

Market Access and Value-added Strategies in the Specialty Crops Industry

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Abstract. Value-added (VA) technologies can help farmers in the specialty crops industry generate new products, increase off-season income sources, expand market access, and improve overall profitability. The United States Department of Agriculture defines VA agricultural products as those that have been changed physically or produced in a manner that enhances their value. Drawing from this definition, we investigated the adoption of VA technologies, such as drying, physical cutting into customer-ready portions, and washing, by specialty crops farmers. The objectives of this study were twofold. First, we analyzed how market access drives specialty crop farmers to adopt VA technologies. Second, we addressed key identification issues by investigating the potential endogeneity between the adoption of VA technologies (vertical diversification) and the number of crops (horizontal diversification), which have not been addressed in the VA technology adoption literature. Data for this study were from a 2019 Web-based survey of specialty crops farmers in the United States. The results suggest that market access, growers' networks, and crop diversification are major drivers of VA technology adoption in the specialty crops industry. The results indicate that farmers who adopted VA technologies experienced economic growth relative to their counterparts.

The shift of agriculture in the United States from resource-led growth to productivity-led growth during the past few decades (US Department of Agriculture Economic Research Service 2017) includes the adoption of value-added (VA) technologies to diversify farming outputs (Cusolito and Maloney 2018). Farmers who adopt VA technologies can increase productivity by using innovative production methods and postharvest procedures to differentiate their produce and access price premiums (Cusolito and Maloney 2018). Therefore, although farmers who add value to their products may experience increased risks, they can be rewarded with higher revenues than their

counterparts by attaining price premiums (Brees et al. 2010).

According to Ernst and Woods (2011), VA technologies include transformation processes for edible specialty crops (e.g., fruits and vegetables). These technologies can help farmers differentiate their farm products. Amanor-Boadu (2007) proposed that VA technologies must satisfy at least one of the two following conditions: one is rewarded for performing any activity that has been traditionally performed at another stage further down the supply chain or one is rewarded for performing an activity that is discovered to be necessary but never has been performed in the supply chain.

Coltrain et al. (2000) defined VA agriculture as economically adding value to a product by changing its current place, time, and characteristics to others more preferred in the marketplace. Lu and Dudensing (2015) proposed VA agriculture as a portfolio of agricultural practices that enable farmers to align

with consumer preferences for agricultural or food products with form, space, time, identity, and quality characteristics that are not present in conventionally produced raw agricultural products. Womach (2005) referred to VA agriculture as the adoption of manufacturing processes that increase the value of primary agricultural goods. This study followed the United States Department of Agriculture (USDA) Rural Business Development definition of VA technologies, which includes practices that change the physical state of produce, such as washing, drying, and cutting specialty crops into customer-ready portions.

To illustrate, instead of selling raw commodities for further processing, farmers can process their produce—such as drying herbs and cutting carrots into ready-to-eat portions. Using these VA practices, farmers can change their position in the supply chain (i.e., from producer to processor and/or retailer) and create closer or direct linkages with consumers. The connection between farmers and consumers can be mutually beneficial because farmers can receive price premiums and consumers can access differentiated products that fit their preferences.

Access to markets is a major factor influencing the adoption of VA technologies (Ruslan et al. 2013). According to Boland et al. (2009), the information provided by the marketplace has been relevant to the success of farmers adopting VA technologies. Information shared by consumers tends to motivate farmers to differentiate and tailor their products (i.e., add value) to meet market trends. Moreover, Grunert et al. (2005) found that access to diverse markets tends to enable better organizational networks and the adoption of VA technologies. Clark (2020) reported that farmers increased farm income more than 2.5-times after adopting VA technologies. Therefore, we expect that farmers selling through more market outlets may be more likely to supply a broader range of differentiated products through the use of post-harvest VA technologies.

The importance of adopting VA technologies is derived from the increased demand for specialty crops in past decades, especially for “ready use” or single-serving foods. This trend presents potential advantages for growers who may be able to capture a larger share of the consumer price by adding value to their specialty crops, which may lead to increased farm revenues (Drabenstott and Meeker 1997; US Department of Agriculture Economic Research Service 2019). Drabenstott and Meeker (1997) reported that increasing revenues from VA technologies benefit the farmers, and that these benefits tend to have spillover effects on rural communities (Drabenstott and Meeker 1997). To illustrate, the market values of fruits and vegetables increased by 134% and 77%, respectively, during 1995 to 2016 (Minor and Bond 2017). According to the 2017 Census of Agriculture (US Department of Agriculture National Agricultural Statistics Service 2020), specialty crops sales reached more than \$87.6 billion. The 2017

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Census of Agriculture reported that 33,523 farms sold more than \$4 billion in VA products in 2016; of these, VA products from horticultural crops accounted for \$2 billion. Yet, these sales are just a small portion of the \$877 billion in sales reported by $\approx 30,000$ food and beverage manufacturers in the United States (US Department of Agriculture National Agricultural Statistics Service 2020).

