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Farmers' Willingness to Pay for Various Features of Electronic Food Marketing Platforms

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Abstract

This study utilizes a choice experiment to evaluate agricultural producers' preferences and willingness to pay (WTP) for five features offered by electronic food marketing platforms. The attributes examined are: an online marketplace, social media advertisement of farms, different operators of the marketing platforms, an online directory, and monthly fee levels. The results in this study indicate heterogeneity in producers' preferences. Specifically, farmers can be divided into two distinct groups: producers interested in electronic food trading platforms, and producers who are not interested in them. Producers in the first group are willing to pay $70 per month for an online marketplace and $152 per month for the service. Lastly, farmers have a slight preference for a for-profit operator when compared to a not-for-profit operator.

Keywords: e-commerce, Latent Class Model, willingness to pay, online food sales

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Introduction

The increased demand for locally grown, and organic food products in conjunction with consumers' concerns about the sustainability of farm practices have created a plethora of new marketing opportunities for agricultural producers and entrepreneurs in the United States (Connolly and Klaiber 2014; LeRoux et al. 2009; Uematsu and Mishra 2011). Direct marketing, specifically farmers' markets, Community Supported Agriculture (CSA), and food hubs, are prominent examples of marketing strategies utilized to satisfy changing consumer preferences (Martinez et al. 2010, Ahearn and Sterns 2013).

However, despite their popularity among consumers and producers, direct marketing options pose a number of challenges—one being increased costs for producers by marketing their products in several locations (Low et al. 2015). Another challenge is the inconvenience that shopping at farmers' markets and CSAs creates for many consumers due to the limited days/hours of operation, as well as the high prices and limited product variability (Hardesty 2008; Tippins et al. 2002; Lucan et al. 2015).

Comparatively, online food retailing is a marketing strategy that has the potential to overcome the aforementioned limitations of direct marketing and potentially revolutionize the way Americans buy food. The distinct advantages of this kind of electronic trade include reduced retail cost, the ability to expand the customer base, a more efficient management of the supply chain, the potential for higher profits, and a time saver for customers (Baourakis et al. 2002; Corbitt et al. 2003; Zapata et al. 2013; Galloway et al. 2011; Heim and Sinha 2001).

Despite these advantages, the majority of online food retail websites developed during the dot-com era failed (Williams 2001; Ring and Tigert 2001). Undeterred by these early failures, farmers and consumers are re-looking at electronic food retailing (Abrams and Sackmann 2014; Mortimer et al. 2016; Begalli et al. 2009). To illustrate, according to the USDA Farm Computer Usage and Ownership, 16% of producers in 2015 conducted agricultural marketing activities over the internet; this percentage was 12% in 2011 (USDA 2015). Furthermore, large corporations such as Amazon (Fresh) and Uber (Essentials) are vying to become the most preferred online grocery store, revealing how popular electronic food retailing has become (Mortimer et al. 2016).

Most of the existing literature on electronic food retailing has focused on: 1) consumers' perceptions towards online grocery shopping (Campo and Breugelmans 2015; Kacen et al. 2013; Chu et al. 2010), 2) examining the factors that influence the adoption of e-commerce by farms and agribusiness (Briggeman and Whitacre 2010; Baer and Brown 2007; McFarlane et al. 2003), and 3) the economic potential of e-commerce for farmers (Zapata et al. 2011; Fox 2009). In contrast, farmers' preferences and willingness to pay for online food marketing platforms remains relatively unexplored in the literature; although, a notable exception is the research of Zapata et al. (2013). However, considering that the success of the online food marketing platforms depends on the participation of producers, understanding farmers' perceptions is an important question. The present study aims to fill this void in research by focusing on farmers' willingness to pay (WTP) for various features of electronic food marketing platforms, such as MarketMaker, Local Orbit, Local Harvest, etc.

Objectives

The main objective of this study is to examine producers' opinions and WTP for various features offered by electronic food marketing platforms. Specifically, the examined features are as follows: different fee requirements, an online marketplace to facilitate transactions, social media advertisement of the farm, an online directory service where farmers can search for potential buyers based on demographic statistics, and different operators for the website (extension services, non-profit organizations, for-profit organizations). Accordingly, the main data source used for this study was an electronic survey administered to four southern states: North Carolina, South Carolina, Florida and Georgia.

