"Milk is Milk"?
Consumer Valuation of rBST-Free Fluid Milk Labeling

Kristin Kiesel*
University of California-Berkeley

Abstract. "Milk is Milk" reads a new campaign currently running in newspapers across the United States. This paper investigates the claim by empirically examining the effect rBST-free product labels on consumer choice of fluid milk. A flexible framework is developed to address complex product brand and attribute decisions at the household level and capture the uncertain nature of product information and associated potential benefits or risks, both in the absence and presence of labeling. Within this framework, predictions about the impact of labeling on consumer choice of fluid milk products, including changes in labeling regulation with regard to organic certification are discussed. The empirical part of this paper focuses on consumer preferences for rBST-free labeled fluid milk using a conditional logit specification. Preliminary results suggest that consumer value the choice between rBST-free labeled and conventional milk products. In addition, considerable heterogeneity in preferences and valuation is suggested by the results. A future research agenda that addresses consumer valuation of divergent labeling policies and regulatory efficiency in a more flexible econometric specification is provided.

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1 Introduction

"Milk is Milk" reads a new campaign currently running in newspapers across the United States. It is initiated by the Center of Global Food Issues and its coalition in hopes of ending the battle over appropriate milk labels and marketing claims.[1] A new dimension of product differentiation in milk products has evolved after the introduction of recombinant Bovine Somatotropin (rBST) in milk production. At the same time, the organic milk industry has become the fastest growing organic food sector in the U.S.

The use of rBST supplements has been an ongoing concern for some consumers, as approximately one third of the U. S. dairy herds, about 3 million dairy cows, currently receive rBST supplements (Monsanto). Questions surrounding the extent of and reasons for consumer preferences for biotech or non-biotech foods continue to arise as the U.S. and its trading partners pursue radically different policies regarding biotech labeling. In addition, product labeling with respect to health and environmental claims is increasingly being used domestically to provide information about otherwise unobservable product characteristics. Milk from treated cows is not subject to any labeling requirements since the FDA has determined it to be safe and not significantly different from milk from non-treated cows.[2] However, states are permitted to set up their own labeling laws. Voluntary labeling for milk products that come from untreated cows is required to be accompanied with a disclaimer citing the lack of scientific evidence for differences between milk produced with and without rBST. The widespread use of these labels triggered an ongoing controversy over false or misleading product labeling with regard to rBST and resulted in state and federal complaints, and lawsuits against dairy producers. At the same time, the U.S. Department of Agriculture (USDA) became involved in certification of organic food products in 2002 by setting a national standard for products labeled as "organic", including non-biotech requirements.

While these developments suggest that health and environmental-related labeling claims are perceived as a successful tool of altering consumer behavior, strong consumer response to rBST-free and organic milk labeling provides challenge for traditional economic theory. These production attributes are not directly linked to any other commonly analyzed food demand dimension such as nutritional value, food safety, quality or taste and, more importantly, scientific

[1] This coalition includes the Center for Science in the Public Interest, the Federal Trade Commission, the National Consumers League, and the U.S. Food and Drug Administration (FDA).
[2] The Center for Disease Control also agrees with this position.

tests are not available that detect differences between these milk products and conventional milk products. Consumers have no way of verifying labeling claims, which defines the production process as a credence attribute. Demand for these products is likely influenced by a combination of subjective health and environmental impact concerns, as well as behavioral and informational aspects. Consumer response to these labels could reflect general preferences for 'natural' food, ethical or religious beliefs, and consideration for animal welfare,[3] and might further suggest a relative importance of stylized facts over scientific assessments for consumption decisions.

Previous studies have presented theoretical analyses of the effects of product labeling on consumer demand, in some cases in the context of household production models (e.g. Smallwood and Blaylock 1991, Caswell and Padberg 1992, Teisl and Roe 1998, Golan, Kuchler, and Mitchell 2000). Teisl and Roe (1998) have emphasized the role of cognitive abilities, information, and time in defining the specific process by which labeling information is translated into consideration of product attributes. Teisl, Roe, and Hicks (2002) have adjusted Stigler and Becker's (1977) model of advertising to incorporate labeling effects. Environmentally related assessments enter the household's indirect utility function and these assessments are made through a household production process of available objective information, prior knowledge, cognitive abilities and time spent to process this information. The theoretical model presented in the next section of this paper differs in that it sets a consumer's information search decision within a random utility specification of a household production model. It provides a flexible framework to address complex product brand and attribute decisions at the household level and capture the uncertain nature of product information and associated potential benefits or risks, both in the absence and presence of labeling.

Previous empirical studies of the effects of food product labeling have tended to focus on the provision of nutritional information. For example, Ippolito and Mathios (1990) found that voluntary nutritional labeling had significant effects on consumer choices while Mojduszka and Caswell (2000), in a test of Grossman's model of voluntary quality signaling, suggested that labeling information provided by firms prior to the Nutrition, Labeling and Education Act (NLEA), was incomplete and not necessarily reliable. Teisl, Bockstael, and Levy (2001) used supermarket purchase data to assess changes in consumer behavior due to changes in nutritional labeling following the NLEA. They found that consumer's purchase behavior was significantly altered, but that purchases of "healthy" goods increased only in some, not

[3] Another consideration could be support of small farming. But in the milk industry, the organic farming sector is more concentrated and vertically integrated than its conventional counterpart (DuPuis 2000).

all, food product categories. In their evaluation of labeling regulations issued under NLEA, Ippolito and Pappalardo (2002) concluded that the nutritional focus in advertising has narrowed substantially and labeling for "healthy" foods did not increase. They particularly emphasize the need for further research regarding which regulatory and legal policies best serve consumer interest.

Evaluating eco-labels, Teisl, Roe, and Hicks (2002) report that dolphin-safe labels resulted in changes in aggregate tuna consumption. Jin (2003) examined effects of an increase in product quality information in a restaurant market and concluded that consumer demand was sensitive to mandatory display of hygiene quality grade cards. She further contends that empirical research has not provided sufficient insight on how changes in information affect market response, mainly due to difficulty of observing exogenous changes in the amount information available to consumers.

Empirical studies of the introduction of rBST on milk demand are mainly limited to the analysis of survey responses (e.g., McGuirk, Preston and Jones 1992, Grobe and Douthitt 1995, Misra and Kyle 1998). Aldrich and Blisard (1998) utilized monthly pooled time-series and regional (cross-section) data for the period 1978 to 1996 to examine whether the use of rBST and expressed consumer concern reduced aggregate fluid milk consumption, but found no evidence of such an effect. Focusing on organic milk, rather than rBST-free milk, Glaser and Thompson (2000) identify price premiums as high as 103 % and high own-price elasticities for organic milk products. Most recently, Dhar and Foltz (2005) used a quadratic almost ideal demand system (AIDS) for differentiated milk types in combination with US supermarket scanner data. They found significant consumer valuation of organic milk and to a lesser extend of rBST-free milk.

