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A PROBABILISTIC DEMAND APPLICATION IN THE AMERICAN CRACKER MARKET

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Abstract

Knowledge of the distribution of consumer buying strategies by producers may permit improved marketing strategies and improved ability to respond to volatile market conditions. In order to investigate potential ways of gaining such knowledge, this study extends the work of Kahneman, Russell, and Thaler through the application of a probabilistic demand framework using Choice Wave theory, based on the Schrödinger Wave Equation in quantum mechanics. Probabilistic variability of response to health information and its potential influence on buying strategies is also investigated, extending the work of Clement, Johnson, Hu, Pagoulatos, and Debertin. In the present study, the domestic cracker market within fourteen U.S. metropolitan areas is segmented, using the Choice Wave Probabilistic Demand approach, into two statistically independent "Consumer Types" of seven metropolitan areas each. The two Consumer Types are shown to have statistically different elasticities than each other and from the combined market as a whole. This approach may provide not only improved marketing strategies through improved awareness of consumer preferences and buying strategies, especially in the volatile agricultural sector, but also may be useful in aiding producers of store brand/private label products in finding desirable markets in which to compete against national brands. The results also suggest that supply/producer-side strategies should take into account the ways in which information, whether under the direct control of the producer or not, may influence and change consumer buying strategies.

Keywords: P*robabilistic demand, Choice Waves, quasi-rationality, private labels, volatility, decision modeling, information*
JEL Codes: *C15; C44; C61; D70; D81; N52*

1. Introduction and Background

Customers employ a plethora of buying strategies. Such a strategy could be as simple as attempting to choose products that have specific desired traits (Wilson and Dahl, 2008). That such a type of strategy exists and can be influenced by outside entities is even noted through advice given in consumer publications. One associated bit of advice appeared in *Food & Wine* and sought to help readers maximize their happiness through buying strategies for wine in different price categories (Isle, 2013). Indeed, consumer choice can sometimes result from factors other than specific product characteristics (Capehart, 2015). For example, a strategy could be one that involves discernment between national brand vs. private label (store brand) products (Volpe, 2011). In the choice between national brand and store brand goods, the decision is primarily reached based on consumer preferences, not socioeconomic factors (Bergès-Sennou et al., 2007). Consumer preferences may be based in large part on consumer perception of the store brand (private label) and may have a temporal effect, i.e., prior experience is considered in making a current decision (Kara et al., 2009). That perception might be colored by general information relevant to the product released by the media based on specific informational labeling, such as regarding a health issue like being "trans-fat free" (Johnson et al, 2011). In that specific case, which is directly relevant to the cracker market, the United States government mandated disclosure of trans-fat content by 2003. Some companies, in light of negative health information being released in the media, sought to get ahead of the curve and remove trans-fats from their products. To differentiate themselves, they often employed a front-of-package "trans fat free" label, similar in nature to the dolphin-safe label adopted by the tuna industry after the development of dolphin-safe tuna nets (Teisl, Roe, and Hicks, 2002). The labels, forming part of the package design, may help to capture the attention of the consumer sufficiently to influence product perception (Clement, 2007). Of further interest is that consumer perception of a product may be influenced by labels and product information, even though those labels may potentially contain erroneous information (Alston et al., 2015).

In addition to the direct influence of consumer preferences, the consumer's strategy may also be in part a response to the price of national brands (Ward et al., 2001). That is, the manner in which a consumer responds to the price of the substitute store brands (private labels) is influenced by the very preferences between national brand and store brand products that also directly influence purchase decisions. However, price may not always be the principle factor, and so different consumers may respond with different strategies in the selection of national brand vs. private label products (Zanoli and Naspetti, 2002). Knowledge of the distribution of such consumer strategies by producers may permit improved marketing and pricing strategies. Furthermore, producers in potentially volatile markets, such as agriculture, may be able to use such information to transfer some of the burden of price fluctuations to certain segments of consumers who show themselves to be less price sensitive (Tangermann, 2011).

Although individuals employ buying strategies, which may be subconscious, the outcome of those strategies may vary for a given individual between different purchase decision points. The utility-maximizing goal of the consumer may be based on one or more specific factors, such as pricing or, as Zanoli and Naspetti (2002) found, pleasure and well-being. The utility maximizing outcome is, however, not necessarily constant across all decision points. At the grocery store, consumers may, for example, potentially choose one brand of a certain product at one time and another brand at another time, but still maximize utility in both instances. In the case of, for example, organic vs. non-organic food products, as in Zanoli and Naspetti (2002), it is certainly possible that a consumer that has a strong preference for organic food, despite its expense and its relative rarity, might still at a given decision point choose to purchase a non-organic food product. That decision, despite the fact it is contrary to the individual's overall preferences, could reasonably be expected to be utility maximizing at the point at which the decision was made. If the reason was the lack of availability of the organic product, then the consumer was choosing the next best alternative, thereby maximizing utility based on available choices. However, if both choices were available, the consumer may still potentially choose the non-organic product to maximize utility at that specific decision point. The reason could be as simple as seeking a bit of variety. In the case of the present study, the same could be said about national brand vs. private label products. It is possible that someone with a strong preference for national brands might, at a given decision point, choose to purchase a private label product and still nevertheless maximize utility at that decision point.

