A Look at the Variations in Consumer Preferences for Farmers' Markets Attributes

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Abstract: The purpose of this study is to determine the effects of physical attributes of farmers' markets on a customer's willingness to attend a particular market. It was found that ease of movement between vendors is the most important attribute while the least important is the availability of seating.

Keywords: Famers' market, choice based survey, consumer preference

Introduction

Farmers' markets continue to rise in popularity as consumer demand for obtaining fresh products directly from the farm increases; as a result, farmer's markets have become an increasingly visible part of the urban-farm linkage (Wolf, Spittler, and Ahern, 2005). In fact, some consumer trends have shown a preference or response for products that are locally grown (Louriero and Hine, 2001). Many studies have shown that consumers perceive that the products at a farmer's market are of higher quality compared to those at a supermarket, but many farmers' markets are inconvenient to access (Wolf, 1997; Wolf, Spittler, and Ahern, 2005; Sommer, Herrick, and Sommer, 1981; Szmigin, Maddock, and Marylyn, 2003). Also, shopping at a farmer's market may be seen as supporting green consumption whereby certain products or practices are actively avoided while certain purchases may represent a positive alternative, e.g. in relation to organic or free-range production (Schaefer and Crane, 2001; Strong, 1996; Szmigin, Maddock, and Marylyn, 2003). However, there exists little to no research connecting the physical attributes (such as parking, restrooms, etc.) associated with a farmers' market to the likelihood of consumer attendance at a given market.

According to Kreman, Greene, and Hanson (2004), customer participation depends primarily on a market's location, since most customers tend to shop at markets close to where they live (Brown, 2002). Other studies indicate that freshness, high quality, fair pricing, pleasant social interaction with farmers and market shoppers, and locally grown foods are attributes commonly sought by consumers attending farmers' markets (Brown, 2002; Lockeretz, 1987). However, Kreman, Greene, and Hanson (2004) focused on whether or not an organic producer is likely to participate in an urban or rural farmers' market setting, in which the results were inconclusive.

Sommer, Herrick, and Sommer (1981) look at the psychology behind consumers' choice to shop at a supermarket versus a farmers' market. The researchers note that the scale, spatial flow, and physical attributes of the two settings are very different. The supermarket is indoors, linear, and highly structured; most farmers' markets are outdoors, nonlinear, with customers going back and forth checking the price of different vendors, which creates a loosely structured system (Sommer, Herrick, and Sommer, 1981). While this study is significant in studying factors other than the products themselves, it is limited to consumer atmosphere variables (i.e. friendly sociable, personal, etc.) that are not necessarily physical attributes of the markets.

Bond, Tillmany, and Bond (2009) attempt to analyze what influences consumer choice of fresh produce location, either directly or indirectly from producers. Along with demographic variables, intrinsic and extrinsic variables of the market and products sold are included within a survey conducted by the National Family Opinion Organization (NFO). Intrinsic variables relate to measures of an individual's perception of quality, while extrinsic relates to the physical attributes of the products and purchase location. Similar variables to those in the current study include convenient purchase location, physical/aesthetic appeal, and social interaction. The current study hopes to incorporate these variables and more in an attempt to determine how consumers are responding to the physical attributes of a farmers' market.

Data

The data for this study was collected through a consumer intercept survey at the local farmers' market in Lubbock, Texas. The survey was designed as a choice based survey, in which the consumer chose an alternative that had a combination of specific attributes rather than rating each attribute individually. The survey design was modeled after Hudson and Lusk's (2004) choice-based experiment from analyzing risk and transaction cost in contracting.

A choice-based conjoint experiment (CBC) method has been used to estimate the utility of product attributes in a variety of settings (Unterschultz et al., 1998; Lusk, Roosen and Fox, 2003; Beggs, Cardell and Hausman, 1981; Adamowicz et al., 1997, 1998; Jayne et al., 1996; Roe, Boyle and Tiesl, 1996). CBC analysis can effectively predict the success of new products (Jayne et al., 1996) and has been shown to be consistent with consumers' revealed preferences (Adamowicz, Louviere, and Williams, 1994; Adamowicz et al., 1997) and has been shown to be robust to hypothetical bias (Carlsson and Martinsson, 2001). Finally, CBC analysis is also appealing because it is based on random utility theory (Louviere, Hensher, and Swait, 2000) and allows for multi-attribute valuation (Hudson and Lusk, 2004).

