Food Distribution Research Society

Journal of Food Distribution Research
Volume 51, Issue 2, pp. 131–157

The Growing Market for Energy and Sports Drinks in the United States: Can Chocolate Milk Remain a Contender?

Yang Hu,[a] Senarath Dharmasena,[bΦ] Oral Capps Jr.,[c] and Ramkumar Janakiraman[d]

[a]*Master's Student, Department of Agricultural Economics, Texas A&M University, College Station, TX 77843-2124, USA*

[b]*Assistant Professor, Department of Agricultural Economics, Texas A&M University, College Station, TX 77843-2124, USA*

[c]*Regents Professor, Department of Agricultural Economics, Texas A&M University, College Station, TX 77843-2124, USA*

[d]*Professor of Marketing, Department of Marketing, Darla Moore School of Business, University of South Carolina, Columbia, SC 29208, USA*

Abstract

U.S. consumption of chocolate milk is growing as an alternative to sports and energy drinks. Using household-level demographic characteristics and purchase data for chocolate milk, energy drinks, and sports drinks, we estimate three beverage demand models. Own-price elasticities of demand for all beverages are inelastic. Household size, age, education, race, region, the presence of children, and gender are determinants of demand for chocolate milk. Chocolate milk is a substitute for energy drinks and a complement for sports drinks. These results are supportive of repositioning of chocolate milk in the sports/energy drinks market.

Keywords: chocolate milk, consumer demand, energy drinks, Nielsen data, sports drinks, Tobit model

[Φ]Corresponding author: Tel: (979) 862-2894
Email: sdharmasena@tamu.edu

Introduction

Total milk production in the United States increased about 32% from 1999 to 2017 (U.S. Department of Agriculture, 2018b, p. 26), while sales have decreased since 2010 (U.S. Department of Agriculture, 2018a). However, from 2010 to 2017, sales of flavored milk have increased by 2.5%. In 2015, sales of chocolate milk reached to about $1,383 million (Statista, 2018a). The extant literature shows that the rise in sales and demand for various dairy alternative beverages might be shaping future of the dairy products in the United States (Dharmasena and Capps, 2014a,b; Copeland and Dharmasena, 2016; Yang 2018).

In contrast, the U.S. liquid refreshment beverage market (comprising carbonated soft drinks, bottled water, ready-to-drink tea and coffee, fruit beverages, energy drinks, and sports beverages, Statista, 2018b) has grown rapidly over the past decade: Sales by volume increased by about 12% in 2017 (Beverage Marketing Corporation, 2018). Currently, energy and sports drinks are two of the most popular beverages in the United Sates.[1] The U.S. market for energy drinks has become a multibillion-dollar business, accounting for 8% by value of the U.S. soft drinks market in 2017. Sales of energy drinks increased from $2.800 billion in 2015 to $2.979 billion in 2017 (Monster Beverage, 2018, p. 8). The sports drinks market is expected to reach $1,135,000,000 by the end of 2023 (Modor Intelligence, 2019). Sales of sports drinks increased about 14% from 2012 to 2015 (Beverage Digest Company, 2015, table G1). This market trend in energy and sports drinks could also be attributed to growth (or lack thereof) in other liquid refreshment beverages, such as diet soft drinks and bottled water. While flavored milk was not included in their study, Dharmasena and Capps (2012) found positive (but statistically not significant) cross-price elasticities between diet soft drinks and isotonics (both energy and sports drinks taken as one aggregated category) and bottled water and isotonics.

Several studies have shown that the consumption of chocolate milk is a viable alternative to consumption of energy and sports drinks. Compared to energy drinks, researchers have found that chocolate milk is better at reducing debilitating muscle breakdown and increasing endurance for those who are physically active (Lunn, 2012). In an experiment, when runners drank fat-free chocolate milk after a strenuous run, on average, they ran 23% longer and had a 38% increase in markers of muscle building compared to when they drank a carbohydrate-only sports beverage with the same number of calories (Lunn, 2012). Karp et al. (2006) emphasized that chocolate milk contained high carbohydrate and protein content, which were effective for recovery from strenuous exercise.

In contrast, one of the most pressing issues concerning energy drinks is the inclusion of stimulants such as caffeine and guarana. Excessive consumption of energy drinks may increase risk of caffeine overdose and result in greater potential for acute caffeine toxicity (Reissig, Strain, and Griffiths, 2009). Initially, the primary consumers of energy drinks were athletes. However, as the market for energy drinks expanded, the majority of energy drinks were targeted at teenagers and young adults 18 to 34 years old (Heckman, Sherry, and Gonzalez de Meija, 2010). According to

[1] Sports drinks provide fluids as well as other substances such as electrolytes (sodium, potassium, and magnesium) and carbohydrates. Energy drinks provide caffeine and other sources of stimulants and sugar (Collins, 2013).

Kaminer (2010), 30% of youths between the ages of 12 and 17 regularly consumed energy drinks. However, excessive caffeine is not recommended for people under the age of 18. Although many brands of energy drinks try to dispel consumer concerns about caffeine, this fact has triggered increased negative media coverage. As a consequence, consumers have looked into healthier alternative beverages.

The ingredient advantage of chocolate milk and the weakened outlook of the conventional milk market in the United States create a unique opportunity for chocolate milk to enter the fast-growing beverage market as an alternative recovery drink. This repositioning could potentially provide an additional occasion for consumers to buy chocolate milk and enhance sales (Markets and Markets report, 2016).

In fact, the dairy industry has been repositioning chocolate milk as a contender in the fast-growing market for protein bars, shakes and energy beverages. Since 2012, the Milk Processor Education Program (MilkPEP), the group responsible for the "Got Milk?" campaign, has invested $15 million a year into a marketing campaign on chocolate milk to strengthen the branding of this beverage as a new-age sports/energy drink (Yang, 2014). Also, MilkPEP has set their next 20-year campaign as "propel milk back into a position of power" (Berry, 2014). In 2012, MilkPEP launched the "My After" campaign to strengthen consumer consciousness that consuming low-fat chocolate milk was better than alternatives for athletes. According to Shoup (2019), after repositioning chocolate milk as a post workout recovery drink vis-à-vis isotonics via a MilkPEP campaign in 2012, U.S. sales of chocolate milk increased by about 8% at the end of year 2015 and were expected to continue growing over the years. This trend could be a direct result of changing consumer perceptions with regards to chocolate milk compared to isotonics.

Additionally, the marketing of chocolate milk—like sports or energy drinks—is aligning with professional athletes and celebrities, incorporating sports games and music to advertise their products. Recently, professional football and basketball players, swimmers, and running groups have been gradually taking chocolate milk as their recovery drink. Chocolate milk has become the official refuel beverage of many prominent sports organizations and teams, like the IRONMAN® triathlon series, the Rock 'N' Roll Marathon series, and the Challenged Athletes Foundation (Milk Processor Education Program, 2014).

Few past studies in the extant literature estimate U.S. demand for chocolate milk and energy drinks. For the period 1996–1998, Maynard and Liu (1999) estimated the own-price elasticity of demand for flavored milk, to be in a range of −1.4 to −1.47. Dharmasena and Capps (2011) used a Heckman sample selection procedure to estimate U.S. demand for chocolate milk for 2008 using a Nielsen Homescan panel data. They estimated the own-price elasticity of demand for chocolate milk to be −0.04.

Capps and Hanselman (2012) employed the Barten synthetic demand system to estimate own-price, cross-price, and expenditure elasticities for major energy drink brands using weekly data from October 2007 to October 2010. They estimated the own-price elasticity of demand for energy drinks to be between −0.99 and −1.69. Also, Dharmasena and Capps (2009) and Dharmasena and

Capps (2012) estimated demand for isotonics in a demand system framework. The own-price elasticities of demand for isotonics varied from −3.87 to −5.96. Although, these studies included conventional milk in the demand modeling, they did not include flavored milk (or chocolate milk) in their work. This large variation in own-price elasticity of demand estimates could be due to various reasons, including

i. product aggregation. Maynard and Liu (1999) considered all flavored milk as one aggregated category, while Dharmasena and Capps (2011) considered chocolate milk as one disaggregated category
ii. level of data used. Maynard and Liu (1999) used weekly national average retail scanner data from 1996–1998, while Dharmasena and Capps (2011) used a cross-sectional dataset of nearly 60,000 households from 2008
iii. model choice. Maynard and Liu (1999) used a linear approximated almost ideal demand system model, while Dharmasena and Capps (2011) used a Heckman two-step sample selection procedure.

