et al. 2010). Over the same period, farmers saw the value of direct marketing sales increase by 49 percent. A direct marketing strategy (DMS) applies to both crop and livestock products/commodities. Examples of DMS employed by farmers included use of farmers markets, you-pick operations, consumer cooperatives, and locally branded meats (Kohls and Uhl, 1998; Buhr, 2004).

DMSs allow producers to receive a better price by directly selling the products to the consumers who have increasing demand for fresh and “local” food due to the growing concern for a healthier diet (Govindasamy et al. 1999; Morgan and Alipoe 2001; Uva 2002). Although there is no clear-cut definition of “local” and what constitutes the “localness” is another on-going debate in the literature (Hand and Martinez 2010; Martinez et al. 2010), some 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 DMS by farm operators (Ilbery and Maye 2005). Finally, since the majority of the food products sold through DMSs is typically sourced locally instead of transported from national or international sources, direct marketing potentially mitigates the impact on the environment by reducing the carbon footprint in the food supply chain.

Although there is a plethora of literature on direct marketing strategies as it pertains to consumer desirability and the attributes of consumers who buy directly from producers, there are relatively fewer studies that focus on the production side (Brown et al. 2006; Govindasamy et al. 1999; Monson et al. 2008), such as examining producer behavior regarding DMSs and how participation in DMSs affects farm business income.

A review of literature reveals two aspects of the current literature on DMSs that is relatively scarce. First, most studies are limited to a regional or state-level analysis. A broad motivation of this study is, therefore, to provide a comprehensive picture of DMSs used in U.S. farming. In particular, we investigate the factors affecting choices of direct sales by farmers in (1) direct-to-consumer outlet, DTC, (such as roadside stand, or on-farm facility, on-farm store, farmer's market, community supported agriculture); (2) intermediated retail outlet, IMOs (such as direct sales of local grocery stores, regional distributor, and state branding programs); and (3) both DTC and IMOs (this combines category 1 and 2 mentioned above).<sup>1</sup> A secondary objective of this study is to assess the impact of choice of direct sales on the financial performance of the business. This study also follows up on the limitations mentioned in Detre et al. (2010) in that we will identify the DMS used by farmers to determine its effect on farm income.

By examining the influence of choice of direct sales on earnings, the study can provide significant information to U.S. farmers on whether a particular choice of direct sales should be part of their farm business management plan, contingent on the type and location of the operation. The analysis is conducted on a national farm-level basis with the unique feature of a large sample, comprising farms of different economic sizes, and in different regions of the United States.

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<sup>1</sup> Farms with no direct sales outlets will be used as the base group.

The empirical approach is based on a discrete choice model where producers select a set of marketing channels for agricultural output. McFadden (1986) developed the economic choice theory underlying the multinomial logit model and highlighted its value in linking discrete choice behavior (choice of market outlet) with continuous decisions (sales revenue in each outlet). Ofek and Srinivasan (2002) demonstrated how market valuation of improved product attributes that account for competition from other brands, potential market expansion, and heterogeneous consumer preferences can be derived from the multinomial logit framework.

We account for selectivity bias in the observed earnings from a marketing outlet, recognizing that producers choose from a set of marketing options to obtain the highest returns. Trost and Lee (1984) initially extended the polychotomous choice model based on a multinomial logit specification with selectivity corrections to show that returns to education are underestimated when selectivity is neglected. We apply a selectivity bias approach for the multinomial logit model from Bourguignon, Fournier, and Gurgand (BFG 2007), highlighting its advantages over current methods in the section that develops the econometric model.

## **2. Literature Review**

The existing literature on DMSs has mainly focused on consumers from two different perspectives (Brown et al. 2006; Monson et al. 2008). First, consumer preferences for locally sourced food (Gallons et al. 1997; Kuches et al. 1999; Ladzinski and Toensmeyer 1983; Lehman et al. 1998; Thilmany and Watson 2004) and secondly, the identification of the characteristics of consumers purchasing agricultural products through DMSs (Eastwood et al. 1987; Govindasamy and Nayga 1997; Kezis et al. 1998; Schatzer et al. 1989; Wolf 1997).

