The Decision to Direct Market: An Analysis of Small Fruit and Specialty-Product Markets in Virginia

Joseph Monson, Denise Mainville, and Nicolai Kuminoff

Farmers are increasingly interested in high-value alternatives to commodity production. Direct marketing is a potentially attractive marketing alternative, having been shown to offer increased net incomes to farmers. Nevertheless, there is a dearth of literature on the determinants of the decision to direct market. This paper uses an ordered logit regression to analyze how farm size, the importance of high-value crops, organic production, experience, and demographic factors affect a producer's reliance on direct markets. The results show that farm size, high-value crop production, non-certified organic production methods, and household size are determinants of the share of total farm output sold though direct marketing outlets.

Farmers in Virginia, as in many areas, are interested in high-value alternatives to commodity production. Agriculture in Virginia is highly diversified, but there is broad recognition that few farmers in the state are able to compete effectively with large-scale producers of major field-crop commodities, such as corn and soybeans grown in the Midwest and other low-cost production regions. Furthermore, Virginia is seeing rapid urban and suburban expansion into rural areas, putting pressure on land prices and limiting the range of acceptable production alternatives. This same expansion, however, also offers farmers new opportunities to increase farm income by selling high-value products to local consumers. As Virginia's producers feel increasing pressure on the commodity front, there is increasing interest in high-value agricultural markets, such as small fruit and other specialty crops, as an alternative.

Small fruits, which include raspberries, strawberries, blackberries, blueberries and other non-tree fruits, have seen increasing demand in recent years as consumers have sought to improve their health through dietary choices (Kaufman et al. 2000). Most small fruits contain high levels of anti-oxidants, which can reduce the risk of cancer and decrease cholesterol levels. Like small fruits, specialty crops, such as herbs and cut flowers, are also an attractive alternative for growers looking to diversify, because their value per acre is substantially greater than traditional commodities.

When farmers contemplate investing in such markets, several considerations must be taken into account. Along with financial and production decisions, new small fruit and specialty-crop growers must also develop a marketing strategy which involves choosing the appropriate market channels to sell their products. Specifically, growers can sell their products directly to consumers through market channels such as farmers markets, pick-your-own operations, farm stands, Internet sales, and Community Supported Agriculture (CSA); or they can sell their products to intermediaries, retailers, restaurants, and a variety of other buyers who in turn add value and sell to consumers. Many farmers use both direct and indirect channels simultaneously. However, direct market channels can be particularly important to farmers as a source of income generation. For example, Govindasamy, Hossain, and Adelaja (1999) analyzed the income differentials between producers in New Jersey who sell direct to consumers versus those who do not direct market and found that producers who use direct markets as their primary channel are more likely to earn higher-than-average incomes.

This study investigates market-channel choice among diversified producers in Virginia. An ordered logit regression is used to analyze the effects of farm and demographic characteristics of producers in Virginia on the probability that a grower will choose to sell a portion of his or her products through a direct market channel. The dependent variable in the model is the share of agricultural sales revenue obtained from direct market channels. Explanatory variables include farm and household demographic and socio-economic characteristics. The data used in the analysis are drawn from a survey of small fruit and specialty-crop producers in Virginia that was undertaken in 2006. An analysis of

Monson is research assistant, and Mainville and Kuminoff are assistant professors, Department of Agricultural and Applied Economics, Virginia Tech, Blacksburg.

how current high-value farmers in Virginia market their products will help producers who are considering high-value production to gain insight into what types of farms are able to compete in direct markets and the constraints they face.

Background and Theory

There is considerable literature on consumers' preferences for agri-food products that are sold through direct market channels (see for example Thilmany, Bond, and Bond 2006; Kuches et al. 1999; Lehman et al. 1998; Gallons et al. 1997; Wolf 1997; Brooker, Eastwood, and Gray 1993; Ladzinski and Toensmeyer 1983). Wolf (1997) found that the majority of consumers in San Luis Obispo County, California purchase produce at farmers markets rather than supermarkets because they prefer produce that looks and tastes fresh, is of a high quality, and is a better value for the price. Likewise, Gallons et al. (1997) determined that consumers in Delaware prefer direct market outlets because they offer a diverse selection of produce, locally grown products, and a way to help support local farmers.