Cirera and Maloney (2017) described the agriculture innovation paradox as follows: why, if returns to the adoption of new technologies are so high, so few farmers adopt them? Recent literature about VA technology adoption reported that farmers can be deterred from innovating because of a lack of access to information, production systems, finance, and markets (Clark 2020). These findings suggest that no single constraint can explain the lack of adoption of VA technologies in the specialty crops industry, and multipronged approaches may be necessary to accelerate the understanding of why farmers adopt VA technologies.

This study investigated the adoption of VA technologies among growers of edible specialty crops. We followed the USDA definition of VA technologies to categorize VA agricultural products as those that have experienced a change in their physical state. We focused on VA technologies associated with specialty crops such as drying, washing, and cutting into customer-ready portions. To illustrate, farmers can cut apples into customer-ready portions, wash and sell them at local markets, or dry and package them into soups, snacks, or spices.

Little is known about the factors that influence farmers to adopt VA technologies in the specialty crops industry. Because most research of VA technology adoption has been focused at the county, state, and regional levels (Monchuk et al. 2007), we focused on the factors influencing specialty crops farmers to adopt VA technologies at the farm level. The objectives of this study were two-fold. First, we analyzed how market access affects the farmer's decision to adopt VA technologies. Asfaw et al. (2014) and Ruslan et al. (2013) reported the link between agricultural innovations and market access. They proposed that through increased market access, farmers obtain information about consumers' preferences, which, in turn, encourages them to differentiate their products through the adoption of VA technologies. Social interactions and market relationships may provide farmers with feedback and price premiums that motivate them to differentiate their products by adding value to their specialty crops. Second, we addressed key identification issues by investigating the potential endogeneity between the adoption of VA technologies (vertical diversification) and the number of crops (horizontal diversification). To date, this has not been addressed in the VA technology adoption literature. Using results from a robust instrumental variable (IV) approach, we proposed that the number of crops among specialty operations influences the adoption of VA technologies, and not the other way

around. In other words, we proposed that by increasing the number of produced and sold crops, farmers are encouraged to adopt VA technologies to increase efficiency and productivity.

Materials and Methods

Data description. Data for this study were from a 2019 web-based survey of specialty crops growers who were part of e-mail lists of growers' associations and the Food Industry MarketMaker database. We compiled 3557 e-mail addresses of growers located in 32 states (i.e., Alabama, Arizona, Arkansas, California, Colorado, Florida, Georgia, Idaho, Illinois, Indiana, Iowa, Kentucky, Louisiana, Maine, Maryland, Massachusetts, Michigan, Minnesota, Mississippi, Montana, New Mexico, New York, North Carolina, North Dakota, Oklahoma, Oregon, Rhode Island, Tennessee, Virginia, West Virginia, Wisconsin, and Wyoming). The list of growers was screened to eliminate duplicate entries and operations. The e-mail databases facilitated access to a wide range of producers growing fruits, vegetables, and herbs (i.e., specialty crops).

Similar to Velandia et al. (2020), we evaluated sample representativeness by comparing the distribution of our survey sample based on acres of specialty crops production to the distribution of specialty crops growers based on the 2017 Census of Agriculture Data. We considered operations from the Census data that reported growing vegetables, fruits, nuts, berries, and other edible specialty crops. Although the survey sample tended to slightly underrepresent specialty crops operations between 1.0 and 99.9 acres and overrepresent farms with 100 acres or more, the farm size distribution from the surveyed sample closely followed the size distribution of specialty crops operations from the United States Census data (Fig. 1).

The Web-based survey was conducted using a mixed-mode design using Qualtrics software. To increase the participation rate, we included an incentive (a \$10 gift card) to the first 1000 farmers who completed the survey. Dillman et al. (2014) noted that including token incentives tends to increase online survey participation. We sent three e-mail reminders at 2-week intervals between March and April 2019. A total of 766 farmers completed the survey, resulting in a response rate of 21.5%, which is considered an acceptable rate for this type of survey (Dillman et al. 2014; Torres et al. 2017). The questionnaire included questions related to the farmer's demographics (i.e., educational attainment, sex, farming experience), farm characteristics (i.e., crops, markets, and growing technologies), and the farmer's network perceptions of their farm and adopting VA technologies. The respective Institutional Review Board approved the questionnaire for compliance with ethical standards for human subjects.

The subsample for this study included 558 operations growing fruits, vegetables, and culinary herbs. Farmers who did not respond to the questions regarding VA

technologies were excluded from the study. We followed the USDA Rural Business Development definition of VA technologies to categorize farmers into two groups according to their adoption of VA technologies used in 2018. The first farmer category, VA, is for farmers who produced VA products such as dried or dehydrated produce, produce cut into customer-ready portions, or prewashed specialty crops. The second category, no VA, included specialty crops operations that answered that they were not using any VA technology in 2018. From the sample of 558 farmers, 293 farmers (52.5%) produced and sold VA agricultural products and 265 (47.5%) were categorized as no VA. We compared farmer categories using multiple comparisons of means using analysis of variance models and Tukey's honestly significant difference test at a 10% significance level. Analyses were conducted using Stata (release 15; StataCorp, College Station, TX).