The contribution of this study to the literature is threefold. First, our focus on the WTP for the aforementioned features of electronic food marketing platforms expands on the work of Zapata et al. (2013). The elicitation of WTP for these features creates a more detailed picture of farmers' reactions towards electronic trade, aside from the extremes of acceptance or rejection. This is an important research topic considering that online platforms can raise revenue by including various features desired by the producers. Second, by including the "operator" attribute, this study sheds light on whether farmers would trust the private sector to develop such websites, or whether they would only trust the extension service to host the websites. To the best of our knowledge, this study is the first effort to answer such a question. Considering the transition of MarketMaker from being administered by the extension service of universities to Riverside Research[1], examining farmers' perceptions towards the host of the website will be extremely helpful in further developing the industry. Third, we include a larger group of farmers in our sample, not just MarketMaker's users as in Zapata et al. (2013). Notably, some in our sample have not used electronic marketing yet. This approach allows for greater insights into farmers' preferences for electronic food marketing platforms.

Survey Design and Implementation

The survey instrument, utilized to achieve the study's objectives, consisted of five sections. The first section included introductory questions to attract the farmers' interest in the survey. Next, the second section included a choice experiment to elicit farmers' WTP for the various features examined. The third section focused on farmers' experiences with electronic commerce. The fourth section asked questions related to the farmers' comfort levels with risk, as well as their trust in various institutions. Finally, the survey closed with traditional demographic questions. Additionally, the clarity of the survey instrument and the wording and order of questions were pretested in a number of focus groups sessions. Notably, the focus groups included farmers, extension service agents, and university professors.

The survey was administered to a sample of vegetable and livestock farmers from four states: North Carolina, South Carolina, Georgia and Florida. There are two reasons why this choice of sample was made. First, fresh fruits and vegetables constitute a substantial portion of direct to consumer marketing outlets (Palma et al. 2013). Specifically, in terms of value, these commodity groups account for 58% of direct to consumer sales (Martinez et al. 2010). Furthermore,

[1] Riverside Research is an independent not-for-profit organization

livestock products such as eggs and steaks; and vegetables are among the most common commodities sold on existing online marketplaces.

Even more, southeastern states have a comparative advantage in the commodity groups of fruits and vegetables due to the climatic conditions of these states (Ahearn and Sterns 2013)[2]. In spite of this fact, the development of direct to consumer marketing outlets in the examined region is limited. To illustrate, the number of farmers' markets per 100,000 residents in Florida and Georgia are 1.1 and 1.2, respectively, as compared to a 2.5 national average (CDC 2013). The latter fact, in conjunction with an increased demand for local foods in the examined region (Ahearn and Sterns 2013; Hodges et al. 2014), indicate an opportunity for the development of alternative marketing outlets such as online food exchanges.

The second reason for this study's sample choice is that the examined region includes a number of major regional urban centers with a plethora of restaurants, e.g., Atlanta, Charlotte, Miami, etc. Restaurants account for a high and continuously increasing portion of local food sales (Low and Vogel 2011; Reynolds-Allie and Fields 2012). However, the lack of infrastructure in the examined region, i.e., a relatively small number of farmers markets, may be a prohibiting factor in the increase of sales to restaurants (Low and Vogel 2011; Reynolds-Allie and Fields 2012). Consequently, the development of a well-designed electronic food exchange platform could help overcome these barriers.

Regarding survey administration, the mailing information for the farmers was obtained through FarmMarketiD.com. An invitation email was sent to the farmers on May 1st, 2014. Following the guidelines provided by Dillman et al. (2009), the initial email provided a brief description of the survey, highlighted the importance of responses, and contained a link to the survey. Additionally, in line with Dillman et al. (2009), an informative subject line, indicating the e-mail is about a survey conducted by Clemson University, was included in the email communications. Moreover, the emails were personalized for each farmer and signed by the researchers. Two reminder emails, including the link for the survey, were sent to the farmers eight and fifteen days after the initial email. Lastly, all email communications were sent from the same email address (Dillman et al. 2009).