One major shortcoming of these studies is the use of aggregate data. Heterogeneity in perceived consumer value could not be addressed directly. In addition, welfare effects of changes in labeling regulations could not be isolated due to the nature of the data sets analyzed. The U.S. fluid milk market provides an appealing case study for empirical examination of effects of different labeling regimes on consumer demand for several reasons. First, the approval of rBST in milk production in 1994 provides one of the earliest examples of biotechnology in food production.[4] Thus, it is possible to incorporate some longitudinal data into the analysis of consumption behavior, a facet that is especially important since market adjustments to labeling initiatives appear to occur slowly over time (Teisl, Roe, and Hicks 2002). Second, fluid milk is a relatively standardized and ubiquitously processed commodity. Finally, and perhaps most importantly, U.S. fluid milk

[4] The FDA approved rBST for general use in November 1993 but, in response to consumer concerns, Congress placed a moratorium on its use until February, 1994.

consumption patterns include differentiated products: privately certified rBST-free labeled, third party and government certified organic products, and conventional fluid milk products that typically include milk from dairy cows receiving rBST supplements.

The data employed in this study contains macro- and micro-level scanner data, including household demographics. These detailed scanner data provide store prices and a number of product characteristics, such as brand name, size, fat content, and package material and enable controls for store level features. Observable household demographics further allow to relate the heterogeneous distribution of consumer preferences with regard to rBST-free and organic food products. Additional secondary information was added to permit product classification according to labeling information.

By providing quantitative evidence of the effects of different labeling regulations on consumer product choice, this paper and its extensions attempt to provide policy-relevant information about the economic value of labeling regulations to agricultural producers, food processors, and consumers alike. Welfare analysis in this context can relate estimates of changes in consumer surplus under different labeling regulations to costs incurred by these regulations. Whereas the theoretical framework presented in this paper is applicable for evaluating changes in labeling regulation with regard to organic certification, ongoing data availability issues restricted the empirical analysis to the evaluation of consumer response to privately certified rBST-free product labels. Preliminary results suggest that consumer value rBST-free labeled milk products. The results further indicate heterogeneity in preferences and valuation of rBST-free labeled milk products. While limited in scope, these findings can be viewed as a first step towards a better understanding of how labeling information affects consumer choice, and towards evaluating economic efficiency of labeling programs. They shape a future research agenda that addresses consumer valuation of divergent labeling policies and regulatory efficiency in a more flexible econometric specification.

The next section describes the theoretical framework and discusses testable predictions. Section 3 links the framework to the econometric model. The dataset is described in detail in section 4 and summary statistics for the selected subsample are provided. Section 5 presents the estimated regression specification and discusses estimation results. The paper concludes with a discussion of limitations and future research.

2 Theoretical Framework

The model presented in this section incorporates key elements of product attribute models (Becker 1965, Rosen 1974) with those of advertising and information search models (e.g. Stigler 1962, Stigler and Becker 1977, Teisl and Roe 1998, and Teisl, Roe, and Hicks 2000) and combines them within a random utility framework. It is assumed that some consumers value milk produced without rBST through subjective quality assessments, such as perceived health risks t, environmental impacts, and ethical considerations. Labeling information facilitates more accurate and standardized assessments of product attributes related to these concerns, and may change a consumer's perceived value.

The amount of search over product attributes is integrated as a choice variable and defines the household's production process of utility maximization over product attributes in purchased goods.[5] More specifically, the household searches for information about product attributes, as well as about associated potential risks and benefits using his own time, information provided by the market, and previously acquired human or consumption capital (H) that includes cognitive ability and scientific comprehension. Information search can therefore reduce uncertainty or randomness in this utility framework.[6] Obtaining relevant information can be viewed as a Bayesian learning process, where the household is likely to have some prior knowledge and beliefs about product attributes and their marginal benefits. The resulting prior probability distribution is then updated using new available information, generated through current period search time and new information provided by the market, such as product labeling information (L).

While this model primarily relies on the household production model to incorporate consumer search both in the presence and absence of labeling, it also includes aspects of hedonic price models (Rosen 1974). Analogous to the hedonic models, utility is derived from product attributes, and product choice depends on the consumer's relative full price of these attributes. A household's marginal willingness to pay reflects both, the marginal willingness to pay a premium for an otherwise identical product, as well as the optimal search time decision.

The resulting constrained utility maximization problem is defined using a random utility function where $\boldsymbol{r}$ denotes a vector of stochastic components corresponding to each product choice:

$$(1) \qquad \max_{\mathbf{x},\mathbf{m},t} \; U(\mathbf{x},\mathbf{m},\mathbf{r}) \;\; \textit{subject to} \;\; Y = \sum_{i=1}^{n} p_i x_i + \sum_{j=1}^{k} p_j m_j + wt.$$

[5] This simplified model is designed to directly apply to the consumer choice between different fluid milk products. In future research, a generalization of the model will be considered that defines the information search as an additional constraint in the household production process of desirable commodities.

[6] With regard to search or experience attributes, uncertainty could eventually be resolved it this framework. Randomness with regard to rBST-free or organic production can not be fully resolved by the consumer.

The vector $\boldsymbol{x}$ includes all consumption goods except fluid milk products and the vector $\boldsymbol{p}$ represents market prices of these commodities. Consumption from among the k specific brands of fluid milk is denoted by $\boldsymbol{m}$, where milk brand j is purchased at price p_j. The household selects search time (t) over milk products and their prices, where the opportunity cost of search time is defined by the wage rate, w, per unit (hour). For reasons of expositional clarity and convenience, the household is assumed to search only over the absence of rBST, organic production, and product price. For modeling purposes, it is also assumed that each household purchases only one brand of milk at each shopping trip. Milk production attributes, such as the use of rBST supplements or organic production, are not known to the consumer with certainty in the absence and presence of labeling. In addition, consumers might be unsure about potential risks and benefits of these production characteristics whether a label is present or not. To account for this uncertainty, a consumer's choice between any given pair of milk products, m_i and m_j, is modeled through random components r_i and r_j, drawn from an unknown distribution. To further simplify the exposition, assume a consumer compares an rBST-free or organic milk product (m_1) to a conventional product (m_2) defined through:

$$E\left[U\left(\mathbf{x}, m_1, r_1\right) - U\left(\mathbf{x}, m_2, r_2\right)\right] = \delta \,. \tag{2}$$

Equation (2) defines a subjective utility difference assessment for a given household between consuming m_1 and m_2, holding constant the choice over the vector of other consumption goods. The expectation is assumed to capture subjective quality assessments formed by a household given his available information and beliefs. δ is likely to vary across consumers because of divergent beliefs, underlying values and subjective risk and benefit assessments, differences in consumer information, search time and search technology. The utility difference also depends on product prices and individual price responsiveness. For identical prices and for households that care about these product attributes, δ is assumed to be positive. Note that as δ approaches zero, the consumer approaches a state of indifference between m_1 and m_2.[7]

Assuming that the second-order conditions are satisfied for the constrained maximization problem, optimal values for the choice variables $\boldsymbol{x}$, $\boldsymbol{m}$, and t can be found through a more general pair-wise comparison of available milk products. The optimal choice of milk product m_i maximizes δ.[8]

[7] This difference could even be negative if consumers value biotechnology improvements for instance.

[8] This utility difference could be viewed as a final comparison between the observed first best and the second best choice given the household constraints. Note that contrary to the hypothetical comparison in (2) the household is also unsure about the actual character of the milk product in this formulation and that δ is now positive given the utility maximization hypothesis.