In addition to studies that describe attributes that consumers desire at direct markets, the literature also analyzes characteristics of consumers who typically purchase products through direct market outlets (see for example Onianwa, Wheelock, and Mojica 2005; Henneberry and Agustini, 2004; Kuches et al., 1999; Govindasamy and Nayga, 1997; Brooker, Eastwood, and Gray 1993). Henneberry and Agustini (2004) portrayed the typical farmers market customer in Oklahoma as female, over 35 years old, highly educated, with an annual household income over $40,000, and living in a two-person household.

While it is important to understand who purchases products directly from farmers and the factors that drive their demand for the products, it is equally imperative to examine factors that influence producers' decisions to supply their products directly to consumers. In comparison to the literature regarding consumer attributes and preferences for direct market channels, there have been few studies conducted regarding producer characteristics.

Although the returns from specific direct outlets may appear attractive, several constraints exist for producers who sell directly to consumers. Uva (2002) cites labor constraints, such as lack of labor, inadequate laborer skills, and high labor costs, as the top barriers direct marketers face. Other barriers include competition from supermarkets, time constraints, and unfavorable locations (Uva 2002). Morgan and Alipoe (2001) also cite location as a factor that plays a pertinent role in determining the success of direct marketing. Specifically, they recommended that direct marketers sell their products at farmers markets located near population centers of large cities.

Drawing from the literature, the following hypotheses about the characteristics of farmers who sell through direct marketing channels are proposed:

Hypothesis 1: As farm size increases, reliance[1] on direct marketing channels will decrease.

Justification: There are several justifications for this hypothesis. First, larger farms are in a better position to overcome the barriers to entry to other potentially lucrative markets, such as supermarkets. For example, larger farms can meet minimum-volume requirements and spread the fixed costs of investments—such as food-safety certification, logistics, Good Agricultural Practices, and other investments that are commonly required by supermarkets—over more output. Additionally, since larger farmers can produce greater volumes, they may have an incentive to economize on their marketing costs by selling to buyers who can absorb a greater share of their production than direct market customers, who tend to make relatively small purchases.

Hypothesis 2: As the share of high-value products in the farm portfolio increases, reliance on direct marketing channels will increase.

Justification: Direct marketing channels offer producers an opportunity to capture a greater share of the total value of their products, although they also must undertake the marketing functions that would otherwise be performed by the wholesaler or retailer. Thus there is an incentive to focus direct marketing efforts on high-value products in order to gain a higher return on these marketing efforts. Furthermore, there is a clear match between the attributes sought by consumers and those provided

[1] Throughout our analysis, we use the term "reliance" to refer to the proportional value of a farmer's total output that is sold through direct marketing channels. A farmer who is more reliant on direct marketing channels sells more of his or her total output directly to consumers.

by producers of high-value products, such as small fruits and specialty products. This pertains to both tangible attributes, including freshness, taste, quality, and variety, as well as to intangible attributes, such as providing economic and social support to local and small farmers.

Hypothesis 3: As producers' experience in agriculture increases, reliance on direct marketing channels will increase.

Justification: Producers who have more experience in production and marketing will be better able to meet the quality expectations of direct market consumers and earn a higher profit. It is also possible that these producers will have more established ties and extended relationship networks within the community, which will enhance their ability to market to locals.

Hypothesis 4: Farmers who use organic production methods but are not USDA-certified will be more reliant on direct marketing channels.

