EFFECTS OF NUTRIENTS, BRAND, AND FLAVOR TYPE ON DEMAND FOR DIFFERENTIATED CHIPS PRODUCTS IN THE U.S.

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Abstract

Recent policy proposals have put product reformulation at the center of debate on how to create a healthier food supply. Yet the effect of policies such as taxation, minimum quality standards or nutritional labeling on manufacturer actions strongly depend on consumer reactions to changes in nutrients and perceived tastiness of consumers among differentiated products. The objective of this article is to disentangle effects of nutrients, brand, and flavor types on market shares and consumer utility. We employ Berry, Levinsohn and Pakes' (1995) random-coefficient logit framework to estimate product-level demand for highly differentiated potato and tortilla chips in the U.S. We are specifically interested in the extent to which heterogeneous consumers respond to variation in nutrient levels, prices, and brand attributes. We find that consumers' utility increases in sodium but decreases in energy and total fat content. Also products carrying a 'reduced fat' claim are valued less. Results further suggest strong impacts of price, brand, and flavor effects on brand-level market shares. We also find evidence of strong interdependencies between nutrients and flavor. Our analysis provides evidence for trade-offs between health and taste, which seem to be determined by the degree to which a specific nutrient is more or less directly linked to sensory perception of a food product.

Keywords: Brand-level demand, differentiated products, health, flavor, nutrients, retail scanner data, random-coefficients logit, product reformulation.

Nutrient profiles of highly processed food products are at the center of the debate around mitigating epidemic diet-related diseases and have been a target of public health policy. While governments have been encouraging consumers to make healthier food choices for quite a while, food manufacturer behavior in reformulating food products to contain lower contents of fat, sodium or sugars has been in the focus only recently. While overwhelming evidence supports constant calls to improve the supply of healthy nutrition, many of the "unhealthy" ingredients are also crucial to the sensory characteristics of processed foods such as saltiness, sweetness, and texture as well as shelf-life.

The ambivalence in the role that nutrients play in consumers' product evaluation puts food manufacturers in situations resembling a Prisoner's Dilemma (Réquillart and Soler 2014). If the 'unhealthy = tasty intuition' described by Ragunathan et al. (2006) holds and consumers perceive less healthy foods to taste better, then manufacturers may lack incentives to reformulate their products towards healthier nutrient profiles, fearing that consumers might infer a loss in taste and switch to a competitor's product. Such a scenario is supported by research showing that consumers are unwilling to trade taste for functional properties (Verbeke 2006) and perceive foods with reduced fat content to be of inferior taste (Hamilton et al. 2000). Moreover, health-related product claims, touted to steer consumer towards healthier choices, may carry a negative halo effect on naturalness or tastiness (Lähteenmäki et al. 2010). Also studies from the field of consumer sciences point to important interdependencies between extrinsic (e.g. claims, price, packaging) and intrinsic characteristics (e.g. nutrients, sensory characteristics) of food in consumer decision making (Enneking et al. 2007; Hoppert et al. 2012, Kähkönen and Tuorila 1999).

A product category that stands exemplary for the 'unhealthy = tasty intuition' dilemma, where indulgence in taste meets heightened levels of unhealthy fats and sodium, is that of chips products. Savory snacks and especially fried chips products are frequently cited as a major contributor to excess intake of energy, fat, and sodium (Barnes et al. 2015; FDA 2003). The effectiveness of policy approaches to reduce chips consumption has recently gained increasing attention of researchers (Dubois et al. 2018). The contribution in this paper is to quantify the magnitude and direction with which product formulation - with a focus on fat and sodium as the stalwarts of taste - affects consumer utility, demand, and brand substitution for differentiated potato and tortilla chips products in the U.S. market.

Despite the recent interest in product reformulation as a public health and nutrition policy tool in the U.S. (Scott and Nixon 2017) studies that model demand-side rather than supply-side behavior still dominate. There is ample evidence regarding consumers' willingness-to-pay for food-health related attributes, e.g. reduced saturated fat (Øvrum et al. 2012), palm oil (Disdier et al. 2013), omega-3 fatty acids (Marette and Millet 2014), and inulin or fiber (Bitzios et al. 2011, Hellyer et al. 2012). Yet, small-sample data, hypothetical choice situations and a focus on functional attributes rather than macro-nutrients as determinants of food-health render this evidence less useful to guiding policy (Øvrum et al. 2012).