While the media has linked chocolate milk to benefits based on healthy ingredients and performance as opposed to isotonics, to the best of our knowledge, economic analysis documenting U.S. demand for chocolate milk and isotonics is currently quite limited.

In this light, a thorough analysis of demand for chocolate milk, energy drinks, and sports drinks is important to uncover not only demand interrelationships among these beverages but also to explore the opportunity to reposition these beverages among consumers in the very competitive dairy marketplace. Additionally, the price sensitivity, substitutes or complements, and demographic profiling with respect to consumption of chocolate milk, energy drinks, and sports drinks are important for manufacturers, retailers, and advertisers of these beverage products for strategic positioning and marketing. Specific objectives of this study are to (i) estimate the own-price, cross-price, and income elasticities of demand for chocolate milk, energy drinks, and sports drinks and (ii) determine the socioeconomic and demographic factors affecting the purchase of chocolate milk, energy drinks, and sports drinks in the United States.

Methodology

Tobit Model

Some households may not have bought chocolate milk, energy drinks, and/or sports drinks during the sampling period. In this case, the dollar amount spent by households on these beverages was recorded as 0. If a fraction of the observations of the dependent variables take this limit value (lower limit being 0), the dependent variable is said to be *censored*. Application of ordinary least squares (OLS) to estimate this kind of situation gives rise to biased estimates, even asymptotically (Kennedy, 2003). As a result, the Tobit model is suggested as a method to explicitly model the censored dependent variables (Tobin, 1958; Heckman, 1979; Kennedy, 2003; Greene, 2003).

The Tobit model is defined as a latent variable model:

(1) $$\boldsymbol{Y} = \beta\boldsymbol{X} + \boldsymbol{\mu}\text{ , if }\beta\boldsymbol{X} + \boldsymbol{\mu} > \boldsymbol{0};\ \mu \sim Normal(0, \sigma^2)$$

and

$$\boldsymbol{Y} = 0, \text{ if } \beta\boldsymbol{X} + \boldsymbol{\mu} \leq \boldsymbol{0}$$

where Y is the censored dependent variable, $\boldsymbol{X}$ is a vector of explanatory variables, β is the vector of unknown parameters to be estimated, and $\boldsymbol{\mu}$ is the normally distributed error with variance σ^2. (Details of the Tobit model are explained in the Technical Appendix.)

Empirical Model

In the given year, some households purchased these products (chocolate milk and isotonics) and some did not. For those households that did not purchase the product, one has to estimate the price paid for the product, had the household purchased the product. This is the imputed price. In calculating the imputed price for those households that did not purchase the product, we first regressed the observed price from those households that purchased the product on three variables: household size, household income, and region where the household is located:

$$P_{i,observed} = \alpha_1 + \alpha_2 HH_{i,income} + \alpha_3 HH_{i,size} + \alpha_4 HH_{i,region} + \mu_i, \tag{2}$$

where $i = 1,2,3,\ldots n$, and n is the total number of households.

These variables and methods are used extensively in the literature to impute missing prices (Kyureghian, Capps, and Nayga, 2011; Alviola and Capps, 2010; Dharmasena and Capps, 2014a). Household income relates to the different levels of product quality as it is reflected by product price. Household region reflects spatial differences in price. Household size not only reflects the composition of the households but also relates to the amount of money households spend on the product, assuming that large households tend to buy less expensive products. The parameters estimated from this auxiliary regression are then used to forecast (impute) a price for those households that did not purchase the product. This imputation procedure addresses two things: (i) the potential endogeneity issue often questioned in the price variable through the use of predicted price as an instrument to observed price and (ii) the biases one would question for not having clustered standard errors with regards to price variables in the Tobit regression. Since we used the household region as an explanatory variable in the price imputation auxiliary regression in imputing prices, standard error results for the price variables in fact are clustered at the state or county level. Therefore, significance levels of price variables in the Tobit regression are calculated using clustered standard errors of those variables in the price imputation auxiliary regressions (Capps, Kirby, and Williams, 1994; Alviola and Capps, 2010; Kyureghian, Capps, and Nayga, 2011; Dharmasena and Capps, 2012). We find that observed price of each beverage category very closely mimics the imputed price.[2]

[2] The mean and standard deviations of imputed and observed prices for each beverage category are shown below:

	Observed Prices (USD/oz)		**Imputed Prices (USD/oz)**	
	Mean	**Standard Deviation**	**Mean**	**Standard Deviation**
Chocolate milk	0.049	0.02	0.051	0.01
Energy drinks	0.129	0.06	0.131	0.01
Sports drinks	0.052	0.15	0.053	0.003

Once the imputed price for each type of beverage is obtained, the explanatory variables to estimate the Tobit model includes prices, household income, presence of children in the household, region, race, employment status, level of education, and gender of the household head. Although economic theory suggests the use of price and income as right-side variables in quantity-dependent demand functions, theory does not suggest the choice of demographic variables to include as conditioning variables. However, considering the beverages considered in this study (chocolate milk, energy drinks, and sports drinks), we relied on such demographic variables used in similar past studies (Dharmasena and Capps, 2014a,b; Zheng et al., 2018) as well as common sense (such as the presence of children, employment status, and region). We did not undertake sequential hypothesis testing on the conditioning variables to find out the variables that should be included in the right side of the regression in this study.

The estimated demand function in general form is as follows:

(3) $$Y_i = \alpha_i + \sum_j \beta_{ij} P_j + \gamma_i I + \theta_i D + \varepsilon_i,$$

where $i = 1, 2, 3\ldots$ 62,029 (the number of households in the sample) and $j = 1, 2, 3$ (the number of products: chocolate milk, energy drinks, and sports drinks); Y_i is the quantity of chocolate milk, energy drinks, and sports drinks in ounces; P_j is the price of each beverage in dollars per ounce;[3] I is household income in dollars;[4] D are the demographic variables (see Table 1 for details), including household head age, household head employment status, household head education, household race, household ethnicity, region, age and presence of children, and gender of household head; $\alpha, \beta, \gamma, \theta$ are the estimated parameters; and ε is a random error term.

We investigated several functional forms, including linear, quadratic, and semi-log. The best functional form was decided based on model fit, significance of the variables, and the results of loss metrics like the Akaike information criterion (AIC). We found that the semi-log functional form outperformed other functional forms in the chocolate milk and sports drinks demand models (natural logarithms of beverage prices, income, and household size were used). However, for the energy drinks demand model, the price of chocolate milk in linear form outperformed price represented in its natural logarithm (which also used the natural logarithms of other price variables, income, and household size). Therefore, we used the semi-log functional form to calculate the conditional and unconditional marginal effects associated with each explanatory variable, except for linear functional form for price of chocolate milk in the energy drink demand model.

The conditional marginal effect for semi-log price variable is given by

(4) $$\frac{\partial E(Y|Y>0)}{\partial p} = \frac{\beta}{p^c}\left(1 - z\frac{f(z)}{F(z)} - \frac{f(z)^2}{F(z)^2}\right).$$

[3] All prices are logged in the chocolate milk equation; energy drinks and sports drinks prices are logged in the energy drinks and sports drinks equations.

[4] Household income is logged in all three equations.