Justification: Participation in organic markets requires a third-party certification of compliance with the USDA's National Organic Standard (NOS) for any farmers who have organic sales of more than $5,000. While organic products are commonly found in mainstream venues such as chain supermarkets, there is anecdotal evidence that many consumers are increasingly feeling a disassociation between organic food and the values, such as local production, small-farm sourcing, and environmental sustainability, that they once associated with organic (see for example Cloud 2007). This is leading to a shift in demand by some consumers from organic foods to local foods. These consumers may still be interested in eating organic, but are less concerned that their food complies with the National Organic Standard. Consumers may also be more willing to trust a producer's claims about the organic production methods used if they have personal relations with the grower and the opportunity to visit his or her production site. Thus it is hypothesized that producers who follow organic production practices but are not certified are more likely to sell through direct marketing channels where they can find willing buyers. At the same time, these producers are generally not able to sell through indirect marketing channels because of the requirement of compliance with National Organic Standard.

Hypothesis 5: Farms in which females are primary decision makers will have a greater reliance on direct marketing channels.

Justification: There is anecdotal evidence that the ratio of women to men in high-value markets, including direct markets, is higher than in commodity markets. Though there is a lack of literature on agricultural markets addressing this hypothesis, literature on sustainable agriculture reports that there is a tendency for women to gravitate toward participation in agricultural systems that are associated with values of diversity, community involvement, decentralization, and quality of life (Chiappe and Flora 1998), all of which are characteristics of participation in direct markets.

Hypothesis 6: As household income increases, reliance on direct marketing channels will increase.

Justification: Higher-income farmers may be wealthier as a result of their participation in direct marketing, or their income may serve as an enabling factor—income from farm and off-farm activities may be used to fund investment in high-value and direct marketing enterprises. Likewise, there is also a trend in Virginia of "returning to the land," where high-income professionals and retirees purchase rural land with the intent of farming as a hobby or retirement activity. It is expected that such farmers would be relatively more attracted to direct marketing activities than to indirect.

Hypothesis 7: As the primary decision maker's degree of education increases, reliance on direct marketing will increase.

Justification: The hypothesis that more-educated producers will be more reliant on direct marketing is justified on the same grounds as higher-income producers, particularly with respect to the tendency for hobby farmers to participate in direct marketing as a way to "get back to the land."

Hypothesis 8: As household size increases, reliance on direct marketing will increase.

Justification: As noted by Uva (2002), labor availability is a major constraint to direct marketers. Households with more members can be expected to have more labor availability to share the tasks of direct marketing. This is particularly important as direct marketers take on marketing functions that are otherwise performed by wholesalers or retailers. Additionally, household labor may also be more trustworthy than hired labor, because household members have incentives that are more compatible with the overall farm goals. This incentive compatibility is particularly important considering the expertise and "good attitude" needed for effective interaction with consumers. Finally, labor costs of family employment can be expected to be lower due to the likelihood that family farm income is shared or that family labor arrangements are informal, and thus not subject to regulatory and fiscal overhead such as taxation and benefits.

Methods

An ordered logit model is estimated using maximum likelihood to provide insight on what factors influence farmers' market channel decisions. The ordered logit model is consistent with the notion that the probability a farmer will sell a specified portion of his or her total output through a direct market channel must lie between zero and one. This is not the case with an ordinary least squares (OLS) linear probability model, which can predict probabilities that are less than zero and greater than one.

An ordered logit model also allows one to examine how a change in any independent variable changes all of the outcome probabilities (Boes and Winkelmann 2006). Thus the probabilities that a farmer will sell certain percentages of his or her output through a direct channel can be determined by evaluating the marginal effects of the model at specified levels. With this information, suggestions can be made to farmers who are looking to change certain characteristics of their farm, such as increasing acreage of specialty crops or obtaining organic certification. While the marginal effects can be used to interpret the magnitude by which a one-unit change in an independent variable will change the probability outcomes, the signs of each statistically significant coefficient in an ordered logit model can also be used to indicate whether the variable has a positive or negative affect on the dependent variable.

Data for Analysis

The data that will be used to estimate the ordered logit model and test the hypotheses were collected in a 2006 mail survey. Given that no comprehensive list of small fruit and specialty-crop producers is available, potential respondents were sought from numerous sources including the Virginia Department of Agriculture and Consumer Services, the Virginia Small Fruit and Specialty Crop Growers Association, and county extension agents in Virginia. In all, approximately 1,250 surveys were distributed, of which 345 surveys were completed and returned. A total sample of 212 respondents are represented in the results; 133 surveys were removed from the sample due to missing data on the variables of interest.