The realization that successful approaches to modify consumption behavior need to be informed by insights on purchase decisions of heterogeneous consumers in their actual market environment has fostered research on the impact of product formulation based on large-scale market data. Kiesel and Villas-Boas (2013) conducted a supermarket experiment implementing in-store nutritional shelf labeling treatments for microwave popcorn. They find 'low calorie' and 'no trans fats' labels to increase sales, while a 'low fat' label decreases sales. A series of studies attempted to explain the structure of nutrient demand through price and income elasticities for nutrients combining demand-system estimates with nutritional values of foods items (e.g. Allais et al. 2011, Beatty and LaFrance 2005, Beatty 2007, Chouinard et al. 2007, and Richards et al. 2012). A second branch of literature employs Euclidian distance measures such as Pinkse et al. (2002)'s Distance Metric (DM) approach to investigate the role that nutrient attribute proximity plays in determining brand-level cross-price elasticities in differentiated food product categories: fruit juice (Pofahl and Richards 2009), ice cream (Richards et al. 2010), yoghurt (Richards et al. 2013), canned soup (Ying and Anders 2013), and functional yoghurt (Bonanno 2013, Bonanno et al. 2015). However, the role of nutrients in these studies is either confined to the outcome variable or to a modifier on price-competition that precludes direct inference on the strategic role essential health and taste characteristics may play in manufacturer strategy, brand market shares, and demand.

The analysis in this paper employs Berry, Levinsohn and Pakes' (1995) random-coefficients logit demand model (BLP) to estimate marginal utilities of product-level nutrients including fat and sodium contents, fat-reduced formulations, brand, and flavor variety that jointly matter to the 'unhealthy = tasty intuition' hypothesis. Our choice of a BLP methodological framework over alternative models (e.g. DM) is based on two major advantages of the more flexible BLP model (McFadden and Train 2000). First, the BLP allows us to directly estimate nutrient effects on utility and market share and to test for heterogeneous consumer valuations of essential health and taste characteristics. Second, the BLP is more flexible in that it only requires product-level sales data, whereas preference heterogeneity can be accounted for with external aggregate socio-economic data readily available from census statistics. BLP-style models have been applied to food markets before, e.g. by Lopez and Lopez (2009) for differentiated milk products, Nevo (2001) and Meza and Sudhir (2010) for breakfast cereals, Villas-Boas (2007) for yoghurt, Villas-Boas and Zhao (2005) for ketchup, and Bonnet and Réquillart (2013) for soft drinks. While the main focus of these studies was on price effects and their implications to market power or tax incidence, the present analysis puts more emphasis on investigating direct effects of nutrients linked to health outcomes and taste on market shares and corresponding substitution patterns. Moreover, we test for interaction effects of demographic characteristics on strength and direction of substitution patterns.

The remainder of this paper is structured as follows. The next Section outlines the BLP framework in the context ingredient and attribute differentiated chips in the U.S. market. Section 3 describes our data sources and construction of key variables. Section 4 presents and discusses our model results, and Section 5 discusses implications for policy and further research.

Random-coefficients logit framework

The merit of Berry, Levinsohn, and Pakes' (1995) random-coefficients logit demand model further developed by Nevo (2001) for our purpose lies in its ability to produce flexible and realistic own- and cross-price elasticities and thus substitution patterns of product-level demand. Products preferred by the same individuals will show stronger substitutive relationships, which is achieved by allowing effects of product-level prices and attributes to vary with observed and unobserved consumer heterogeneity. The starting point of the model is the indirect utility u_{jit}, that consumer i receives from product j in market t:

(1) $$u_{ijt} = \alpha_i\left(y_i - p_{jt}\right) + \boldsymbol{x}'_j\boldsymbol{\beta}_i + \xi_{jt} + \varepsilon_{ijt}, \quad i = 1, \dots, I_t, \quad j = 1, \dots, J_t, \quad t = 1, \dots, T.$$

In eq. (1), y_i is consumer i's income, p_{jt} is product j's price in market t and α_i is the marginal utility of income. $\boldsymbol{x}'_j$ is a vector of K observable product characteristics and $\boldsymbol{\beta}_i$ is a $K \times 1$ vector of parameters. Central to the framework are the unobserved product characteristics ξ_{jt}. Unobserved by the researcher but observed by consumers and manufacturers, these are relevant for price formation and, thus, a potential source of endogeneity. This issue will be addressed below. ε_{ijt} is an error term with mean zero (Nevo 2000; Vincent 2015).