The mailing list included 5,000 farmers, with the overall response rate at 3.3% and the effective response rate at 2.5% (123 usable surveys). Notably, the relatively small sample size is a limitation of this study. However, the use of small sample sizes is not uncommon among studies that utilize surveys to examine factors potentially influencing farmers' decisions. For example, Kisaka and Obi (2015), Amanor-Boadu (2013), and Tavernier et al. (2006) used observations obtained from samples of 144, 120, and 144 questionnaires, respectively, to investigate: 1) the factors that influence growers' decisions to participate in land management schemes, 2) producer characteristics that influence their decision to adopt agri-tourism and, 3) the relationship between production practices and food labeling. Furthermore, a low response rate is not uncommon in similar surveys. For instance, Zapata et al. (2013) reported a response rate of 8.9% for an email

[2] For instance, Georgia, and Florida are among the top five states in terms of vegetable production and North Carolina and Georgia are among the top 10 states in terms of livestock sales (Census of Agriculture 2012).

survey among registered MarketMaker users (compared to 15.7% of the paper version). A potential explanation for the low response rate is that farmers are not familiar with electronic marketing platforms yet, and they are not accustomed to online surveys that include choice experiments. Also, online surveys tend to have significantly lower response rates (Hamilton 2009; Hudson et al. 2004). However, low response rate is only weakly related to response bias as mentioned in Zapata et al. (2013), Brick et al. (2003), Krosnick (1999), and Keeter et al. (2000).

Choice Experiment Design

A choice experiment was utilized to elicit farmers' preferences and WTP for the various features potentially offered by an electronic trade platform. Specifically, in the second section of the survey, farmers were presented with a series of choice scenarios. In each scenario they were asked to select among two different website alternatives, or to indicate that they prefer none of them (opt-out). The website alternatives were different in the number of features offered and/or in the monthly fee required from the farmers. Before the choice experiment, farmers were provided with a detailed instruction page describing the experiment and each of the features. Specifically, the following features were examined: online directory, demographic research tool, social media advertisement, online marketplace, the type of service providers, and a monthly fee (Table 1). The selection of these features is based on previous literature (Zapata et al. 2013; Montealegre et al. 2007), and the feedback received from the focus groups and research of online food marketing platforms available during the period of this study.

Table 1. Choice Experiment Attributes and Levels

		Levels					
Attribute	**Description**	1	2	3	4	5	6
Service Provider	The host agent of the website.	State University Extension Service	Local Gourmet (A privately owned, for profit business)	Local Food Hub Association (Not for Profit Association)			
Online Marketplace	Sell products and receive payments online.	No	Offered and no commission is required	Offered, with a 2% commission on sales required	Offered, with a 4% commission on sales required		
Social Media Advertisement	Advertise your business on social media.	Yes	No				
Demographic Statistics	Provide income, gender and other demographic statistics of targeted markets by zip code.	Yes	No				
Monthly Fee	A fee that the farmer has to pay in order to use the website.	$20/month	$40/month	$60/month	$80/month	$100/ month	$120/ month

To further explain the attributes examined, the online directory allows farmers to search the website's database for potential buyers. This option is offered as a feature for all non-opt-out alternatives. The demographic research tool is an expansion of the online directory. Specifically, this tool allows the farmers to use the website database in order to search for demographic characteristics, income level, race distribution, etc. at a specific zip code. As a result, if this is offered, farmers can target specific niche markets. Next, if the social media advertisement feature is offered, the farmer has the ability to advertise his/her farm on the social media accounts of the food exchange website. Furthermore, with this option, the advertisements can be delivered directly to specific groups of consumers. Additionally, the online marketplace refers to the ability of buying and selling directly from the website, i.e., consumers can pay online with their credit/debit card. Lastly, service provider, refers to the host agency of the website.

The demographic research tool and social media advertisement have two levels (offered or not offered). The online marketplace feature consists of four levels. The first level reflects whether or not the feature is supported. If the feature is supported, three additional levels indicating different commission fees based on the sales are included. The service provider has three levels (university extension service, for-profit organization, not-for-profit organization). Lastly, there are six different monthly fee levels ($20/month, $40/month, $60/month, $80/month, $100/month, and $120/month), which reflects the observed market price of these services. A sample choice set is presented in Figure 1.

One hypothesis in this study was that higher monthly fees would reduce the probability of growers' participation in an online marketing outlet. On the other hand, the existence of an online marketplace was expected to increase the probability of participation. Furthermore, the a-priori hypothesis was that the existence of a demographic research tool would increase the probability of participation since growers can increase their profits by price discrimination through targeting specific market segments.