On one hand, the described type of variability in consumer choice could be explained away as a simple matter of changing tastes and preferences, which itself challenges classical economic assumptions (Kahneman, 2003). Other explanations that have been proposed include the concept of deviation from classical rationality, forming a group of consumers termed *quasi-rationals*, who do not maximize utility in the same way that classical rational consumers do (Russell and Thaler, 1985). Alternatively, that scenario may be conceptualized as a probabilistic continuum of choices and outcomes such that the individual maximizes utility at each decision point (Johnson, 2012). That is, even though different outcomes may exist at different decision points, those outcomes nevertheless may be those that maximize utility for the individual at that specific point and in accordance with that individual's strategy to maximize utility. It may be a whim, or it may be a well-thought-out deviation from the individual's norm. It should be considered, however, that a consumer's utility maximization strategy is based on information available at each decision point, and so at each decision point is only as good as the quality of information the individual has. However, based on the information that the individual has, the consumer seeks to maximize utility at each decision point, which may be lifetime utility or short-term utility, depending on the strategy employed by the individual. Indeed, an individual's strategy for lifetime utility maximization may change over the years to be focused more on the short-term or on the long-term. Some individuals, even with good information, may trade long-term benefit for short-term gains (Acquisti and Grossklags, 2005). The information each individual has at any given decision point may differ from that of other individuals, thereby potentially leading to different outcomes as each individual seeks to maximize utility. Individuals furthermore may process the same information differently to reach different outcomes. That such outcomes may exist, which are deviations from classical rationality, implies that the actual market outcome may be different than that predicted by classical microeconomics (Akerlof and Yellen, 1985). Thus producer-side and policy decisions that are made based on assumptions of universal rationality run the risk of being erroneous and therefore could be improved in quality through the addition of a behavioral component (Korobkin and Ulen, 2000).

In terms of a market as a whole, one approach is simply to consider each and every consumer as an individual, each with unique behavioral traits. That approach is, of course, fraught with obvious practical problems. However, consider that, since a market is the aggregate of individuals, there may emerge trends in which there are groups of consumers that behave similarly on average. There may be one group average within the sample, or there may be more than one consumer group, each with its own behavioral average. If there exist two or more types of consumers whose behavior is, on average, statistically independent of each of the other groups, then they are terms Consumer Types and may be mathematically modelled probabilistically by a *choice wave* (Johnson, 2012).

The choice wave, which is an economic analog to the Schrödinger Wave Equation in quantum physics, is a probabilistic representation of utility-maximizing levels of consumption over time. Until a consumer makes a choice, the decision, in this framework, is conceptualized as a probability wave of all possible utility-maximizing choices that the consumer could make. At the point of decision, the choice wave collapses to the chosen level of consumption with probability = 1 (because the choice has been made). The most likely outcome of any arbitrary choice wave is its expectation value, and so in the Choice Wave Probabilistic Demand framework, demand and expenditure are expressed in terms of their expectation value.

Choice waves comprise a probabilistic component of utility, resulting in a utility function that has both a deterministic component and a probabilistic component. The choice wave derives from a Market Potential Function (MPF), which is a probabilistic version of the budget constraint in the form of an infinite potential well. The functional form of the choice wave is such that the probability that expenditure lies somewhere within the range specified by the MPF is 1, and the probability expenditure lies outside the range of the MPF is 0.

While strictly speaking each individual has a choice wave defining that individual's choice probability, the different consumer types in a market may be represented by a choice wave of a single "representative consumer" whose outcome is the mean of that consumer type. Since choice waves are, by their very nature, orthogonal to each other, the different consumer types do not exist in each other's space and may be and should be modelled separately. On the other hand, if they do exist in some way within each other's space, then they are not orthogonal, but are linear combinations of each other (Johnson, 2015). The knowledge of this information can be useful to the segmentation of data for more accurate and meaningful analysis. For example, two orthogonal consumer types will necessarily have separate own-price, cross-price, and income elasticities in demand system analysis.

This study applies the Choice Wave Probabilistic Demand mathematical framework to the analysis of revealed preferences of consumers through observation of their purchase decisions in the American cracker market. The market for private label (store brand) crackers vs. all other crackers is considered for fourteen American metropolitan areas between April 2002 and April 2005, with weekly data. That period is of significance because it was approximately in the middle of the data set, 2003, that the U.S. government mandated trans fat content to be included on package labeling. That makes it an even more interesting period of study since the presence of such additional information, both directly on product packaging and through various media sources before and after the time of the mandate, might influence consumer buying strategies. Also, because, in advance of the government mandate, some firms modified their processes to produce a trans-fat free product and then informed the public of this through product labeling, such information was available to the public overall for some products during the period before 2003. Most if not all such products that voluntarily adopted product labeling in advance of the government mandate were national brand products, with some private label products continuing to contain trans fats. The precise dates of adoption of voluntary labels or transition to trans-fat free, however, is difficult if not impossible to obtain, because companies refused to share that information. That is not surprising, given the competitive nature of business and the need for secrecy. In any case, the 2002-2005 data set for fourteen U.S. metropolitan areas not only is sufficient by itself to demonstrate the process of application of the Choice Wave probabilistic demand technique to empirical data, it provides that analysis in the realm of a period of significant health information that could easily influence consumer behavior and buying strategies (Johnson et al., 2011).