The individual-specific taste parameters ($\alpha_i \;\; \boldsymbol{\beta}_i$) are a function of population-wide means, demographic variables, and a standard-normal random term as depicted in eq. (2):

(2) $$\begin{pmatrix}\alpha_i\\ \boldsymbol{\beta}_i\end{pmatrix} = \begin{pmatrix}\alpha\\ \boldsymbol{\beta}\end{pmatrix} + \boldsymbol{\Pi}\boldsymbol{D}_i + \boldsymbol{\Sigma}\boldsymbol{v}_i, \qquad \boldsymbol{v}_i \sim N(0, \boldsymbol{I}_{K+1}),$$

$\boldsymbol{D}_i$ is a vector of d observed demographic variables (e.g. income, age, etc.), $\boldsymbol{v}_i$ are unobserved individual characteristics such as health status or food-health attitudes (Nevo 2000). $\boldsymbol{\Pi}$ is a $(K+1) \times d$ matrix of coefficients capturing demographic effects on taste parameters, and $\boldsymbol{\Sigma}$ is a diagonal scaling matrix with elements $\sigma_1, \dots, \sigma_{K+1}$.

The definition of the outside good completes the set-up and ensures that the aggregate demand for the category under observation can be modeled in relation to other categories (BLP 1995). For the utility of the outside good $j = 0$, indirect utility is $u_{i0t} = \alpha_i y_i + \xi_{0t} + \pi_0 \boldsymbol{D}_i + \sigma_0 \boldsymbol{v}_i + \varepsilon_{i0t}$, which is usually normalized to zero (Nevo 2000, Vincent 2015).[1]

Combining equations (1) and (2) gives:

(3) $$u_{ijt} = \alpha_i y_i + \delta_{jt}(\boldsymbol{x}_j, p_{jt}, \xi_{jt}; \boldsymbol{\theta}_1) + \mu_{ijt}(\boldsymbol{x}_j, p_{jt}, \boldsymbol{v}_i, \boldsymbol{D}_i, \boldsymbol{\theta}_2) + \varepsilon_{ijt}$$

$$\delta_{jt} = \boldsymbol{x}'_j \boldsymbol{\beta} - \alpha p_{jt} + \xi_{jt}, \qquad \mu_{ijt} = [-p_{jt}, \boldsymbol{x}_j]' \cdot (\boldsymbol{\Pi}\boldsymbol{D}_i + \boldsymbol{\Sigma}\boldsymbol{v}_i),$$

$$\boldsymbol{\theta}_1 = (\alpha, \boldsymbol{\beta}), \qquad \boldsymbol{\theta}_2 = (vec(\boldsymbol{\Pi}), vec(\boldsymbol{\Sigma}))$$

In eq. (3), indirect utility consists of a part that does not vary across single consumers, named δ_{jt}, which entails observed product characteristics $\boldsymbol{x}_j$ and observed product prices in each market, p_{jt}, evaluated by the population-average taste parameters $\boldsymbol{\beta}$ and α. A second term, μ_{ijt}, is an individual-specific deviation from mean utility generated by interactions of prices and product attributes with observed and unobserved individual characteristics. The final part captures random demand shocks ε_{ijt}.The income part, $\alpha_i y_i$, will cancel out in the derivation of choice probabilities, since it is common to all available alternatives (Nevo 2000).

[1] A basic assumption regarding choice behavior is that consumers choose only one unit of the good that gives the highest utility. Regarding the case of chips, which are often consumed in social settings, we follow Nevo (2000) in that the framework's proceeding "can be viewed as an approximation of the true choice model" (p. 520) in cases where the one-unit assumption may not hold.