Brown et al. (2006) identified demographic and economic factors that influence DMS sales in West Virginia counties. Factors such as median housing value, population density,

proximity to Washington D.C., and diverse fruit and vegetable productions are found to have a positive impact on county-level DMS sales. The authors also found that retired, part-time, or limited resource farmers generated a lower income from a farmers' market.

Monson et al. (2008) employed an ordered logit model to explain farms' reliance on DMS sales in terms of share of DMS sales in total farm sales using data from a mail survey of Virginia farmers. The authors concluded that farm size, household size, high-value crop enterprises, and non-certified organic production are positively correlated with higher share of DMS sales to total farm sales. Monson et al. (2008), in their survey of Virginia farmers, found that smaller farms, farms that typically do not produce many small fruits, farms that are non-USDA certified organic, and farms with small households are the ones most likely to engage in direct marketing. An interesting feature of Monson et al. (2008) is that the dependent variable is a proxy for adoption intensity of DMSs, although the authors could not distinguish between DMSs that contribute to the share of DMS sales in total farm sales.

In contrast, Govindasamy et al. (1999) estimated a binary logit model to examine the impact of adopting a series of what they term "non-traditional agricultural activities" including DMSs on the probability of earning "higher" income per acre<sup>2</sup> using a survey from New Jersey farmers. They identified factors that contributed to higher income per acre, such as use of agrotourism and direct sales to consumers. Although this study does not account for adoption intensity of DMSs, it could capture heterogeneous effects of non-traditional agricultural activities on income per acre.

Using 2002 Agricultural Resource Management Survey (ARMS) and a double hurdle approach Detre et al. (2010) investigate the adoption of direct marketing strategy and its impact

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<sup>2</sup> Govindasamy et al. (1999) set cut-off points of higher and lower income at median and 75<sup>th</sup> percentile.

on gross sales. The authors found that production of organic crops and the regional location of the farm were important factors in adoption of direct marketing strategies. Farmers who adopted direct marketing strategies were likely to have higher income. However, it should be pointed out that the study by Detre et al. (2010) was limited in several ways. For example, the authors did not identify the types of direct marketing strategies used by the farmer; secondly, the share of income from each direct marketing strategy was not reported or estimated in their model; thirdly, the authors failed to assess the impact of choice of sales outlets on farm business income separately. Finally, the authors do not correct for sample selection bias in their study.

Goodsell, Stanton, and McLaughlin (2007) provide a detailed listing of the direct marketing opportunities available to livestock and poultry producers, including but not limited to: classic farm stands, farm to retail, farmers' markets, farm to school, farm to restaurant, fundraising dinners, fairs and festivals, and mail orders. They indicate that the process of establishing a DMS 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.

### **3. Econometric Model of Choice of Sales Outlets and Earnings in Chosen Outlet**

Producers choose their marketing plans and assess outside options that are available before participating in any marketing channel. The farm income earned from sales depends on the farmer's experience in producing and selling farm products, the farmer's comparative advantage in bargaining and marketing skills combined with differences in the regional development and accessibility of outlets for farm products. Selectivity bias may be present in the econometric model explaining the choice of marketing outlets used by producers.

The 2008 ARMS surveys queried farm operators on choices of sales (marketing) outlets and income earned when producers choose different market outlets to sell commodities. Based



on this information, a set of three marketing outlets was identified. The marketing outlets included (1) DTC outlets only, (2) Intermediated outlets only (IMOs), and (3) both DTC and IMOs outlets.

The producer's choice of a marketing strategy is based on utility maximization among  $M$  alternatives, where utility  $y_j^*$  depends on features of the outlets and the producer's marketing expertise. The marketing strategies include the choice to market through any one outlet, any two outlets, all the outlets, or none of the outlets (no direct sales). The utility of the producer who chooses from  $M$  ( $j = 1, 2, \dots, M$ ) mutually exclusive marketing plans depends on a set of observable exogenous variables  $Z$ , estimated parameters  $\gamma$ , and an unobservable stochastic component  $\eta_j$ :

$$(1) \quad y_j^* = Z\gamma_j + \eta_j, \quad j = 1, \dots, M$$

We observe only whether a marketing plan is chosen so that  $y_j = 1$  if plan  $j$  is chosen and  $y_j = 0$  otherwise.

