Investigating Economic and Demographic Factors Affecting Consumer Demand for Coconut-milk in the United States

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Abstract

Data from U.S. households for calendar year 2014 were used in examining demographic and economic factors affecting demand for dairy alternative beverages such as coconut milk, almond milk, soymilk, and lactose free milk using Heckman two-step procedure. Preliminary analysis of data reveal that the own-price elasiticity of demand for almond milk, soymilk, dairy milk in the United States is -3.50, -1.68,and -0.53 respectively. Soymilk is found to be a substitute for almond milk and white milk, while white milk was found to be a substitute for soymilk. Income, age, employment status, education level, race, ethnicity, region and presence of children in a household are significant drivers of demand for soymilk and almond milk. Sample selection bias was statistically significant.

Keywords: Dairy alternative beverages, coconut-milk, almond milk, soymilk, lactose free milk probit model, Heckman two-step procedure, Nielsen Homescan data

JEL Classification: D11, D12

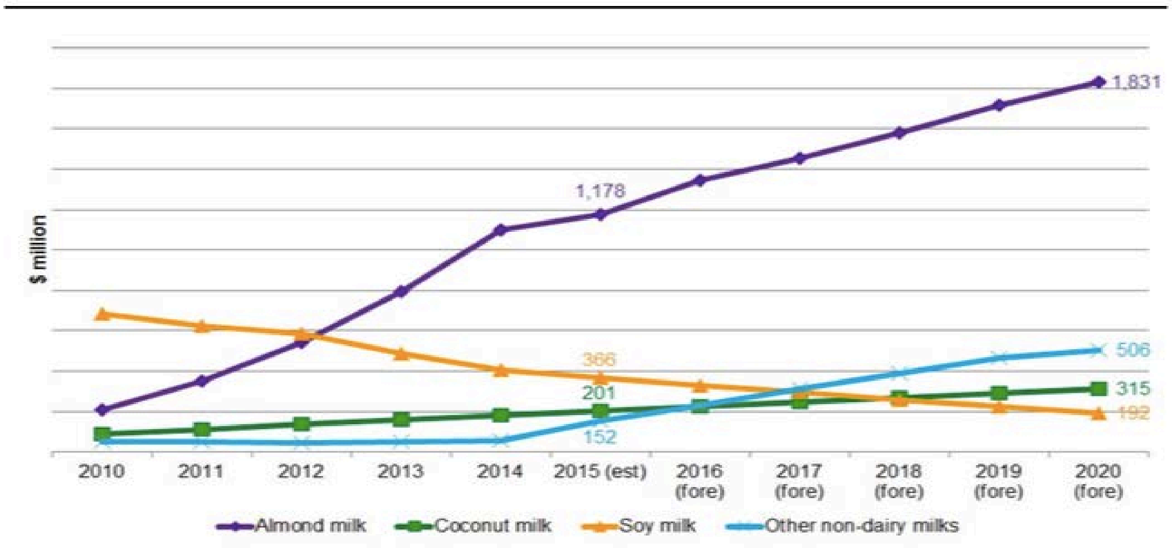
Background and Justification

The Dairy Alternative Beverages Market

Dairy alternative beverages are plant-based milk which is extracted through grains, nuts and seeds. Unlike the regular dairy beverages they have low cholesterol and low fat content. With the increase in awareness, rising health concerns, and the increasing vegan population, in the United States, the demand for dairy alternative beverages is increasing in the past decades. According to the "*Global Dairy Alternative Beverages Market 2014-2018*", the global dairy alternatives market is estimated to grow at a rate of 16% over the period 2013-2018. In terms of value, the global dairy alternative beverages market is projected to reach about $19.5 billion by 2020. In 2014, the global consumption of dairy alternatives was 583.2 KT, and is projected to grow at a rate of about 15.2% from 2015 to 2020 (Dairy Alternatives Market-Global Forecast to 2010).