The individuals considered are the representative consumers for each metropolitan area. In the classical approach, an empirical model would consider the entire market as a whole and estimate demand accordingly. Geographical or demographic variability might be investigated through the use of panel data, dummy variables, or other means. Those methods may very well provide useful and insightful results. It may, however, be more useful to investigate the possibility of different Consumer Types, i.e., independent groups of utility-maximizing consumers that choose different consumption bundles from the total market result. The Choice Wave approach can be beneficial for that purpose. This study demonstrates the mechanism for searching out possible different Consumer Types and modelling them according to Choice Wave theory. Using the data set from the American cracker market, an Almost Ideal (AI) demand system incorporating choice waves is estimated and compared to an AI model incorporating the data set for the entire combined market.

2. Empirical Approach

The presence of statistically different Consumer Types in the market is tested for by performing statistical tests on the data. In the cracker market data, there are fourteen metropolitan areas, each with an average level of private level and national brand consumption over the time frame of the study. Using statistical *t*-tests, the fourteen metropolitan areas were grouped into two groups of seven metropolitan areas each such that the following conditions held: 1) the per-capita-weighted group mean expenditure on private label and national brand crackers for each group of seven metropolitan areas is statistically different from the group mean expenditure for the other group; 2) The mean expenditure on private land and national brand crackers for each metropolitan area is not statistically different from the mean expenditure of the group of which it is a member; and 3) The mean expenditure on private label and national brand crackers for each metropolitan area is statistically different from the mean expenditure of the other group to which it does not belong. Note that the choice of two Consumer Types of seven metropolitan areas each were chosen such that the three conditions held and no other possible grouping of the fourteen metropolitan areas existed such that the three conditions held. The frequency distribution of market share in the cracker market is shown in Fig. 1.

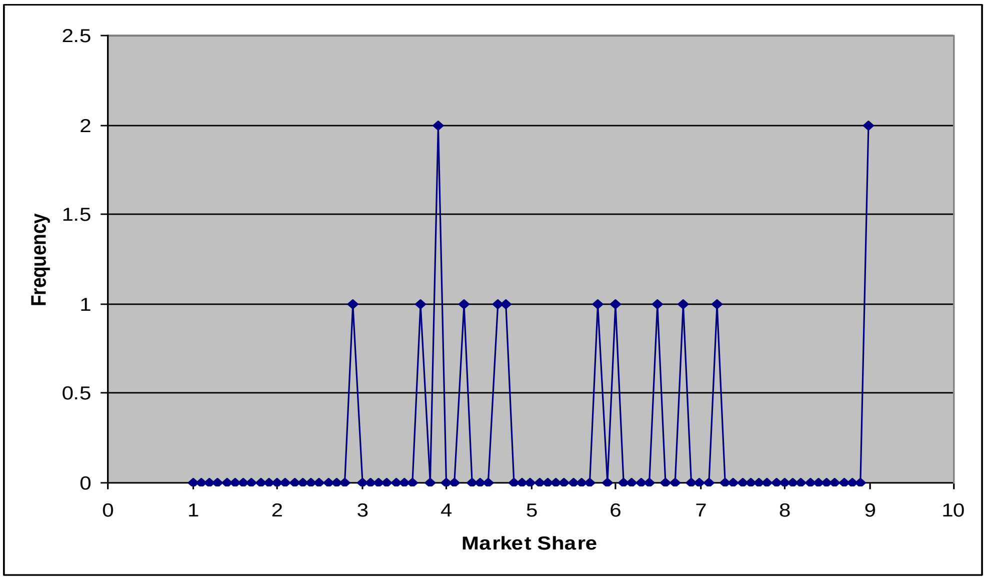

Figure 1. Distribution of Metropolitan Areas in the American Cracker Market

A cursory observation of Fig. 1 suggests that there may be as many as four different Consumer Types. However, though a visual inspection is a reasonable starting point, is can be deceiving. The t-tests mentioned above suggest instead that there are only two distinct Consumer Types that meet the criteria to be modelled by Choice Waves. So, the two groups of seven metropolitan areas each comprise the two Consumer Types, denoted as Type A and Type B. The size variables for each Consumer Type that will be incorporated into the choice waves are M_A and M_B, each valued at 7 metropolitan areas. The two Consumer Types are represented by wave functions ${}_A\Psi_n(e)$ and ${}_B\Psi_{n'}(e)$ respectively, where n and n' are the wave states of the two Consumer Types (Johnson, 2012)[1].