Given the choice of marketing plan one (the decision to use a single marketing channel), the local sales related income earned by the farmer is

$$(2) \quad y_1 = X\beta_1 + u_1$$

where  $X$  is the set of exogenous variables affecting income earned from the marketing strategy and  $\beta$  is the set of estimated parameters. The idiosyncratic error term  $u_1$  satisfies  $E(u_1 | X) = 0$  and  $\text{Var}(u_1 | X) = \sigma^2$ . The estimation strategy accounts for correlation between the stochastic components  $\eta_j$  and  $u_1$ .

Following BFG, the  $M$ th marketing strategy is observed only if  $y_M^* > \max(y_j^*)$  where  $j \neq M$ . This condition is equivalent to  $Z\gamma_M > \varepsilon_M$ , where

$$(3) \quad \varepsilon_M = \max(y_j^* - \eta_M), \quad j \neq M$$

When the  $\eta_j$  elements are independent and identically Gumbel distributed, the cumulative distribution function is  $G(\eta) = \exp(-e^{-\eta})$  and the density function is  $g(\eta) = \exp(-\eta - e^{-\eta})$ , leading to the multinomial logit (MNL) model. The probability that the Mth alternative is preferred is

$$(4) \quad P_M = \frac{\exp(Z\gamma_M)}{\sum_j \exp(Z\gamma_j)}$$

The MNL model offers a framework for dealing with selectivity effects in discrete choice models and has distinct theoretical and empirical advantages. Basuroy and Nguyen (1998) show that the MNL framework is appropriate for establishing equilibrium in market shares and assessing the impact of optimal firm responses to entry and potential market expansion. Choice models based on the MNL formulation are commonly used in marketing science applications and yield optimal pricing policies, which align with observed sales and pricing strategies of firms (Cattani 2007). The parameters of the MNL model can be estimated by maximum likelihood but the estimation of the equation for income earned requires additional assumptions.

BFG define standard normal variables,  $\eta_j^*$ , as

$$(5) \quad \eta_j^* = \Phi^{-1} [G(\eta_j)]$$

where  $\Phi$  is the standard normal cumulative distribution function and assume that the expected values of  $u_1$  and  $\eta_j^*$  are linearly related for every  $j$ ,

$$(6) \quad E[u_1 | \eta_1 \dots \eta_M] = \sigma \sum_{j=1, \dots, M} r_j^* \eta_j^*$$

The correlation coefficient between  $u_1$  and  $\eta_j$  is represented by  $r_j$  while  $\sigma$  is the standard deviation of the disturbance term from the earned organic income equation. For the multinomial logit model, BFG derive the conditional expectation of  $\eta_j^*$ . Given that the first marketing option is chosen ( $j=1$ ), the outcome equation for income earned,  $y_1$  is

$$(7) \quad y_1 = X \beta_1 + \sigma \left[ r_1^* m(P_1) + \sum_{j=2, \dots, M} r_j^* m(P_j) \frac{P_j}{P_j - 1} \right] + w_1 \quad .$$

In this equation  $P_1$  is the probability that the first alternative is preferred,  $m(P_1)$  is the conditional expectation of  $\eta_j^*$ ,  $m(P_j)$  represents the conditional expectation of  $\eta_j^*$  and  $m(P_j) \cdot \frac{P_j}{P_j - 1}$  is the expectation of  $\eta_j^*$  for all  $j \neq 1$ . Each conditional expectation can be computed numerically. The residual error term is  $w_1$  and is independent of the regressors. In the first stage, the discrete choice model from equation (4) is estimated by maximum likelihood methods to obtain  $\hat{\gamma}$ . Given that marketing plan 1 is chosen, the second stage as specified in equation (7) is estimated by OLS, recognizing that the disturbances are heteroskedastic and correlated across the sample observations.

The BFG approach for dealing with selectivity has advantages over current methods. The method identifies not only the direction of the bias related to the choice of marketing plan, but also which marketing plan is the source of the bias. This is accomplished by estimating a different selectivity term for each marketing strategy, rather than following Lee's approach that estimates a single selectivity effect for all strategies together. The selectivity correction accounts for all the correlations between the disturbance terms of the earned income equations and the unobservable stochastic components driving the choice of marketing plan. Restrictive assumptions, that are required to implement commonly used selectivity methods, are relaxed.