The Dairy alternative beverages market can be segmented into four divisions: Soymilk, Almond Milk, Coconut Milk, and Others (rice milk, hazelnut milk, hemp milk, and oat milk). *Soymilk* used to be dominated in the dairy alternative beverages market. However, in recent years, consumer migrated from soymilk to other dairy alternatives such as almond milk and coconut milk due to taste, health concerns and calories. It is estimated that sales of soymilk in U.S. declined 5.8% from $981 million in 2009 to $924 million in 2010, and another 8.5% in 2010 reaching $846 million in 2011. In 2012, almond milk has overtaken soymilk and has become America's most popular plant-based milk alternative accounting for 4.1% of total milk sales (KCT.org, 2014). In 2014, *Almond Milk* took the top spot of U.S. dairy alternative beverages market with 65.5% of the market share, which puts soymilk in the second spot with a 30% share of the market. To put this into context, almond milk had captured only 3% of the market in 2008. Almond milk aids in improving the immune function and helps in reducing the risk of osteoporosis. Moreover, it contains no hormones and is prescribed by dermatologists to patients with acne. Almond milk is a good source of unsaturated fats, is rich in proteins and omega fatty acids, and is derived from natural almond oils. It helps in improving vision, strengthens the bone, maintains cardiovascular health, building strong muscles, and aids in controlling the blood pressure. Considering all the advantages of almond milk, it has a great potential to growth in the U.S. dairy alternative beverages market. As it shown in the Information Resources Inc. (IRI), Chicago, refrigerated almond milk dollar sales increased 24% in the 52 weeks ending May 17, 2015. Other dairy alternative beverages like *Coconut Milk* also show great potential for growth. According to data from Information Resources Inc. (IRI), Chicago, refrigerated coconut milk dollar sales grew by 9.2% in the 52 weeks ending May 17, 2015. Coconut milk took the fourth-largest part of the dairy alternatives segment, with 3% market share last year(2015) (Soy and Almond Milk Production in the U.S., 2015).

The following figure shows the total retail sales and forecast of dairy alternative milk from 2010 to 2020.



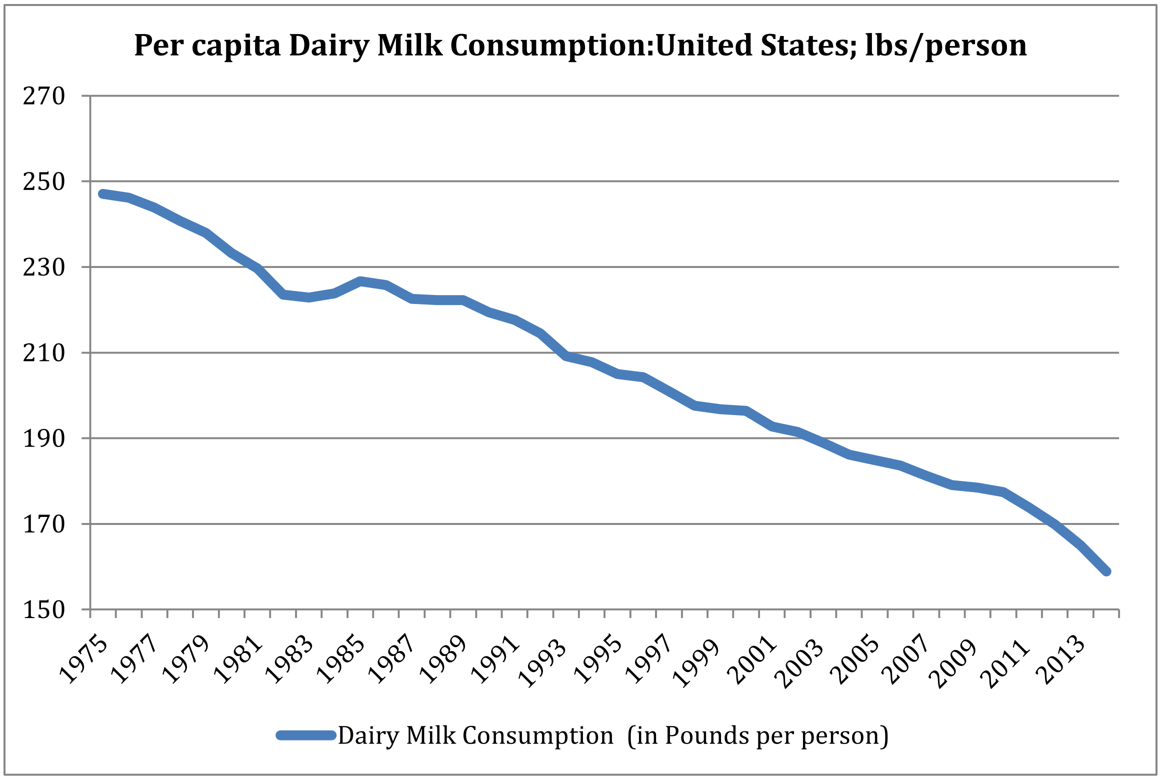
Source: Based on Information Resources Inc., InfoScan Reviews; SPINS; USDA Economic Research Service; US Census Bureau, Economic Census/Mintel

The Traditional Dairy Milk Market

While the dairy alternative beverages market is increasing in the United States, the traditional dairy milk market has been decreasing during past two decades. Per capita milk consumption has been falling for years: it dropped 25% from 1975 through 2012. Milk's rate of decline in 2011 and 2012 was the highest in more than a decade (Star Tribune reports). Today's consumers want healthier refreshment, variety and convenience in their beverages. Most traditional beverage categories continue to struggle and lose ground to newer niche concepts (Gary Hemphill, managing director of research, B.M.C.).