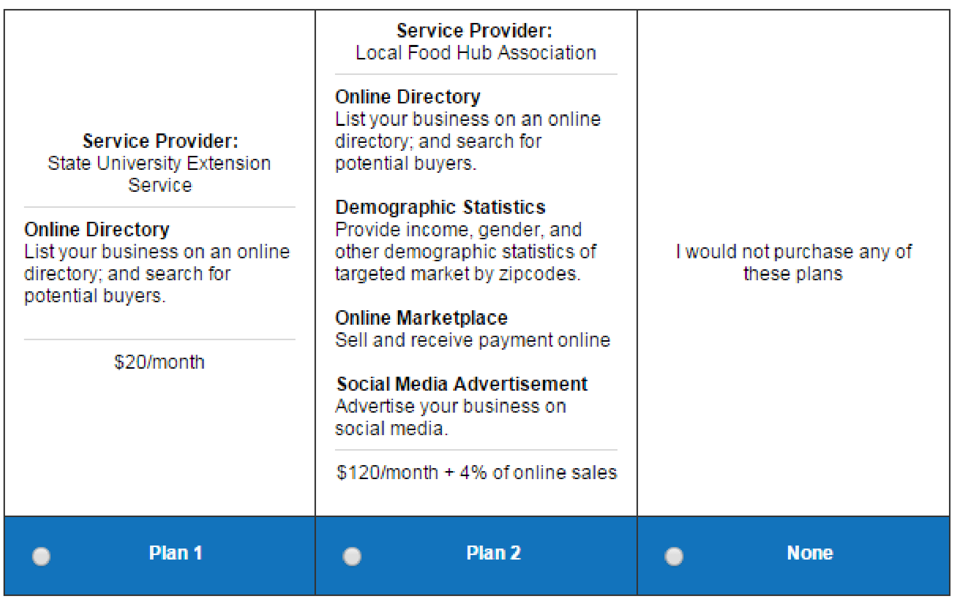

Figure 1. Sample Choice Experiment

Given the five attributes and their levels, a full factorial design resulted in 288 unique profiles[3]. Since it was not practical to evaluate all of these combinations, a D-optimality fraction design

[3] 2*4*3*6*2 =288

was adopted. The final experiment included sixty unique choice profiles. In order to avoid responders' fatigue, but still create a reasonably long survey, thirty-two choice sets were generated and divided into four blocks. Thus, each responder had to answer eight choice sets. Huber and Zwerina (1996) illustrated the importance of utility balance in avoiding unrealistic choice profiles. A Bayesian Experimental Design approach was therefore adopted, in which a set of priors was utilized. Our final experiment design achieved a D-optimal score of 89.94.[4]

Model Specification and Estimation

Lancaster's (1966) theory of demand provided the underlying theoretical framework for this study. Specifically, it was assumed that farmers would select the e-commerce website option that maximizes their utility, which is a function of the different features offered by the website. Following McFadden's (1974) Random Utility Theory, a farmer *i* random utility from selecting the alternative *j* from a choice set *t* can be expressed as:

$$(1)\ \mathrm{U}_{ijt} = \mathbf{x}_{ijt}\boldsymbol{\beta} + \varepsilon_{ijt}$$

where $\mathbf{x}_{ijt}\boldsymbol{\beta}$ is the deterministic component representing the vector of attributes, and ε_{ijt} is a random component unobserved by the researchers, following an IID maximum value Type I distribution.

Multiple techniques have been developed to estimate the probability of an individual selecting alternative *j* (Train 2009). Two estimators were used in this study: a Random Parameter Logit (RPL) and a Latent Class (LC) model. These models were used because they have many desirable attributes. Specifically, in contrast to the traditional, conditional logit formulation, RPL and LC are highly flexible and relax the restrictive independence of irrelevant alternatives assumption. Furthermore, both RPL and LC account for unobserved preference heterogeneity. Additionally, the LC formulation enables researchers to identify preference clusters, thus providing more information to explain preference heterogeneity. Lastly, both formulations allow for unrestricted substitution patterns and correlation in unobserved factors over time (Train 2009; Patunru et al. 2007; Ouma et al. 2007).

Under the latent class model, the probability that an individual farmer *i* choosing alternative *j* in choice set *t*, given that the farmer belongs to class q is estimated as:

$$(2)\ \mathrm{P}_{it|\mathrm{q}}(j=1) = \frac{\exp(\alpha \mathrm{c}_{ijt} + \mathbf{x}'_{it,j}\boldsymbol{\beta}_{\boldsymbol{q}})}{\sum_{\boldsymbol{j=1}}^{\mathbf{J}} \exp(\alpha \mathrm{c}_{ijt} + \mathbf{x}'_{\boldsymbol{it,j}}\boldsymbol{\beta}_{\boldsymbol{q}})}$$

where the price, c_{ijt}, is separated from the rest of the attributes in vector **x**. We used a number the minimum of the Akaike Information Criterion and the Bayesian Information Criterion to determine the number of classes (Greene and Hensher 2003).