(3) $$U\left(\mathbf{x}^*, m_i, r_i\right) - U\left(\mathbf{x}^*, m_j, r_j\right) = \delta^*\left(Y, p, w, L, H\right), \text{ for all } i \neq j$$

$\delta^*(.)$ can be viewed as the stochastic indirect utility difference function or , alternatively, a household chooses milk product m_i that maximizes his stochastic indirect utility $V^*(Y, p, w, L, H)$. This choice specification has a behavioral component. The optimal choice does not depend on the product attributes *per se* but on the individual's knowledge and perceived value of these product attributes. He will choose the product that he knows the most about with respect to its desirable attributes and its own search time constraints. The resulting probability that milk product m_i will be selected can be defined as:

(4) $$P\left(m_i = 1\right) \equiv P\left(U_i - U_j = \delta^*\right), \text{ for all } i \neq j.$$

If a consumer values the information provided on a product label, the following prediction with respect to labeling of product m_i (L_i) can be specified as:[9]

(5) $$\frac{\partial P(m_i = 1)}{\partial L_i} \geq 0.$$

In this context, labeling is treated as a continuous variable to emphasize the possibility of an increase in the quality of labeling information. Labeling with regards to desirable attributes can affect product demand in several ways: it advances information production technology, it could expand full income by reducing search costs, and it could result in substitution effects in consumption due to increased reliability of information provided, and resulting adjustment of product attribute assessment and revaluation of perceived benefits. The presence of a label or standardization of labeling claims and certification can improve the information production technology available to a given household through a decrease in search time and simplification of comparisons across products.[10] In practice, and to the extent that it is measurable, labeling information is often discrete. For example, rBST-free milk may be unlabeled (*L1*), or it may be voluntarily labeled as rBST-free (*L2*). Another labeling regime entails certification by an independent agency, as is the case for labeled organic milk products (*L3*) which must be rBST-free to be certified organic. Finally, government certification defines the highest level of labeling quality in this setting (*L4*).[11] If a consumer values the attribute, the likelihood that milk product m_i will be chosen increases is therefore assumed to increase along those levels:

[9] Without a specified functional form, comparative static results cannot be formerly derived. In addition, most behavioral and psychological aspects still lack consistent mathematical specification in the existing literature. Therefore, the emphasis in this paper will be on a discussion of model prediction rather than on mathematical derivation.
[10] An increased reliability of information due to changes from a voluntary labeling regime to a certified labeling regime could, for instance, be viewed as a mean-preserving reduction in spread if the household already has a consistent product attribute assessment. The mean could be affected if the label results in a reclassification of the product.
[11] As mentioned above, households have no way of verifying the claims made on a label. For some consumers, some levels of labeling, e.g. mandatory, government certified labels might remove all uncertainty regarding product attributes, but uncertainly about risks and benefits might remain.

(6) $$P\left(m_i = 1 \middle| L1_i\right) < P\left(m_i = 1 \middle| L2_i\right) < P\left(m_i = 1 \middle| L3_i\right) < P\left(m_i = 1 \middle| L4_i\right).$$

Additional information that increases human capital regarding rBST will also influence the likelihood of purchase of a given milk product m_i. For example, new information that portrays rBST negatively (positively) with regards to health and environmental risks could increase (decrease) the probability that rBST-free milk products will be chosen through a decrease in uncertainty about possible risks. The effectiveness of the "Milk is Milk" campaign, or media coverage of law suits regarding misleading or false labeling claims, could be analyzed in this way.[12]

While this predicted probability increase (decrease) could occur with or without additional labeling information, a change in H is also likely to alter the labeling effect. Labeling can become more (less) valuable to consumers as their expected difference in utilities changes. But even the mere existence of a label, especially with regard to health and environmental claims, might influence the household's decision-making process through a change in perceived valuation of addressed attributes. A label might suggest potential benefits or risk to the consumer that make these attributes worth pointing out. Labeling regulations can strengthen this perception significantly. A governmental certification of organic production, for instance, makes the claim more official and separates it from a pure marketing strategy. Labeling and its regulations might add intrinsic value for the consumer in that it might suggest superiority of a product with respect to health and environmental aspects. In the above prediction with regard to increased quality of labeling, this possible effect can be conceptualized as a first order stochastic dominance of the labeled product m_i. These ideas are related to what is described as *reference dependence* and *framing* in the behavioral economics literature (e.g. Kahneman and Twersky 2000). Ariely, Loewenstein, and Prelec (2003), for instance, argue that initial valuations of products are strongly influenced by 'anchors' which can be both monetary and non-monetary signals, and subjects react much more to this initial information than to subsequent information. Their experiments illustrate *coherent arbitrariness* in preferences, a phenomenon in which people form a somewhat arbitrary valuation for new products, but adjust subsequent consumption in a coherent way. In the labeling context, people might be unsure about the value of rBST-free or organic production and might therefore use the product label to form an initial valuation. Hence, governmental certification might result in a higher valuation if the new label is used as a new anchor. This argument is especially appealing since consumers have no means of updating their valuation after purchase and consumption.[13] Applied in a more general context, this reasoning might further suggest that

[12] These effects are more complex as they again depend on the consumer's perception of information and information sources.
[13] Consumption of peers is also likely to serve as an anchor in those situations where consumer needs to assign initial value to unfamiliar products or attributes.

people focus on initial reports and stylized facts portrayed in the media when forming preferences for non- biotech and organic products, and do not update their valuation appropriately to new available information that might be more detailed or scientifically sound.[14]

Consumer valuation of a certain labeling regime can be assessed through a measure of *compensating variation*, the amount of money an individual would need to be compensated with to be as well off as under the current labeling regime. The indirect compensation function can be related to changes in indirect utility if preferences over price stay constant (Hurwicz and Uzawa 1971):

(7) $$CV = V_1^*(Y, p, w, L_1, H_1) - V_0^*(Y, p, w, L_0, H_0).$$

In the literature on product introduction, this effect is sometimes referred to as the *variety effect* (e.g. Hausman and Leonard 2002, Dhar and Foltz 2005).

Predictions about price effects cannot be derived from this framework because prices enter the constraint. If income effects are relatively small, Marshallian demand functions will not differ significantly from Hicksian demand functions. Small income elasticities for fluid milk estimated in previous studies, e.g. Heien and Wessels (1988), suggest that own-price effects for fluid milk products are likely to be negative for the Marshallian demand functions derived from this model.

Inequalities (5) and (6) represent the primary model predictions and consumer valuation can be investigated using post regression estimation of the compensating variation as described in (7). Due to ongoing data availability problems, consumer valuation of organic labeling and changes to the USDA certified organic standard can not be empirically investigated and will be addressed in future research.[15]

3 Econometric model

Additional assumptions relate the described utility framework to econometric discrete choice models that can be empirically estimated (McFadden 1975, Nevo 2000, Train 2003). Assuming utility is linear in product attributes and random components yields:[16]

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[14] An example is the common belief that consumption of organic products supports small scale and regional farming which is not consistent with recent developments in the organic food sector.

[15] The current available data set does not include the years after the introduction of the new organic standard. Provision of all relevant data form 1997 -2002 through a cooperative agreement with the USDA-ERS is still pending.

[16] Under fairly general conditions, any function can be approximated arbitrarily close by one linear in parameters. Furthermore, the focus of this analysis is the choice of fluid milk brands based on their attributes. The utility is assumed to be quasi-linear such that the choice of $\boldsymbol{x}$ will be unchanged for different utility functions and can be suppressed.

(8) $U_i = A_i\beta - r_i$.

In equation (8), the vectors A_i indicate the attributes of milk brand m_i, and the vector β represents the weights placed on each of these attributes. If there are a number of households *(h)* that exhibit heterogeneous preferences and that choose among different milk products *(i)* at different points in time *(t)* :

(9) $U_{ibt} = A_{ibt}\beta_{bt} - r_{ibt}$.