The following graph shows the per capita dairy milk consumption in United States from 1975 to

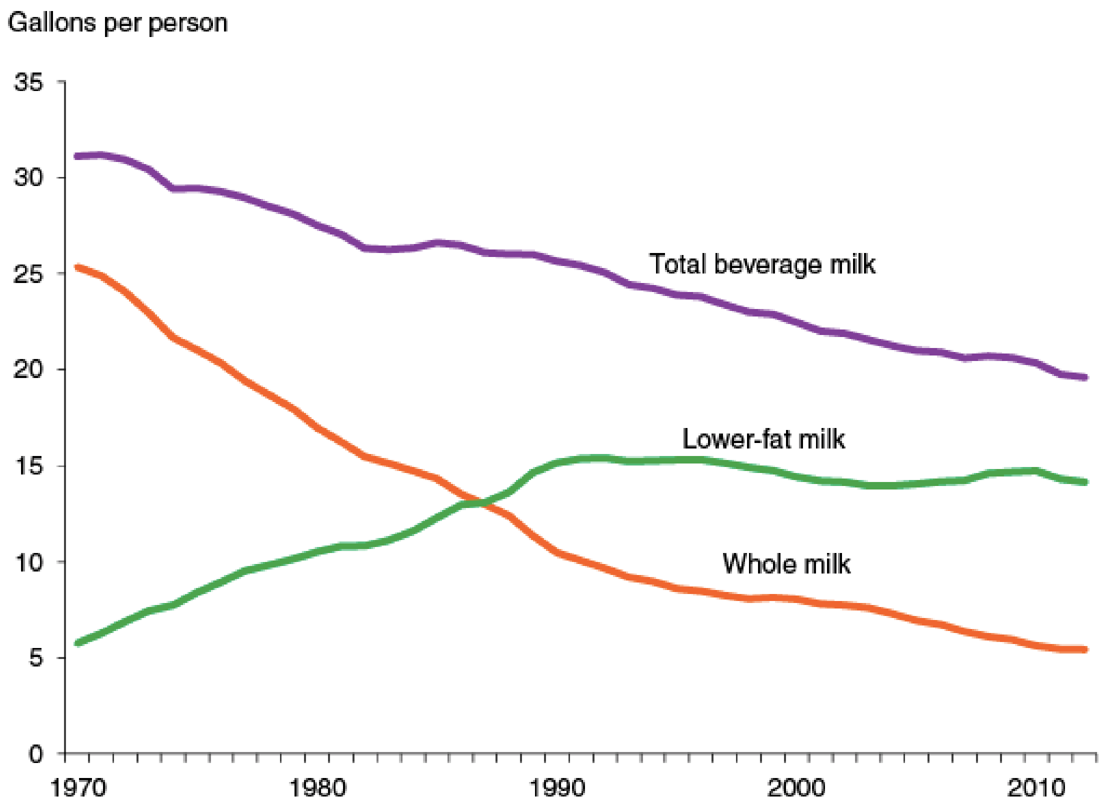
2014 (in pounds per person)



Source: USDA

While Americans continue to drink about 8 ounces of dairy milk, they are consuming it less frequently than in the past. Researchers said that competition from other beverages—especially carbonated soft drinks, fruit juices, and bottled water—is likely contributing to the changes in frequency of dairy milk consumption. In addition, substitutes for cow's milk (including almond milks, coconut milk, and soymilk) have provided alternatives for consumers.

The following graph shows the consumption of total beverage milk, low-fat milk and whole milk in United States from 1970 to 2012.



Source: USDA, Economic Research Service, Food Availability Data System

From the above graph, we can see that the people in the United States tend to drink more low-fat milk, and the consumption of whole milk is decreasing significantly since 1970s. Since dairy alternative beverages contain less fat, it might be one of the reasons why it's a popular substitute for dairy milk. To make their product more competitive, dairy milk companies is going to force stressing the protein levels of their products, along with other healthy added ingredients such as "ancient grains." More flavored milks will be introduced as well as additional organic milk products.