As Schmertmann (1994) initially noted, Lee's (1983) approach implies a set of strong restrictions. First, unobservable factors that influence the choice of alternative 1 against any other alternative are correlated in the same direction with unobservable factors influencing the observed outcome  $y_1$ . That is, the correlations between  $u_i$  and  $(\eta_j - \eta_1)$  are the same sign for all  $j$ . A second and more stringent restriction results when the selection model is based on the

multinomial logit model and the residual terms ( $\eta_j - \eta_1$ ) are assumed to be identically distributed. In this case, the correlations are restricted to be identical. However, it should be noted that Lee's method tends to perform poorly in comparison with the new BFG's approach.

Finally, the choice of marketing outlets (DTC, IMOs, and both DTC and IMOs) will be estimated using the BFG method<sup>3</sup> and the selectivity term will then be used in the farm financial performance equation.

#### **4. Data**

The study employs data obtained from the nationwide 2008 Agricultural Resource Management Survey (ARMS) collected 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. Data are collected from one operator per farm, the senior farm operator, who makes most of the day-to-day management decisions. For the purpose of this study, we excluded operator households organized as nonfamily corporations or cooperatives and farms run by hired managers.

Operators associated with farm businesses representing agricultural production in the 48 contiguous states make up the target population of the survey. USDA defines a farm as an establishment that sold or normally would have sold at least \$1,000 of agricultural products during the year. Farms may be organized as sole proprietorships, partnerships, family corporations, non-family corporations, or cooperatives. In addition to farm economic data, the

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<sup>3</sup> Park (2009) notes that the less restrictive BFG model reveals an absence of significant selectivity effects for the diversified marketing option. This indicates that ordinary least squares (OLS) is the preferred estimation method for total farm sales from the diversified marketing plan.

2008 ARMS also collected information on the farm household of the principal operator.. It contains detailed information on off-farm hours worked by spouses and farm operators, the amount of income received from off-farm work, net cash income from operating another farm/ranch, net cash income from operating another business, and net income from share renting.

The 2008 ARMS queried farm operators on choices of sales (marketing) outlets and income earned when producers choose different market outlets to sell commodities. The survey instrument contains specific questions pertaining to the use of direct marketing strategy by farmers. Specifically, the survey queried farmers whether they have used the following direct marketing outlets: (1) roadside stand or on-farm facility, (2) on-farm stores, (3) farmers' markets, (4) community supported agriculture (CSA), (5) regional distributors, (6) state branding programs, and (7) direct sales to local grocery stores, restaurants and other retailers. Based on this information, a set of three marketing outlets was identified. The first group—direct-to-consumers outlets only (DTC)—includes 10 percent of the producers. The second group, intermediated retail outlets only (IMOs)—accounts for seven percent of the produces. The third group includes farmer who used both DTC and IMOs outlets, and includes 4 percent of the producers. Farms with no direct sales outlets were used as the base group and comprise 79 percent of the farms in the 2008 ARMS dataset.

## **5. Results and Discussion**

Table 2 reports parameter estimates of the choice of direct marketing model used by farmers in the US. Note that the base group for comparison is farmers with no direct marketing sales. The coefficient of Internet connectivity options (*connectoptns*) is positive and significant in the case of intermediated marketing outlets (IMOs), suggesting that, in comparison to farmers with no direct marketing outlets, farmers who have Internet connection are more likely to adopt

IMOs. This result perhaps suggest having Internet may be proving beneficial to farmers in searching for information on additional markets, by providing the farmer with additional marketing outlets that are more profitable and easier in application, and increasing demand for the products over what would be found in the traditional market place. On the other hand, the coefficient of *intntfrmnews*, Internet used for farm-related news, is negative and statistically significant for the DTC marketing choice. Results suggest that an additional hour spent on the Internet for farm-related news leads to a decrease in DTC marketing choice. A possible explanation is that farmers using Internet for farm-related news may be growing commodity program crops, hence searching information related to government programs and information regarding farming techniques, machinery, fertilizer, and services provided by University Extension and private sector firms.

An interesting finding in table 2 is a positive and significant coefficient of *intntcommc*, Internet used for farm-related commerce, suggesting that farming operations using Internet for commerce are more likely to use DTC, IMOs, and both forms of direct marketing strategies. This result is consistent with the findings of Mishra, Williams, and Detre (2009) who conclude that farmers with Internet connections are more likely to explore additional marketing outlets for their farm products. Results in table 2 indicate that farming operations purchasing a higher number of their farming inputs near the farm (*farminpTWN*) are less likely to use IMOs and both DTC and IMOs as a choice of direct marketing outlets. It is likely that farms purchasing most of their inputs near the farm are likely to be smaller farms located in rural areas, where access to IMOs might be more limited.