Table 1 provides a descriptive statistics summary of the variables used in the analysis. The dependent variable, Direct, is an ordered variable that takes on a discrete value of 0 through 10, representing the share of each producer's sales made direct to consumers in ten-percent increments. Table 2 reports the distribution of observations across these categories. Over 80 percent of the surveyed farmers reported some direct marketing, and approximately one-third of the surveyed farmers reported selling more than 80 percent of their output directly to consumers.

The remaining variables listed in Table 1 explain the variation in the dependent variable. AcreFarm is a continuous variable that represents the total acreage each farmer had in production during the 2005 growing season. The survey respondents were also asked to further classify their total production acreage into specific product categories. AcreFrut, AcreVeg, AcreRow, AcreLvst, AcreSF, and AcreSpec are continuous variables that represent the number of acres each farmer devoted to producing fruit (excluding small fruit), vegetables, row crops, livestock and dairy, small fruit, and specialty crops respectively. AcreFarm need not equal the sum of AcreFrut, AcreVeg, AcreRow, AcreLvst, AcreSF, and AcreSpec, because land is often devoted to other activities, such as production of hay or Christmas trees, or may be left idle during a given season.

A set of six new variables that represent percentages of the total acres each producer devoted to each product category in 2005 was calculated using the acreage variables described above. These variables represent the share of total acres farmed that are dedicated to fruit excluding small fruit (FruitP), vegetables (VegtblP), row crops (RowCrpP), livestock (LvstckP), small fruit (SmllFrtP), and specialty crops (SpecCrpP). SmllFrtP, for example, was calculated by dividing AcreSF by AcreFarm and multiplying the result by one hundred, and represents the percentage of total acres devoted to small fruit production. These variables are used to

Table 1. Descriptive Statistics.

Variable	Description	N	Min.	Max.	Mean	Std. dev.
Direct	Ordered % of sales direct to consumers[a]	212	0	10	5.453	4.091
AcreFarm	Total acres farmed	212	0.333	1850	114.101	223.821
AcreFrut	Total acres of fruit (excluding small fruit)	212	0	550	18.714	67.918
AcreVeg	Total acres of vegetables	212	0	175	6.769	22.905
AcreRow	Total acres of row crops	212	0	450	12.336	49.621
AcreLvst	Total acres livestock	212	0	800	42.041	121.967
AcreSF	Total acres of small fruit	212	0	10	0.740	1.807
AcreSpec	Total acres of specialty crops	212	0	6	0.187	0.574
FruitP	= (AcreFrut/AcreFarm)*100	212	0	100	16.322	30.617
VegtblP	= (AcreVeg/AcreFarm)*100	212	0	100	14.691	28.299
RowCrpP	= (AcreRow/AcreFarm)*100	212	0	100	7.270	20.742
LvstckP	= (AcreLvst/AcreFarm)*100	212	0	100	18.139	30.656
SmllFrtP	= (AcreSF/AcreFarm)*100	212	0	100	6.796	19.745
SpecCrpP	= (AcreSpec/AcreFarm)*100	212	0	100	4.045	15.484
OrgNoD	Dummy = 1 if no organic production	212	0	1	0.708	0.456
OrgNCrtD	Dummy = 1 if organic, but not certified	212	0	1	0.222	0.416
OrgCrtD	Dummy = 1 if certified organic[b]	212	0	1	0.071	0.257
YrsFrmD1	Dummy = 1 if farmed land 0-5 years	212	0	1	0.175	0.380
YrsFrmD2	Dummy = 1 if farmed land 6-20 years	212	0	1	0.340	0.475
YrsFrmD3	Dummy = 1 if farmed land 20+ years	212	0	1	0.292	0.456
YrsFrmD4	Dummy = 1 if inherited farmed land	212	0	1	0.193	0.396
FemaleD	Dummy = 1 if female	212	0	1	0.245	0.431
EducD	Dummy = 1 if have at least Bachelor's	212	0	1	0.618	0.487
Income	Annual household income ($10,000)[c]	212	3	12	7.321	3.289
HouseHld	Number of individuals living in household	212	1	7	2.830	1.480