[4] JMP 10 DOE procedure was used for the derivation of the optimal design

In contrast, building on the choice probability of conditional logit, the Random Parameter Logit allows the estimated parameter to disperse, following a specified distribution $f(\boldsymbol{\beta})$. The choice probability of choice *j* being selected in choice set *t* is then,

$$(3)\ P_{ijt} = \int \frac{e^{\alpha c_{ijt} + \mathbf{x}'_{it,j}\boldsymbol{\beta}_q}}{\sum_k e^{\alpha c_{ijt} + \mathbf{x}'_{it,j}\boldsymbol{\beta}_q}}\, f(\boldsymbol{\beta}) d\boldsymbol{\beta}$$

The price coefficient is assumed to be fixed. This assumption helps avoid price dispersion around zero as it implies exorbitant willingness to pay (Meijer and Rouwendal 2006; Train and Weeks 2005).

Results

Table 2 reports the descriptive statistics for our sample of 123 respondents. The majority of the farmers who answered the survey were from North Carolina (49%), followed by Georgia (24%). Regarding the type of enterprises, 72% of the respondents had livestock operations, and 50% had horticulture operations (Table 2).

Table 2. Sample Statistics

Age			**State**		
	Mean	59.65			
	Std. Dev	11.62		FL	6.02%
				GA	24.10%
Gender				NC	49.40%
				SC	18.07%
	Male	65.85%		Other	2.41%
	Female	14.63%			
	Undisclosed	19.51%	**Types of Operation**		
Ethnic				Livestock	72.73%
				Horticulture	50.51%
	White	79.67%		Field Crops	21.21%
	Non-white	2.44%		Honey	3.03%
	Undisclosed	17.89%		Others	23.23%
			Acreage		
				Mean	235.32
				Std. Dev.	272.54

This finding is not surprising considering that Georgia and North Carolina are among the top ten states in livestock sales (USDA Census of Agriculture, 2012). The average age of the respondents was 59.6 years old, with 80% of them being white and 14% female. These numbers closely reflect the US average of sixty years, 92% white, and 14% female (USDA Census of Agriculture, 2012). The average farm size for our sample (235 acres) was lower than the national average (435 acres). However, it closely represented the average for the four states we examined.[5] Lastly, 11% of the respondents (thirteen farmers) mentioned that they had experience with electronic marketing platforms. For comparison, NASS (2015) reported that 16% of U.S. farmers use internet for marketing activities.

Results from the Random Parameter Logit Model

The simulated maximum likelihood estimates for the RPL model are reported in Table 3. The model was estimated using 500 Halton draws. Prior to the estimation of the RPL model, a conditional logit model was estimated (Table 4). The results indicate that the RPL model provided a better fit for the data as compared to the conditional logit model. This difference can be attributed to the fact that the RPL accounts for heterogeneity of preferences. The random variable "opt-out" represents the third choice in the choice sets. This option was selected if the farmers would rather not choose any of the offered alternatives. For the RPL model, this variable had a statistically significant positive coefficient. This finding suggests that, on average, farmers would not lose utility if an electronic marketing platform was not offered to them (Table 3). However, the statistically significant standard deviation indicates that there are growers who actually desire this alternative. This finding further validates the heterogeneous preferences among the farmers.

Table 3. Random Parameter Logit Model

	Estimates		S.E.	Std. Dev.		S.E.
Opt Out	4.3723	***	0.9468	5.6779	***	1.0566
[No Demographic Tool]						
Demographic Tool	-0.1349		0.1438	0.2476		0.3079
[No Online Marketplace]						
Online Marketplace	0.9101	***	0.3053	0.7718	**	0.3730
Online Marketplace + 2% commission	0.2373		0.2750	0.4581		0.5023
Online Marketplace + 4% commission	-0.7094		0.4956	1.8592	***	0.4474
[No Social Media Advertisement]						
Advertisement on Social Media	0.0997		0.1682	0.6249	***	0.2268
[Not for Profit Operator]						
For Profit Operator	0.3420	*	0.1859	0.1236		0.4503
Extension Operator	0.0897		0.1926	0.1875		0.5428
Price	-0.0476	***	0.0078			
AIC	692.2					
Log-likelihood	-329.09					
McFadden R^2	0.6823					

Notes. Significance level * = 10 % ** = 5% *** = 1%

[5] Average farm size for FL, GA, NC and SC is 199 acres, 225 acres, 2013 acres and 200 acres respectively (USDA Census of Agriculture 2012)

In line with our hypothesis, the monthly fee variable had a statistically significant, negative coefficient. Thus, ceteris paribus, the higher the monthly fee the lower the probability that a grower would participate in an electronic food exchange platform. This finding is consistent with the pricing policy of some of the existing online food exchange platforms. For example, Clemson Area Food Exchange, Farmigo, and MarketMaker do not require a monthly fee.