Note that the attributes have an additional index *h* to address heterogeneity in attribute perception across households related to variation of δs across households in the theoretical framework.[17] The vector A_{ibt} therefore indicates attributes as perceived by a given household and β_{bt} indicates household-specific weights placed on them. Relating this linear formulation back to underlying comparison of utility differences allows isolating the described behavioral and informational aspects:

(10) $P\left(m_{it} = 1\right) \equiv P\left(U_{ibt} > U_{jbt}\right) \equiv P\left(r_{ibt} < r_{jbt} + (A_{ibt} - A_{jbt})\beta_{bt}\right)$, for all $i \neq j$.

The probability that a milk product is chosen depends on the product attributes as perceived by the household, as well as the marginal value the household assigns to them. The remaining uncertainty about true product attributes and its potential risks and benefits further determines the household choice by reducing utility assuming consumers are risk avers in this decision process and want to eliminate uncertainty.

While the random component, *r*, specified in the utility framework is taken into account by a single households stochastic utility maximization, an additional source of randomness arises from an econometrician's point of view. Unobservable household and product characteristics might influence a household choice. Household demographics, *D*, will be used to account for preference heterogeneity as related to observable household characteristics:[18]

(11) $U_{ibt} = A_{it}\beta + (A_{it} \times D_b)\gamma + \varepsilon_{ibt}$.

The specified random term, ε_{ibt}, now does not correspond to randomness incorporated in a household's choice *per se* anymore, but relates the observable part of the decision-making process in the model specification to remaining unobservable choice determinants and data problems. Distributional assumptions about this error term, drive the econometric model choice, but also affect estimation results in many ways. The complexity of the household's decision

[17] While product attributes and rBST-free labeling remains constant over the time period investigated, the attribute vector is further indexed by *t* to account for variations in product prices over time.
[18] Differences in attribute perceptions can not be investigated empirically with the available data and will enter into the error term.

process motivates a multivariate generalized extreme value specification of the error terms and a mixed multinomial logit or random coefficient logit specification that allows a simultaneous estimation of heterogeneous consumer preferences. However, a conditional logit model that includes product characteristic and household demographic interaction terms will be specified and estimated in this paper.[19] Empirical industrial organization in general, and welfare analysis in differentiated product markets and non-market valuation of environment-related goods in particular, have long been faced with tradeoffs between computational ease and relaxation of restrictive assumptions to more accurately model the problem at hand. While a number of recent papers discuss the latest innovations in empirical discrete choice models and attempt to reduce difficulty of their use (e.g. Berry, Levinsohn, and Pakes 1995, Nevo 2000, Swait, Adamowicz, and van Bueren 2004), static cross sectional analyses are still the dominating approach (Swait et all 2004). The model choice in this paper reflects these tradeoffs and is mainly based on computational convenience. The author is well aware of its restrictive character and attempts to balance the discussion of preliminary results with a consideration of model limitations. The estimation technique and presented results can be viewed as first step to investigate the possibilities and limitations of the available dataset as well as the nature of the household's decision-making process and preference heterogeneity.

Conditional logit specification

Under an *iid* logistic distributional assumption for the econometric residuals ε_{ibt}, the probability that a household's product choice corresponds to milk product m_i is defined as:

$$(12) \qquad P_{bt}(m_i = 1) = \frac{e^{A_{it}\beta + (A_{it} \times D_b)\gamma}}{\sum_{k=1}^{n} e^{A_{kt}\beta + (A_{kt} \times D_b)\gamma}}$$

The underlying *iid* assumption is restrictive. Unobserved portions of the utility from one milk product alternative might be related to the unobserved portion of another alternative. In addition, this assumption is problematic in a time series setting, if households chose repeatedly over the investigated period. The logistic distributional assumption further implies substitution patterns across alternatives that are characterized by independence of irrelevant alternatives. But, the probability of choosing between one specific conventional and rBST-free milk product is likely to be affected by changes with regard to another rBST-free product. As mentioned above, a mixed logit specification enables relaxation of these

[19] In either case, the task of statistical inference should also allow for Bayesian updating analogous to that described in the theoretical model. Future research will also consider Bayesian estimation methods.

assumptions and will be pursued as an area for future research. The later presentation of results and conclusions will reflect upon these limitations.

Consumer surplus and compensating variation estimation

The above distributional assumptions result in a closed form solution for consumer surplus (CS) associated with a set of alternatives. These estimates of changes in consumer surplus provide a welfare estimate of a household's compensating variation for a change in product attributes or product labeling as described in the theoretical framework (Small and Rosen 1981). Given its beliefs and available information set, a household chooses the product alternative that provides the highest expected utility. Expected consumer surplus, CS_{ht} can therefore be defined as:

$$(13) \qquad CS_{ht} = \frac{1}{\alpha_h} \max_j \left(U_{hjt} \forall j \right),$$

where α_{ht} denotes the marginal utility of income. The negative of the price coefficient can be used as an estimate of α_{ht} in this formulation.[20]

Again, since the maximum expected utility is unobservable, the following expected consumer surplus formulation from the researcher's perspective can be specified:

$$(14) \qquad E\left(CS_{ht}\right) = \frac{1}{\alpha_h} E\left[\max_j \left(A_{jt}\beta + (A_{jt} \times D_h)\gamma + \varepsilon_{jht} \forall j \right) \right]$$

If each ε_{iht}, is *iid* extreme value and utility is linear in income, then:

$$(15) \qquad E\left(CS_{ht}\right) = \frac{1}{\alpha} \ln\left(\sum_{j=1}^{J} e^{A_{jt}\beta + (A_{jt} \times D_h)\gamma} \right) + C .$$

The change in consumer surplus that results from a change in product alternatives or product choices can be computed as:

$$(16) \qquad \Delta E\left(CS_{ht}\right) = \frac{1}{\alpha} \left[\ln\left(\sum_{j=1}^{J} e^{A^1_{jt}\beta + (A^1_{jt} \times D_h)\gamma} \right) - \ln\left(\sum_{j=1}^{J} e^{A^0_{jt}\beta + (A^0_{jt} \times D_h)\gamma} \right) \right],$$

where the superscripts 0 and 1 refer to prior to and after the change, respectively. This measure of consumer valuation can be computed using estimated regression coefficients and simulating the counterfactual where certain products were not available or did not have certain product attributes.

[20] This formulation assumes that the marginal utility of income stays constant for a given household. Hence, a one unit decrease in price amounts to a one unit increase in income.

4 Data Description and Summary Statistics

To evaluate consumer choices with regards to differentiated milk products in this econometric framework, a household panel dataset for the years 1997-1999, collected by Information Resources, Inc. (IRI) was utilized. IRI tracks 27 markets that consist of 19 metropolitan areas, 6 geographically-dispersed markets and two non-metropolitan areas. The dataset contains macro- and micro-level data, including household demographics. A random sample of 55,000 households is tracked and demographic weighting procedures are employed to adjust for any differences in the panel sample and population demographics. Each panel household can shop at almost any store within their market area, and must present an identification card to the cashier upon checkout. Complete demographic information for participating households is collected by annual custom analysis.