The statistical tests performed to split the market data into two groups of seven metropolitan areas is consistent with the theoretical assumption that the Choice Waves of the representative consumer of each Consumer Type are orthogonal, but that the Choice Waves of other members within each Consumer Type are not orthogonal to the Choice Wave of the

[1] The specific number, n, of the wave state is only important in solving some theoretical models of the choice wave. Otherwise, particularly when empirical analysis is the end goal, it usually suffices simply to acknowledge that there are two separate wave states, thereby implying orthogonality within the n-dimensional Hilbert space of the market framework.

representative consumer, but rather are linear combinations of each other. Because of that Type-level orthogonality, the two types exist outside each other's space, but the members of each Type exist within each other's space. Therefore, the two Types are estimated as two separate demand systems.

The cracker market data was aggregated into "private label crackers" and "all other crackers" so that the system is not brand-specific, and hence avoids problems of price endogeneity (Villas-Boas and Winer, 1999). Statistical tests are performed to demonstrate that the results yielded by a Choice Wave AI model are different from those of a full market AI model estimation, i.e., an estimation with a data set comprising all fourteen metropolitan areas. Following Johnson (2007) and Johnson (2012), the probabilistic demand system is expressed using choice waves for two Consumer Types in Eqns. 1 and 2.

$$\langle X \rangle = \frac{\frac{C_n M_n}{n\pi p_x}\int_0^I e\left|{}_A\Psi_n(e)\right|^2 de\hat{A} + \frac{C_{n'} M_{n'}}{n'\pi p_x}\int_0^I e\left|{}_B\Psi_{n'}(e)\right|^2 de\hat{B}}{M_n + M_{n'}} \tag{1}$$

$$\langle X' \rangle = \frac{M_n I\hat{A}}{p_{x'}} + \frac{M_n I\hat{B}}{p_{x'}} - \frac{\frac{C_n M_n}{n\pi p_x}\int_0^I e\left|{}_A\Psi_n(e)\right|^2 de\hat{A} + \frac{C_{n'} M_{n'}}{n'\pi p_x}\int_0^I e\left|{}_B\Psi_{n'}(e)\right|^2 de\hat{B}}{M_n + M_{n'}} \tag{2}$$

where $I = c(u, p)$ in the AI model (Deaton and Muellbauer, 1980) and e is expenditure. In the choice wave framework, demand is expressed as an expectation value. The expectation value of demand for private label crackers is $\langle X \rangle$ and that of all other crackers is $\langle X' \rangle$. The terms C_n and $C_{n'}$

are weighting terms (Johnson, 2012). The corresponding expenditure equations are simply Eqn. 1 and 2 multiplied by their respective prices.

3. Application to the AI Demand System

The AI model is of flexible functional form, resulting in demand functions derived therefrom being first-order approximations to an arbitrary set of demand functions derived from utility-maximizing behavior (Alston, Foster, and Green, 1994). That has the advantage of producing first-order approximations even in the absence of the assumption of classical utility maximizing behavior. To move from a theoretical Choice Wave Demand System to a Choice Wave Linear Approximate AI (CWLA/AI) system that can be estimated, Eqns. 1 and 2 are first expressed in terms of expenditure share in Eqns. 3 and 4. Eqn. 3 comprises the two expenditure share equations for Consumer Type A for private label and all other crackers, while Eqn. 4 is the same system for Consumer Type B.

$$\Delta\langle w_{A,PvtLab} \rangle = \frac{\frac{C_n\, M_n}{n\pi}\int_0^{I=c(u,p)} e\left|{}_A\psi_n(e)\right|^2 de\hat{A}}{M_n + M_{n'}} \tag{3}$$

$$\Delta\langle w_{A,Other} \rangle = M_n c(u,p)\hat{A} - \frac{\frac{C_n\, M_n}{n\pi}\int_0^{I=c(u,p)} e\left|{}_A\psi_n(e)\right|^2 de\hat{A}}{M_n + M_{n'}}$$

$$\Delta\langle w_{B,PvtLab} \rangle = \frac{\frac{C_{n'}\, M_{n'}}{n'\pi}\int_0^{I=c(u,p)} e\left|{}_A\psi_{n'}(e)\right|^2 de\hat{B}}{M_n + M_{n'}} \tag{4}$$

$$\Delta\langle w_{B,Other}\rangle = M_{n'}c(u,p)\hat{B} - \frac{\frac{C_{n'}\,M_{n'}}{n'\pi}\int_0^{I=c(u,p)} e\left|\,_A\psi_n'(e)\right|^2 de\hat{B}}{M_n + M_{n'}}$$

Conversion of Eqns. 3 and 4 into estimable forms yields of Eqns. 5 and 6 (Alston, Foster, and Green, 1994).