Results in table 2 indicate a positive and significant association between the number of crops grown by the farm and choice of direct marketing outlets. In particular, the coefficient of

*NUMherf* is positive and significant for DTC and both DTC and IMOs marketing outlets, when compared to the base group (no direct marketing sales). A higher Herfindahl index indicates a diversified farm and it can be argued that diversified farms are seeking several marketing outlets, including direct sales (DTC) and intermediated outlets (IMOs). Our results are consistent with the findings of Park and Lohr (2006). Finally, beginning farmers (*begfarmer*), those who began farming after 1997, are more likely to choose DTC as their choice of direct marketing strategy. The finding here suggests that entrants in farming may be more educated and are likely to engage in off-farm work (Mishra et al. 2002). Further, the new entrants are more likely to operate small and diversified farms, located near metro-areas, where the demand for local food items and fresh produce is greater than for farms located in more sparsely populated areas.

Following Park (2009) we investigated the impact of choice of direct marketing outlets on the gross income of farming operations. In this study the dependent variable, gross farm income, is the logarithm of total value of farm sales in 2008 and we use the BFG method as outlined in the econometric section of this paper. The estimated coefficients from the BFG model were used to estimate the gross farm income equation with the results presented in Table 3.

The BFG selectivity effects are presented by the  $M(P_i)$  terms related to the alternative direct marketing strategies in the multinomial logit model. The four strategies generate four selectivity terms. The results reveal a set of consistent results across marketing options, IMOs and both DTC and IMOs. The implications for farmer who are deciding on direct marketing strategies are addressed and the coefficients from the BFG model are discussed.

The selectivity correction terms,  $M(P_i)$ , are significant in the choice of DTC and IMOs outlets, indicating the presence of sample selection effects. Accounting for selectivity is essential to ensure that the coefficients in the total value of farm sales equation are estimated consistently.

For each total farm sales model, a positive (negative) selectivity coefficient for a given direct marketing option indicates higher (lower) earnings for the farmer relative to a randomly chosen producer (Dimova and Gang 2007). In particular, this finding reflects that farmers with unobserved attributes linked to lowering total farm sales shift to an alternative direct marketing strategy.

Note the positive selectivity effect (estimated value of 2.153 for the  $M(P_1)$  coefficient) for the DTC outlet in the total farm sales model for the DTC strategy. This is due to higher than expected farm sales for a focused direct marketing strategy (DTC outlet) as farmers with unobservable attributes, that do not enhance farm sales in DTC outlet, have migrated toward the DTC outlet. The selectivity coefficient related to the both DTC and IMOs,  $M(P_3)$ , is negative and significant in the DTC outlet. Farm sales marketed through DTC outlet are overestimated (biased downward) if the selectivity correction is neglected. The three significant selectivity coefficients in the DTC, IMOs, and both DTC and IMOs outlet model confirm the value of the BFG model in accounting for the impact of unobserved attributes of farmers when estimating the returns to the choice of direct marketing strategies. The less restrictive BFG model offers a more complete understanding of total farms sales from direct marketing strategy.

We also evaluate the coefficients from the BFG model. Results in table 3 indicate that farms operated by male farmers have significantly higher total farm sales for each direct marketing strategy (DTC, IMOs, and both DTC and IMOs). This finding is not a surprising result as more than 90 percent of farm operators in the US are male. Another variable that is significant for each strategy is the portfolio of input acquisition and management practices used by the farm operator (*sellskill*). For producers marketing through DTC outlets, elasticities indicate that one additional input acquisition and management practice adopted by the farm operator increases



total farm sales by 0.51 percent. Growth in farm sales (*gvsalgr*) from the previous year is negatively associated with total current farm sales. Results indicate that one percent increase in the farm sales from previous year is associated with decreases in total farm sales in the current year of 0.55 percent, in all three direct marketing strategies (DTC, IMOs, and both DTC and IMOs). Finally, our results suggest a positive relationship between farming operations receiving any Federal, State, or local farm program payments (*FSLfarmpmt*) and higher farm sales, in all three direct marketing strategies compared to the base case of no participation in direct marketing.