The household level purchase data tracks daily purchases, but does not provide the exact unit price and store-level promotion information. The store level data tracks these exact prices weekly, and consists of weekly purchases at a given store. It also includes information on price promotions, product features and product displays. Both datasets allow unique identification of the market and store the purchases occurred and could be merged. To provide comparisons of fairly homogeneous products, the analysis focuses on fluid milk, excluding buttermilk, flavored milk, and soy milk. Store level and household level purchase data for 2313 different fluid milk products was extracted from an original data set that included all beverages purchases in 180 grocery stores across the 27 markets.[21] These products are identified by their universal product code (UPC). Certain product attributes such as brand name, size, fat content (whole and low fat), and packaging material could also be identified in the data. However, other attributes such as lactose-free, protein-added, and rBST-free and organic production are not tracked by the data unless they appear as part of the product name. While some comprehensive information regarding rBST use and organic production is available at the brand level, most of the identification regarding these choice relevant attributes had to be done at the UPC level. Feasibility and comparison of actual choices in a given store at a given point in time required further narrowing of the dataset. A single store was selected at random from a subset of stores that had differentiated milk products available over the entire time period. The majority of branded milk products and more importantly, rBST-free and organic products are offered mainly in half-gallon sizes. Only substitution patterns within this size are considered in this paper. While organic milk was available in the time period

[21] The tracked supermarkets include all major chains such as Safeway, Kroger, Dominick's, Jewel, A&P, etc along with smaller chains and independent grocery stores. Non-food outlets such as Walmart, drugstores, and vending machines are not included.

investigated, availability at main stream supermarkets was limited. In addition, observations at the household level for any given store did not provide enough cross-sectional and time-series variations to be included in the data analysis.

A list of rBST-free products is provided by *Rural Vermont* and *Mothers and Others* and was combined with information regarding rBST-free labels provided by the CGFI.[22] The selected store is located in New York and offers 26 milk products in half gallon sizes over the time period investigated. All milk processors that offered products at this selected store where contacted by phone to verify information regarding rBST- free status and product labeling and allowed identification of additional attributes. Lactose-free products were excluded from the analysis, since households that make these choices might have limited substitutes within the milk category investigated. The corresponding household panel sample consists of 601 households.

Household income, presence of children, and age of household members are considered as household characteristics that affect heterogeneous preferences regarding rBST status of a given milk product. Household income is measured as a categorical variable in the data set. Combined pre-tax income brackets might not reflect scaling relevant for diverse product choice of milk. An indicator variable that observes whether a household owns or rents its home was also included in the final dataset to capture income differences across households on a different scale. The presence of children variable in the data relates to the age of children, rather than the number of children in a given household. In addition, reported age brackets might be influenced by a coding error. Consequently, a household size variable is added as an alternative way to address preference heterogeneity as related to children. The age of the female head of household is used to capture heterogeneity related to age differences, based on the assumption that women have more weight on food purchasing decisions.[23] Relevant household demographics are only extracted for the first year such that these household characteristics stay constant over the time period estimated. Corresponding average sample household demographics in comparison to national population averages are summarized in Table1.

To address the potential endogeneity of prices, weekly commodity trading prices at the Chicago Mercantile Exchange of nonfat dry milk and whole milk powder reported in *Dairy Market News* are added to the dataset.[24] For the

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[22] The list compiled by Rural Vermont and Mothers and Others is available at: http://www.organicconsumers.org/rbgh/rbghlist.cfm#rBGHfree. The primary focus of the information complied by CGFI is on misleading labeling claims. Nevertheless, brand names, exact labels and in some cases even photos are provided at http://www.stoplabelinglies.com/report/report.html.

[23] For households without a female head, male head age was used instead. Alternative measures of a households age structure such as the mean household age were also considered and did not alter the regression results significantly.

[24] About 80% of raw fluid milk is regulated under marketing orders and federal support prices. These prices do not vary significantly over time and could therefore not be used as instruments. Electronic copies of Dairy Market News are available through the ERS-USDA web page at: http://www.ams.usda.gov/dyarchive/DMN_Historic_Reports/history.htm.

same reason, a dummy indicating package material was added. Product identification variables are also included in the dataset to capture unobserved constant product attributes that may affect choices and may be correlated with prices. Descriptive statistics of the regression variables are reported in Table 2.

5 Regression Specification and Estimation Results

The following conditional logit regression specification is restricted to purchasing of half-gallon fluid milk in at least one of the 152 weeks included. It further only investigates the milk product choice, abstracting from the possibility of purchase of multiple units. The following underlying utility structure with regard to milk product choice is proposed:

(17a) $$U_{ibt} = \beta_{0,i} + \beta_1 price_{it} + \beta_2 feature_{it} + \beta_3 whole_i + \beta_4 proteinadd_i + \beta_5 kosher_i + \beta_6 rbst\_free_i + \varepsilon_{ibt},$$

(17b) $$\beta_6 = \gamma_0 + \gamma_1 income_h + \gamma_2 children_h + \gamma_3 age_h + \mu_h,$$

(17c) $$\begin{aligned} U_{it} &= \beta_{0,i} + \beta_1 price_{it} + \beta_2 feature_{it} + \beta_3 whole_i + \beta_4 proteinadd_i + \beta_5 kosher_i + \gamma_0 rbst\_free_i + \\ &+ \gamma_1 rbst\_free_i * income_h + \gamma_2 rbst\_free_i * children_h + \gamma_3 rbst\_free_i * age_h + \tilde{\varepsilon}_{ibt} \end{aligned}$$

Product price, fat content (whole), protein enhancement, kosher and rBST-free production are included as direct observable product attributes. A variable that identifies whether a product was featured in the store is also included, recognizing that it might increase the utility of that product by drawing more attention to the product and its attributes, and in some cases, reduces the price or offers unit discounts.[25] This product attribute relates back to the theoretical framework, as it might reduce search costs for this product and its attributes while at the same time reducing uncertainty. A product-specific constant is also included in the regression to capture the average utility effect of all unidenified product specific attributes that affect choice.

For simplicity, heterogeneity in preferences is only considered with regards to rBST as denoted in equation (17b). Reparameterizing the average weight placed on the rBST characteristic yields equation (17c).[26] Equation (17c) defines the underlying utility structure that is used to estimate average consumer choice probabilities of milk products among all available alternatives at the selected store for a given week.

In this regression specification, an increase in income is expected to increase preferences for rBST-free labeled milk products due to the fact that increased income allows a household to consider additional product characteristics beyond price and nutritional value. Potential long term health risks associated with the use of rBST might be of particular

[25] The price used in the estimation is the final price that accounts for this possible price reduction or unit discounts.
[26] This refinement allows consideration of heterogeneity about the mean marginal utilities according to demographic characteristics.

concern for families with children. And finally, it is hypothesized that younger people might be better informed about the controversy regarding rBST and might be more likely to be sensitive to this issue. Other available demographics such as education, race, or occupational choices were not included, as they do not provide clear predictions regarding rBST preferences. An increase in education can, for instance, allow consumers to make better informed choices, but confidence in scientific assessments and support of technological innovations might counterbalance these effects.[27]

If preferences vary systematically along these observed variables, heterogeneity can be incorporated into the standard logit model as described above. However if preferences are at least partially random, as indicated by the inclusion of μ_h, this model is a misspecification. The resulting error term $\tilde{\varepsilon}_{iht}$ is necessarily correlated over alternatives, since μ_h enters each alternative and therefore captures possible remaining unobserved heterogeneity in preferences, as well as effects of possible omitted variables. Logit models seem fairly robust to misspecification, such that average preferences could still be estimated correctly by the proposed model (Train 2003).