However, operating an online food exchange platform is not a costless endeavor. Thus, entrepreneurs need to identify alternative sources of revenue. Two potential strategies are to charge a progressively increasing fee based on the features offered, e.g., LocalOrbit, Direct Local Food, or to charge a commission based on sales, or a markup price, e.g., Farmigo, Clemson Area Food Exchange. As a result, it is important to identify which features the producers value the most and are consequently willing to pay a premium price for, if those features are provided.

One of the most commonly offered features is a demographic tool. This allows producers to identify potential customers based on their gender, age, location etc. As seen in Table 3, a demographic tool does not increase the probability of participation. This finding is in line with the results of Zapata et al. (2013) and Cho and Tobias (2010). The former illustrated that 80% of the registered MarketMaker users never, or rarely, used the website to search for potential buyers and sales opportunities. This percentage was even higher (88%) when growers were asked how often they utilized MarketMaker to find a target market for their products. The latter researchers conducted a survey among New York MarketMaker participants, illustrating that only thirty-two out of 137 responders frequently used MarketMaker to search for sales contracts. A potential explanation for these findings is that farmers do not have the time and/or the knowledge to efficiently utilize such a tool.

Considering that almost 80% of Americans use social media, advertisements of the farm operation on those sites can increase the customer base both for the website and the farmers. A number of platforms advertise the farms that are registered on their website through their social media accounts. The results of the RPL formulation indicate that, on average, farmers would not lose utility if this feature was not offered (Table 3). Thus, offering this feature would not increase the probability that a farmer would register for the marketing platform. However, the statistically significant standard deviation indicates heterogeneity of preferences among farmers. This tells us that some farmers are interested in advertising through social media, which points to the potential to market this feature to a niche segment of farmers.

Another commonly offered feature is an online marketplace. If this is offered, buyers can buy products directly from the website using their credit/debit cards. The positive and statistically significant coefficient associated with this variable indicates that if an online marketplace is offered, the probability that a farmer would participate in the food exchange platform increases. The existence of an online marketplace allows entrepreneurs to raise revenues by charging a commission fee. For the objectives of this study, we examined two potential levels of commission fees at two percent and four percent. Although the coefficients were not statistically significant (Table 3), the percentage of farmers who prefer the online marketplace was reduced from eighty-eight percent (no fee) to thirty-five percent if a four percent fee was added. Accordingly, one of the objectives of this study was to examine if farmers have a preference towards the potential host of the electronic marketing platform. This question is paramount for two reasons. First, if growers do not trust for-profit operators, the potential development of these marketing platforms may be substantially restricted. Second, MarketMaker is transitioning from the extension service to Riverside Research, a not-for-profit entity. This transition may be hindered if farmers do not trust private entities. The findings of the study indicate that farmers were more likely to participate in the marketing platform if the host was a for-profit operator, as compared to a not-for-profit one (Table 3).

Results from the Latent Class Model

Despite its advantages, RPL formulation has some drawbacks. Specifically, the RPL model assumes that preferences are continuously distributed and that it is not possible to identify the sources of heterogeneity from the RPL formulation (Patunru et al. 2007). In order to overcome these problems, we estimated a latent class model. This approach allowed for parameter estimates to vary among the different classes.

Considering there is no prior literature regarding the examined classes, we initially investigated scenarios with three or more classes. However, the latent class model failed to converge. The model provided the best fit when two classes were identified. Table 4 (see Appendix) reveals a substantial difference between the two classes. Specifically, the coefficient for the opt-out variable in class 1 was statistically significant with a positive coefficient. On the other hand, the opt-out variable had a statistically significant negative coefficient for the second group (Table 4). This finding indicates that farmers in the first group would not lose utility if an online food marketing option was not offered to them. However, farmers in the second group would suffer a utility loss if they did not have the option of these electronic marketing platforms. Based on this differentiation, we named the first as the “not interested group” and the second as the “interested group”.