At given prices, attributes, mean utilities, and parameters for demographic effects, the choice of product j over all other products $l = 0, 1, \ldots, J$ depends on the values of observed and unobserved individual characteristics $(\boldsymbol{D}_i, \boldsymbol{v}_i, \varepsilon_{i0t}, \ldots, \varepsilon_{iJt})$ (Nevo, 2000). The set A_{jt} in eq. (4) contains all those values that lead individuals to choose brand j in market t:

(4) $$A_{jt}(\boldsymbol{x}_{\cdot t}, p_{\cdot t}, \delta_{\cdot t}; \boldsymbol{\theta}_2) = \left\{ \left(\boldsymbol{D}_i, \boldsymbol{v}_i, \varepsilon_{i0t}, \ldots, \varepsilon_{iJt}\right) \middle| u_{ijt} > u_{ilt} \forall l = 0, 1, \ldots, J \right\}$$

The market share of product j in market t is then the total share of consumers in the entire market defined by A_{jt}. BLP (1995, p. 864) recommend to obtain these market shares in two steps as follows. First, assuming $\boldsymbol{D}_i$ and $\boldsymbol{v}_i$ as given and integrating over $\boldsymbol{\varepsilon}_{it} = (\varepsilon_{i0t}, \ldots, \varepsilon_{iJt})$ yields the choice probabilities for individuals conditional on their observed and unobserved characteristics. Assuming ε_{ijt} are distributed type-I extreme value, the individual probabilities or shares can be written as

(5) $$s_{ijt} = Pr_{ijt} = \int_{A_{ijt}} dP(\boldsymbol{\varepsilon}_{it} | \boldsymbol{D}_i, \boldsymbol{v}_i) \qquad \text{or}$$

(5') $$Pr_{ijt} = \frac{e^{\delta_{jt} + \mu_{ijt}}}{1 + \sum_{m=1}^{J} e^{\delta_{mt} + \mu_{imt}}}.$$

Second, integrating out over the distributions of $\boldsymbol{D}_i$ and $\boldsymbol{v}_i$ (i.e. basically computing a weighted average of individual consumer types' choice probabilities by those consumer types' frequency in the population) yields the overall shares of product j in market t:

(6) $$s_{jt} = \int_{\boldsymbol{v}_i} \int_{\boldsymbol{D}_i} Pr_{ijt} dP_{\boldsymbol{D}}(\boldsymbol{D}) dP_{\boldsymbol{v}}(\boldsymbol{v}).$$

In contrast to the basic logit model, there is no closed form for the integral in eq. (6) (BLP 1995), hence, the market share has to be computed by simulation (Nevo 2000, p. 532). It can be approximated by Monte Carlo integration with R random draws of $\boldsymbol{D}$ and $\boldsymbol{v}$ from the distributions $P_{\boldsymbol{D}}(\boldsymbol{D})$ and $N(0, \boldsymbol{I}_{K+1})$ (Vincent 2015, p. 856):

(7) $$s_{jt} = \frac{1}{R} \sum_{i=1}^{R} Pr_{ijt} = \frac{1}{R} \sum_{i=1}^{R} \frac{exp\left[\delta_{jt} + \left(\boldsymbol{x}'_{jt}, -p_{jt}\right)(\boldsymbol{\Pi D}_i + \boldsymbol{\Sigma v}_i)\right]}{1 + \sum_{m=1}^{J} exp\left[\delta_{mt} + (\boldsymbol{x}'_{mt}, -p_{mt})(\boldsymbol{\Pi D}_i + \boldsymbol{\Sigma v}_i)\right]}.$$

Eq. (7) is the basis for the estimation algorithm described below. Necessary data inputs are market shares, prices and attributes from product-level sales data, draws from census data for socio-economic characteristics, Halton random draws for unobserved consumer characteristics, and initial starting values for parameters.

Estimation procedure

Technically, the BLP approach obtains values for parameters of interest (such as marginal utilities of price and attributes or interaction effects between attributes and consumer characteristics) by simulating market shares which match observed market shares as closely as possible. These simulated market shares are computed based on product-level data such as prices and attributes, characteristics of randomly drawn consumers in a market and taste parameters guided by a random-coefficients logit model according to eq. (7). Parameters assume arbitrary values initially and are then refined in an iterative simulation and estimation process.