Table 1. Summary Statistics of the Variables Used in the Model

Variable	Mean	Standard Deviation
Price		
Of chocolate milk ($/ounce)	0.049	0.024
Of energy drinks ($/ounce)	0.129	0.056
Of sports drinks ($/ounce)	0.052	0.149
Household size	2.360	1.290
Household income ($thousands)	58.32	31.93
Age of household head		
25–29	0.018	0.042
30–34	0.038	0.191
35–44	0.147	0.354
45–54	0.276	0.447
55–64	0.297	0.457
65 or older	0.222	0.415
Employment status		
Part-time	0.178	0.383
Full-time	0.390	0.488
Education		
High school	0.237	0.425
Undergraduate	0.618	0.485
Post-college	0.120	0.325
Race		
Black	0.094	0.292
Asian	0.029	0.166
Other	0.040	0.196
Hispanic	0.051	0.220
Region		
New England	0.045	0.208
Middle Atlantic	0.131	0.337
East North central	0.181	0.385
West North central	0.086	0.281
South Atlantic	0.198	0.398
East South central	0.060	0.237
West South central	0.102	0.303
Mountain	0.073	0.260
Presence of children		
Children less than 6 years	0.028	0.164
Children 6–12 years	0.052	0.223
Children 13–17 years	0.067	0.249
Children under 6 and 6–12 years	0.024	0.154
Children under 6 and 13–17 years	0.004	0.064
Children 6–12 and 13–17 years	0.033	0.179
Children under 6, 6–12, and 13–17	0.005	0.070
Head of household		
Female head only	0.250	0.433
Male head only	0.096	0.295

Source: Nielsen Homescan data 2011, calculations by authors.

Notes: Base categories for categorical explanatory variables: age of household less than 25, employment status: neither full-time nor part-time, education less than high school, race white, region pacific, no children, and female and male household heads.

The unconditional marginal effect for semi-log price variable is given by equation (5) below:[5]

(5) $$\frac{\partial E(Y)}{\partial p} = \frac{\beta}{p^u} F(z),$$

where is the average price in the censored sample and is the average price of the full sample. Conditional and unconditional own-price, cross-price, and income elasticities are represented as follows:

Conditional elasticities:

(6) Own-Price: $$\varepsilon_{ii}^{C} = \frac{\beta}{p_i^C}\left(1 - z\frac{f(z)}{F(z)} - \frac{f(z)^2}{F(z)^2}\right)\frac{p_i^C}{Q_i^C};$$

(7) Cross-Price: $$\varepsilon_{ij}^{C} = \frac{\beta}{p_j^C}\left(1 - z\frac{f(z)}{F(z)} - \frac{f(z)^2}{F(z)^2}\right)\frac{p_j^C}{Q_i^C};$$

(8) Income: $$\varepsilon_{I}^{C} = \frac{\beta}{I_i^C}\left(1 - z\frac{f(z)}{F(z)} - \frac{f(z)^2}{F(z)^2}\right)\frac{I_i^C}{Q_i^C};$$

where ε_{ii}^{C} is the conditional own-price elasticity for the *i*th beverage; ε_{ij}^{C} is the conditional cross-price elasticity for beverage *i* with respect to a change in price of beverage *j*; and ε_{I}^{C} is the conditional income elasticity for the *i*th beverage.

If the price variable enters demand model as linear price (as in price of chocolate milk in the energy drinks demand model), the conditional cross-price elasticity is

(9) $$\varepsilon_{ij}^{C} = \beta\left(1 - z\frac{f(z)}{F(z)} - \frac{f(z)^2}{F(z)^2}\right)\frac{p_j^C}{Q_i^C}.$$

The unconditional own-price, cross-price, and income elasticities are denoted by

(10) Own-Price: $$\varepsilon_{ii}^{u} = \frac{\beta}{p_i^u} F(z)\frac{p_i^u}{Q_i^u};$$

(11) Cross-Price: $$\varepsilon_{ij}^{u} = \frac{\beta}{p_j^u} F(z)\frac{p_j^u}{Q_i^u};$$

(12) Income: $$\varepsilon_{I}^{u} = \frac{\beta}{I_i^u} F(z)\frac{I_i^u}{Q_i^u};$$

[5] Note the presence of the p^u term in the denominator. This is just the same equation as noted in (A4) of the Technical Appendix, adjusted for the semi-log model.

where ε_{ii}^{u} is the unconditional own-price elasticity for the *i*th beverage; ε_{ij}^{u} is the unconditional cross-price of beverage *i* with respect to change in price of beverage *j*; and ε_{I}^{u} is the unconditional income elasticity for the *i*th beverage.

If the price variable enters the demand model as linear price (as in the price of chocolate milk in the energy drinks demand model), the conditional cross-price elasticity is given by

$$(13) \qquad \varepsilon_{ij}^{u} = \beta F(z)\frac{p_j^u}{Q_i^u},$$

where I^c is conditional mean income and I^u is unconditional mean income, Q_i^C is the conditional mean quantity, and Q_i^u is the unconditional mean of quantity. From equation (6), we obtain the changes in the probability of being above the limit (probability of purchase) for each beverage category in response to a change in any explanatory variable.

$$(14) \qquad \frac{\partial F(z)}{\partial X} = \frac{1}{E(Y|Y>0)}\left(\frac{\partial E(Y)}{\partial X} - F(z)\frac{\partial E(Y|Y>0)}{\partial X}\right).$$

The significance level considered in this study is at 0.05 (i.e., any *p*-value less than or equal to 0.05 results in statistical significance).

Data

The data used in this study were based on the 2011 Nielsen Homescan panel (the most recent data available at the time of this research),[6] which provides detailed beverage-purchase information from 62,029 U.S. households.[7]

Table 1 presents summary statistics for all variables included in the model. Quantity purchased is standardized as liquid ounces per household per year, and expenditures are expressed in dollars per household per year.[8] A *unit value*, which is taken as a proxy for price, is generated by dividing total expenditure by quantity for each beverage. This unit value variable is considered to be the

[6] Disclaimer: Researcher(s) own analyses calculated (or derived) based in part on data from The Nielsen Company (US), LLC and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researchers and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

[7] Nielsen Homescan data are a nationwide panel of households that scan their food purchases for at-home use from all retail outlets (grocery stores, department stores, convenience stores, drug stores, and club stores). The data include detailed product characteristics, quantities, and expenditures for each food item purchased by each household as well as socioeconomic and demographic characteristics of each household.

[8] The quantity of each beverage (chocolate milk, sports drinks, and energy drinks) purchased by each of the household in ounces per household per year is created by aggregating all transactions at the universal product code (UPC) level of many products of chocolate milk, sports drinks and energy drinks purchased by each household during calendar year 2011 (the latest year of data available at the time of this study). The associated expenditures with regards to purchase of these beverages are also aggregated up from each transaction to create total expenditure in dollars per household per year.

price paid for each beverage category and is expressed as dollars per ounce. The mean prices for chocolate milk, energy drinks, and sports drinks are \$0.049/oz, \$0.129/oz, and \$0.052/oz, respectively. Note that chocolate milk is the least expensive of the three beverages.

Household size is separated into nine groups based on the number of household members. If the number of household members is more than nine, the value of household size is assigned to be nine. The mean household size is 2.36 members.

Household income is reported as a categorical variable with several income classes. In this study, household income is converted to a continuous variable by taking the mean value of the respective income class reported for each household. The mean household income is \$58,320.

The reference category for the age of the household head is considered to be less than 25 years. Households aged 25–29 years (1.8% of households in the sample) and households aged 30–34 years (3.8% of households in the sample) are small proportions of the sample. Household heads aged 35–44 years constitute 14.7% of the sample; 27.6% of the household heads fall in to the 45–54 years category. Household heads who are 55–64 years make up 29.7% of the sample. Household heads over 65 years of age account for more than 20% of the sample.

Employment status is an indicator variable representing whether the household head is employed full-time (39%), part-time (17.8%), or neither. We treat household heads with neither full-time nor part-time as the reference category in this study.

We also consider the education status of households. The reference category is a household with a household head with less than a high school education. 23.7% of the household heads have a high school degree, 12% of household heads earned a post-college education, and more than 60% of household heads had undergraduate degrees.

Race is grouped as white, black, Asian, Hispanic, and other. The white category is used as the reference category for this analysis. 9.4% of the sample is black. Asian household heads account for 2.9% of the sample. 4% of the household heads belong to the “other” race category. 5.1% of household heads are Hispanic.