The model indicates that 82% of the sample farmers belonged in the “not interested” group, and 18% in the “interested” group (Table 4). This finding aligns with the current statistic that only 16% of the farmers in USA use electronic marketing approaches (NASS, 2015). Furthermore, in line with the findings of the RPL model, the estimates from the Latent Class formulation indicate that farmers in the “interested group” were more likely to participate in an electronic marketing platform if an online marketplace option was offered. The probability that growers would participate was reduced if the monthly cost increased, ceteris paribus (Table 4). In contrast to the RPL formulation however, there was no statistically significant evidence to support the hypothesis that the probability of participation was affected by the operator of the platform.

Willingness to Pay Estimation

The aforementioned results provide a general picture of the various features of an electronic marketing platform valued most by the producers. In order to create a more detailed explanation, the farmers WTP for the different attributes were estimated. Effect coding was utilized to avoid confounding interpretations of the base category (no online marketplace, no demographic research tool, no social media advertisement, not-for-profit organization) with the base category of the opt-out option (Bech and Gyrd-Hansen 2005). The WTP for an attribute is calculated as:

$$(4)\ WTP_{attribute} = -2 \times \frac{\beta_{attribute}}{\alpha}$$

Tables 5 and 6 provide the WTP estimates based on the LCM and the RPL models, respectively. Furthermore, considering the heterogeneity of preferences among farmers and the objectives of this study, the coefficients and the standard deviation of the RPL model were used to estimate the WTP for the mean, median, 75^{th} and 90^{th} percentile level (Table 6). The mean and standard error of the WTP were estimated using 1,000 draws of the Krinsky and Robb simulation (Hole 2007; Krinsky and Robb 1986).

Table 5. Willingness to Pay Estimates of Interested Farmers from Latent Class Model

Attributes	**Mean**		**S.E.**
	($/month)		
Opt Out	-152.94	***	20.9696
Demographic Tool	2.67		9.2104
Online Marketplace	70.50	***	21.1966
Online Marketplace + 2% commission	13.57		17.3836
Online Marketplace + 4% commission	-30.80		27.2632
Advertisement on Social Media	14.93		10.3081
For Profit Operator	21.97		15.3324
Extension Operator	3.38		15.2633

The results indicate that producers who belonged in the interest group were willing to pay $152.94/month in order to register with an electronic marketing service (Table 5). This number is greater when compared to the findings of Zapata et al. (2013), but not unreasonable considering that 12% of the farmers surveyed by Cho and Tobias (2010) indicated that MarketMaker helped them increase their sales at more than $1,000.

Regarding the possible features of the electronic platform, producers who belonged in the interest group were willing to pay $70/month if an online marketplace was offered without a commission fee. None of the other features examined were found to have a statistically significant WTP coefficient. These findings indicate that the potential revenue sources for the electronic food trading platforms were relatively limited, even when only producers who belong in the interested group were considered. Thus, the operators may need to charge consumers a small fee instead of the farmers.

Table 6. Willingness to Pay Estimates from Random Parameter Logit Model

Attributes	**Positive %**	**Mean**		**S.E.**	**Median**	**75th Percentile**	**90th Percentile**
		($/month)			($/month)	($/month)	($/month)
Opt Out	77.94%	183.77	***	48.27	194.14	35.29	-102.70
Demographic Tool		-5.67		5.93			
Online Marketplace	88.08%	38.25	***	12.67	38.31	58.74	81.13
Online Marketplace + 2% commission		9.97		11.64			
Online Marketplace + 4% commission	35.14%	-29.82		21.95	-26.45	25.64	71.10
Advertisement on Social Media	43.66%	4.19		7.35	5.40	21.29	39.12
For Profit Operator		14.37	*	8.18			
Extension Operator		3.77		8.05			

Notes. Significance level * = 10 % ** = 5% *** = 1APPENDIX: A Sample Choice Set

The WTP estimates from the RPL model (Table 6) indicate that the average grower would require compensation to participate in the marketing platform. This finding is not surprising considering the RPL model included the full sample, in comparison to the LC model where the uninterested farmers were filtered out. However, as seen in Table 6, the farmers at the 90^{th} percentile were willing to pay $102.7/month to subscribe for the marketing platform. These results further validate the hypothesis that there is a small number of entrepreneur farmers with a strong interest to participate in electronic marketing platforms. Lastly, in accordance with our expectations, the producers' WTP for an online marketplace increased towards the 90^{th} percentile (Table 6).