[a] Assigned a value based on percentage of total farm output sold directly to consumers as follows: 0% = 0, 1–10% = 1, 11–20% = 2, 21–30% = 3, 31–40% = 4, 41–50% = 5, 51–60% = 6, 61–70% = 7, 71–80% = 8, 81–90% = 9, 91–100% = 10.

[b] Also includes observations that are currently in the process of becoming certified organic.

[c] Assigned a value based on annual household income as follows: Below $20,000 = 1, $20,000-$39,999 = 3, $40,000-$59,999 = 5, $60,000-$79,999 = 7, $80,000-$99,999 = 9, more than $100,000 = 12.

Table 2. Frequency of the Dependent Variable.

Value	Frequency	% Total farm output sold directly to consumers	Percentage	Cumulative percentage
0	42	0%	19.81	19.81
1	24	1%-10%	11.32	31.13
2	7	11%-20%	3.30	34.43
3	11	21%-30%	5.19	39.62
4	6	31%-40%	2.83	42.45
5	13	41%-50%	6.13	48.58
6	5	51%-60%	2.36	50.94
7	8	61%-70%	3.77	54.72
8	20	71%-80%	9.43	64.15
9	10	81%-90%	4.72	68.87
10	66	91%-100%	31.13	100.00

test Hypothesis 2, with the acreage share of small fruit and specialty crops representing high-value crops, and vegetables, fruits (excluding small fruit), livestock, and row crops representing commodity production.

The survey results also provide information regarding two additional sets of farm characteristic variables that will be pertinent in explaining the percentage of total products each producer sells through direct market channels. First, farming experience, which pertains to Hypothesis 3, is measured by the number of years of farming experience each respondent had. The experience variable is represented using several dummy variables—for example, YrsFrmD1 equals 1 if the respondent has farmed his or her land for zero to five years, and equals 0 otherwise (see Table 1 for the complete explanation of the other three experience dummy variables). In addition to farming experience, the survey results present information on each farmer's decision to implement organic production practices. Similar to the experience variables, this information is broken up into a set of dummy variables to represent the following three categories: the producer does not use organic production methods (OrgNoD), the producer uses organic production methods but is not certified organic (OrgNCrtD), and the producer is certified organic or currently in transition to becoming certified organic (OrgCrtD). The use of organic production methods is relevant to Hypothesis 4.

In addition to the farm characteristics, four demographic variables are included in the analysis: EducD, FemaleD, Income, and HouseHld. EducD is a dummy variable equal to 1 if the primary decision maker for the farming operation has a Bachelor's degree or higher, FemaleD is a dummy variable equal to 1 if the primary decision maker is female, and HouseHld measures the number of individuals currently living in the surveyed household. Income measures annual household income. In the actual survey, respondents reported their income in $20,000 increments (e.g., "between $20,000 and $39,999"). We translated these categories into numerical values by assigning each household the median level of income in their reported category.[2]

Compared to the average farm in Virginia, the average farm in our sample is somewhat smaller

[2] The survey data on income and household size were both top-coded. The highest category for household size was "more than 6" and the highest income interval was "more than $100,000." Respondents in these categories were assigned values of 7 and $120,000, respectively. In an alternative specification, we used dummy variables for each income interval. This did not have a meaningful impact on magnitude or statistical significance of our econometric results.

(114 acres compared to 181 acres) and is more likely to have a female as the primary decision maker (25 percent compared to 14 percent). While state-level statistics on marketing channel choices are not available, it seems likely that reliance on direct marketing may also differ between the average small fruit and specialty-crop producer and the average farmer in the state. At the same time, the average farm in our sample is quite similar to the average Virginia farm when compared along other dimensions, such as household size: 53 percent of households in our sample have two people, compared to 51 percent for the state as a whole (National Agricultural Statistics Service 2004). Of course, our econometric results are most relevant for the small fruit and specialty-crop producers who are the focus of our study.