$$\Delta\langle W_{A,PvtLab}\rangle = \eta_{A0} + \beta_{A1}\Delta logP_{A,PvtLab} + \beta_{A2}\Delta logP_{A,Other} + \kappa_A \Delta log\left(\frac{\bar{X}_A}{P}\right) + \varepsilon_{A1} \quad (5)$$

$$\Delta\langle W_{A,Other}\rangle = \eta_{A0} + \alpha_{A1}\Delta logP_{A,PvtLab} + \alpha_{A2}\Delta logP_{A,Other} + \kappa_A \Delta log\left(\frac{\bar{X}_A}{P}\right) + \varepsilon_{A2}$$

$$\Delta\langle W_{B,PvtLab}\rangle = \eta_{B0} + \beta_{B1}\Delta logP_{B,PvtLab} + \beta_{B2}\Delta logP_{B,Other} + \kappa_B \Delta log\left(\frac{\bar{X}_B}{P}\right) + \varepsilon_{B1} \quad (6)$$

$$\Delta\langle W_{B,Other}\rangle = \eta_{B0} + \alpha_{B1}\Delta logP_{B,PvtLab} + \alpha_{B2}\Delta logP_{B,Other} + \kappa_B \Delta log\left(\frac{\bar{X}_B}{P}\right) + \varepsilon_{B2}$$

where $logP$ is the Laspeyres price index (Greenlees and McClelland, 2008; Alston, Foster, and Green, 1994) using the average first-period market share across all metropolitan areas, and the standard AI restrictions imposed (Deaton and Muellbauer, 1980). The first-differenced form of the AI model is used to alleviate autocorrelation in the panel data system. Because of the orthogonality of the Consumer Types, these two demand systems, i.e., Eqns. 5 and 6, exist outside each other's space and therefore are estimated entirely separately.

4. Analysis of Empirical Results

Both demand systems estimated were free from heteroskedasticity according to the Huber-White test. The estimated coefficients of the estimation of Eqns. 5 and 6 were statistically compared to the estimated coefficients of a single demand system estimated for all fourteen metropolitan area representative consumers combined. Both Type A and Type B coefficients were universally statistically different from the estimated coefficients of the combined model at the 95% level. The coefficients of Type A and Type B were also statistically different from each other at the 95% level. These tests reject the null hypotheses that 1) Type A is not different from the combined market; 2) Type B is not different from the combined market; and 3) Type A is not different from Type B. Table 1 shows the metropolitan areas in each Type. Tables 2 - 4 contain the results of the combined and type estimations.

Table 1. Metropolitan Area Representative Consumers in Each Consumer Type

TYPE A	TYPE B
Baltimore	Buffalo
Boston	Columbus
Charlotte	Des Moines
Chicago	Houston
Dallas	Kansas City
Hartford	Los Angeles
Washington, D.C.	Louisville

Table 2. AI estimation Results for the Combined 14 Metro-Area Market

Variable	Coefficient	Std. Error	t-value	Pr > |t|
Intercept	-0.00006	0.00034	-0.17	0.8623
Price (Private Label) ***	-0.0318	0.0072	-4.44	<0.0001
Price (All Other) ***	0.0318	0.0072	4.44	<0.0001
Expenditure ***	-0.0371	0.0030	-12.53	<0.0001

Note: R^2 = 0.5922 , *** *Denotes statistical significance at the 99% level*

Table 3. AI estimation Results for Consumer Type A

Variable	Coefficient	Std Error	t-value	Pr > |t|
Intercept	-0.0001	0.0004	-0.33	0.7412
Price (Private Label) ***	-0.0265	0.0055	-4.83	<0.0001
Price (All Other) ***	0.0265	0.0055	4.83	<0.0001
Expenditure ***	-0.0319	0.0026	-12.25	<0.0001

Note: R^2 = 0.5318, *** *Denotes statistical significance at the 99% level*

Table 4. AI estimation Results for Consumer Type B

Variable	Coefficient	Std Error	t-value	Pr > |t|
Intercept	0.00001	0.00046	0.02	0.9806
Price (Private Label) ***	-0.0382	0.0085	-4.49	<0.0001
Price (All Other) ***	0.0382	0.0085	4.49	<0.0001
Expenditure ***	-0.0418	0.0043	-9.79	<0.0001

Note:R^2 = 0.4786, *** *Denotes statistical significance at the 99% level*

In order to determine if differences in Consumer Types in this market are due to supply side effects, analysis on the ratio of national chain grocery stores to local markets was performed. Private label crackers (as well as other private label goods) are expected to be more prevalent at the national and regional chain grocery stores, and so such a test was deemed necessary to partly rule out supply-side effects in explanation of differences between Consumer Type.