Regions are New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific (Table 2 summarizes the classification of regions by state). The Pacific region is treated as the reference category for this analysis. 4.5% of the household heads are from New England, 13.1% from the Middle Atlantic, 18.1% from the East North Central, 8.6% from the West North Central, 19.8% from the South Atlantic, 6% from the East South, 10.2% from the West South, and 7.3% from the Mountain region.

The variable with respect to the presence of the children in the households is classified into eight categories based on the age of children. The reference category considered in this study is households with no children. The other seven categories are households with children under the age of 6 (2.8%), children 6–12 years (5.2%), children 13–17 years (6.7%), children under 6 and

Table 2. Census Bureau Regions and States

New England	Middle Atlantic	East North Central
Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont	New Jersey, New York, Pennsylvania	Indiana, Illinois, Michigan, Ohio, Wisconsin
West North Central	**South Atlantic**	**East South Central**
Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota	Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia	Alabama, Kentucky, Mississippi, Tennessee
West South Central	**Mountain**	**Pacific**
Arkansas, Louisiana, Oklahoma, Texas	Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming	Alaska, California, Hawaii, Oregon, Washington

Source: U.S. Department of Commerce Economics and Statistics Administration, U.S. Census Bureau (https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf)

6–12 years (2.4%), children under 6 and 13–17 years (0.4%), children 6–12 and 13–17 years (3.3%), and children under 6, 6–12, and 13–17 years (0.5%).

The reference category for households' gender variable is defined as a household with both female and male household heads. If the household is headed by both female and male, we considered the female's demographic characteristics. Households headed by females made up 25% of the sample. Male-only household heads composed 9.6% of the dataset.

Results and Discussion

Table 3 shows the summary statistics for price, quantity, and market penetration (number of households purchasing the beverage under consideration out of total of households sampled) for the three respective beverage categories.

Table 3. Summary Statistics for Price, Quantity and Market Penetration in 2011 in the United States

	Chocolate Milk	Energy Drinks	Sports Drinks
Market penetration (%)	26	7	36
Average price ($/ounce)	0.05	0.13	0.05
Average conditional quantity (ounces)	423	441	757
Average unconditional quantity (ounces)	110	32	271

Notes: The market penetration numbers are the number of households that purchased these beverages out of total number of households in the sample.

Table 4 presents the Tobit regression results. The price of energy drinks, the price of chocolate milk, and the price of sports drinks are statistically significant factors affecting the demand for all

Table 4. Tobit Regression Results for Chocolate Milk, Energy Drinks, and Sports Drinks

	Sports Drinks			Energy Drinks			Chocolate Milk		
Variable	***p*-Value**	**Std. Err.**	**Estimate**	***p*-Value**	**Std. Err.**	**Estimate**	***p*-Value**	**Std. Err.**	**Estimate**
Intercept	<0.0001	251.97	−7,004.03	<0.0001	288.98	−5,204.96	<0.0001	203.73	−4,813.94
Price									
Of chocolate milk	0.0118	32.92	−78.12	<0.0001	54.50	2,460.87	<0.0001	20.75	−1,008.42
Of energy drink	<0.0001	61.04	−319.24	0.0064	902.13	−1,506.67	0.0030	49.50	−146.67
Of sports drink	<0.0001	17.36	−1,639.65	<0.0001	30.47	−179.82	<0.0001	16.11	−161.25
Household size	<0.0001	10.14	163.54	<0.0001	14.79	145.63	<0.0001	8.07	75.45
Household income	0.0070	14.11	38.04	0.6707	21.14	8.99	0.0926	10.99	−18.49
Age of household head									
25–29	0.6371	177.83	−83.88	0.537	221.90	−136.99	0.8037	149.88	−37.25
30–34	0.4827	173.66	−121.92	0.3412	216.38	−205.93	0.7670	146.06	43.27
35–44	0.3384	170.89	−163.61	0.0202	212.59	−493.84	0.5875	143.86	78.05
45–54	0.1620	170.45	−238.37	0.0037	211.88	−614.89	0.4818	143.49	100.96
55–64	0.0028	170.49	−509.21	<0.0001	212.32	−962.17	0.9101	143.47	16.20
65 or older	<0.0001	171.07	−720.42	<0.0001	214.45	−1,369.22	0.1933	143.85	−187.13
Employment status									
Part-time	0.5045	22.68	−15.14	0.1739	35.59	−48.40	0.5185	17.65	−11.39
Full-time	0.0605	20.04	37.61	0.0174	30.72	73.05	0.8770	15.68	−2.43
Education									
Education high school	0.2024	53.38	68.05	0.0177	77.11	−182.90	0.5002	40.73	−27.46
Education undergraduate	0.9075	52.47	−6.10	<0.0001	75.58	−328.26	0.0056	40.11	−111.11
Education post-college	0.0114	57.49	−145.52	<0.0001	85.35	−576.51	<0.0001	44.36	−237.18
Race									
Black	0.5169	27.49	−17.81	0.4847	42.83	−29.92	<0.0001	23.84	−336.19
Asian	0.0007	47.66	−161.99	0.0004	73.46	−261.00	<0.0001	40.30	−243.60
Other	0.0493	42.07	82.72	0.0314	58.73	126.41	0.0246	34.58	−77.73
Hispanic	0.5968	37.19	19.67	0.0449	52.44	105.14	0.0156	30.84	−74.54

Continued on next page…

Table 4 (continued).

	Sports Drinks			Energy Drinks			Chocolate Milk		
Variable	***p*-Value**	**Std. Err.**	**Estimate**	***p*-Value**	**Std. Err.**	**Estimate**	***p*-Value**	**Std. Err.**	**Estimate**
Region									
New England	0.0878	45.03	76.86	<0.0001	71.06	−451.73**	0.2667	36.89	−40.97
Middle Atlantic	0.2765	33.27	36.20	<0.0001	49.02	−374.22**	<0.0001	26.78	169.63**
East North central	0.8758	32.59	5.09	<0.0001	45.99	−401.72**	<0.0001	24.81	116.35**
West North central	0.5158	37.49	−24.36	<0.0001	54.27	−349.84**	<0.0001	28.19	161.00**
South Atlantic	<0.0001	29.72	165.20**	<0.0001	42.80	−337.75**	0.0091	24.48	63.86**
East South central	<0.0001	39.71	296.76**	<0.0001	59.74	−298.10**	<0.0001	31.26	201.58**
West South central	<0.0001	33.86	252.84**	0.0071	47.62	−128.10**	<0.0001	27.67	120.92**
Mountain	0.0019	37.41	116.00**	0.1333	52.27	−78.48	0.0317	30.59	−65.70**
Presence of children									
Children less than 6 years	0.0012	50.72	−164.76**	0.0069	73.50	−198.69**	0.1028	40.23	65.63
Children 6–12 years	0.0107	37.48	95.67**	0.0659	56.54	−104.01	<0.0001	29.99	155.27**
Children 13–17 years	<0.0001	32.90	480.68**	<0.0001	46.87	265.72**	<0.0001	26.66	173.56**
Children under 6 and 6–12 years	<0.0001	56.39	−320.62**	<0.0001	85.45	−460.37**	0.0203	44.47	103.17**
Children under 6 and 13–17 years	0.8474	110.97	21.36	0.2788	159.94	−173.20	0.0893	88.59	150.50
Children 6–12 and 13–17 years	<0.0001	47.92	293.44**	0.0325	71.41	−152.66**	0.0038	38.87	112.65**
Children under 6, 6–12, 13–17	0.8988	106.02	−13.48	0.0349	152.28	−321.23**	0.2196	84.23	103.38
Head of household									
Female head only	<0.0001	23.89	−233.51**	0.1780	36.70	49.42	0.0002	18.47	−69.18**
Male head only	0.0844	31.68	−54.66	<0.0001	46.48	291.32**	<0.0001	25.34	−101.56**
Sigma	<0.0001	7.70	1,541.74**	<0.0001	17.98	1,531.57**	<0.0001	6.79	1,141.31**

Notes: Double asterisks (**) indicate statistical significance with a *p*-value of 0.05.