We use a recent implementation of the BLP model for Stata by Vincent (2015) for estimation that closely follows Nevo (2001)'s outline of the estimation algorithm (Vincent 2015, p. 859). Simulation of market shares and elasticities requires values for ν and D. These are retrieved in an initial stage by making R draws of individuals for each market (i.e. for each state-quarter) from census data (yielding vectors of demographic variables) as well as random draws from a standard-normal distribution. These values will be kept for the entire estimation throughout. The first step of each iteration provides values for mean utility levels δ_{jt} conditional on starting values for $\mathbf{\Pi}$ and $\mathbf{\Sigma}$. Observed market shares $s_{\cdot t}$ are set equal to simulated market shares $s(\delta_{\cdot t}, \boldsymbol{\theta}_2)$ and this system of nonlinear equations is solved for δ_{jt} by the following contraction mapping routine:

(8) $$\delta_{\cdot t}^{h+1} = \delta_{\cdot t}^{h} + \ln s_{\cdot t} - \ln s(\delta_{\cdot t}, \boldsymbol{\theta}_2).$$

Estimates of the mean utilities δ_{jt} allow to derive the demand-side unobservables ξ_{jt} in a second step, which are given by $\xi_{jt} = \delta_{jt} - \boldsymbol{x}'_{jt}\boldsymbol{\beta} + \alpha p_{jt}$. These unobservables are assumed to be correlated with product prices and are therefore a potential source of endogeneity. Estimation is based on GMM with the sample moment conditions $\overline{\boldsymbol{h}}(\boldsymbol{\theta}) = T^{-1}\sum_{t=1}^{T} \boldsymbol{Z}'_t\, \boldsymbol{\xi}_t$, where $\boldsymbol{Z}_t$is a $J \times l$ set of instruments. The GMM objective function is then $Q = \overline{\boldsymbol{h}}(\boldsymbol{\theta})'\boldsymbol{A}_T\overline{\boldsymbol{h}}(\boldsymbol{\theta})$, with $\boldsymbol{A}_T$ being a positive-definite weighting matrix (Vincent 2015, p.860). A parameter search retrieves $\boldsymbol{\theta}'_1 = (\alpha, \boldsymbol{\beta}')$ and $\boldsymbol{\theta}'_2 = (\, vec(\mathbf{\Pi}), \sigma_1, \dots, \sigma_{K+1})$ where $\boldsymbol{\theta}_1$ is written as a function of $\boldsymbol{\theta}_2$, and the optimization routine solves for the latter (see Nevo 2001, 2000, and Vincent 2015 for more detail).

Instrumental variables

Literature discusses a series of possible instruments to account for potentially endogenous prices. A first set of potential instruments are product characteristics of each respective product (since they affect quality and thus price) and aggregate characteristics of other products (since quality of potential substitutes on the market also affects price-setting behavior; BLP 1995, Reynaert and Verboven 2014). A second set of potential instruments are manufacturer cost shifters such as prices of energy, of raw material inputs (like potatoes, corn, and frying fats in the case of chips), as well as retail labor wage. A third set of instruments are average prices of products in neighboring markets controlling for brand-specific means via brand dummies. The remaining part of consumer valuation of a product is then state-specific and not correlated to consumers' valuation in other states (Nevo 2001, p. 320). Hence, variation of average prices in other markets provides info on exogenous changes in marginal costs (Hausman 1996, Nevo 2001, Meza and Sudhir 2010). The basic assumption here is that there are no common demand shocks inducing correlated consumer valuation of a certain product over time across different states.

Elasticities

The BLP own- and cross-price elasticities for market shares are given by (Nevo 2000; Vincent 2015):

$$\text{(9)} \qquad e_{jkt} = \frac{\delta s_{jt}}{\delta p_{kt}} \cdot \frac{p_{kt}}{s_{jt}} = \begin{cases} -\frac{p_{jt}}{s_{jt}} \int_{\boldsymbol{v}_i} \int_{\boldsymbol{D}_i} \alpha_i Pr_{ijt} \left(1 - Pr_{ijt}\right) dP_{\boldsymbol{D}}(\boldsymbol{D}) dP_{\boldsymbol{v}}(\boldsymbol{v}) & \text{if } \; j = k, \\ \frac{p_{kt}}{s_{jt}} \int_{\boldsymbol{v}_i} \int_{\boldsymbol{D}_i} \alpha_i Pr_{ijt} Pr_{ikt} dP_{\boldsymbol{D}}(\boldsymbol{D}) dP_{\boldsymbol{v}}(\boldsymbol{v}) & \text{otherwise.} \end{cases}$$

e_{jkt} gives the percent change in market share of product i caused by a one-percent change in price of k in market t. Stronger or weaker substitution patterns between different products at the market level emerge from consumers having similar (or different) choice probabilities for products featuring similar (or different) characteristics (Vincent 2015). For example, when Hispanics have a higher preference for tortilla chips, they are more likely to choose any brand of tortilla chips, resulting in stronger substitution between those in markets with a high share of Hispanics. Elasticities are retrieved from simulation analogous to that of market shares in eq. (7).