## **6. Conclusions**

In the era of a global economy, farmers face increasing pressure in developing a portfolio of various marketing channels and in bargaining competitively with increasingly sophisticated marketing participants in the supply chain of agricultural products in local and regional markets. Many farmers begin selling directly through farmers' market, roadside stand, community supported agriculture, and other intermediated channels like regional distributor, state branding program, direct sales to grocery stores, local restaurants, and other retailers. This research assists producers by examining the direct marketing strategies and identifies specific farm and demographic factors associated with enhanced earnings, given the choice of direct marketing outlet. The econometric model applies a more effective approach to correct for selectivity bias that more accurately identifies the returns to different marketing outlets used by US farmers.

Results from the discrete model (multinomial logit model) highlight variables that may influence the choice of direct marketing outlets by farmers in the US. Extension agents, crop consultants, and marketing analysts can adapt this information to predict the type of marketing outlet that a given farmer might use and provide better information for farmers. Getting an

Internet connection and using the Internet for farm commerce, increases the likelihood that a farmer uses intermediated marketing outlets (IMOs). On the other hand, using the Internet for farm commerce and growing a diversified selection of products (more enterprises) increases the likelihood that a farmer uses direct to consumer marketing outlets (DTC). Using the Internet for farm related news decreases the likelihood of participation in direct to consumer marketing outlets (DTC). Finally, farming operations purchasing a higher number of their farming inputs near the farm are less likely to use IMOs and both DTC and IMOs as a choice of direct marketing outlets.

The three selectivity coefficients in the DTC, two in IMOs and both DTC and IMOs outlet models confirm that the BFG selectivity model is appropriate for the analysis of marketing choices of US farmers. Total farm sales through DTC are downward biased since farmers who are better suited to market through multiple outlets (both DTC and IMOs) are better suited to market through DTC have moved toward this marketing strategy. An accurate evaluation of the projected earnings from the DTC outlet must account for selectivity effects.

From the total earnings equation we find that male farm operators have higher earnings, even after accounting for selectivity effects. The portfolio of input acquisition and management practices used by the farm operator is positively related with total farm sales for all direct marketing choices. Participation in Federal, State, or local farm program payments is also positively and significantly related with total farm sales in all three direct marketing strategies. Finally, results indicate that regardless of the direct marketing strategy used, the previous year's farm sales have an adverse effect on current year's total farm sales.

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**Table 1: Variable Definition and Summary Statistics**

Variable	Description	Direct-to-Consumers (DTC) outlets <sup>1</sup>	Intermediated (IMOs) outlets <sup>2</sup>	DTC & IMOs <sup>3</sup>
		Mean (Std. Dev)	Mean (Std. Dev)	Mean (Std. Dev)
<i>connectops</i>	Internet connectivity options	1.0536 (0.8020)	1.2262 (0.9521)	1.2021 (0.9225)
<i>intntfrmnews</i>	Internet used for farm-related news (hours/week)	3.9157 (6.4432)	5.1429 (7.7012)	5.7447 (8.3123)
<i>intntcommc</i>	Internet used for farm-related commerce (hours/week)	3.5785 (8.0845)	5.2560 (9.9880)	6.0319 (10.8086)
<i>farminpTW</i>	Inputs available near farm (count of five inputs) <sup>4</sup>	2.2375 (1.7773)	2.0774 (1.6953)	2.0426 (1.6779)
<i>hldcongdtw</i>	Household consumer good available for purchase near farms (=1 if good available, otherwise) <sup>5</sup>	0.3372 (0.4736)	0.3512 (0.4787)	0.3298 (0.4726)
<i>hlddurgdtw</i>	Household durable good available for purchase near farms (=1 if goods available, otherwise) <sup>6</sup>	0.2414 (0.4287)	0.2321 (0.4236)	0.2234 (0.4188)
<i>DISTherf</i>	Distribution component of Herfindahl index for crops sold by the producer	0.1009 (0.1913)	0.0981 (0.2039)	0.1444 (0.2293)
<i>NUMherf</i>	Number component of Herfindahl index for crops sold by the producer	0.1762 (0.2629)	0.1592 (0.2488)	0.2367 (0.2760)
<i>begfarmer</i>	Operator began operating this farm after 1997	0.1686 (0.3751)	0.1369 (0.3447)	0.1277 (0.3355)
				539853.700 0
<i>tvalfrmsal</i>	Total value of farm sales in 2008 (used in logarithm)	393612.100 (5326.46)	637123.5000 (604976.50)	(561575.90 )
<i>age</i>	Age of operator (used in logarithm)	56.6015 (12.4860)	57.5893 (11.1007)	56.7979 (11.57)
<i>male</i>	Gender of operator (=1 if male)	0.8927 (0.3100)	0.9345 (0.2481)	0.9468 (0.2256)
<i>reasPRC</i>	Farm inputs for which price was a major reason for NOT purchasing in the nearest town	0.5862 (1.1982)	0.8452 (1.455)	0.7128 (1.2752)