Econometric Model

In order to examine farmers' decisions to sell a portion of their products through direct channels instead of indirect channels, we estimate an ordered logit model by maximum likelihood. Let Direct* represent the monetary and psychological benefits to a farmer from direct marketing, which we do not directly observe. These unobserved benefits can be related to a set of explanatory variables as follows:

$$\text{(1)}\quad \text{Direct*} = \beta_1\text{AcreFarm} + \beta_2\text{FruitP} + \beta_3\text{VegtblP} + \beta_4\text{RowCrpP} + \beta_5\text{LvstckP} + \beta_6\text{SmllFrtP} + \beta_7\text{SpecCrpP} + \beta_8\text{OrgNCrtD} + \beta_9\text{OrgCrtD} + \beta_{10}\text{YrsFrm1} + \beta_{11}\text{YrsFrm2} + \beta_{12}\text{YrsFrm3} + \beta_{13}\text{FemaleD} + \beta_{14}\text{EducD} + \beta_{15}\text{Income} + \beta_{16}\text{Househld} + \mu\ ,$$

where the variables are defined in the Data for Analysis section and in Table 1, the βs are parameters to be estimated, and μ is an error term representing all unobserved variables that influence a farmer's decision to sell through direct market channels. Note that OrgNoD and YrsFrm4 are omitted from the model to avoid perfect collinearity among the explanatory variables.

An individual farmer's (unobserved) benefits from direct marketing can be related to his or her (observed) marketing channel choice as follows:

$$\text{(2)}\quad Direct = j \text{ if } \gamma_j < \text{Direct*} < \gamma_{j+1}\ ,\ j = 0,1,\ldots,10\ ,$$

where j indexes the 11 different values for the dependent variable shown in Table 2, $\gamma_0 = -\infty$, $\gamma_{10} = \infty$, and $\gamma_1 \ldots, \gamma_9$ are parameters to be estimated. Assuming the econometric error term, μ, follows a logistic distribution, all the parameters of the model can be recovered from maximum-likelihood estimation using STATA software (Baum 2006). The estimation results can then be used to predict the probability that a farmer will sell a given share of his or her crop directly to consumers. Furthermore, the results can be used to analyze the sensitivity of those predicted probabilities to marginal changes in the explanatory variables (Wooldridge 2006).

Results and Interpretations

Table 3 presents the estimated parameters and their corresponding standard errors for the ordered logit model.[3] As is often the case with micro survey data, the pseudo-R^2 measure for goodness-of-fit is low (0.054).[4] Nevertheless, the model correctly predicts behavior for 36 percent of the farmers in the sense that it assigns the highest probability to the incremental outcome for the dependent variable that corresponds to the farmer's actual market-channel choice. Furthermore, 48 percent of the model's predictions fall within the actual category chosen by each farmer, the immediate category above the actual level, or the immediate category below the actual level. The variance of the error term does not

[3] In order to test the sensitivity of the results to the alternative assumption that the econometric error term is normally distributed, an ordered probit model was estimated using the same data and variables. The results were nearly identical.

[4] In an alternative specification, the dependent variable was aggregated into three categories: those that primarily rely on indirect marketing channels to sell their products (sell ten percent or less through direct channels), those that use a mixture of direct and indirect channels to sell their product (sell between 11 percent and 80 percent through direct channels), and those that primarily rely on direct marketing channels to sell their products (sell more than 80 percent through direct channels). Not surprisingly, reducing the number of discrete outcomes for the dependent variable made it easier to explain observed behavior. The pseudo R-squared increased from approximately five percent to 11 percent, and the percentage of observations correctly predicted by the model increased from 36 percent to 50 percent. However, the parameter estimates and their standard errors were essentially the same as in Table 3.