Conclusions

While several studies have examined consumers' preferences for online grocery shopping (Campo and Breugelmans 2015; Kacen et al. 2013; Chu et al. 2010), the literature on producers' perceptions of and their WTP for electronic food marketing platforms remains relatively unexplored (Zapata et al. 2013). Moreover, to the best of our knowledge, no previous study has examined producers' WTP for the various features offered by electronic food exchange websites. However, understanding producers' valuation of these features is critical in the success of electronic food marketing platforms, especially as the competition among different providers increase.

This study utilized a choice experiment in conjunction with RPL and LC models to investigate livestock and fresh vegetable producers' preferences for five features offered by electronic marketing platforms. The attributes examined include the service provider, the online marketplace, the provision of demographic statistics, social media advertisements, and different levels of monthly fees. Accordingly, the main data source for this study was an online survey. Subsequently, the results of the RPL model indicate that, on average, the possibility that a farmer would participate in electronic food marketing platforms increases if the website offers an online marketplace. Similarly, producers are more likely to subscribe to an electronic food marketing platform if the host of the website is a private, for-profit company, as compared to a not-for-profit entity. In line with previous studies, the results indicate that the existence of a demographic tool does not have a statistically significant impact on the probability of joining a food exchange website. Lastly, in line with our initial expectations, the service fee has a statistically significant negative impact, indicating that a higher fee would reduce the probability that a producer would subscribe to an online food marketing platform.

Estimating the LC model allowed us to split producers into two groups based on their preferences for the electronic marketing platform. The first group included growers that would not suffer a utility loss if the electronic platform was not offered to them. The majority of the sample farmers belonged to that group. Comparatively, the second group included farmers that would suffer a utility loss. The LC model estimates indicate that farmers in the latter group were WTP $152 per month for the services of an electronic marketing platform. Furthermore, producers in the "interested" group were WTP $70 per month if an online marketplace was offered without a commission fee.

A limitation of this study should be acknowledged. Specifically, despite the fact that farmers were contacted three times and every possible effort was made to ensure a high response rate, the response rate and the sample size were relatively low. Although this is somewhat expected for online farmer surveys (Zapata et al. 2013), it may prohibit the generalization of our findings to the population. However, to the extent that these survey respondents represent vegetable and livestock producers in the examined region and other areas, the results provide insights into which attributes of online marketplaces farmers value most. This information is important for entrepreneurs as well as applied researchers and extension specialists in their endeavors to create a successful online marketplace.

This study lays the foundation for a number of possible future research endeavors. Future work should expand the analysis to more states and different regions to examine if there is consistency in these findings. Also, it would be interesting to evaluate the preferences of farmers under different potential revenue options from the online platforms, in addition to the cost. Lastly, examining what factors may increase the interest of the non-interested group is also important if we want to avoid potential failures in the future.

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Appendix

Table 4. Latent Class Model

Dependent Variable = Choice	**Two Classes Model**						**One Class/ Conditional Logit**		
	Uninterested Farmers **Class 1**			Interested Farmers **Class 2**					
Coefficients	Estimates		S.E.	Estimates		S.E.	Estimates		S.E.
Price	-0.0574	***	0.0113	-0.0229	***	0.0043	-0.0213	***	0.0030
Opt Out	1.4489	***	0.3963	-1.7481	***	0.3031	1.1022	***	0.1693
Demographic Tool	-0.1890		0.1919	0.0305		0.1032	-0.0007		0.0801
Online Marketplace	-0.1529		0.3715	0.8058	***	0.2041	0.4022	***	0.1342
Online Marketplace + 2% commission	-0.4069		0.4182	0.1551		0.1864	-0.0022		0.1436
Online Marketplace + 4% commission	-0.0095		0.3744	-0.3521		0.2821	-0.2930		0.1950
Advertisement on Social Media	-0.1048		0.2181	0.1707		0.1122	0.0480		0.0855
For Profit Operator	0.1291		0.2639	0.2511		0.1620	0.1314		0.1121
Extension Operator	0.2128		0.2789	0.0386		0.1608	0.1127		0.1172
Class Probability	0.8210	***	0.0351	0.1790	***	0.0351			
Number of Parameters	19						9		
Number of Individual	123						123		
Number of Choice Sets	943						943		
Log likelihood	-348.65						-526.45		
AIC	735.3						1070.9		
BIC	827.43						1114.54		
Pseudo R2	0.6635						0.0608		

Notes. Significance level * = 10 % ** = 5% *** = 1%