Relating the regression specification back to the comparison of utility differences in the theoretical framework, emphasizes that the absolute level of utility is irrelevant to the household's choice. The choice probability only depends on differences in utility. This carries through in the researcher's model. Not all of the parameters can be identified from the data. In equation (17c), all included variables except for product-specific constants vary across products. The first product-specific constant was therefore normalized to zero. Related to this issue is the scaling parameter implied by a normalization of the error variance in the derivation of the underlying logit formula. The true error variance can be expressed as a multiple of the normalized variance, such that the estimated coefficients indicate the effect of each observable variable relative to the variance of the unobserved factors.[28] A larger variance in unobserved factors therefore leads to smaller coefficients and vice versa. Marginal rates of substitutions are not affected by this scaling, since the scale parameter drop out of the ratios.

Endogeneity control

In addition, the final regression model needs to address possible endogeneity of prices in this demand related setting. Rivers and Vuong (1988) discuss a two-step approach for discrete choice models. At the same time, their procedure leads to a simple test for endogeneity. Product prices for a given product and a given week are estimated in a first stage as a

[27] In his influential article in Science in 1999, Beachy for instance called for advocacy by scientists in favor of biotechnology.
[28] The error variance in the logit model is not separately identified and only information about the signs of the error terms is available post estimation.

function of supply and demand shifters, assuming these variables are exogenous to the pricing mechanism by a firm. Weekly commodity trading prices at the Chicago Mercantile Exchange of nonfat dry milk and whole milk powder are used as the main instruments for weekly retail product prices. These prices are interacted with product dummies for whole and low fat milk, respectively, to allow for time-series, as well as cross-sectional variation. These primary instruments are chosen based on the fact that raw milk prices account for 62% of retail milk prices (U.S.G.A.O. 2001) and are not correlated with consumer demand for milk. In addition, an indicator of package material (carton) is included to capture possible cost differences in packaging. The first stage Ordinary Least Squares (OLS) regression also includes demand shifters specified in the above model. It is assumed that they are exogenous to the pricing decision in that they require long term investments. Decisions about the offered product mix are therefore assumed to be made prior to considerations of retail prices. The vector of OLS residuals will be included in the second stage conditional logit estimation to correct for bias of coefficients due to possible endogeneity issues. While this procedure offers a straight forward way of correcting for endogeneity, it also adds another source of scaling. Each coefficient increases in value relative to its unscaled counterpart, unless price is truly exogenous (Wooldridge 2002).

Consumer valuation

The obtained second stage regression coefficients can be used to compute consumer valuation of rBST-free products and labeling information as described above. In this formulation, product differentiation with respect to rBST-content will be treated as a change in product attributes. The estimated coefficients will provide the underlying average preference structure. Regression variables relating to the rBST characteristic will be set to zero to simulate a change in labeling and product attributes. If in the absence of product labels, the projected search cost of obtaining this information would outweigh potential benefits, or available information would not be considered reliable enough to influence consumer choice, the resulting estimate of consumer valuation would solely relate to valuations of labels. Since inferences about this unlabeled status cannot be made, the estimated valuation corresponds to both preferences over the attribute as well as the valuation of voluntary product labels. This measure will not be influenced by the above described scaling since it is based on differences in consumer surplus. [29]

Estimation results

[29] An alternative approach could consider a hedonic price equation that allows to approximate consumer valuation through an estimated marginal willingness to pay measure for rBST-free labels. The limited size of the data set especially with regards to the number of brands available at the selected store and the observed price variation pattern (see Table 6) make this approach not feasible at this point. It will be considered in future estimations that utilize an expanded data set.

Stata 8.0 was used to apply the above utility specification in a pre-coded conditional logit routine. Due to the nature of the code and post estimation interpretation with respect to probability changes, the data was restricted to one choice per week per household. Multiple observations of the same product choice by a given household in a given week were aggregated to a single observation, while observations for households with multiple cross product choices were excluded from the regression.[30] Estimated coefficients are summarized in Table 3. Column 1 corresponds to the basic model, only including average preferences for identified product attributes. The price coefficient in this specification is negative and significant. Featuring a product in store, and whole fat content affects average utility of a given product positively. Kosher milk production decreases average utility in this sample. Protein enhancement does not significantly influence the choice of milk products in this sample and model specification. In addition, average preferences for rBST-free products are positive but not statistically significant.[31] The second column (2) is included as a robustness check for the coefficient estimates. This regression specification does not control for protein enhancement.[32] The coefficient estimates in the third column consider heterogeneous preferences with regard to rBST. This reported regression differs from the specification discussed above, in that a dummy indicating whether a household owns or rents its home is used instead of the categorical income variable and reflects a broader scaling of income differences. Inclusion of the income variable resulted in mainly positive, but insignificant and varying coefficients across alternative model specifications. It is very likely that the scaling of income differences applied in the data does not accurately explain differences in preferences related to income. The results in column 3 were reproduced using an income dummy that equals one if a given household income was above the mean income in the sample. The specification also includes a household size variable, rather than a dummy variable, indicating presence of children in a given household. Including an indicator variable for the presence of children directly in the regression produced counter-intuitive negative and significant coefficient estimates that were not robust to alternative model specifications. These difficulties might reflect on the nature of the sample. As previously discussed, the information about presence of children might be affected by a coding error. But more importantly, preferences within the subgroup of families might still vary significantly based on income or other non-observed household characteristics, such as number of children. Furthermore, the age structure in this sample differs significantly from the national population in that the sample

[30] Due to this restriction, the number of households in the sample decreased by 4 households.
[31] Using the standard errors in a Wald test, the null hypothesis of no effect cannot be rejected at the 10% significance level.
[32] Regressions excluding all kosher products produced similar overall results. While coefficient estimates, consumer welfare estimates, and likelihood ratio test results do not change, significance of interaction terms changes somewhat due to differences in the resulting selection of household consumption patterns. The reported regression results are preferred due to a greater number of observations and resulting higher cross sectional variation.

population seems significantly older. The estimated coefficients could be influenced by comparison of average preferences of older households with higher income or other unobserved characteristics to younger households with lower income, other unobserved differences, and children. The inclusion of differences in demographics with regard to age and income in a linear functional form might not be able to fully control for these complex interdependencies, especially since only 155 households in the sample are reported to have children, and only 36 of these have children under 6 years. Thus, the subsample of families might not be big enough and the resulting average estimates might be biased.

Compared against a restricted model that does not include the mean effect of rBST and interaction terms related to average preferences in a likelihood ratio test, the model specification in column (3) was found to be jointly significant at the 1% significance level. Both, the average effect of ownership and the average effect of an increase in age have the predicted sign, but are not statistically significant individually at the 10% level.[33] These low individual significance levels might again be influenced by consumer heterogeneity of preferences for rBST-free milk that is not fully captured by the chosen econometric model and regression specification.[34] The last column in Table 3 adds residuals obtained from a first stage regression as described above.[35] The null hypothesis of no endogeneity of prices could be rejected in a Wald test at the 10% significance level. The coefficients reported in this column (4) are employed in the nonlinear functional formulation of consumer surplus and consumer valuation.