Table 3. Ordered Logit Estimation Results (N=212).

Variable	Coefficient	Std. err.	z-stat.	p-value
AcreFarm	-0.0010	0.0006	-1.69	0.091
FruitP	-0.0128	0.0048	-2.69	0.007
VegtblP	0.0029	0.0049	0.60	0.551
RowCrpP	-0.0101	0.0064	-1.58	0.114
LvstckP	-0.0075	0.0051	-1.48	0.139
SmllFrtP	-0.0133	0.0070	-1.91	0.057
SpecCrpP	-0.0036	0.0094	-0.38	0.702
OrgNCrtD	1.2015	0.3675	3.27	0.001
OrgCrtD	0.7202	0.5373	1.34	0.180
YrsFrmD1	0.1703	0.4580	0.37	0.710
YrsFrmD2	-0.1929	0.3726	-0.52	0.605
YrsFrmD3	0.3345	0.3833	0.87	0.383
FemaleD	0.4349	0.3185	1.37	0.172
EducD	-0.3057	0.2764	-1.11	0.269
Income	-0.0474	0.0402	-1.18	0.238
HouseHld	-0.1731	0.0906	-1.91	0.056
Log-likelihood function	-410.791			
Chi-squared	46.63			0.0001
Pseudo R-squared	0.054			

seem to depend on any of the independent variables, because the normal standard errors, presented in Table 3, closely match the "heteroskedasticity-robust" standard errors for the same model. In fact, there were no major changes in the levels of significance for each variable when robust standard errors were used.

The hypotheses outlined in the Background and Theory section were evaluated at a 0.10 level of significance (with 196 degrees of freedom). As shown in Table 3, the coefficients on AcreFarm and OrgNCrtD are statistically significant with the expected signs. These results support the hypotheses that as farm size increases, producers become less reliant on direct marketing channels to sell their output, and that if a producer uses organic production methods but does not become USDA-certified, he or she is more likely to rely on direct marketing channels to sell his or her output.

Two other variables carried statistically significant coefficients but with the opposite sign than we had expected. Specifically, the coefficient on the variable representing reliance on high-value markets, the share of small fruit in farm income, is negative, rather than positive as expected. This result would imply that, all else constant, as the contribution of small fruit to farm sales increases, farmers tend to rely less on direct markets for this revenue. (The production of specialty products, another high-value product, had no statistically significant effect on direct marketing's contribution to farm revenue.) One explanation for this contradictory result might stem from the fact that high-value products generally tend to be more time- and management-intensive to produce. Therefore, as a producer devotes more of his land to small fruit or specialty crops, he or she will need to allocate more time toward production activities and less time toward marketing activities, which can be passed onto intermediary or retail buyers along indirect marketing channels.[5] The coefficient on HouseHld is also statistically significant, but in the opposite direction than we expected, indicating that farmers with larger households tend to sell a smaller percentage of their output through direct channels. Finally, the coefficients on the experience variables (YrsFrmD1, YrsFrmD2, and YrsFrmD3) and on demographic variables FemaleD, Income, and EducD were not statistically different from zero.

In order to gain insight into the magnitude of the change in the probability that a farmer will sell a certain portion of his or her total output through direct market channels, the marginal effects for various levels of the dependent variable were calculated and are presented in Table 4. These results are particularly meaningful for this study because recommendations about market channel choices can be made to farmers who are considering a change in any of the variables for which statistically significant coefficients were found. An infinite number of interpretations can be calculated using the marginal effects depending on the base values chosen for different variables. A few are interpreted below for illustration.

There is a 20.8-percent probability that the average farmer in the sample will sell none of his total output through direct channels. Yet suppose the

[5] We would like to thank an anonymous reviewer for suggesting this explanation.

Table 4. Marginal Effects of the Ordered Logit Estimation[a] (N=212).