Table 5. χ^2 Tests for Joint Significance of Demographic Variables Considered

Chocolate Milk		Energy Drinks		Sports Drinks	
***p*-Value Associated with χ^2**	**Label**	***p*-Value Associated with χ^2**	**Label**	***p*-Value Associated with χ^2**	**Label**
<0.0001	agehh2529 = 0	<0.0001	agehh2529 = 0	<0.0001	agehh2529 = 0
	agehh3034 = 0		agehh3034 = 0		agehh3034 = 0
	agehh3544 = 0		agehh3544 = 0		agehh3544 = 0
	agehh4554 = 0		agehh4554 = 0		agehh4554 = 0
	agehh5564 = 0		agehh5564 = 0		agehh5564 = 0
	agehhgt64 = 0		agehhgt64 = 0		agehhgt64 = 0
0.8042	emphhpt = 0	0.0015	emphhpt = 0	0.0428	emphhpt = 0
	emphhft = 0		emphhft = 0		emphhft = 0
<0.0001	eduhhhs = 0	<0.0001	eduhhhs = 0	<0.0001	eduhhhs = 0
	eduhhu = 0		eduhhu = 0		eduhhu = 0
	eduhhpc = 0		eduhhpc = 0		eduhhpc = 0
<0.0001	black = 0	0.0003	black = 0	0.0009	black = 0
	oriental = 0		oriental = 0		oriental = 0
	other = 0		other = 0		other = 0
<0.0001	newengland = 0	<0.0001	newengland = 0	<0.0001	newengland = 0
	middleatlantic = 0		middleatlantic = 0		middleatlantic = 0
	eastnorthcentral = 0		eastnorthcentral = 0		eastnorthcentral = 0
	westnorthcentral = 0		westnorthcentral = 0		westnorthcentral = 0
	southatlantic = 0		southatlantic = 0		southatlantic = 0
	eastsouthcentral = 0		eastsouthcentral = 0		eastsouthcentral = 0
	westsouthcentral = 0		westsouthcentral = 0		westsouthcentral = 0
	mountain = 0		mountain = 0		mountain = 0
<0.0001	aclt6_only = 0	<0.0001	aclt6_only = 0	<0.0001	aclt6_only = 0
	ac6_12only = 0		ac6_12only = 0		ac6_12only = 0
	ac13_17only = 0		ac13_17only = 0		ac13_17only = 0
	aclt6_6_12only = 0		aclt6_6_12only = 0		aclt6_6_12only = 0
	aclt6_13_17only = 0		aclt6_13_17only = 0		aclt6_13_17only = 0
	ac6_12and13_17only = 0		ac6_12and13_17only = 0		ac6_12and13_17only = 0
	aclt6_6_12and13_17 = 0		aclt6_6_12and13_17 = 0		aclt6_6_12and13_17 = 0
<0.0001	fhonly = 0	<0.0001	fhonly = 0	<0.0001	fhonly = 0
	mhonly = 0		mhonly = 0		mhonly = 0

Notes: The χ^2 value is calculated using likelihood ratio produced for each demographic variable (presence and absence of the joint restriction).

three beverage choices. Significant demographic variables affecting demand for chocolate milk are household size, age, education, race, region, presence of children, and gender of the household head. Household income did not have a significant effect on the demand for chocolate milk. Significant demographic variables affecting demand for energy drinks are household size, age, employment status, education, race, region, presence of children, and gender of the household head. Household income did not have a significant effect on the demand for energy drinks. Significant demographic determinants affecting demand for sports drinks are household income, household size, age, education, race, region, the presence of children, and gender of the household head.

Table 5 reports the results of χ^2 test of the joint effects of categorical variables. Almost all categorical variables are significant determinants of demand for all three beverages. The employment status categorical variable was not significant in the chocolate milk demand equation.

Table 6 reports the conditional marginal effects and Table 7 reports the unconditional marginal effects. Note that conditional marginal effects are generally higher in absolute value compared to unconditional marginal effects. Table 8 reports changes in the probability of purchase associated with each explanatory variable for each beverage. Note that all of these numbers are calculated at the sample median. For brevity, we only report the conditional marginal effects and associated probabilities in this article.

There is a 2.2%, 1.7% and 4% probability of increasing the purchase of chocolate milk, energy drinks, and sports drinks with every additional member added to a given household, which is about 19, 25, and 57 additional ounces of the respective beverages per household per year.

Compared with a household head less than 25 years of age, households with a head older than 65 years had 5%, 16% and 18% less probability of purchasing chocolate milk, energy drinks, and sports drinks, respectively, which is 47, 232 and 249 fewer ounces of these respective beverages per household per year. Compared to the base age category, households with a head between 35 and 54 years of age purchased about 42 ounces per household per year more chocolate milk and about 267 and 138 ounces per household per year less energy and sports drinks. Households with a head of less than 25 years of age purchased more energy and sports drinks compared to households in other age categories.

Households with a head employed full-time showed a higher probability of purchasing energy and sports drinks, about 12 and 13 more ounces per household per year. Households with a head who has post-college education had about a 3%–7% less probability of purchasing sports drinks, energy drinks, and chocolate milk, which is about 50, 97, and 60 fewer ounces, respectively, per household per year compared to the base category of households with a head with less than a high school education.

Households with a head classified as black, Asian, or other had a 10%, 7%, and 2% less probability of purchasing of chocolate milk compared to those household with heads classified as white, equivalent to about 84, 61 and 20 fewer ounces of chocolate milk per household per year.

Table 6. Median Conditional Marginal Effect

Variable	Chocolate Milk	Energy Drinks	Sports Drinks
Household size	19.04	24.64	56.48
Age of household head			
25–29	−9.40	−23.17	−28.95
30–34	10.90	−34.83	−42.07
35–44	19.69	−83.53	−56.46
45–54	25.47	−104.01	−82.26
55–64	4.08	−162.76	−175.72
65 or older	−47.22	−231.61	−248.61
Employment status			
Part-time	−2.87	−8.19	−5.22
Full-time	−0.61	12.36	12.98
Education			
High school	−6.93	−30.94	23.48
Undergraduate	−28.04	−55.53	−2.10
Post-college	−59.85	−97.52	−50.22
Race			
Black	−84.43	−5.06	−6.15
Asian	−61.47	−44.15	−55.90
Other	−19.61	21.38	28.55
Hispanic	−18.81	17.78	6.79
Region			
New England	−10.34	−76.41	26.52
Middle Atlantic	42.81	−63.30	12.49
East North central	29.36	−67.95	1.76
West North central	40.63	−59.18	−8.41
South Atlantic	16.16	−57.13	57.01
East South central	50.87	−50.42	102.41
West South central	0.23	−21.67	87.25
Mountain	−16.58	−13.27	40.03
Presence of children			
Children less than 6 years	16.56	−33.61	−56.85
Children 6–12 years	39.18	−17.59	33.01
Children 13–17 years	43.79	44.95	165.88
Children under 6 and 6–12 years	26.04	−77.88	−110.64
Children under 6 and 13–17 years	37.98	−29.30	7.37
Children 6–12 and 13–17 years	28.43	−25.82	101.26
Children under 6,6–12,and 13–17	26.08	−54.34	−4.65
Head of household			
Female head only	−17.46	8.36	−80.58
Male head only	−25.63	49.28	−18.86

Table 7. Median Unconditional Marginal Effects

Variable	Chocolate Milk	Energy Drinks	Sports Drinks
Household size	14.92	7.71	40.50
Age of household head			
25–29	−7.37	−7.25	−20.77
30–34	8.56	−10.90	−30.19
35–44	15.44	−26.14	−40.52
45–54	19.97	−32.55	−59.03
55–64	3.20	−50.94	−126.10
65 or older	−37.03	−72.49	−178.41
Employment status			
Part-time	−2.25	−2.56	−3.75
Full-time	−0.48	3.87	9.31
Education			
High school	−5.43	−9.68	16.85
Undergraduate	−21.98	−17.38	−1.51
Post-college	−46.93	−30.52	−36.04
Race			
Black	−66.53	−1.58	−4.41
Asian	−48.21	−13.82	−40.12
Other	−15.38	6.69	20.49
Hispanic	−14.75	5.57	4.87
Region			
New England	−8.10	−23.91	19.03
Middle Atlantic	33.57	−19.81	8.97
East North central	23.02	−21.27	1.26
West North central	31.86	−18.52	−6.03
South Atlantic	12.63	−17.88	40.91
East South central	39.89	−15.78	73.49
West South central	23.93	−6.78	62.62
Mountain	−13.00	−4.15	28.73
Presence of children			
Children less than 6 years	12.99	−10.52	−40.80
Children 6–12 years	30.72	−5.51	23.69
Children 13–17 years	34.35	14.07	119.04
Children under 6 and 6–12 years	20.41	−24.37	−79.40
Children under 6 and 13–17 hears	29.78	−9.17	5.29
Children 6–12 and 13–17 years	22.29	−8.08	72.67
Children under 6, 6–12, and 13–17	20.46	−17.01	−3.34
Head of household			
Female head only	−13.69	2.61	−57.83
Male head only	−20.10	15.422	−14.47