Through the consumer intercept survey, 34 total surveys were collected with 4 being incomplete and omitted from the analysis. The survey was limited to the Lubbock, Texas farmers' market due to time and monetary constraints on the part of the researchers. Also, surveys were only administered at one gathering of the farmers' market, again due to time constraints. The research was approved by the Texas Tech University Human Research Protection Program prior to administering the survey.

Along with demographic variables, the consumer was asked to designate the reason they had attended the farmers' market and then state their choice between two separate combinations of attributes. In the current study, we are interested in six attributes of a farmers' market, each with two levels. A full factorial design would result in $2^6 = 64$ possible sets of attributes. Due to the impractical nature of administering such a full factorial design survey, we employ a fractional design (Louviere, Hensher, and Swait, 2000). Using the FACTEX procedure in SAS version 9.3, we first generated the full factorial design. Proc OPTEX was then used to generate a saturated, orthogonal, design, which resulted in 22 sets of attributes. The 22 sets were randomly paired to generate 11 choice sets. Each of the 11 choice sets were randomly selected and assigned to one of two blocks. Each participant was then randomly presented with either a block of 6 choice sets or a block of 5 choice sets. One of the scenarios is shown in Table 1.

Table 1: Example of choice based survey design.

Parking Location	Parking Distance	Restrooms	Cover/Shade	Seating	Ease of Moving Between Vendors	Select One
Lot	5 min or less	No	Yes	Yes	Yes	
Street	> 5 min	No	Yes	Yes	Yes	
						Select One
Street	5 min or less	Yes	Yes	Yes	Yes	
Street	> 5 min	Yes	Yes	Yes	No	
						Select One
Lot	5 min or less	Yes	Yes	No	Yes	
Lot	> 5 min	Yes	Yes	Yes	Yes	
						Select One
Street	5 min or less	No	Yes	No	Yes	
Street	5 min or less	No	Yes	Yes	No	
						Select One
Street	5 min or less	Yes	No	No	Yes	
Lot	5 min or less	Yes	No	Yes	Yes	
						Select One
Lot	> 5 min	No	No	Yes	No	
Street	5 min or less	Yes	No	Yes	No	

Economic Framework/Methods

Discrete choice models describe decision makers' choice among alternatives. The decision makers can be people, households, firms, or any other decision-making unit, and the alternatives might represent competing products, courses of action, or any other options or items over which choices must be made (Train, 2009).Train (2009) states that the probability that the agent chooses a particular outcome from the set of all possible outcomes is simply the probability that the unobserved factors are such that the behavioral process results in that outcome. Also, it is imperative to clarify that discrete choice models are usually derived under the assumption of utility-maximizing behavior by the decision maker.

The probability function for discrete choice is generally represented by the following:

$$P(y|x) = Prob(I[h(x,\varepsilon) = y] = 1) \qquad (1)$$

$$= \int I[h(x,\varepsilon) = y] f(\varepsilon) d\varepsilon. \qquad (2)$$

Stated in this form, the probability is the integral of an indicator for the outcome of the behavioral process over all possible values of the unobserved factors. In order to evaluate the probability one of three possibilities must be executed – complete closed-form expression, complete simulation, or partial simulation/partial closed form (Train 2009).

Discrete choice models have certain properties that define how the choice set, or set of alternatives, is structured. First, the alternatives must be mutually exclusive from the decision maker's perspective. Choosing one alternative necessarily implies not choosing any of the other alternatives. Second, the choice set must be exhaustive, in that all possible alternatives are included, and third, the number of alternatives must be finite. (Train, 2009).

Train (2009) mentions two articles, Thurstone (1927) and Marschak (1960), in which Thurstone developed original concepts on whether respondents can differentiate varying levels of stimulus and Marschak interpreted the stimuli as utility and provided a derivation from utility maximization. Following Marschak's initiative, most models that can be derived in this way are called random utility models (RUMs) (Train, 2009).