Table 5. Statistical t-test for Type A vs. Combined Results

Private Label Coefficient	National Brand Coefficient	Expenditure Coefficient
t = 7.33	t = -7.33	t = -16.67

Note: t-critical = 2.093, 95% confidence level

Table 6. Statistical t-test for Type B vs. Combined Results

Private Label Coefficient	National Brand Coefficient	Expenditure Coefficient
t = 7.17	t = -7.17	t = 11.18

Note: t-critical = 2.093, 95% confidence level

Table 7. Statistical t-test for Type A vs. Type B Results

Private Label Coefficient	National Brand Coefficient	Expenditure Coefficient
t = -14.42	t = 14.42	t = -24.78

Note: t-critical = 2.093, 95% confidence level

Table 8. Grocery Store Ratio Test Results

Avg Stores - Type A	631.5714	
Avg Stores - Type B	709.7143	
Avg Chain Stores - Type A	46.0000	
Avg Chain Stores - Type B	57.7143	
Stores per capita - Type A	8.477336	(per 10,000)
Stores per capita - Type B	7.773344	(per 10,000)
Chains to Total - Type A	0.0027	
Chains to Total - Type B	0.0026	
t-statistic	0.0328	
t-crit	2.4470	(99% conf.)
Avg Pop Type A	937050.9000	
Avg Pop Type B	1078432.0000	
Std Dev Pop Type A	918222.7000	
Std Dev Pop Type B	1305066.0000	
t-test	-0.2344	

Table 9. Elasticities

COMBINED DATA SET ELASTICITIES

MODEL	**Own-Uncomp**	**Cross-Uncomp**	**Own-Comp**	**Cross-Comp**	**Income**
Private Label	-1.5519	1.2387	-1.5349	1.5349	0.3131
All Other	-0.0707	0.0315	0.0877	0.9123	1.0392

TYPE A CONSUMER ELASTICITIES

MODEL	**Own-Uncomp**	**Cross-Uncomp**	**Own-Comp**	**Cross-Comp**	**Income**
Private Label	-1.4590	1.0485	-1.4368	1.4368	0.4105
All Other	-0.0599	0.0262	0.9179	0.0821	1.0337

TYPE B CONSUMER ELASTICITIES

MODEL	**Own-Uncomp**	**Cross-Uncomp**	**Own-Comp**	**Cross-Comp**	**Income**
Private Label	-1.6653	1.4382	-1.6530	1.6530	0.2271
All Other	-0.0821	0.0380	0.9056	0.0944	1.0441

The per capita ratio of national and regional grocery store chain locations to local market locations was calculated for each metropolitan area. The average ratio was calculated for each Consumer Type. A series of statistical *t*-tests were performed (see Tables 5 – 7). The ratios of each Consumer Type were not statistically different at the 99% confidence level, and so it is suggested that the availability of private label crackers is statistically the same between Consumer Types. Given the result of the statistical test performed, such a supply-side effect is likely not indicated as an explanatory factor of differences between Consumer Types. Additionally, a *t*-test was performed to test for the statistical difference between the mean populations of each Consumer Type. As shown in Table 8, the populations of each Consumer Type are statistically the same.

Table 9 provides the elasticities for the combined (total market) data set and the two segregated Consumer Types. Both the own- and cross-price elasticities in both the compensated and uncompensated categories were very similar for the category of all other crackers. There was far more difference between Type A and Type B, and also between each of the two Types and the combined data set for Private Label crackers. The same was true for the income elasticities. The results in Table 9 suggest that it is price sensitivity regarding private label crackers that defines the two Consumer Types, and there is little difference in preference regarding all other crackers (including national brands) between the two Consumer Types.

5. Discussion

The application of the Choice Wave Probabilistic Demand approach to the estimation of an AI model of the private label cracker market successfully demonstrated that each of the two Consumer Types, each comprising seven metropolitan areas, have different empirical results, both from each other within the CWLA/AI estimation and from the LA/AI estimation of the whole market of fourteen metropolitan areas. The Consumer Types were identified by statistical testing of the data prior to estimation and modelled mathematically with Choice Waves. The orthogonality of Choice Waves implies that the demand systems of the two Consumer Types both may be and ought to be modelled separately. The split-market estimation suggested by the Choice Wave approach provides an alternative method for modeling the market that gives insight into how different segments of the market behave. The Choice Wave approach also provides information to firms that could be used to price their products differently within different markets (where each Consumer Type comprises a separate market). An estimation performed under the Choice Wave approach has the underlying provision that consumers can choose different consumption bundles at each time of choice/purchase, while still universally maximizing utility with respect to the consumption of crackers. This expands beyond quasi-rationality to a concept of probabilistic rationality at each consumer's decision point. That is, following prior research, the Choice Wave approach provides a model in which consumer choice is probabilistic across time, but the consumer nevertheless maximizes utility at each decision point.

Extending to consumer buying strategies, such strategies do not necessarily have absolute outcomes, but various outcomes with different probabilities of occurrence. That could be thought of as Plan A, Plan B, Plan C, and so on, where Plan A might be the most likely choice, Plan B is the second-most likely, and so on, as one possible distribution of outcome probabilities. Thus a Choice Wave is a representation of the average strategy employed by consumers within a Consumer Type. Furthermore, consumer decisions are not only a response to preferences, but are also based on response to price. The response to price is in turn based in part on the consumer's preferences for each of the goods in a specific market. Preferences are in part determined by information made available to the consumer, both directly by producers and their agents and through the media. Gaining insight into the buying strategies of Consumer Types may benefit producers by suggesting more appropriately targeted marketing and pricing policies and tactics, as well as policies pertaining to the promulgation of information and response to third-party information outside of the direct control of the firm.