Research on the Demand for Dairy Alternative Beverages Market

While the research about dairy alternative beverages' benefits with emphasis on the healthy ingredient and performance edge are abundant, when it comes to the demand analysis for dairy alternative beverage, especially the economic and demographic factors, the research is scarce. Fengxia Dong (2006) researched the Asian diary market considering the effects of demographics, income, and prices. By using Heien and Wessells's technique, he found that dairy product consumption growth is decomposed into contributions generated by income growth, population growth, price change, and urbanization and these contributions are quantified. He also found that dairy market growth would be mostly driven by income and population growth and, as a result, would raise world dairy prices. Dharmasena and Capps (2014) used data from U.S. households for year 2008 to exam market competitiveness of soymilk via tobit procedure. They found that unconditional own and cross-price elasticities are larger than their conditional counterparts. Income, age, employment status, education level, race, ethnicity, region and presence of children are significant drivers affecting the demand for soymilk. They also found that white milk and flavored milk are competitors for soymilk, and soymilk is a competitor for white milk. Copeland and Dharmasena (2015) investigated the growth of the dairy alternative beverage market in the United States. By using household-level purchase data from 2011 Nielsen Homescan panel and tobit econometric procedure, they estimated the conditional and unconditional own-price, cross-price and income elasticities for soymilk and almond milk. They also found that incomes, age, employment status, education level, race, ethnicity, region and presence of children are significant drivers affecting the demand for dairy alternative beverages. However, according to best of our knowledge, authors could not find a study investigating consumer demand for coconut milk.

Coconut Milk Market in the United States

Coconut-milk has been used primarily in Southeast Asian cooking for ages. Recent years, consumers are showing new interest in coconut milk as a substitute of dairy beverage. With the 2014 Innova trend report showing that coconut milk product introductions grew 36% from 2012 to 2013, it's proving to be a popular addition to many consumers' kitchens. Also, the Packaged Facts report noted that coconut milk dollar sales were up double-digits from 2013 to 2014.

The potential reasons that made coconut milk become popular are likely as follows: (1) compared with traditional dairy beverage, coconut milk has more flavors such as: vanilla, original, unsweetened and chocolate, which provide more choices for consumers. (2) Coconut milk contains more calcium and vitamin than dairy milk. For example, due to fortification, Silk Coconut milk has a mildly nutty taste with 50% more calcium than dairy milk. It's also a great source of vitamin D because of the same reason. (3) Coconut milk has fewer calories and fat than milk, which may be better for consumers who intend to drink it regularly. (4) Lactose intolerance is ubiquitous and coconut milk is a good substitute for milk for those people who are lactose intolerant. Approximately 65% of the human population has a reduced ability to digest lactose after infancy. Lactose intolerance in adulthood is most prevalent in people of East Asian descent, affecting more than 90% of adults in some of these communities. In the United States, as many as 90% of Asian Americans and 75% of African Americans and Native Americans are lactose intolerant. Coconut milk is a good substitute of milk for those people. (5) With greater consumer awareness of coconut water as a beneficial sports drink substitute, people are becoming more interested in coconut-based products.

Despite so many advantages that coconut milk has, market researches noticed that repeat purchases are weak in coconut milk, partly due to the flavor, which is not as universally appealing as that of almond milk. Another reason might be the rising costs for coconut milk producers have been partially passed on to consumers, which has reduced demand. Therefore, to uncover the market competitiveness of coconut milk, in the dairy alternative beverage marketplace in the United States, further research is warranted.

Objectives

Based on the fact that the dairy alternative beverage market is competitive and dynamic while research about the market demand for those beverages is scarce, information about the price sensitivities, substitutes or complements and demographic profiling with respect to consumption of those beverages is important for related manufacturers, retailers, advertisers and other stakeholders. More specifically, the main objectives of this study are to (1) analyze the demographic and economic factors that influence decision to purchase coconut milk, almond milk, soymilk, dairy milk (regular) and dairy milk (lactose free); (2) estimate the income elasticity, own-price elasticity and cross-price elasticity of those beverages; (3) once the decision to purchase these beverages is made, we want to find out the factors that determine the volume of consumption; (4) make some suggestion with respect to marketing as well as advertising strategies for those beverages in the dynamic and competitive marketplace.