In a RUM model, the researcher does not observe the decision maker's utility, but observes some attributes of the alternatives as faced by the decision maker, labeled $x_{nj} \forall j$, and some attributes of the decision maker, labeled s_n, which then specifies a function that relates these observed factors to the decision maker's utility (Train, 2009). The function is defined as $V_{nj} = V(x_{nj}, s_n) \; \forall j$ and is often referred to as the representative utility. This representative utility function is not equal to a decision maker's utility function because there are factors that the researcher cannot observe which is denoted by ε_{nj}. Thus, the equation for utility is represented by $U = V + \varepsilon$, such that utility is composed of representative utility and the unobservable portion of utility.

So, the probability that decision maker *n* chooses alternative *I* is

$$P_{ni} = Prob\left(U_{ni} > U_{nj} \forall\, j \neq i\right) \qquad (3)$$

$$= Prob\left(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj} \forall\, j \neq i\right) \qquad (4)$$

$$= Prob\left(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj} \forall\, j \neq i\right). \qquad (5)$$

This probability is a cumulative distribution, namely, the probability that each random term $\varepsilon_{nj} - \varepsilon_{ni}$ is below the observed quantity $V_{ni} - V_{nj}$. Using the density $f(\varepsilon_n)$, this cumulative probability can be rewritten as

$$P_{ni} = Prob\left(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj} \forall\, j \neq i\right) \qquad (6)$$

$$= \int_{\varepsilon} \; I\left(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj} \forall\, j \neq i\right) f(\varepsilon_n) d\varepsilon_n \,, \quad (7)$$

Where I(•) is the indicator function, equaling 1 when the expression in parentheses is true and 0 otherwise. This is a multidimensional integral over the density of the unobserved portion of utility, $f(\varepsilon_n)$. Different discrete choice models are obtained from different specifications of this density, that is, from different assumptions about the distribution of the unobserved portion of utility (Train, 2009).

Within the framework of discrete choice and RUMs there are a set of specific statistical models used to estimate consumers' representative utility. The one most applicable to the proposed research is the logit model. Its popularity is due to the fact that the formula for the choice probabilities takes a closed form and is readily interpretable. Originally, the logit formula was derived by Luce (1959) from assumptions about the characteristics of choice probabilities, namely the *independence from irrelevant alternatives* (IIA) (Train, 2009). The purpose of this model is to specify the shape of the distribution function F with the logistic density

$$f(t) = \lambda(t) = \frac{e^t}{(1+e^t)^2}. \tag{8}$$

An advantage of the logit model is that the cumulative distribution function F=Λ can be computed explicitly, as

$$\Lambda(t) = \int_{-\infty}^{t} \lambda(s)ds = \frac{e^t}{1+e^t} = \frac{1}{1+e^{-t}}. \tag{9}$$

Logit models are non-linear in nature and the parameters can be estimated by maximum likelihood (ML). If the observation within a data set are mutually independent, then the likelihood function is given by $L(p) = \prod_{i=1}^{n} p^{yi}(1-p)^{1-y}$ and the log-likelihood by

$$\log\big(L(p)\big) = \sum_{(i;y_i=1)} \log(p) + \sum_{(i;y_i=1)} \log(p-1) \tag{10}$$

$$= \sum_{i=1}^{n} y_i \log(p) + \sum_{i=1}^{n}(1-y_i)\log(1-p). \tag{11}$$

Maximizing this with respect to p we get the ML estimator $\hat{p} = \sum_{i=1}^{n} y_i/n$.

The logit model has the property that the average predicted probabilities of success and failure are equal to the observed fractions of successes and failures in the sample. The ML first order conditions have a unique solution, because the Hessian matrix is negative definite. This simplifies the numerical optimization, and in general the Newton-Raphson iterations will converge rather rapidly to the global maximum (Heij et al., 2004).

The general logit model allows for marginal effects that are somewhat larger around the mean and in the tails but somewhat smaller in the two regions in between. The logit model is used when the tails of the distribution of data are of importance. This is the case when the choices are very unbalanced, in the sense that the fraction of individuals with $y_i = 1$ differs considerably from $\frac{1}{2}$ (Heij et al., 2004).