Empirical model specification. Econometric models were used in this study. Using a standard probit, our primary goal was to investigate the impact of market access on the adoption of VA technologies among specialty crops farmers. We also addressed the potential simultaneous causality that may arise from the relationship between the adoption of VA technologies (vertical diversification) and the number of crops grown by a farmer (horizontal diversification) because these two types of agricultural diversification can be common among specialty crops growers (Barbieri and Mahoney 2009). Similar to Ahmadzai (2017), we used an IV approach to control the possible endogeneity from unobserved characteristics that may lead a farmer to adopt VA technologies. Although we proposed that crop diversity may influence farmers to adopt processing technologies that add value to their agricultural products, lower risk, and increase revenue, it may be argued that the adoption of VA technologies can increase the likelihood to produce more crops to take advantage of the technology investment.

A probit model of the decision to adopt VA technologies. A probit regression model was used to estimate how the choice of market channel drives the decision to adopt VA technologies:

$$Y_i^* = \Phi(\beta_0 + \text{market}_{1i}\beta_1 + X_{2i}\beta_2), \quad [1]$$

where the dependent variable Y was the binary decision to adopt VA technologies. Farmers were grouped into two categories: those who used VA technologies for their specialty crops operations in 2018 (VA) and those who did not use any VA technologies (no VA). Therefore, the dependent variable had the value $Y = 1$ if the farmer self-reported the adoption of VA technologies (e.g., drying or dehydrating, washing, or cutting specialty crops into customer-ready portions) in 2018; otherwise, the value was $Y = 0$.

Similar to Torres et al. (2017) and Aggarwal et al. (2018), we proposed that market access can drive the adoption of new practices,

such as VA technologies. Social interactions and market relationships, especially those developed at the marketplace, may provide farmers with feedback and price premiums and motivate them to differentiate their products by adding value to specialty crops. Our hypothesis was that a farmer's decisions regarding market access can influence the adoption of VA technologies. Similar to Gollop and Monahan (1991), we deconstructed the key explanatory variable (market) into two components: number of sales methods used (first bracket) and distribution of sales per method (second bracket):

$$\text{market} = \left(1 - \frac{1}{\text{methods}}\right) + \sum_i \left(\frac{1}{\text{methods}^2} - \text{share}_i^2\right) \quad [2]$$

The first bracket in Eq. [2] accounts for the number of sales methods (market diversification index) used by the farmer, including farm stands, farmers' associations, community-supported agriculture, farmers markets, food hubs, grocery stores, internet orders, processors, restaurants, school districts, wholesalers, and other markets. According to Eq. [2], the market diversification index increases as the number of methods of sales used increases. For example, a grower using five market outlets would have a value of 0.8 for the first bracket, whereas a farmer selling only through a farmers' market (one market outlet) would have a value of zero. In other words, a larger number of selling methods used by the farmer illustrates a larger degree of market diversification.

The second bracket in Eq. [2] illustrates the distribution of sales methods (market distribution index), representing the proportion of sales through market outlets. For example, a farmer who reported selling crops in the same proportion (50/50) using farmers' market and wholesale would have a distribution component of -0.25 or $\frac{1}{2^2} - (0.5^2 + 0.5^2) = -0.25$. However, a producer who sells 90% of products through farmers' markets and only 10% via wholesale would have a diversification component of $\frac{1}{2^2} - (0.9^2 + 0.1^2) = -0.57$. In other words, a larger negative number in the diversification component would indicate an unequal distribution of sales.

Table 1 describes the explanatory variables in the set of covariates X_{2i} in Eq. [1]. The parameter vector $\beta = (\beta_0, \beta_1, \beta_2)$ was estimated, and $\Phi(\cdot)$ is the standard normal probability distribution function. The set of covariates X_{2i} contains important factors influencing the adoption of VA technologies, such as farmer demographics, farm characteristics, farmer attitudes, and network and information variables. The demographics of farmers included educational attainment, sex, race, part-time farming or full-time farming, and years of farming experience. Farm characteristics included the number of crops produced, number of family members working at the farm, number of employees hired

(permanent and temporary), total owned and rented land, the legal structure of the farm, and percentage of the farm income from specialty crops. Farm size was based on the USDA Economic Research Service categorization of family farms. Small operations were those reporting gross sales from \$5000 to \$99,999. Medium farms reported gross sales of \$100,000 to \$250,000. Large operations reported gross sales more than \$250,000 in 2018. Farmers were also asked if they perceived sales. The number of employees increased from 2018 to 2019. We used the United States Census regions to group farmers from the Midwest and compared the results to those of their counterparts in other regions. The rationale for this grouping was based on the fact that grouping growers into more categories would result in some groups with few observations because of small sample sizes. The Midwest region grouped farms located in Illinois, Indiana, Iowa, Michigan, Minnesota, North Dakota, and Wisconsin.