<i>reasQUA</i>	Farm inputs for which QUALITY was a major reason for NOT purchasing in the nearest town	0.1877 (0.6788)	0.1786 (0.5614)	0.2021 (0.5599)
<i>reasSUP</i>	Farm inputs for which SUPPLIER SERVICES was a major reason for NOT purchasing in the nearest town	0.7165 (1.7574)	0.7083 (1.5984)	0.8298 (1.6825)
<i>hrsOperpd</i>	Hours of paid labor per week by other farm operators	30.0690 (103.8307)	54.7619 (170.037)	54.6809 (144.7276)
<i>hrsWrkrpd</i>	Hours of paid labor per week by workers	1342.9120 (5326.46)	1779.5420 (5155.18)	1626.8090 (5876.995)
<i>majgrainSHR</i>	Share of sales accounted for by major grains	0.0660 (0.2190)	0.0859 (0.2565)	0.0557 (0.2010)
<i>R</i>		0.2310	0.2091	0.2571
<i>vegSHR</i>	Share of sales accounted for by vegetables	(0.3820)	(0.3738)	(0.3829)
<i>frutntSHR</i>	Share of sales accounted for by fruits and nuts	0.2014 (0.3765)	0.1654 (0.3509)	0.2105 (0.3739)
<i>sellskill</i>	Portfolio of input acquisition and management practices used by operator (5 practices) <sup>7</sup>	1.5134 (1.3576)	2.0000 (1.3668)	2.1170 (1.3667)
<i>gvsalgr</i>	Growth in total value of farm sales from previous year	0.0181 (0.6342)	0.1111 (0.6796)	-0.0221 (0.6811)
<i>rechnthosp~t</i>	Operator received income from recreation and agri-tourism activities (=1 if yes, 0 otherwise)	0.0498 (0.2179)	0.0476 (0.2135)	0.0851 (0.2805)
<i>FSLfarmpmts</i>	Operation received Federal, State, or Local Farm Program payments (=1 if yes, 0 otherwise)	0.2644 (0.4418)	0.2917 (0.4558)	0.2660 (0.4442)
<i>cfrm</i>	Internet connection through farm residence or office (=1 if yes, 0 otherwise)	0.7509 (0.4333)	0.7976 (0.4029)	0.8404 (0.3682)
<i>cofffrm</i>	Internet connection through off-farm residence or office ((=1 if yes, 0 otherwise)	0.1915 (0.3942)	0.2619 (0.4409)	0.2128 (0.4115)
<i>cfld</i>	Internet connection in the field ((=1 if yes, 0 otherwise)	0.0459 (0.2098)	0.0714 (0.2583)	0.0532 (0.2256)
<i>cpacc</i>	Internet connection through public-access internet site ((=1 if yes, 0 otherwise)	0.0268 (0.1619)	0.0417 (0.2004)	0.0319 (0.1767)
<i>celsewh</i>	Internet connection elsewhere ((=1 if yes, 0 otherwise)	0.0383 (0.1923)	0.0536 (0.2258)	0.0638 (0.2457)

Sample size	261	168	94
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<sup>1</sup> Farmer markets products to roadside stands or on-farm facility, on-farm store, farmer's market, community supported agriculture.

<sup>2</sup> Farmer markets products to regional distributor, state branding program, direct sales to grocery stores, restaurants, or other retailers.

<sup>3</sup> Includes both DTC and IMOs.