Data and Methodology

DATA

The data we used for this study is the 2014 Nielsen Homescan scanner data. There are two types of scanner data that are collected on consumer and/or purchase/consumption: point-of-sale scanner data and household-based scanner data. **Point-of-sale scanner data** are collected at cash registers and identify the products, quantities sold, and prices paid. Point-of-sale scanner data have been used in academic research since the early 1980s. On the other hand, household-based scanner data are a relatively recent innovation. **Household-based scanner data** come from a sample of households that scan universal product codes (UPCs) of all purchased products after each shopping trip. These data are unique in that they provide information on household demographic characteristics that are not available in store scanner data. Moreover, because the household scanner data panelists are instructed to scan all purchases from all outlets, it’s more like a first-hand data and thus more accurate and complete than point-of-sale scanner data. In this paper, we use household-based scanner data to do all the analysis.

Nielsen started collecting in-home household scanner data in 1989. Both the number of the U.S. Homescan panelists and the number of projectable geographic areas have expanded substantially over the years. The Nielsen Homescan data consist of a panel of households who record their grocery purchases. The purchases data can come from a wide variety of store types, including traditional food stores, supercenters and warehouse club and online merchants. Interested consumers who are 18 or older register online to participate and are asked to supply demographic information. Consumers must report data for at least 10 of 12 months during the year to be included in the static sample.

Methodology

In this paper, first, we plan to find out the demographic factors affecting consumer's decision to buy dairy alternative beverages such as coconut milk, almond milk and soymilk. In other words, try to calculate the factors affecting the probability of consumption of those beverages. We are using probit model to achieve this objective. Once the decision to purchase the beverage is made, we will use conditional demand function to estimate factors affecting the volume of purchase of each beverage. This procedure is formally known as Heckman two-step (Heckman, 1979) sample selection procedure.

The Probit Model

In this study, there is large number of households who didn’t buy dairy alternative beverages. This decision to purchase or not to purchase could be affected by various socio-economic-demographic factors. Buy or not-to buy is a dichotomous discrete (“one” if buy and “zero” if do not buy) and this kind of consumption behavior leads to corner solutions for some nontrivial fraction of the population. Application of ordinary least squares to estimate this kind of regression gives rise to biased estimates even asymptotically (Kennedy 2003). In this case, a binary probit model is used to generate probability of consumption of dairy alternative beverages given a host of demographic factors and a weighted average price of dairy alternative beverages such as coconut milk, almond milk, soymilk and dairy milk (regular and lactose free. The stochastic model underlying the Probit Model generally represented as follows:

(1) $P_i = F_p(X_i'\beta) = F_p(Z_i) = \int_{-\infty}^{Z_i} \frac{1}{\sqrt{2\pi}} e^{Z_i^2/2} ds$

where X' are explanatory variables and β are regression coefficients. Because buy or not-to buy is a dichotomous problem, we need to run the index values Z_i through a standard normal cumulative distribution function, $F_p(Z_i)$. Thus, we get at probabilities P_i that are bounded by 0-1 interval.

For the dichotomous event, we have:

(2) $P_r(Z = 1|X, \beta) = F_p(Z_i)$

(3) $P_r(Z = 0|X, \beta) = 1 - F_p(Z_i)$

We use maximum likelihood estimation technique to estimate the unknown parameters, β.

First, let us take a sample of *n* individual observations on individual choices y_i. The probability density functions of the observable variables y_i can be specified as follows:

(4) $g(y_i) = P_i^{y_i}(1 - P_i)^{1-y_i}$

Joint probability density function of the sample of *n* independent observations is the product of the *n* probability density functions $g(y_i)$. Mathematically:

(5) $g(y_1, y_2, y_3, \cdots, y_n) = \prod_{i=1}^{n} g(y_i)$

Substituting (4) in (5) gives us the following:

(6) $g(y_1, y_2, y_3, \cdots, y_n) = \prod_{i=1}^{n} P_i^{y_i}(1 - P_i)^{1-y_i}$

Because

(7) $P_i = F_p(Z_i) = F_p(x_i'\beta)$

Substituting (7) in (6) gives us the following likelihood function:

(8) $g(y_1,\ y_2, y_3, \cdots,\ y_n) = \prod_{i=1}^{n} F_p(x_i'\beta)^{y_i}[1 - F_p(x_i'\beta)]^{1-y_i}$

(9) $l(\beta) = \prod_{i=1}^{n} F_p(x_i'\beta)^{y_i}[1 - F_p(x_i'\beta)]^{1-y_i}$

In probit model estimation either the researcher can maximize (9) and solve for βs or can maximize the log of the likelihood function stated in equation (10):

(10) $l(\beta) = \sum_{i=1}^{n} y_i \ln(F_p(x_i'\beta)) + \sum_{i=1}^{n}(1 - y_i) \ln(1 - F_p\ (x_i'\beta))$