Because improved technologies are not adopted immediately, Maertens and Barrett (2013) highlighted the role of networks in mediating the adoption of agricultural innovations. The farmer's network variable was defined as 1 if the farmer reported that family, friends, or farmers in the community adopted VA technologies. Valuable sources of information included information obtained from industry, other farmers, and extension personnel. Attitudinal questions were used to examine the perceptions of agriculture and VA technologies of farmers. Likert-type scales were chosen to capture respondents' perceptions because they are easy for individuals to answer in a survey and produce good results (Lusk and Coble 2005). The producer's perceptions of agriculture and their business profitability were rated using a 5-point Likert-like scale (1, strongly disagree; 5, strongly agree). Perception variables included whether farmers agreed that they should receive government support to add value to produce, and whether they should receive financial assistance to accommodate the changing regulatory landscape. We also asked farmers if they were satisfied with their farm business, if they had a positive experience trying new farming technologies to increase profits, and if it was difficult to find reliable customers for VA produce.

Addressing endogeneity. The regressor used in Eq. [1] raised the concern of endogeneity from a possible bias caused by simultaneous causality between the adoption of VA technologies (vertical diversification) and the number of crops produced (horizontal diversification). Simultaneous causality occurs when the causality can happen in both directions: from the regressors (i.e., independent variables) to the dependent variable, and from the dependent variable to the regressors (Bascle 2008). Ignoring potential endogeneity can lead to endogeneity bias and, consequently, result in the inconsistent effects of crop diversification on the adoption of VA technologies (Bascle 2008).

We consider that endogeneity may be caused by the relationship between adopting VA technologies and diversifying the crop mix. For example, one can assume the

farmer's decision to increase the crop mix might be driven by an investment in a dryer (i.e., VA technology). A farmer may want to increase the return on investment of the dryer by increasing the number of crops grown, dried, and sold. In the other direction of simultaneous causality, farmers growing a diverse number of crops may want to take advantage of their wide variety of products; therefore, they may be more likely to adopt VA as a strategy to increase their farm income. We proposed that the number of crops produced on the farm influences the decision to adopt VA technologies, and not the other way around. We developed a two-stage probit approach with endogenous regressors to address the possibility of endogeneity. Using an IV approach, we aimed to find a variable that influences the potential endogenous regressor (number of crops) but is not related to the farmer's decision to adopt VA technologies (VA).

We proposed the use of farming technologies (e.g., artificial lighting, aeroponics, aquaponics, hoop houses, hydroponics, greenhouses, plasticulture, and irrigation) as the instrument for the variable number of crops. According to the diversification literature, farmers using farming technologies tend to report, on average, six additional crops in their crop mix (Lancaster and Torres 2019). The use of these growing technologies can help farmers extend the farming season, increase yield, and improve pest management, which tend to influence the adoption of a greater number of crops in their operations (Carey et al. 2009). The IV captured the effect of the potential endogenous regressor (number of crops) on the dependent variable (VA) by influencing only the potential endogenous variable and not influencing the dependent variable.

We considered the following two-stage model in which Y_{1i}^* is the dependent variable in Eq. [3] ($Y = 1$ if the farmer self-reported the adoption of VA technologies; $Y = 0$ otherwise) and Y_{2i} is the potentially endogenous regressor in the equation (number of crops) in Eq. [4]. The variable Y_{1i}^* in Eq. [3] is latent; therefore, it is not directly observed. Instead, the binary outcome Y_1 is observed, with $Y_1 = 1$ if $Y_{1i}^* > 0$, and $Y_1 = 0$ if $Y_{1i}^* \leq 0$. The equation of primary interest is Eq. [3], whereas Eq. [4] is the first-stage or reduced-form equation, that is:

$$Y_{1i}^* = \beta \text{ncrops} + X_{1i} \gamma + u_i \quad [3] \text{ (Structural equation)}$$

$$Y_{2i} = X_{1i} \pi_1 + IV \pi_2 + v_i \quad [4] \text{ (Reduced-form)}$$

where $i = 1, \dots, N$; X_1 is a $K_1 \times 1$ vector of exogenous regressors, and IV is the instrumental variable (farming technologies) that affects Y_2 but can be excluded from Eq. [3] because it does not directly affect Y_1 (Cameron and Trivedi 2009). The results of the first-stage equation from Eq. [4], which was modeled as an ordinary least square to explain the variation of the

Table 1. Description of farmer demographics, farm characteristics, and behavioral variables for the sample of specialty crops farmers participating in an online survey about the adoption of value-added (VA) technologies (N = 558).