Table 8. Median Change in Probability of Purchase Associated with each Explanatory Variable

Variable	Chocolate Milk	Energy Drinks	Sports Drinks
Household size	0.022	0.017	0.040
Age of household head			
25–29	−0.010	−0.016	−0.021
30–34	0.013	−0.024	−0.030
35–44	0.023	−0.057	−0.040
45–54	0.029	−0.071	−0.059
55–64	0.004	−0.110	−0.127
65 or older	−0.054	−0.157	−0.179
Employment status			
Part-time	−0.003	−0.006	−0.004
Full-time	−0.001	0.008	0.009
Education			
High school	−0.008	−0.021	0.017
Undergraduate	−0.032	−0.038	−0.002
Post-college	−0.069	−0.066	−0.037
Race			
Black	−0.098	−0.003	−0.004
Asian	−0.071	−0.030	−0.041
Other	−0.023	0.015	0.020
Hispanic	−0.022	0.012	0.005
Region			
New England	−0.012	−0.052	0.019
Middle Atlantic	0.049	−0.043	0.009
East North central	0.034	−0.046	0.002
West North central	0.047	−0.040	−0.005
South Atlantic	0.019	−0.039	0.042
East South central	0.059	−0.034	0.075
West South central	0.047	−0.015	0.063
Mountain	−0.019	−0.009	0.030
Presence of children			
Children less than 6 years	0.019	−0.023	−0.041
Children 6–12 years	0.045	−0.012	0.025
Children 13–17 years	0.050	0.030	0.121
Children under 6 and 6–12 years	0.030	−0.053	−0.078
Children under 6 and 13–17 hears	0.044	−0.020	0.006
Children 6–12 and 13–17 years	0.033	−0.017	0.074
Children under 6, 6–12, and 13–17	0.030	−0.037	−0.005
Head of household			
Female head only	−0.020	0.006	−0.058
Male head only	−0.029	0.033	−0.014

Considering energy and sports drinks, households with heads classified as other purchased about 21 and 29 more ounces per household per year compared to the base category, White. Household head with Hispanic origin purchased about 19 fewer ounces chocolate milk per household per year and about 18 and 7 more ounces of energy and sports drinks per household per year.

Compared to the Pacific region, households in the East South Central purchased the highest amounts of chocolate milk and sports drinks, about 51 and 102 ounces per household per year. With about 5% less probability, households in New England purchased the least amount of energy drinks, about 76 fewer ounces per household per year than the average.

Compared to households with no children, households with children 13–17 years of age purchased the highest amount of chocolate milk and sports drinks, about 44 (5% more probability) and 166 (12% more probability) more ounces per household per year, respectively. Households with children under 13 years of age purchased the lowest amount of sports drinks, about 111 fewer ounces than those with no children.

Households with male household heads purchased chocolate milk with 3% less probability (about 26 fewer ounces per household per year) and energy drinks with about 3% more probability (about 49 more ounces per household per year) compared to those with both a male and a female head.

Table 9 reports the median values of the respective conditional and unconditional elasticities for all beverages. The unconditional elasticity estimates are generally more elastic than the conditional elasticities, since the unconditional market includes consumers of these beverages who are potential buyers who might have a wide spectrum of products available to them compard to those who are more committed to purchase chocolate milk, energy drinks, and sports drinks (conditional sample of buyers). For brevity, we discuss only the conditional own- and cross-price elasticities. The conditional own-price elasticity of demand for chocolate milk is −0.62, which means that consumers are relatively insensitive to price changes. The conditional cross-price elasticities of

Table 9. Median Unconditional and Conditional Own-Price, Cross-Price, and Income Elasticities of Demand

	Chocolate Milk	**Energy Drinks**	**Sports Drinks**
Unconditional elasticities			
Chocolate milk	−2.05**	−0.30**	−0.33**
Energy drinks	0.25**	−3.08**	−0.37**
Sports drinks	−0.09**	−0.36**	−1.78**
Income	−0.04	0.02	0.03
Conditional elasticities			
Chocolate milk	−0.62**	−0.09**	−0.10**
Energy drinks	0.05**	−0.60**	−0.07**
Sports drinks	−0.04**	−0.15**	−0.75**
Income	−0.01	0.00[a]	0.02

Notes: Double asterisks (**) indicate statistical significance with a *p*-value of 0.05.
[a]The income elasticity of energy drinks is 0.004, which is rounded to 0.00 for this table.

demand of chocolate milk with energy drinks and sports drinks are −0.09 and −0.10, which implies that energy drinks and sports drinks are complementary beverages for chocolate milk in consumption. The conditional income elasticity of demand for chocolate milk is −0.01, but this estimate was not statistically significant.

The conditional own-price elasticity of demand for energy drinks is −0.60. The cross-price elasticities of demand for energy drinks with chocolate milk and sports drinks are 0.05 and −0.07, respectively. Therefore, chocolate milk is a substitute for energy drinks, but sports drinks are complementary to energy drinks. The income elasticity for energy drinks is 0.004, which was not statistically significant.

The conditional own-price elasticity of demand for sports drinks is −0.75. The cross-price elasticities of demand for sports drinks with chocolate milk and energy drinks are −0.04 and −0.15, respectively. Therefore, chocolate milk and energy drinks are complements to sports drinks. The income elasticity of demand for sports drinks is 0.02, which was not statistically significant.

Since chocolate milk, energy drinks, and sports drinks have inelastic own-price elasticities of demand, the prices of these products can be increased at the retail level (to purchasing households) to increase the retail level revenue. However, on the other hand, since the energy drinks and sports drinks are complements to chocolate milk, price increase in sports drinks and energy drinks will decrease consumption of chocolate milk. Nonetheless, this effect will be small given small (in terms of percentage changes) cross-price elasticities associated with chocolate milk. A similar argument applies for sports drinks, since both chocolate milk and energy drinks are complements for sports drinks. Since chocolate milk is a substitute for energy drinks, a price increase in chocolate milk will increase purchases of energy drinks. However, the effect will be small (in terms of percentage change) since the cross-price elasticities are small.

Having a mix of cross-price elasticities (some are complements in some equations and substitutes in other demand equations) is common in demand analysis (even with the imposed symmetry restriction for underlying parameters in complete demand models, such as almost ideal demand system). In this study, although the cross-price elasticities are small in magnitude, they are still significant. A small cross-price effect does not allude to the magnitude of the complementary and/or substitutability effect but only the percentage change. To see the change in magnitude (change in volume of one beverage to change in volume of another beverage), one has to calculate diversion ratios (Capps and Dharmasena, 2019), which is not the focus of this study.

Another school of thought in the profession shows that small cross-price elasticities support the contention that firms in an imperfectly competitive environment do not worry much about price changes among competing products since their marketing strategy is mostly about nonprice competition such as product differentiation via branding and packaging to establish a niche market. In our study, energy drinks and sports drinks are complements to chocolate milk in consumption, with very small cross price effects (elasticities). According to aforementioned line of thinking, chocolate milk manufacturers might not be interested in how energy and sports drink manufacturers price their products but rather pay attention to the price changes of their own product (own-price elasticity of demand of chocolate milk) in marketing the product. A similar argument can be applied to energy drink manufacturers not paying much attention to price changes among chocolate milk and sports drinks and sport drinks manufactures not paying much attention to chocolate milk and energy drinks in pricing their respective products. However, this argument cannot be fully supported in this research since we are not conducting the study at the brand level of each product. Nonetheless, this is an important area to investigate as we see manufactures of food and beverage products gravitate toward non-price competition via differentiating their products through branding and packaging.