Above maximum likelihood estimator for probit model has large sample properties where, with large *n*, the maximum likelihood estimator β has a sampling distribution that is approximately normal with mean β and covariance matrix:

(11) $cov(\widehat{\beta}) = (X'DX)^{-1}$

where *X* is the (*n* × *k*) design matrix of observations on *k* explanatory variables for *n* individuals. Design matrix has diagonal elements as depicted in equation (12):

(12) $d_i = \frac{[f(x_i'\beta)]^2}{F(x_i'\beta)[1-F(x_i'\beta)]}$

where $f(x_i'\beta)$and $F(x_i'\beta)$ are the probability density function and cumulative distribution function for standard normal random variable, respectively.

Unlike the usual linear statistical model, the parameter value of β in probit model cannot be directly interpretable as the effect of change of explanatory variable on the mean of the dependent variable. Let us differentiate equation for probit model (1) with respect to X_{ik}. With the help of the chain rule in differentiation, we can write the following:

(13) $\frac{\partial P_i}{\partial X_{ik}} = \frac{\partial F(Z_i)}{\partial Z_i} * \frac{\partial Z_i}{\partial X_{ik}} = f(Z_i) * \beta$

where $f\ (Z_i\ )$is the probability density function of the standard normal distribution.

Therefore, to calculate the marginal effect of a continuous explanatory variable in probit model, first we need to calculate the probability density value for a given value of explanatory variable and multiply that by the parameter estimate of the respective explanatory variable.

Marginal effect calculation for a discrete explanatory variable (0-1 type dummy variable) is different from above approach. The appropriate marginal effect for a binary independent variable, say d, would be as follows:

(14) $\frac{\partial P_i}{\partial d_{ik}} = f(x_i'\beta, d = 1) - f(x_i'\beta, d = 0)$

where $f\ (x_i'\beta)$ is the probability density function of the standard normal distribution.

The Heckman Two-Step Analysis

The first stage of the Heckman-two-step sample selection procedure, involves in decision to purchase each beverage. It is modeled through a probit model (as explained above). A binary dependent variable is observed (purchase or not purchase), where purchase is represented by one (1) and not purchase is given by a zero (0). The latent selection equation can be written as follows;

(15) $Z_h = w_h' \gamma + \varepsilon_h$

where Z_k represents a latent selection variable (buy or not to buy type dichotomous variable),

(16) $Z_h = \begin{cases} 1 \ if \ \ Z_h > 0 \\ 0 \ if \ \ Z_h < or = 0 \end{cases},$

w_h is a vector of explanatory variables in the latent decision making variable, γ_h is a vector of parameters to be estimated in the decision making equation, ε_h is the error term, and $h = 1,2,....., N$ is the number of observations (in our work the number of households in the sample) in the sample. Modeling above equation 2 through probit model gives us following relationships;

(17) $\Pr[Z_h = 1] = \phi(w_h, \gamma)$ and

(18) $\Pr[Z_h = 0] = 1 - \phi(w_h, \gamma)$

where ϕ is the normal cumulative probability distribution function (cdf). The first stage estimation provides estimates of γ and the inverse of the Mills Ratio (IMR hereinafter). We also generate the associated probability density function (pfd). Inverse of Mills Ratio is calculated taking the ratio of pdf to cdf. Mathematically, it is as follows;

for $Z_k = 1$,

(19) $IMR_h = \frac{\varphi(w_h \hat{\gamma})}{\phi(w_h \hat{\gamma})}$,

where φ represents the probability density function. Inverse mills ratio is a monotone decreasing function of the probability that an observation is selected into the sample, $\phi(w_k \hat{\gamma}_k)$ (Heckman, 1979). In particular,

(20) $\lim_{\phi(Z_{hi}) \to 1} IMR_h = 0$

(21) $\lim_{\phi(Z_{hi}) \to 0} IMR_h = \infty$

(22) $\frac{\partial IMR_h}{\partial \phi(Z_h)} < 0$

The calculated IMR, will be used as an additional explanatory variable in the second stage volume equation, which takes care of the sample selection bias in the data. Second stage equation is given as follows;

(23) $E[Y_h \mid Z_h = 1] = X'_h \beta + \alpha \frac{\varphi(w_h \hat{\gamma})}{\phi(w_h \hat{\gamma})}$

(24) $E[Y_h \mid Z_h = 1] = X'_h \beta + \alpha I\hat{MR}_h$

where X_k is a vector of explanatory variables considered in the second stage. Importantly, only observations associated with non-zero observations on Y_k are considered here. The IMR calculated using information retrieved from first stage probit model is used as an explanatory variable in the second stage (see equations 23 and 24 above). Presence of a sample selection bias in data will be communicated through statistical significance of the coefficient associated with IMR, i.e. α_k . If α_k is statistically not different from zero, we conclude that there is no sample selection bias in the data and result in the following regression model;

(25) $E[Y_h \mid Z_h = 1] = X_h'\beta_i$

It is important to know that the explanatory variables in first stage and second stage equations may or may not be the same. In our work, the price variables in both equations do not. However, rest of the demographic variables is exactly the same in the first stage and second stage.