Additionally, the outcomes of the utility maximization strategy at the decision points may be short-run or lifetime, depending on the strategy employed by the consumer. Different Consumer Types may employ different strategies, based in part on available information, and information provided to the consumer may potentially alter the strategy of the consumer. Indeed the strategy itself does not have to be constant. A consumer's Plan A, Plan B, and so on could be the result of different strategies, each with a probability that the consumer will follow each strategy. So, there also exists the potential for manipulation of consumers by influencing their choice of strategy in a way beneficial to the firm through influencing information that may cause such an influence on choice of consumer strategy. The Choice Wave, as a probabilistic representation, provides a framework for depicting the various possible outcomes, given the strategy or strategies followed by consumers. In the case of changing strategies, the probabilities of various outcomes change due to the accompanying Choice Waves changing along with the strategies.

To accomplish the goal of increasing insight into probabilistic consumer behavior, the theoretical mathematical framework of Choice Wave Probabilistic Demand provides a means for splitting data sets into sub-sets according to revealed consumer preferences and consumer strategies rather than according to arbitrary measures such as demographics. The resulting sub-sets are orthogonal in hyperspace and therefore are statistically independent. Measures such as demographics, however, may still be useful. They may in fact provide further insight into the Consumer Types themselves. However, what Choice Wave theory says is that the *first* means of segmenting a market data set should be according to Consumer Type, which is based on revealed preferences and buying strategies, i.e., the actions of the very consumers themselves. Because the use of a Choice Wave framework allows data sets to be split not by adding variables for each Consumer Type, but rather to be separated completely into sub-sets, each in their own hyperspace, multiple demand curves result, with one for each Consumer Type. Then other factors, such as demographics, may be able to be used as needed and appropriate to gain further understanding of the composition of each Consumer Type. By following this approach, empirical estimation may be expanded in such a way that more accurate and useful information may be obtained in order to achieve the firm's goal of improved insight into consumer behavior and buying strategies that then may be used to enhance their own marketing efforts and production strategies.

In the case of the metropolitan areas in the present study, they are internally demographically diverse. Yet the metropolitan areas were still separable by Choice Waves into two distinct and statistically independent Consumer Types. That implies different marketing strategies may be needed for one group of seven metropolitan areas than would be needed in the other group of seven. The findings in the present study suggest that there may be two different buying strategies present in the market. Such buying strategies may potentially be influenced by targeted programs such as the earlier example in *Food & Wine*. In general, that strategies within each Consumer Type may be influenced by information is consistent with Clement (2007) and Johnson et al. (2011). In the cracker market, consumer response to health information pertaining to trans fats, which had mandatory disclosure approximately in the middle of the data set, may in part be behind the presence of the two Consumer Types. For example, on average, the two Consumer Types might differ in how health information influences their buying strategies regarding crackers. Insofar as differences in Consumer Type may, at least in part, be related to processing of health information, the results suggest, consistent with Wilson and Dahl (2008), that such information may influence desired product traits between the two Consumer Types. Indeed, the differences in processing of that information may be part of the impetus behind the formation of the two statistically different Consumer Types. Because desirability of product traits is subject to influences such as information, it is not necessarily constant, consistent with Kahneman (2003). There is a probability that any given individual will modify the buying strategy in a specific way based on stimuli such as, but certainly not limited to information. Consumer Types are formed when there exist a number of individuals with expectation values of the probability functions of their possible choices that are not statistically different from the mean expectation value of its own group, but is statistically different from the mean expectation value of any other Consumer Types that may exist in the market. Even given the expectation value of expenditure for each Consumer Type, the Choice Wave framework still allows for consumers to make variable choices, i.e., make choices from time to time that differ from the product that they are most likely to choose and still nevertheless maximize utility. Those choices may maximize short-run or lifetime utility, consistent with Acquisti and Grossklags (2005). Individuals clearly may also make choices at a given decision point that differ in specific value from the expectation value of the Consumer Type to which they belong. As the Choice Waves of the individuals exist within the hyperspace of their Consumer Type and outside the hyperspace of all other Consumer Types, such behavior is still necessarily consistent with the behavioral expectations of that Consumer Type.

Furthermore, considering market volatility within the agricultural sector, the information suggested in this study through the Choice Wave Probabilistic Demand approach may be useful in identifying segments of the total market according to price elasticity. Producers in the agricultural sector and other potentially volatile sectors may, therefore, be able to transfer some of the burden of price fluctuations to those Consumer Types that are more price inelastic. In addition, consulting the own and cross-price compensated and uncompensated elasticities, it can be seen that the difference in values between Consumer Types A and B is much greater for private label than other brands. Since there is only a slight difference regarding other brands, there may be additional opportunity for store brands in the metropolitan areas of Consumer Type B. In general, an approach such as this make be useful for determining areas in which store brands and private labels may be able best to compete.