Conclusions

Using household-level purchase data for chocolate milk, energy drinks, and sports drinks and selected demographic characteristics from the 2011 Nielsen Homescan data, we estimated three beverage demand models to show that chocolate milk is a substitute for energy drinks. Sports drinks are complementary to energy drinks. Chocolate milk and energy drinks are complements to sports drinks.

Household size, age, education, race, region, presence of children, and gender of the household head are significant determinants of demand for chocolate milk. Household size, age, employment status, education, race, region, presence of children, and gender of household head significantly affect demand for energy drinks. Significant demographic variables affecting the demand of sports drinks are household size, age, education, race, region, presence of children, and gender of household head.

Limitations and Implications

It is important to note that the data used in this work only capture purchases of chocolate milk, energy drinks, and sports drinks for consumption at home. As a result, this study does not capture household behavior with respect to away-from-home consumption of theses beverages. The total number of households in the 2011 Nielsen dataset was about 62,000. When constructing the data sample for those households that purchased chocolate milk, energy drinks, and sports drinks, we considered households that purchased at least one of these beverages per month in all 12 months. In that way, the market penetration of chocolate milk consumer stood at 26%. That is to say, 26% of households purchased chocolate milk (they might also have purchased isotonics). In the same light, the market penetration for energy drinks and sports drinks was 7% and 36%, respectively. These households might have purchased other beverages as well. There might be households that did not purchase any of these beverages considered in this study, which were obviously excluded from the sample (and this study). In other words, our sample of households is conditioned on purchasing at least one of the beverages considered in the study. However, if we take one of the beverages (say chocolate milk), the conditional sample of households is at 26%, while the unconditional sample of households for chocolate milk is at 74% (100% − 26%). A similar argument applies for energy drinks and sports drinks.

Based on the extant literature, it is well documented that chocolate milk has been repositioned in the U.S. market for physically active consumers as an alternative post-workout recovery drink. However, since the physical activity levels of household members is not available in the data sample we used in this study, we could not estimate demand for chocolate milk, energy drinks, and sports drinks delineated by physical activity level of households. Inclusion of such variables in the demand model would be useful future research. It should also be noted that some sports drinks are carbonated, although in this study our interest was to aggregate all sports drinks into one category. Therefore, we did not include two categories of sports drinks (carbonated and noncarbonated) in this study. This disaggregation is identified as fruitful future research. Additionally, other beverages in the market may affect demand for the three beverages identified in this study. They could be included in the mix of beverages in future studies.

Our finding that chocolate milk is a substitute for energy drinks is promising for various constituents in the chocolate milk supply chain, such as producers and advertisers. Also, since this study finds that chocolate milk acts as a complement to sports drinks, it can be stated that households that buy sports drinks also tend to buy chocolate milk. Given the complementarity of the beverage products in demand (as shown by cross-price elasticities, except for chocolate milk in the energy drinks equation), price competition does not yield any gains for the seller in terms of marketing the product as well as to gain market share. However, this study is important in terms of appropriately positioning the beverage(s) in the market (niche marketing to specific groups) uncovered by demographic factors affecting demand for chocolate milk, energy drinks, and sports drinks. The results from this study support the milk market's repositioning of chocolate milk in the isotonics complex to gain more market share while increasing consumption among those who already consume chocolate milk. Further, the somewhat elastic unconditional own-price elasticities show that consumers in the unconditional sample (the larger sample) tend to respond to price changes more than the consumers in the conditional sample where respective own-price elasticities are virtually inelastic. This also attests to the fact that consumers in the conditional sample are more loyal to their product through habit formation and less prone to switching consumption patterns.

Acknowledgments

Yang Hu thanks Dr. Senarath Dharmasena for his guidance throughout this research project, conducted as part of her master's thesis research at Texas A&M University. In addition, Hu thanks Drs. Capps and Janakiraman for their input. We thank the selected presentation paper audience of the Southern Agricultural Economics Association annual meeting held in San Antonio, TX, February 2016, for their comments on an initial draft of this paper. Also, we thank two anonymous reviewers and the JFDR editor, Dr. Andrew Muhammad, for their comments, which substantially improved the quality of this paper. Finally, yet very importantly, we would like to thank JFDR Technical Editor Amy Bekkerman for excellent technical edits provided on this paper.

References

Alviola, P.A., and O. Capps, Jr. 2010. "Household Demand Analysis of Organic and Conventional Fluid Milk in the United States Based on the 2004 Nielsen Homescan Panel." *Agribusiness* 26(3): 369–388.

Amemiya, T. 1973. "Regression Analysis When the Dependent Variable Is Truncated Normal." *Econometrica* 41(6): 997–1016

Berry, D. 2014, March 27. "Feed Them Milk: A New and Needed Approach to Nourishing Americans." *Berry on Dairy.* Available online: http://berryondairy.blogspot.com/2014/03/feed-them-milk-new-and-needed-approach.html [Accessed January 28, 2016].

Beverage Digest Company. 2015. *Beverage Digest Fact Book 2015: Statistical Yearbook of Non-Alcoholic Beverages*, 20th ed. Bedford Hills, NY: Beverage Digest.

Beverage Marketing Corporation. 2018. Available online: http://www.beveragemarketing.com [Accessed September 24, 2018].

Capps, O., Jr., and S. Dharmasena. 2019. "Enhancing the Teaching of Product Substitutes/Complements: A Pedagogical Note on Diversion Ratios." *Applied Economics Teaching Resources* 1(1): 32–45.

Capps, O., Jr., and R.D. Hanselman. 2012. "A Pilot Study of the Market for Energy Drinks." *Journal of Food Distribution Research* 43(3): 15–29.

Capps, O., Jr., R. Kirby, and G. Williams. 1994. "A Comparison of Demand for Meat Products in the Pacific Rim Region." *Journal of Agricultural and Applied Economics* 19(1):210–224.

Collins, K. 2013, February 18. "Healthtalk: What's the Difference between Sports Drinks and Energy Drinks? My Teenager Drinks a Lot of Both." *AICR Health Talk, American Society for Cancer Research*. Available online: https://www.aicr.org/press/health-features/health-talk/2013/feb2013/sports-energy-drinks-teens.html.

Copeland, A., and S. Dharmasena. 2016. "Impact of Increasing Demand for Dairy Alternative Beverages on Dairy Farmer Welfare in the United States." Paper presented at the annual meeting of the Southern Agricultural Economics Association, San Antonio, Texas, February 6–9.

Dharmasena, S., and O. Capps Jr. 2009. "Demand Interrelationships of At-Home Nonalcoholic Beverage Consumption in the United States." Paper presented at the annual meeting of the Agricultural and Applied Economics Association, Milwaukee, Wisconsin, July 26–28.

Dharmasena, S., and O. Capps, Jr. 2011. "Is Chocolate Milk the New-Age Energy/Sports Drink in the United States?" Paper presented at the annual meeting of the Southern Agricultural Economics Association, Corpus Christi, Texas, February 5–8.

Dharmasena, S., and O. Capps, Jr. 2012. "Intended and Unintended Consequences of a Proposed National Tax on Sugar-Sweetened Beverages to Combat the U.S. Obesity Problem." *Health Economics* 21(6): 669–694.

Dharmasena, S., and O. Capps, Jr. 2014a. "Unraveling Demand for Dairy-Alternative Beverages in the United States: The Case of Soymilk" *Agricultural and Resource Economics Review* 43(1): 140–157.

Dharmasena, S., and O. Capps, Jr. 2014b. "U.S. Demand for Wellness and Functional Beverages and Implications on Nutritional Intake: An Application of EASI Demand System Capturing Diverse Preference Heterogeniety." Paper presented at the annual meeting of the Agricultural and Applied Economics Association, Minneapolis, Minnesota, July 27–29.