Choice of explanatory variables in the first and second stage has an implication on the derivation and interpretation of marginal effects associated with variables in the second stage. This is because in the second stage, we have the IMR term augmenting the regular regression function with other explanatory variables. Therefore, in calculating marginal effects, the influence of IMR and its associated regression coefficient on other regression coefficients have to be taken into consideration.

Suppose X_{kj} denote the *j*th regressor that is common to both first stage regressors, w_k and, second stage regressors, X_j . Differentiating equation 24 with respect to *j*th regressor, the marginal effect is given by the following relationship (following explanation is borrowed from Saha, Capps and Byrne (1997));

(26) $\dfrac{\partial E[Y_h \mid Z_h = 1]}{\partial X_{kj}} = \beta_{ij} + \alpha_i \dfrac{\partial (IM\hat{R}_{hi})}{\partial X_{hj}}$

It is evident from 26 that marginal effect of the *j*th regressor on Y_{ki} consists of two parts: a change in X_j which affects the probability of consuming the commodity (this effect is represented by $\frac{\partial(IM\hat{R}_{hi})}{\partial X_{hj}}$ in 13); a change in X_j which affects the level of consumption (or expenditure of consumption) which is conditional upon the household choosing to consume the *i*th commodity (this is represented by β_{ij} in 26). The former of the above two expression is important, because the sign and magnitude of the marginal effect depends not only on the β_{ij}, but also that of the $\frac{\partial(IM\hat{R}_{hi})}{\partial X_{hj}}$. According to Saha, Capps and Byrne (1997), after some simplification we get arrive at the following relationship for the Heckman second stage marginal effects,

(27) $M\hat{E}_{kj} = \frac{\partial E[y_k \mid Z=1]}{\partial X_{kj}} = \beta_j - \alpha\gamma_{ij}\{W\gamma IMR_k + (IMR_k)^2\}$

In general the marginal effect $M\hat{E}_{kj} \neq \hat{\beta}_j$; however the only case where $M\hat{E}_{kj} = \hat{\beta}_j$ is where $\hat{\alpha} = 0$ which is a situation where the errors in the first-stage and second-stage estimation equations have zero covariance. It must be noted that the $M\hat{E}_{kj}$ estimation depends on a local set of co-ordinates. Therefore, we estimate the $M\hat{E}_{kj}$ at the sample means. Following equation 28 shows this result. For simplicity, let us denote IMR in the letter λ.

(28) $M\hat{E}_{kj}\mid_{samplemean} = \hat{\beta}_j - \hat{\alpha}_i\hat{\gamma}_j\{(\overline{W}\hat{\gamma})\overline{\hat{\lambda}} + \overline{\hat{\lambda}}^2\}$

where $\overline{W}$ denotes the vector of regressor sample means in the probit equation (the first stage equation of the Heckman two-step model and

(29) $\bar{\hat{\lambda}} = \dfrac{\varphi(\overline{W}\hat{\gamma})}{\phi(\overline{W}\hat{\gamma})}$

is the inverse Mills ratio evaluated at those means.

The Heckman two-step demand model for say coconut-milk can be written as follows:

$$
\begin{aligned}
q_i = {} & \beta_1 + \beta_2 P_i + \beta_3 AGEHH2529_i + \beta_4 AGEHH3034_i + \\
& \beta_5 AGEHH3544_i + \beta_6 AGEHH4554_i + \beta_7 AGEHH5564_i + \beta_8 AGEHHGT64_i + \\
& \beta_9 EMPHHPT_i + \beta_{10} EMPHHFT_i + \beta_{11} EDUHHHS_i + \beta_{12} EDUHHU_i + \\
& \beta_{13} EDUHHPC_i + \beta_{14} REG\_CENTRAL_i + \beta_{15} REG\_SOUTH_i + \\
& \beta_{16} REG\_WEST_i + \beta_{17} RACE\_BLACK_i + \beta_{18} RACE\_ORIENTAL_i + \\
& \beta_{19} RACE\_OTHER_i + \beta_{20} HISP\_YES_i + \beta_{21} AGEPCLT6\_ONLY_i + \\
& \beta_{22} AGEPC6\_12ONLY_i + \beta_{23} AGEPC13\_17ONLY_i + \\
& \beta_{24} AGEPCLT6\_6\_12ONLY_i + \beta_{25} AGEPCLT6\_13\_17ONLY_i + \\
& \beta_{26} AGEPC6\_12AND13\_17ONLY_i + \beta_{27} AGEPCLT6\_6\_12AND13\_17_i + \\
& \beta_{28} MHONLY_i + \beta_{29} FHONLY_i + \beta_{30} INCOME_i + \alpha_i IMR + \varepsilon_i
\end{aligned}
\tag{30}
$$