Variable	Description
Market Variables	
Market diversification index	Diversification index (measured with the Herfindahl index) for the number of sales methods, which denotes the number of methods used to sell products
Market distribution index	Diversification index (measured with the Herfindahl index) for the distribution sales methods, which denotes the percentage sales through each method
Farmer Demographics	
College	1 = individual has a college degree or completed postgraduate work; 0 = otherwise
Female	1 = if farmer is female; 0 = otherwise
Minorities	1 = if farmer is black, African American, American Indian, Asian, multiracial, or other; 0 = otherwise
Years farming	Years of farming
Part-time	1 = if respondent farms part-time; 0 otherwise
Farm Characteristics	
DTC markets	1 = if farmer only used direct-to-consumers market channels such as farmers' markets, community-supported agriculture, etc.; 0 = otherwise
Number of crops	Number of crops produced
Family	Number of family members working on the farm
Employees	Number of employees
Total land	Total owned and rented land in acres
Sole proprietorship	1 = if the business structure of the farm is a sole proprietorship; 0 = otherwise
Medium farm	1 = if annual gross sales are between \$100,000 and \$250,000; 0 = otherwise
Large farm	1 = if annual gross sales are larger than \$250,000; 0 = otherwise
Sales growth	1 = if gross sales increased in 2018; 0 = otherwise
Employment growth	1 = if number of employees increased in 2018; 0 = otherwise
Midwest region	1 = in Illinois, Indiana, Iowa, Michigan, Minnesota, North Dakota, and Wisconsin; 0 = otherwise
Networks	
VA networks	1 = if family, friends and/or farmers in the community have adopted cut or dry strategies for their business; 0 = otherwise
Industry associations	1 = if industry associations were a useful source of information; 0 = otherwise
Farmers association	1 = if other farmers were a useful source of information; 0 = otherwise
University Extension	1 = if university extension was a useful source of information; 0 = otherwise
Perceptions	
Government support	1 = if farmer somewhat or strongly agrees that farmers should receive government support to add value to produce; 0 = otherwise
Financial assistance	1 = if farmer somewhat or strongly agrees that farmers should receive financial assistance to be able to accommodate the changing regulatory landscape; 0 = otherwise
Satisfied	1 = if farmer somewhat or strongly agrees with the satisfaction of the farm business; 0 = otherwise
Positive VA experience	1 = if farmer somewhat or strongly agrees that have they had a positive experience with trying new farming technologies to increase the profits; 0 = otherwise
Difficult to find VA customers	1 = if farmer somewhat or strongly agrees that it is difficult to find reliable customers for value-added produce; 0 = otherwise

potentially endogenous variable (number of crops) as a function of farming technologies and exogenous variables. Therefore, the first-stage equation was used to identify the strength and validity of farming technologies. The two-stage model is an alternative estimation procedure with normal errors (Newey and West 1987) that uses a minimum chi-squared estimator (χ^2 test). This estimator also assumes multivariate normality and homoscedasticity.

Results and Discussion

Descriptive statistics. Table 2 describes the explanatory variables with mean differences for all the variables used in the models by the type of farmer. The first bracket of the market variable (i.e., market diversification index) is significantly higher for VA farmers (0.52) when compared with the index for farmers that do not adopt VA technologies (0.33) ($P < 0.01$). In other words, VA farmers tend to sell their produce through more markets compared with farmers who do not use VA technologies. Female farmers represented one-third of the total sample data, which is consistent with national statistics indicating that 36% of

farmers in the 2017 Agriculture Census were women (US Department of Agriculture National Agricultural Statistics Service 2020). Interestingly, more women are VA farmers (38%) than no VA producers (26%) ($P < 0.05$). This concurs with findings of Dias et al. (2019), which indicated that a more significant proportion of female farmers adopt VA technologies to increase farm revenue, whereas men tend to focus on increasing yield.

On average, farmers adopting VA technologies increased their crop numbers by more than twice (20) compared to those not adding value to their crops (8) ($P < 0.01$). These results are consistent with those of De Benedictis et al. (2009), who found that specialty crops operations tend to increase the crop portfolio as they move out of early development stages; in this case, this occurred when operations started to adopt diversification strategies. Expectedly, fewer VA farmers (29%) reported farming part-time, which was significantly lower than the 37% of no VA farmers ($P < 0.05$). According to Jablonski et al. (2020), agricultural operations that add value to their products tend to be more labor-intensive

than their counterparts and may require farmers to farm full-time.

Although there is no significant difference across farm types regarding the number of employees or family working at the farm, farmers adopting VA technologies, on average, reported significantly higher employment growth in their operations (17%) in 2018 than non-VA farmers (12%) ($P < 0.1$). Similarly, farmers adopting VA technologies reported, on average, more growth in sales (37%) in 2018 than their counterparts (30%) ($P < 0.1$). These results suggest that farmers who adopt VA technologies experience more economic growth than their counterparts.

Maertens and Barrett (2013) highlighted the importance of networks to agricultural technology adoption. Our findings indicated that 37% of farmers who adopted VA technologies knew at least one member of their community (e.g., family, friends, or farmers) who has adopted VA technologies. This value was significantly lower for the farmers who did not adopt VA ($P < 0.01$). Interestingly, among all sources of information (i.e., industry, farmers, and university cooperative extension services), only information from industry associations was significantly useful for VA

Table 2. Descriptive statistics of the full sample of farmers and mean comparisons of farmer categories from the sample of specialty crops farmers participating in an online survey about the adoption of value-added (VA) technologies among specialty crops growers in 32 states of the United States (full sample, N = 558; VA, N = 293; no VA, N = 265).