Heckman, J.J., 1979. "Sample Selection Bias as a Specification Error." *Econometrica* 47(1): 153–161.

Heckman M.A., K. Sherry, and E. Gonzalez de Meija. 2010. "Energy Drinks: An Assessment of Their Market Size, Consumer Demographics, Ingredient Profile, Functionality, and Regulations in the United States." *Comprehensive Reviews in Food Science and Food Safety* 9(3): 303–317.

Kaminer Y. 2010. "Problematic Use of Energy Drinks by Adolescents." *Child and Adolescent Psychiatric Clinics of North America* 19(3): 643–650.

Karp, J.R., J.D. Johnston, S. Tecklenburg, T.D. Mickleborough, A.D. Flye, and J.M. Stager. 2006. "Chocolate Milk as a Post-Exercise Recovery Aid." *International Journal of Sport Nutrition & Exercise Metabolism* 16(1): 78–91.

Kennedy, P. 2003. *A Guide to Econometrics*. Cambridge, MA: MIT Press.

Kyureghian, G., O.Capps, Jr., and R.Nayga. 2011. "A Missing Variable Imputation Methodology with an Empirical Application." *Advances in Econometrics* 27A: 313–337.

Lunn, W.R., S.M. Pasiakos, M.R. Colletto, K.E. Karfonta, J.W. Carbone, J.M. Anderson, and N.R. Rodriguez. 2012. "Chocolate Milk and Endurance Exercise Recovery: Protein Balance, Glycogen and Performance." *Medicine & Science in Sports & Exercise* 44(4): 682–691.

Maynard, L.J., and D.Y. Liu. 1999. "Fragility in Dairy Product Demand Analysis." Paper presented at the annual meeting of the Agricultural and Applied Economics Association Meeting, Nashville, Tennessee, August 8–11.

McDonald, J.F., and R.A. Moffitt. 1980. "The Uses of Tobit Analysis." *Review of Economics and Statistics* 62(2): 318–321.

Milk Processor Education Program. 2014. *Built with Chocolate Milk*. Available online: http://builtwithchocolatemilk.com/ [Accessed January 28, 2016].

Modor Intelligence. 2019. *United States Sports Drink Market - Growth, Trends and Forecast (2020 - 2025)*. Available online: https://www.mordorintelligence.com/industry-reports/united-states-sports-drink-market [Accessed September 24, 2018].

Monster Beverage. 2018. *Monster Beverage Corp Form 8-K 2018*.Available online: https://sec.report/Document/0001104659-18-002859/

Reissig, C.J., E.C. Strain, and R. R. Griffiths. 2009. "Caffeinated Energy Drinks—A Growing Problem." *Drug and Alcohol Dependence* 99: 1–10.

Shoup, M.E. 2019, June 1. "Does Chocolate Milk Really Help with Post-Workout Recovery? For Most Athletes the Answer Is Yes." *Dairy Reporter*. Available online: https://www.dairyreporter.com/Article/2016/06/01/Does-chocolate-milk-really-help-with-post-workout-recovery.

Statista. 2018a. *Retail Sales Growth of Flavored Milk in the United States in 2018, by Brand.* https://www.statista.com/statistics/296166/us-retail-dollar-sales-of-flavored-milk-by-type/ [Accessed September 24, 2018].

Statista. 2018b. *Liquid Refreshment Beverage (LBR) Brands – Statistics & Facts*. Available online: https://www.statista.com/topics/2071/liquid-refreshment-beverage-lrb-brands-statistics-and-facts/ [Accessed January 27, 2020].

Tobin, J. 1958. "Estimation of Relationships for Limited Dependent Variables." *Econometrica* 26(1): 24–36.

U.S. Department of Agriculture. 2018a. *Estimated Fluid Milk Products Sales Report*. Washington, DC: U.S. Department of Agriculture, Agricultural Marketing Service, EFMS-EFMS-0618, August.

U.S. Department of Agriculture. 2018b. Livestock, Dairy, and Poultry Outlook: May 2018.Washington, DC: U.S. Department of Agriculture, Economic Research Service, Situation and Outlook Report, LDP-M-287, May.

Yang, J.L. 2014, January 31. "Beverage of Champions: Chocolate Milk Gets an Olympic-Style Makeover." *Washington Post.* Available online: https://www.washingtonpost.com/business/economy/beverage-of-champions-chocolate-milk-gets-an-olympic-style-makeover/2014/01/31/a13261b6-89c8-11e3-916e-e01534b1e132_story.html.

Yang, T. 2018. "U.S Demand for Dairy Alternative Beverages: Hedonic Metric Approach." PhD dissertation, Texas A&M University.

Zheng, W., S. Dharmasena, O. Capps, Jr., and R. Janakiraman. 2018. "Consumer Demand for and Effects of Tax on Sparkling and Non-Sparkling Bottled Water in the United States." *Journal of Agribusiness in Developing and Emerging Economies* 8(3): 501–517.

Technical Appendix

For Tobit model (Tobin, 1958; Heckman, 1979; Kennedy, 2003; Greene, 2003), there are two expectations of Y dependent variable: the conditional expectation, $E(Y|Y>0,\boldsymbol{X})$, and the unconditional expectation, $E(Y)$. Equation (A1) expresses the conditional expected value of Y and equation (A2) the unconditional expected value (see McDonald and Moffitt, 1980; Tobin. 1958; Amemiya, 1973).

(A1) Conditional expectation: $E(Y|Y>0,\boldsymbol{X}) = \boldsymbol{X}\beta + \sigma\left(\frac{f(z)}{F(z)}\right)$;

(A2) Unconditional expectation: $E(Y) = E(Y|Y>0) * P(Y>0|\boldsymbol{X})$;

$$= E(Y|Y>0) * F(z);$$

$$= \boldsymbol{X}\beta F(z) + \sigma(f(z));$$

where $z = \frac{\boldsymbol{X}\beta}{\sigma}$ is the standardized linear combination of structural coefficients and explanatory variables; $\lambda = \frac{f(z)}{F(z)}$ is called the inverse Mills ratio, the ratio between the standard normal probability density function, pdf ($f(z)$) and standard normal cumulative density function, cdf ($F(z)$). In the Tobit model, the coefficients represent the effect of explanatory variables, X, on the latent dependent variable. Therefore, the coefficients associated with each explanatory variable must be transformed to obtain meaningful marginal effects.

There are two types of marginal effects. First, the conditional marginal effect reflects the impact of any explanatory variable on the dependent variable for those households that bought the product. Second, the unconditional marginal effect represents the impact of any explanatory variable of the dependent variable, regardless of whether the household buys the product.

Based on McDonald and Moffitt (1980) and Dharmasena and Capps (2014a), if X_i is a continuous variable, the conditional marginal effect of X_i on $E(Y|Y>0,\boldsymbol{X})$ is represented by

(A3) $$\frac{\partial E(Y|Y>0)}{\partial \boldsymbol{X}} = \beta\left(1 - z\frac{f(z)}{F(z)} - \frac{f(z)^2}{F(z)^2}\right).$$

The unconditional marginal effect of X_i on $E(Y)$ is shown by

(A4) $$\frac{\partial E(Y)}{\partial \boldsymbol{X}} = \beta F(z).$$

From equation (A2), we know that $E(Y) = E(Y|Y>0) \times F(z)$, therefore

(A5) $$\frac{\partial E(Y)}{\partial \boldsymbol{X}} = F(z)\frac{\partial E(Y|Y>0)}{\partial \boldsymbol{X}} + E(Y|Y>0)\frac{\partial F(z)}{\partial \boldsymbol{X}}.$$

The marginal effect of X_i is represented by the sum of the change in the expected value of *Y* being above the limit (the conditional marginal effect) weighted by the probability of being above the limit ($[F(z)]$) and the change in the probability of being above the limit weighted by the conditional expected value of *Y* (McDonald and Moffitt, 1980).

The elasticity of *Y* with respect to x_i, conditional on $Y > 0$, is

(A6) $$\frac{\partial E(Y|Y>0)}{\partial x_i} \times \frac{x_i}{E(Y|Y>0)}.$$