The specific model used in this study is the conditional logit model which is represented by

$$Prob(y_i = j = \frac{e^{\beta' x_{ij} + \alpha' w_i}}{\sum_{j=1}^{J} e^{\beta' x_{ij} + \alpha' w_i}} = \frac{e^{\beta' x_{ij}} e^{\alpha_i' w_i}}{\sum_{j=1}^{J} e^{\beta' x_{ij}} e^{\alpha_i' w_i}}. \qquad (12)$$

Utility depends on x_{ij}, which includes aspects specific to the individual as well as to the choices. It is useful to distinguish them. Let $z_{ij= [x_{ij}, w_i]}$. Then x_{ij} varies across the choices and the possibly across the individuals as well. The components of x_{ij} are typically called the attributes of the choices. But w_i contains the characteristics of the individual and is, therefore, the same for all choices (Greene, 2003). Again, the statistical program used to perform this analysis was STATA.

When estimating any regression, there are three specific estimation issues that must be accounted for: heteroskadasticity, autocorrelation, and multicollinearity. To address heteroskadasticity, robust standard errors were used to identify if there is any such problem. The issue of autocorrelation is not a prominent issue when using discrete choice models, other than the idea of the order effect. The order effect refers to the structure of the survey in which a respondent may deviate from the truthful preference revelation. However, this issue is most commonly associated with price variables and is not expected to be a problem in the current study. Finally, multicollinearity is not predicted to be a concern in this study as the variables in question are unrelated.

Results

First, the effects of the conditional logit model were estimated (Table 2). It is imperative to note that demographic variables were not included into the regression at this time. This allows for the main effects of the regression to be identified. The fixed effects of the model are shown in table 3.

Table 3: Conditional Logit Regressions Results- Main Effects

Variable	Estimated Coefficient	Robust Std. Err.	t-value	Odds ratio
Parking Distance	1.095785	0.3094251	3.54**	2.99153
Parking Location	1.249486	0.3350908	3.73**	3.488549
Restrooms	2.358868	0.4565402	5.17**	10.57897
Cover	1.538109	0.5457831	2.82**	4.655778
Seating	-1.14845	0.3342922	-3.44**	0.317128
Movement	2.668891	0.664174	4.02**	14.42396
χ^2	262.28**			
Number of observations	326			

** Statistically significant at the 0.01 level

From the odds ratio, the attributes can be ranked from highest importance to lowest importance, which is the following: Ease of movement between vendors, availability of restrooms, access to covering or shade, if the consumers have to park in a lot or on the street, how far away they have to park from the market, and the least important attribute is the availability of seating. All of the attributes are statistically significant at the 99% level, even though the estimated coefficient of the seating variable is negative.

More specifically, it can be noted that a consumer is 14.5 times more likely to attend a farmers' market that has easy movement between vendors than one that has poor spatial flow. This result is consistent with that of Sommer, Herrick, Sommer's (1981) study about consumer psychology and market choice. Also, it is important for a farmers' market to have access to restrooms, as a consumer is about 10.6 times more likely to attend one if restrooms are available than one that does not have one available.

Some possible explanations for the results stem from the demographic variables. The average consumer that attends a farmers' market in Lubbock, Texas, has about one child living in their household under the age of 18. This could mean that consumers are conscious of restroom availability for young children that go to the market with their parents. Also, this means that consumers may be attending farmers' markets in groups and prefer the ease of movement so that they are can shop with their group.

Conclusion

From the results, it is apparent that the physical attributes of the farmers' market has a significant influence over a consumer's choice on whether or not to attend. This information can be used by the Lubbock farmers' market in order to better itself. This study can be furthered with multiple farmers' markets within an area and why consumers are choosing to attend one over another.

Consumers are placing value on the physical attributes of the farmers' market is an important concept to take into account in future research. Future research should include demographic variables into the analysis and willingness to pay measurements which requires the implementation of other types of econometric models. Also, the inclusion of the "reason" for attending the farmers' market might have an effect on the reason a consumer attends one market over another. All of these variables will be important in determining how a farmers' market can improve on their marketing strategies in order to attract more customers.

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