<sup>4</sup> Includes fuel, fertilizer and chemicals, feed and seed, machinery and implements, farm credit.

<sup>5</sup> Includes groceries, clothing, household supplies, etc.

<sup>6</sup> Includes cars, trucks, appliances, furniture, etc.

<sup>7</sup> Includes forward purchasing of inputs, use of farm management services, comparative pricing across multiple suppliers, attempting to negotiate price discounts, and participating in buying clubs.

Source: Agricultural and Resource Management Survey, 2008.



**Table 2: Parameter estimates for choice of direct marketing outlets by farm in the US.**

Variable	Direct-to-consumer (DTC) outlet		Intermediated (IMOs) outlet		DTC & IMOs outlet	
	Estimate	T-ratio <sup>a</sup>	Estimate	T-ratio	Estimate	T-ratio
<i>Constant</i>	-2.4809*	-13.47	-3.4062*	-13.39	-3.5450*	-14.33
connectoptns	0.0395	0.33	0.3264*	2.39	0.1022	0.74
intntfrmnews	-0.0534*	-2.46	-0.0191	-0.83	0.0006	0.03
intntcommc	0.0424*	2.53	0.0556*	3.24	0.0788*	5.42
farminpTWN	-0.0500	-0.94	-0.1702*	-2.10	-0.1308*	-1.80
hldconsgdTWN	-0.2270	-0.94	0.3644	1.05	-0.1202	-0.37
hlldurgdTWN	0.0276	0.11	-0.1733	-0.48	0.0491	0.15
DISTherf	-0.9525	-1.24	0.0444	0.04	0.1844	0.24
NUMherf	1.7283*	3.19	-0.9067	-0.89	2.4828*	4.02
begfarmer	0.7347*	3.47	0.3860	1.14	0.3783	1.16

<sup>a</sup> Asterisk indicates asymptotic t-values with significance at  $\alpha = 0.10$  or higher level.

**Table 3: Parameter estimates for direct marketing outlets and its impact on financial performance of farms in the US.**

*Dependent variable*= total value of farm sales in 2008 (in logarithm)

Variable	Direct-to-consumer (DTC) outlet		Intermediated (IMOs) outlet		DTC & IMOs outlet	
	Estimate	T-ratio <sup>a</sup>	Estimate	T-ratio	Estimate	T-ratio
<i>Constant</i>	-6.0299	-0.73	-6.0300	-0.73	-6.0299	-0.73
lage	-0.5862	-0.73	-0.5862	-0.74	-0.5862	-0.70
male	0.9166*	2.40*	0.9166*	2.43	0.9166*	2.28
reasPRC	-0.1476	-0.82	-0.1476	-0.79	-0.1476	-0.82
reasQUA	-0.0596	-0.09	-0.0596	-0.09	-0.0596	-0.09
reasSUP	0.1354	0.50	0.1354	0.51	0.1354	0.53
hrsOperpd	0.0057	1.42	0.0057	1.56	0.0057	1.59
hrsWrkrpd	0.0001	0.54	0.0001	0.56	0.0001	0.66
majgrainSHR	1.2246	1.50	1.2246	1.53	1.2246	1.59
vegSHR	-0.6304	-1.49	-0.6304	-1.56	-0.6304	-1.38
frutntSHR	-0.2129	-0.42	-0.2129	-0.45	-0.2129	-0.41
sellskill	0.5108*	4.07	0.5108*	3.93	0.5108*	4.24
gvsalgr	-0.5528*	-1.70	-0.5528*	-1.71	-0.5528*	-1.73
rechnthosp~t	0.0223	0.02	0.0223	0.02	0.0223	0.02
FSLfarmpmts	0.8945*	2.34	0.8945*	2.25	0.8945*	2.28
M(P <sub>1</sub> )	2.1527*	1.67	2.1527*	1.69	2.1527	1.58
M(P <sub>2</sub> )	-11.4646	-1.56	-11.4646*	-1.70	11.4646*	-1.68
M(P <sub>3</sub> )	-11.3736*	-2.67	-11.3736*	-2.54	11.3736*	-2.74
M(P <sub>4</sub> )	-16.7967*	-1.92	-16.7967*	-1.94	16.7967*	-1.96

<sup>a</sup> Asterisk indicates asymptotic t-values with significance at  $\alpha = 0.10$  or higher level.