Variable	Full Sample		VA Technologies			No VA Technologies	
	(N = 558)		(N = 293)			(N = 265)	
	Mean	SD	Mean	SD		Mean	SD
Market diversification index	0.43	0.31	0.52	0.28	***	0.33	0.32
Market distribution index	-0.50	3.91	-0.66	5.20		-0.32	1.50
College ⁱ	0.66	0.47	0.67	0.47		0.64	0.48
Female ⁱ	0.33	0.47	0.38	0.49	**	0.26	0.44
Minorities ⁱ	0.06	0.24	0.06	0.24		0.06	0.23
Midwest region ⁱ	0.52	0.50	0.50	0.50		0.54	0.50
DTC markets	0.39	0.49	0.38	0.49		0.39	0.49
Number of crops	14.28	14.61	20.35	14.83	***	7.57	11.01
Years farming	23.66	15.65	22.66	15.54		24.76	15.73
Family	2.72	1.77	2.83	1.87		2.61	1.64
Employees	15.16	42.01	16.97	49.91		13.14	31.01
Total land	277.67	742.64	238.49	622.70		321.28	855.82
Sole proprietorship ⁱ	0.41	0.49	0.41	0.49		0.42	0.49
Part-time ⁱ	0.32	0.47	0.29	0.45	**	0.37	0.48
Medium farm ⁱ	0.13	0.33	0.12	0.32		0.14	0.34
Large farm ⁱ	0.23	0.42	0.23	0.42		0.24	0.43
Sales growth ⁱ	0.34	0.47	0.37	0.48	*	0.30	0.46
Employment growth ⁱ	0.15	0.35	0.17	0.38	*	0.12	0.32
VA networks ⁱ	0.27	0.45	0.37	0.48	***	0.17	0.38
Industry associations ⁱ	0.69	0.46	0.65	0.48	**	0.73	0.44
Farmers association ⁱ	0.88	0.33	0.89	0.31		0.86	0.35
University extension ⁱ	0.83	0.37	0.82	0.39		0.85	0.36
Government support ⁱ	0.34	0.48	0.38	0.49	*	0.30	0.46
Financial assistance ⁱ	0.54	0.50	0.59	0.49	**	0.48	0.50
Satisfied ⁱ	0.65	0.48	0.61	0.49	**	0.69	0.46
Positive VA experience ⁱ	0.55	0.50	0.61	0.49	***	0.49	0.50
Difficult to find VA customers ⁱ	0.34	0.47	0.40	0.49	***	0.27	0.45

*, **, ***Significant at $P < 0.1$, 0.05 , and 0.01 , respectively.

ⁱ The mean is the percentage of respondents with that attribute.

farmers. Approximately 73% of non-VA farmers considered industry associations to be a useful source of information; conversely, 65% of their counterparts reported that they considered this source of information useful ($P < 0.05$).

We found that all the perceptions of VA technologies evaluated in our model were statistically significant across farmer categories. A higher proportion of VA farmers perceived they should receive government support to add value to their crops ($P < 0.1$) and financial assistance to be able to accommodate the changing regulatory landscape compared to non-VA operations ($P < 0.05$). More VA farmers reported a positive experience with VA technologies to increase profits ($P < 0.01$) and declared that it was more difficult to find reliable customers for VA produce ($P < 0.01$) than non-VA farmers. In contrast, VA farmers were significantly less satisfied with their farm business than their counterparts ($P < 0.05$).

Regressions results. This study provides empirical evidence of the effect of market access and other key drivers on the farmer's decision-making process regarding VA technologies. Table 3 reports the coefficients, standard errors, and marginal effects from the standard probit and the IV probit regressions. Table 3 shows that results from the IV approach were consistent with the standard probit. To illustrate, we found that standard errors and robust standard errors were

similar, suggesting the lack of heteroskedasticity in our data (King and Roberts 2015).

Results of the first stage (reduced form) of the IV probit regression provided the validity of our IV approach (available on request). The statistically significant results and strong correlation between farming technologies (IV) and the number of crops (potential endogenous variable) illustrate the strength and power of the IV used in this model. Consistent with Lancaster and Torres (2019), we found that farming technologies were a major factor influencing crop diversification among specialty crops operations, demonstrating the relevance of the IV approach.

A key finding was the fact that in the IV probit estimations, the parameter p from the Wald test of exogeneity was not statistically significant ($P = 0.36$) (Table 3). A p that is not statistically significant is equivalent to the number of crops being unlikely to be endogenous relative to the adoption of VA technologies. Therefore, there was insufficient evidence for declining the null hypothesis that the model is exogenous. In other words, endogeneity is not likely to be an issue in the analysis; therefore, we used the marginal effect results from the standard probit (Table 3) to explain how market access and other factors influence the decision to adopt VA technologies among specialty crops operations. A reason why endogeneity was not an issue may be the extensive list of covariates included in the model.

The findings also provided evidence that the number of crops produced by farmers is a crucial factor influencing the adoption of VA technologies, and not the other way around.