Variable	0	1	3	5	8	10
AcreFarm	0.0002*	0.0001	0.0000	-0.0000	-0.0000	-0.0002
FruitP	0.0021**	0.0008**	0.0001	-0.0000	-0.0005*	-0.0022**
VegtblP	-0.0005	-0.0002	-0.0000	0.0000	0.0001	0.0005
RowCrpP	0.0017	0.0006	0.0001	-0.0000	-0.0004	-0.0018
LvstckP	0.0012	0.0005	0.0001	-0.0000	-0.0003	-0.0013
SmllFrtP	0.0022*	0.0008*	0.0001	-0.0000	-0.0005	-0.0023*
SpecCrpP	0.0006	0.0002	0.0000	-0.0000	-0.0001	-0.0006
OrgNCrtD	-0.1346***	-0.0738***	-0.0259**	-0.0180	0.0094	0.2664***
OrgCrtD	-0.0946	-0.0465	-0.0137	-0.0064	0.0148	0.1488
YrsFrmD1	-0.0266	-0.0108	-0.0022	0.0001	0.0056	0.0311
YrsFrmD2	0.0335	0.0113	0.0014	-0.0013	-0.0074	-0.0319
YrsFrmD3	-0.0497	-0.0215	-0.0050	-0.0009	0.0099	0.0637
FemaleD	-0.0626	-0.0282	-0.0071	-0.0019	0.0119	0.0847
EducD	0.0548	0.0172	0.0017	-0.0026	-0.0121	-0.0489
Income	0.0078	0.0029	0.0005	-0.0002	-0.0017	-0.0083
HouseHld	0.0285*	0.0106*	0.0020	-0.0006	-0.0062	-0.0302*
Probability of outcome	0.2077	0.1376	0.0654	0.0720	0.1000	0.2254

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

[a] Marginal effects were evaluated at the means for all continuous variables, at zero for all dummy variables, at Income = 7 ($60,000-$79,999 range), and at HouseHld = 3. The Income and HouseHld levels represent the nearest discrete values to their respective sample means.

For neatness of the Table, only outcomes 0, 1, 3, 5, 8, and 10 are shown, which represent farmers who sell no output, a small percentage, 25 percent, 50 percent, 75 percent, and all output through direct channels, respectively.

farmer decides to produce all of his or her output organically, without becoming officially certified. Now there is only a 7.3 percent probability (0.208 – 0.135) that the average farmer will sell none of his total output through direct channels. Similarly, there is a 22.5 percent probability that an average farmer in the sample will sell between 91 percent and 100 percent of his total output through direct channels. However, if the farmer decides to devote one percent more of his land to small fruit production and implement organic production methods without becoming officially certified, the probability that he will sell between 91 percent and 100 percent of his total output through direct channels more than doubles to 48.9 percent (0.225 – 0.002 + 0.266).

Conclusion

The results from this analysis add to the current literature on direct markets. In particular, this study provides insight about four characteristics of small fruit and specialty-product producers who direct market all or a portion of their total output—namely, producers who operate smaller farms, are less reliant on small fruit, implement organic production without USDA certification, and live in smaller households are more likely to sell their products through direct outlets.

The estimated marginal effect matrices from the ordered logit model provide results that are economically significant to producers, especially those who rely on farming for their main source of income. Such marginal effects can be evaluated for individual farmers, both in and out of the sample, who have a unique set of farm characteristics and demographic backgrounds. The results from these calculations are particularly important to farmers in Virginia and other regions who are interested in diversifying into high-value agricultural-product markets such as small fruit or specialty crops. Specifically, these results can provide insight about the reliance on direct markets to other farmers who share similar characteristics. With this information farmers can assess their options more accurately, and make more informed decisions about their market channel choices.

Our analysis could be extended in future research to investigate how a farmer's choice among specific crops influences his or her reliance on direct marketing. We were unable to explore this question in our study since the survey asked farmers to report their information in broad crop categories. Meanwhile, within categories such as "small fruit production" there may be considerable variation in the tradeoff between the costs and benefits from management and direct marketing, which could influence a farmer's choice to direct market. Investigating this issue in future work would require collecting product-specific data and extending the ordered logit model to consider individual crops.

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