References

Acquisti, A., & Grossklags, J. (2005). “Privacy and Rationality in Individual Decision Making.” *IEEE Security & Privacy.* Vol.3. No. 1.

Akerlof, G. A., & Yellen, J. (1985). “Can Small Deviations from Rationality Make Significant Differences to Economic Equilibria?” *American Economic Review.* Vol. 75. No. 4.

Alston, J. M., Foster, K. A., & Green, R. D. (1994). “Estimating Elasticities with the Linear Approximate Almost Ideal Demand System: Some Monte Carlo Results,” *The Review of Economics and Statistics.* Vol. 76. No. 2

Alston, J. M., Fullera, K. B., Lapsley, J. T., Soleasa, G., & Tumbera, K. P. (2015). “Splendide Mendax: False Label Claims About High and Rising Alcohol Content of Wine.” *Journal of Wine Economics*. Vol. 10. Iss. 3.

Bergès-Sennou, F., Hassan, D., Monier-Dilhan, S., & Raynal, H. (2007). “Consumers' decision between private labels and national brands in a retailer's store: a mixed multinomial logit application,” *Mediterranean Conference of Agro-Food Social Scientists. 103rd EAAE Seminar ‘Adding Value to the Agro-Food Supply Chain in the Future Euromediterranean Space,’* Barcelona, Spain.

Capehart, K. W. (2015). “Fine Water: A Hedonic Pricing Approach.” *Journal of Wine Economics.* Vol. 10. Iss. 2.

Clement, J. (2007). “Visual influence on in-store buying decisions: an eye-track experiment on the visual influence of packaging design.” *Journal of Marketing Management*. Vol. 23. Iss. 9-10.

Deaton, A., & Muellbaeuer, J. (1980). “An Almost Ideal Demand System,” *The American Economic Review.*

Isle, R. (2013). “Taste vs. Price: How to Find Wine Value.” *Food & Wine.* http://www.foodandwine.com/articles/taste-vs-price-how-to-find-wine-value

Greenlees, J. S., & McClelland, R. B. (2008). “Addressing misconceptions about the Consumer Price Index,” *Monthly Labor Review*, August.

Rutherford, J. (2007). “Health Information and Consumer Types in the Domestic Cracker Market,” Doctoral Dissertation, University of Kentucky.

Rutherford, J., Hu, W., Pagoulatos, A., & Debertin, D. (2011). “Response to General Health Information in the Food Industry: A Panel Case Study in the Domestic Cracker Market.” *Journal of Food Products Marketing*. Vol. 17. No. 1.

Rutherford, J. (2012). “The Choice Wave: An Alternative Description of Consumer Behavior,” *Research in Business and Economics Journal*, Vol. 5.

Rutherford, J. (2015). “Decline in Church Giving in the United States During the Recession: A Spatial Application of Choice Waves,” *Journal of Behavioral Studies in Business*, Vol. 8.

Kara, A., Rojas-Méndez, J. I., Kucukemiroglu, O., & Harcar, T. (2009). “Consumer preferences of store brands: Role of prior experiences and value consciousness.” *Journal of Targeting, Measurement and Analysis for Marketing*. Vol. 17. No. 2.

Kahneman, D. (2003). “A Psychological Perspective on Economics.” *American Economic Review*. Vol. 93. No. 2.

Korobkin, R. B., & Ulen, T. S. (2000). “Law and Behavioral Science: Removing the Rationality Assumption from Law and Economics.” *California Law Review.* Vol. 88. No. 4.

Russell, T., & Thaler, R. (1985). “The Relevance of Quasi Rationality in Competitive Markets,” *The American Economic Review.*

Tangermann, S. (2011). “Policy Solutions to Agricultural Market Volatility: A Synthesis,” *ICTSD Programme on Agricultural Trade and Sustainable Development,* Issue Paper No. 33.

Teisl, M. F., Roe, B., & Hicks, R. (2002). “Can Eco-Labels Tune a Market? Evidence from Dolphin-Safe Labeling.” *Journal of Environmental Economics and Management*. Vol. 43. Iss. 3.

Villas-Boas, J. M., & Winer, R. S. (1999). “Endogeneity in Brand Choice Models,” *Management Science*, Vol. 45, No. 10.

Volpe, R. (2011). "The Relationship Between National Brand and Private Label Food Products Prices, Promotions, Recessions, and Recoveries," *Economic Research Service Economic Research Report*, Number 129.

Wilson, W. W., & Dahl, B. L. (2008). “Procurement Strategies to Improve Quality Consistency in Wheat Shipments.” *Journal of Agricultural and Resource Economics*. Vol. 33. No. 1.

Ward, M. B., Shimshack, J. P., Perloff, J. M., & Harris, J. M. (2001). “Effects of the Private-Label Invasion in Food Industries.” *American Journal of Agricultural Economics.* Vol. 84. No. 4.

Zanoli, R., Naspetti, S. (2002). "Consumer motivations in the purchase of organic food: A means-end approach." *British Food Journal.* Vol. 104. Iss. 8.