Probit results from Table 3 provided robust empirical evidence that the first component (market diversification index) of our key explanatory variable equation (market) significantly influenced the farmer's decision to adopt VA technologies. On average, the probability of adopting VA technologies significantly increased by 28.7% as the market diversification index increased ($P < 0.01$). This result suggests that the number of markets accessed is a significant factor determining the adoption of VA technologies. One explanation may be that farmers accessing more market channels have more exposure to a diverse range of consumer trends and demands; therefore, they are more likely to adopt VA technologies to differentiate their products. We can infer that accessing various markets can impact the diversity and differentiation strategies in the specialty crops industry. Therefore, we expect that farmers located in remote areas with less market access may not be driven to add value to their produce through VA technologies, and policies encouraging the adoption of VA technologies among those farmers may not be as efficient as those targeting farmers near or in urban areas. Policymakers can use these findings to consider whether market access policies

Table 3. Standard probit and instrumental variable (IV) probit estimation results of the factors influencing the adoption of value-added (VA) technologies among specialty crops growers in 32 states of the United States.

	Probit				IV Probit		
	Coeff.	SE	Marginal Effect		Coeff.	SE	
Market diversification index	0.98	0.26	28.69	***	0.73	0.38	*
Market distribution index	-0.01	0.02	-0.32		-0.01	0.02	
College	-0.05	0.15	-1.57		-0.06	0.15	
Female	0.09	0.15	2.50		-0.01	0.18	
Minorities	-0.25	0.28	-7.42		-0.23	0.28	
Midwest region	-0.19	0.14	-5.51		-0.22	0.14	
DTC markets	0.34	0.16	9.94	**	0.29	0.17	*
Number of crops	0.04	0.01	1.09	***	0.05	0.02	***
Years farming	0.00	0.00	0.02		0.00	0.00	
Family	0.11	0.04	3.22	***	0.11	0.04	***
Employees	0.00	0.00	0.08		0.00	0.00	*
Total land	0.00	0.00	0.00		0.00	0.00	
Sole proprietorship	0.06	0.15	1.83		0.02	0.16	
Part-time	0.04	0.16	1.22		0.12	0.18	
Medium farm	-0.38	0.21	-11.31	*	-0.37	0.21	*
Large farm	-0.04	0.21	-1.17		-0.04	0.21	
Sales growth	0.00	0.15	-0.05		-0.07	0.17	
Employment growth	0.44	0.20	13.02	**	0.44	0.21	**
VA networks	0.47	0.15	13.68	***	0.38	0.18	**
Industry associations	-0.25	0.16	-7.22		-0.21	0.16	
Farmers association	-0.06	0.21	-1.73		-0.10	0.22	
University extension	-0.07	0.20	-2.13		-0.01	0.21	
Government support	0.17	0.16	5.06		0.17	0.17	
Financial assistance	0.01	0.16	0.43		0.01	0.16	
Satisfied	-0.30	0.14	-8.68	**	-0.25	0.15	*
Positive VA experience	0.24	0.14	7.03	*	0.22	0.14	
Hard to find VA customers	0.42	0.14	12.48	***	0.40	0.15	***
Constant	-1.30	0.36		***	-1.38	0.38	***
Observations			491			491	
Probability > χ^2			0.00			0.00	
Pseudo R ²			0.25				
Wald test of exogeneity (<i>p</i>)						0.83	

Coeff = coefficients; SE = standard errors from the probit regressions.

*, **, ***Significant at $P < 0.1$, 0.05, and 0.01, respectively.

and incentives are associated with the adoption of VA technologies.

Results from the standard probit regression illustrated that increasing the number of crops grown can significantly drive the adoption of VA technologies. For example, increasing the crop mix by one crop can increase the likelihood to adopt VA technologies by 1.1% ($P < 0.01$). It seems that horizontal diversification has a significantly positive effect on vertical diversification (VA technologies) for specialty crops growers. Our results were similar to those of Morris et al. (2017), who found that crop diversification tends to influence technology adoption.

Farmers selling only to DTC markets were 9.9% more likely to adopt VA technologies than their counterparts ($P < 0.1$). We expect that local markets may be providing farmers with social interactions with customers, which, in turn, can be a source of information to tailor products and access price premiums for differentiated VA products. However, Low et al. (2020) found that employment was not significant when adding value to agricultural products. Deogharia (2018) reported that farmers adopting VA technologies hired more labor. Our results suggest that labor was a significant driver for VA agriculture in the specialty crops industry. Results from Table 3 suggest that having one more family member involved in the agricultural operations increased

the likelihood of the farmer adopting VA technologies by 3.2% ($P < 0.01$). For our sample of farmers, it seemed that the family's participation in the farm positively influenced the adoption of VA technologies. Additionally, Table 3 illustrates that experiencing employment growth was positively correlated with the adoption of VA technologies ($P < 0.05$). According to Jablonski et al. (2020), agricultural operations adding value to their products tended to be more labor-intensive than their counterparts.

The effects of networks have been reported as a significant factor in the technology adoption process (Maertens and Barrett 2013). Results from the standard probit indicated that having a family member, friends, or fellow farmers in the community who have adopted VA technologies increased the probability of VA technology adoption by 13.7% ($P < 0.01$). Our result is consistent with that of studies reporting the importance of networks to the technology adoption process (Ward and Pede 2015). Farmers that agreed that it is difficult to find reliable customers for VA produce were 12.5% more likely to adopt VA technologies ($P < 0.01$). Because farmers adopting VA are the ones looking for markets for their VA products, it is expected that they would tend to perceive access to customers as a barrier.