The coefficients reported in Table 3 correspond to changes in utility and will be affected by scaling, as discussed above. The magnitude of the coefficients does not directly relate to the probability of product choice. This link is provided in Table 4. The average predicted probability of a specific milk product choice equals 6.46 %. This probability decreases by 3.65% if the price of this product increases by $1. This increase corresponds to average price increase of 55%. A 1% increase in price is estimated to decrease the average choice probability by 0.0652%. Store feature and whole fat content increase the average choice probability by 2.60% and 19.9% in this sample.[36] The increase in choice probability due to rBST-free product labels equals 6.37%. An increase in the household size from 2 to 3 in the sample, is further estimated to increases this average probability by 0.77%, suggesting that on average, households are more likely to chose rBST-free milk if they have children. However, this inference is not statistically significant for the given sample. The second column of

[33] The effect of ownership is statistically significant at the 10.3 % significance level.
[34] While these findings limit the interpretation of the presented estimation results, they also motivate a more flexible and less restrictive model specification such as a mixed logit approach for future research.
[35] 22 out of 26 of the input price proxies, the proxy for package material, and all demand shifters except *feature* were statistically significant at the 10% level or lower in the first stage regression. Estimation results other than the R^2 for this regression are not reported.
[36] Note that the relatively strong preference for whole milk might be partly due to the age structure of the sample.

Table 4 reports average odd ratios, indicating that homeowners are more likely to choose rBST-free products. An increase in household size also makes a household on average more likely to choose an rBST-free product. An increase in age reduces the probability on the other hand.

Table 5 summarizes average consumer surplus measures. Average prices are reported in Table 6 and allow for comparison of these estimates. The average consumer surplus and consumer valuation is equated by first averaging across each household and then averaging over all households. Note that less weight can be placed on the estimates of consumer surplus with and without choice restriction, since these estimates will be influenced by scaling. In addition, these numbers do not directly relate to one unit of half-gallon fluid milk. The econometric model and regression specification abstracted from the continuous choice dimension of a households utility maximization process. Before aggregation of multiple units of the same milk product and exclusion of cross product choice, the sample average consumption is 1.21 units per week. The difference in consumer surplus as a measure of compensating variation or consumer valuation relates back to differences in utility and is therefore identified in the model. Average consumer valuation of fluid milk product choice in the presence of rBST-free labels equals 48 cents.[37] Figure 1 graphs the distribution of consumer surplus. Heterogeneity in consumer valuation in the sample was directly investigated by graphing the distributions separately for included household characteristics. The heterogeneity in preferences as suggested by the signs of the estimated coefficients on the included interaction terms is confirmed in these graphical analyses. AS mentioned previously, the effect of children could not be directly included in the model. However, differences in consumer valuation resulting from the presence of children are suggested by comparison of consumer valuation for families versus households without children. These distributional differences are illustrated in Figure 2. The mean consumer valuation for families equals 54 cents, while the mean for households without children equals .46 cents, a 17% difference. Considerable average consumer benefits due to product differentiation and labeling of rBST-free milk products can further be illustrated by further aggregation of these estimates. Adjusting the average valuation by the sample average consumption of 1.21 units per week, results in an average consumer valuation of 40 cents per half-gallon. The annual average consumer benefit amounts to $9.93 if only half-gallon milk consumption is considered. This estimate is based on the sample average annual consumption of 24.83 units. Estimated

[37] The consumer surplus and compensating valuation measures were derived as nonlinear functions of coefficient estimates and variable values. A nonparametric bootstrap procedure with 20 repetitions was used to derive confidence intervals for these estimation results. The procedure did not provide valid standard errors since the estimator is not normally distributed. While none of the estimated differences in consumer valuation are less than zero, the derived 95% confidence interval covers zero and reflects a high variation of the estimates across samples. This variation might again suggest strong preference heterogeneity across households as the bootstrap samples consist of random subsets of repeated purchase choice for the households included in the sample.

consumer valuation could also be related to the average annual per capita milk consumption of 22.9 to 23.4 gallons for 1997-1999. Estimates could be weighted by the observed heterogeneity in preferences, or these differences could be used to put an upper and lower bound on aggregated consumer benefits. Due to the limited sample size, restriction to half-gallon and single store substitution patterns, and differences in household demographics relative to the national average, these computations are not reasonable at this point.

6 Conclusions and Extensions

This paper attempts to provide a flexible framework to address complex product brand and attribute decisions households are faced with on a day-to-day basis. The model reflects on the uncertain nature of product information and potential benefits or risks, both in the absence and presence of labeling, and provides predictions about the impact of labeling on consumer choice of fluid milk products. Additional assumptions allowed to translate model predictions into an econometric logit specification that is empirically investigated using household panel data on fluid milk purchases.

While the theoretical framework extends to the evaluation of changes in labeling regulations with regard to organic certification, ongoing data availability issues limited the empirical analysis to evaluation of consumer response to one type of product labeling. In this first step, estimated consumer valuation refers to average preferences for rBST-free milk and valuation of information presented on the label. The complexity of the available data, combined with the sophistication of recently developed discrete choice estimation techniques, further limited the scope of the empirical analysis. Household purchase data for a single store and substitution patterns of half-gallon fluid milk products only were considered over a time period from 1997 to 1999. Results are further limited by assumptions underlying the pursued conditional logit specification. Accounting for clustering of error terms for households that repeatedly choose milk products at different points in time for instance, essentially reduces the number of observations to the number of households in the sample and would likely reduce the significance of detected effects. At the same time, an increase in the scope of the considered purchase decisions to other product sizes, multiple stores, a given market, and ultimately, the entire data set could counter balance and possibly outweigh this expected decrease in significance.

In analyzing the claim made in newspaper adds, greater weight should be applied to the trends portrayed by the preliminary regression results presented in this paper, rather than specific hypothesis testing of individual or joint significance of coefficients. In this regard, estimation results suggest that "Milk is <u>not</u> Milk", and consumers value the

choice between rBST-free labeled and conventional milk products. Consumer valuations further seem to be influenced by heterogeneity of preferences. Comparison of average consumer valuation for households with and without children for instance, indicates an increase in average valuation for families included in the sample, while the encountered difficulties of directly including an indicator for children in the regression further suggests that average household demographics do not fully capture preference heterogeneity.

Future research will have to address limitations of this study. Two main directions are proposed: First, the robustness of these results will be improved by expanding the data investigated. This extension would for instance provide a better understanding of whether the specification problem with regard to the presence of children was mainly driven by a coding error, and the limited sample size , or stems from consideration of average differences in household demographics. Mixed logit or random coefficient logit models will further be employed and allow relaxation of restrictive distributional assumptions through incorporation of random preference variations, unrestricted substitution patterns, and correlation in unobserved factors over time. An additional alternative hedonic price estimation for rBST-free product labels could strengthen the results through comparison of estimated marginal willingness to pay measures and estimated consumer valuation in the logit specification.

Upon data availability, developed procedures will be applied to changes in labeling regulations of organic milk and define the final stage of this research. The change in labeling regulation provides a natural experiment and can be viewed as an exogenous change in the information provided by the market. Comparisons of household purchase behavior before and after the new government-certified organic standard would enable estimation of consumer valuation directly related to changes in labeling regulations. In this setting, aggregated consumer benefit estimates could be linked to costs incurred by government certification and ultimately allow welfare analysis regarding labeling regulation efficiency. At the same time, this research could provide a deeper understanding of the effects of labeling regulations on consumer purchase decisions and of how preferences regarding organic or non-biotech production evolve.

Table 1: Average household demographics

	Sample Population		National Population[1]
Household demographics	Mean	Standard Deviation	Mean
Female age	57.70	15.35	36.5
Household size	2.61	1.34	2.59
Home owners	0.69	0.46	0.66
Household income (category)	6.72	2.91	56.60 (9)[2]
Households with children under 18 years	0.260	0.439	0.360
Households with children under 6 years	0.060	0.238	0.074

[1]National population mean based on 2000 census data[38]
[2]National average income is measured in thousand dollars which corresponds to category 9 in the data set.