where $i = 1, \ldots\ldots, n$ is the number of observations (households in our work) in the model. q_i corresponds to the quantity of purchase of coconut milk and P_i variable represent the price of all beverage products considered in this study. We have defined the variables in the above equation 30 in Table 1. In the equation 30, *IMR* stands for the inverse Mills ratio and α_i corresponds to the coefficient associated with *IMR*. Presence of sample selection bias is determined looking at the significance of α_i . If we have sample selection bias, we have to do an adjustment to the coefficient estimates in the second stage estimation in trying to get at correct marginal effects. Procedure to adjust for marginal effects was elaborated in the preceding section.

As such, we will calculate marginal effects associated with each explanatory variable. The level of significance we will be using in this study is 0.05. We further conduct an *F*-test for demographic variable categories to find statistically significant demographics.

Results and Discussion

We will be in position to estimate own-price, cross-price and expenditure elasticities for the separable group of goods, namely coconut milk, almond milk, soymilk, dairy milk. Also, we will be profiling demographic characteristics of consumers with regards to these food groups. Preliminary analysis of data reveal that the own-price elasiticity of demand for almond milk, soymilk, dairy milk in the United States is -3.50, -1.68,and -0.53 respectively. Soymilk is found to be a substitute for almond milk and white milk, while white milk was found to be a substitute for soymilk. Income, age, employment status, education level, race, ethnicity, region and presence of children in a household are significant drivers of demand for soymilk and almond milk.

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Table 1 Description of the Right-Hand Side Variables Used in the Econometric Analysis

Variable	Explanation
PRICE	Price of each beverage (Coconut-milk, almond milk, soymilk, lactose free milk, regular dairy mailk)
AGEHHLT25	*Age of Household Head less than 25 years (Base category)*
AGEHH2529	Age of Household Head between 25-29 years
AGEHH3034	Age of household Head between 30-34 years
AGEHH3544	Age of household Head between 35-44 years
AGEHH4554	Age of household Head between 45-54 years
AGEHH5564	Age of household Head between 55-64 years
AGEHHGT64	Age of household Head greater than 64 years
EMPHHNFP	*Household Head not employed for full pay (Base category)*
EMPHHPT	Household Head Part-time Employed
EMPHHFT	household Head Full-time Employed
EDUHHLTHS	*Education of Household Head: Less than high school (Base category)*
EDUHHHS	Education of Household Head: High school only
EDUHHU	Education of Household Head: Undergraduate only
EDUHHPC	Education of Household Head: Some post-college
EAST	*Region: East (Base category)*
MIDWEST	Region: Central (Midwest)
SOUTH	Region South

WEST	Region West
WHITE	*Race White (Base category)*
BLACK	Race Black
ASIAN	Race Asians
RACE_OTHER	Race Other (non-Black, non-White, non-Oriental)
HISP_NO	*Non-Hispanic Ethnicity (Base category)*
HISP_YES	Hispanic Ethnicity
NPCLT_18	*No Child less than 18 years (Base category)*
AGEPCLT6_ONLY	Age and Presence of Children less than 6-years
AGEPC6_12ONLY	Age and Presence of Children between 6-12 years
AGEPC13_17ONLY	Age and Presence of Children between 13-17 years
AGEPCLT6_6_12ONLY	Age and Presence of Children less than 6 and 6-12 years
AGEPCLT6_13_17ONLY	Age and Presence of Children less than 6 and 13-17 years
AGEPC6_12AND13_17ONLY	Age and Presence of Children between 6-12 and 13-17 years
AGEPCLT6_6_12AND13_17	Age and Presence of Children less than 6, 6-12 and 13-17 years
FHMH	*Household Head both Male and Female (Base category)*
MHONLY	Household Head Male only
FHONLY	Household Head Female only