Conclusions

This study aimed to provide a better understanding of the following agriculture innovation paradox proposed by Cirera and Maloney (2017): why, if returns to the adoption of new technologies are so high, so few farmers adopt them? Our findings show that factors such as market access, sex, labor, crop diversification, and networks motivated specialty crops farmers to adopt VA technologies. In contrast, the adoption of VA technologies was deterred by farm location, perceptions, and farm size. Promoting these drivers and reducing the most important barriers to adopt VA technologies can be essential to designing and delivering initiatives that support specialty crops farmers to differentiate and access markets.

The first component of the market vector elucidates the importance of market diversification for VA agriculture. We propose that farmers with greater market diversification might have a better understanding of market trends and decide to adopt VA technologies to tailor and differentiate their raw agricultural products to meet consumer demand. It is possible that the marketplace gives signals to farmers that encourage them to adopt VA technologies. For example, farmers with close relationships with end consumers at local markets may be more likely to gather information

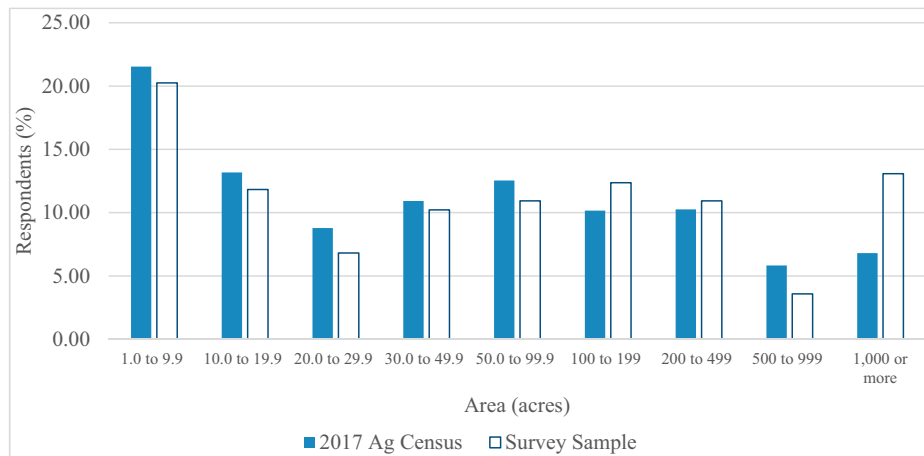


Fig. 1. Percentage of farms in each farm size category based on acres of specialty crops production according to the 2017 Census of Agriculture data and the survey sample from a 2019 survey of specialty crops growers registered in the Food Industry MarketMaker and grower associations databases.

about the attributes, presentations, and forms of VA produce that meet their needs. Obtaining a higher share of consumers' dollars in local markets may allow farmers to invest in technologies that differentiate their products and contribute to the farmer-consumer relationship.

Our results have clear policy implications. Policymakers and agricultural associations or agencies (i.e., Farm Bureau) should focus their efforts to promote programs that link farmers with buyers and build new market opportunities. Our results show the importance of providing funding for the development of extension programs to increase market access, such as the Market Access Program, Local Agriculture Market Program (Farmers' Market and Local Food Promotion Program), and Specialty Crops Block Grant Program. We expect that as extension programs provide market education strategies to support farmers' access to new markets, this will impact the adoption of VA technologies. Researchers should further investigate the effect of accessing different market outlets on the adoption of new technologies and long-term sustainability of agriculture.

We found that farmers located in the Midwest are less likely to adopt VA technologies. One explanation for this may be that the lack of highly populated areas and markets may deter farmers from adopting new technologies to satisfy differentiated markets. Because markets tend to be more regional than national in nature, results from this study suggest that, to be effective, policies and strategies to improve market access should focus on regions or states.

This study also contributes to the diversification literature by indicating that the decision to diversify horizontally (i.e., producing more crops) is not endogenous to the decision of adopting VA technologies. Our results suggest that horizontal diversification may help specialty crops farmers spread risk through more crops, improve the cash flow, and increase financial resilience (McNamara and Weiss 2005), which, in turn, seem to be motivating farmers to adopt VA technologies.

These results show that programs aimed at supporting crop diversification and market access, such as the USDA Sustainable Agricultural Research and Education program, may also influence the adoption of VA technologies in the specialty crops industry. Extension personnel might promote increasing the farmers' crop mix to promote the adoption of VA technologies and innovation in the specialty crops industry.

Our results indicate the importance of labor availability for the success of VA agriculture. Our results are consistent with those of Lobao and Stofferahn (2008), who conducted a review of 70 years of research to find the key correlation between community economic growth and family organized farms. We found that increasing the number of family members working at the farm operation increases the likelihood of adopting VA practices. We also found a positive correlation between VA technologies and employment growth, thus suggesting that the benefits of VA agriculture tend to have spillover effects in rural communities. Policymakers can use our results to promote the positive externalities of adopting VA technologies for rural economic development, such as the VA producer grant funded by USDA-Rural Development.

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