Table 2: Descriptive statistics

Variables	Observations	Mean	Standard Deviation	Minimum	Maximum
Choice	130198	0.065	0.246	0	1
Price	130198	1.800	0.550	0.99	3.19
Store feature	130198	0.098	0.297	0	1
Whole	130198	0.2420	0.428	0	1
Protein added	130198	0.116	0.320	0	1
Kosher	130198	0.242	0.428	0	1
rBST-free	130198	0.620	0.485	0	1
rBST-free*own	130198	0.419	0.494	0	1
rBST-free*hhsize	130198	1.500	1.541	0	8
rBST-free*age	130198	37.339	31.521	0	92
rBST free*hhinc	130198	4.083	3.943	0	12
rBST-free*child	130198	0.130	0.336	0	1
rBST-free*youngchild	130198	0.028	0.164	0	1
Home owners	130198	0.676	0.468	0	1
Household size	130198	2.413	1.258	1	8
Age	130198	60.230	14.966	21	92
Household income	130198	6.585	2.935	1	12
Children	130198	0.209	0.407	0	1
Young Children	130198	0.043	0.202	0	1
First stage residual	129111	0.001	0.146	-0.940	0.529
Carton	130198	0.711	0.453	0	1
Whole milk powder input price	154	1.297	0.137	1.12	1.653
Nonfat powdered milk input price	155	1.062	0.039	1.013	1.155

Note: summary statistics reported are weighted by the number of purchasing decisions per household and therefore might differ from values reported in Table 1.

[38] Available at: http://www.census.gov/main/www/cen2000.html

Table 3: Regression coefficients

Dependent variable: choice of milk product m_i				
Independent variables	**basic model (1)**	**restricted model (2)**	**heterogeneous preferences (3)**	**heterogeneous preferences (4)**
Price	-0.768***	-0.723***	-0.725***	**-0.660*** **
	(0.094)	(-0.070)	(0.070)	**(0.089)**
Store feature	0.494***	0.503***	0.503***	**0.470*** **
	(0.048)	(0.046)	(0.046)	**(0.048)**
Whole	3.475***	3.534***	3.529***	**3.601*** **
	(1.009)	(1.006)	(1.006)	**(1.008)**
Protein added	0.122			
	(0.172)			
Kosher	-0.275**	-0.298**	-0.200**	**-0.282** **
	(0.112)	(0.107)	(0.107)	**(0.110)**
rBST -free	1.024	1.107	1.046	**1.110**
	(1.013)	(1.006)	(1.014)	**(1.016)**
Interaction terms	no	no	yes	**yes**
rBST -free*own			0.078	**0.082[1]**
			(0.050)	**(0.051)**
rBST -free*hhsize			0.051***	**0.048** **
			(0.020)	**(0.020)**
rBST -free*age			-0.002	**-0.002**
			(0.002)	**(0.008)**
Partial effect of rBST -free			1.102	**1.153**
(at mean values)			(1.006)	**(1.007)**
Endogeneity Control	no	no	no	**yes**
First stage residual				**-0.223***
				(0.130)
First stage R^2				**0.9307**
Log likelihood	-19296.824	-19297.075	-19289.204	**-19102.744**
Pseudo R^2	0.1542	0.1541	0.1545	**0.1560**

Note: All regressions include product dummies. Standard errors are reported in parentheses. *, **, and *** denote coefficients that are statistically different from 0 at the 10%, 5% and 1% level.
[1]The p-value for this coefficient is 0.103

Table 4: Estimated average probability changes and odd ratios

Dependent variable: choice of milk product m_i		
	heterogeneous preferences and endogeneity control (4)	
	Probability (in%)	Odd ratios
Mean	6.46	
Independent variables		
Price	-3.65***	0.517***
Store feature	2.60***	1.60***
Whole	19.90***	36.639***
Kosher	-1.56**	0.754***
rBST-free	6.37	3.034
Preference heterogeneity		
rBST -free*own		1.086
rBST -free*hhsize		1.049***
rBST -free*age		0.998

Note: *, **, and *** denote values that are statistically different from 0 at the 10%, 5% and 1% level. Standard errors are adjusted in these computations and p-values are identical to these for the corresponding coefficient estimates.

Table 5: Estimated consumer surplus measures

Expected average consumer valuation			
	Observations	Mean	95% Confidence Interval[2]
Unrestricted consumer surplus	597	5.905	2.788 - 33.813
Restricted consumer surplus[1]	597	5.420	3.156- 32.617
Consumer surplus difference	597	0.484	-.369 - 1.266

Note: Values are averaged across households.
[1] These values correspond to the counterfactual that restricts the household choice to conventional fluid milk.
[2] Confidence intervals were computed using a nonparametric bootstrapping procedure with 20 repetitions. Bias corrected confidence intervals are reported due to the fact that the estimator is not normally distributed.

Table 6 : Mean price differences

	Observations	Mean	Standard Deviation	Minimum	Maximum
Overall unit price	2292	1.788	0.549	.99	3.19
rBST-free labeled unit price	1422	1.756	0.565	1.3	3.19
Conventional unit price	870	1.840	0.518	.99	2.69
Private label unit price	686	1.732	0.469	.99	2.69

Note: Reported mean price differences are influenced by price differences for whole and low fat milk. Low fat milk is relatively more expansive, and the group of rBST-free products include relative more low-fat milk products then the group of conventional milk products.

Figure 1: Average sample consumer valuation of rBST-free milk

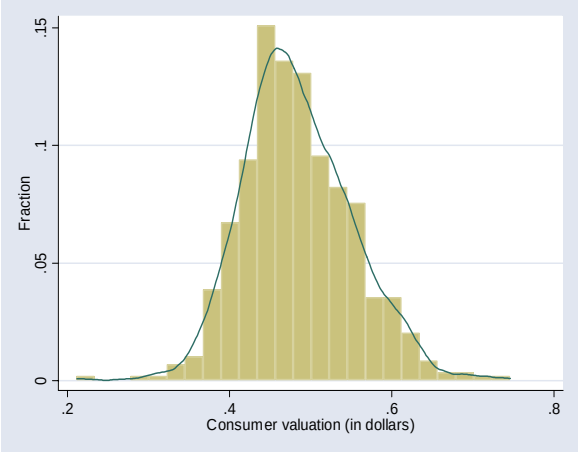
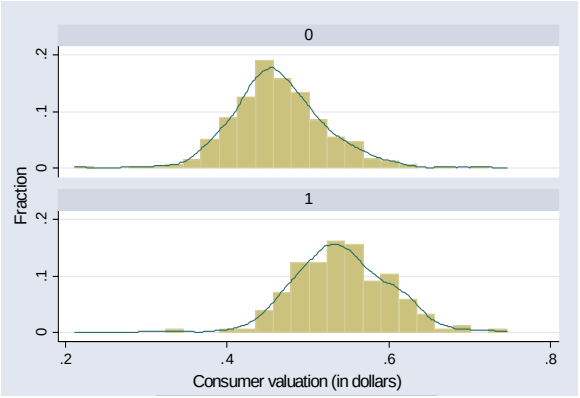


Figure 2: Heterogeneity of consumer valuation regarding the presence of children



Note: 0=no children

7 References

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