Retail, attribute and consumer demographic data

The empirical analysis for potato and tortilla chips employs weekly (w1/2004 to w22/2007, 178 weeks) store-level scanner data for 250 U.S. outlets of a major North American retail chain provided by the SIEPR-Giannini Data Center (2016). The data consist of Universal Product Code (UPC)-level sales quantity, net revenue, gross revenue, and retailer wholesale prices. We aggregate weekly store level information for each product to state-quarter observations, which serves as our definition of a "market". Our main reason for defining markets at the state-quarter level are an adequate number of stores for which information is available as well as sufficient observations in the demographic census data from which we draw random samples for simulations. From the available category sales data for savory snacks we select the top 20 potato and tortilla chips products by market share in Dollar revenues on the national level. Data for 14 quarters (with exceptions), 10 states[2] and 20 products yield 2,520 observations in total (with some zero observations).

The 20 products all belong to brands owned by PepsiCo–Frito Lay. Given the quasi-monopolistic position of this company in the chips market, this is no surprise. We also tried to include more products to have more variation with respect to ownership. However, other brands such as Herr's and Jay's are only marketed at the East Coast, leaving us with zero market shares for many state-quarter observations which led to major estimation difficulties. We do not perceive the focus on only one firm as a major limitation to the present analysis, since we focus exclusively on consumer choice and not on supply-side effects. The available brands and products offer enough variation in terms of price and attributes to estimate effects on utility and market shares.

Product-related variables

Key model variables generated from the scanner data set are product-level market shares s_{jt}, which we define as a product's net revenue per state and quarter divided by the total revenue across all brands sold per state and quarter. Our price variable is each product's net unit price, computed from product net revenue data after accounting for price discounts and divided by servings sold per quarter and state. We retrieve information on relevant product attributes at

[2] Selected states are AZ, CA, CO, IL, MD, OR, PA, TX, VA, and WA; not included are AK, DC, NM, NJ, HI, ID, MT, NE, and SD due to remoteness or insufficient number of stores.

UPC-level from ShopWell (2015) and Mintel's Global New Products Database (Mintel 2015), manufacturer homepages, and retailer websites.

Collected attribute information includes package size (oz.), recommended serving size (oz.), contents of energy (kcal), energy from fat (kcal), amount of total fat (g), amount of saturated fatty acids (g), amount of trans-fats (g), sodium content (mg), carbohydrates (g), sugar (g) and vitamin C as proportion of daily recommended intake. We follow the convention on nutrient facts panels to express nutrient contents per serving, which was one ounce for all products considered. To capture the impact of brand, flavor and product form-specific differentiation we generate a set of additional attribute variables including a dummy for potato versus corn chips and several flavor-style dummies (e.g. BBQ), brand dummies (e.g. Doritos), and product form dummies (e.g. Ripples).

Table 1: Variable definitions and summary statistics

Variable	Definition	Mean	Median	SD	Min	Max	CV
Market share	Share of net revenues (total revenues per state-quarter)	0.037	0.027	0.03	0.00	0.19	0.81
Price	Net price per serving (net revenues/number of servings sold)	0.211	0.192	0.05	0.13	0.40	0.24
Energy	Energy per serving (Mcal/oz.)	0.148	0.150	0.01	0.11	0.16	0.08
Total fat	Total fat per serving (g/oz.)	8	10	2.11	1.5	10	0.25
Sodium	Sodium per serving (g/oz.)	0.183	0.190	0.03	0.11	0.23	0.17
Reduced	= 1 if product is clearly visible as low-fat/low-energy option	0.111	0	0.31	0	1	2.83
Energy from fat	Energy from fat per serving (kcal/oz.)	76	80	18.49	15	90	0.24
Saturated fat	Saturated fat per serving (g/oz.)	2.0	2.5	1.00	0	3	0.50
Fat ratio	Ratio of saturated/total fats	0.22	0.25	0.09	0	0.3	0.40
Package size	Package size (oz.)	11.9	11.5	1.56	4.25	16	0.13

Source: Own computation.

Table 1 provides variable definitions and summary statistics for market shares, prices, and product attributes. Products included in this analysis account for roughly 70 % of all chips sales within the observed retail chain. The average market share of the 20 selected chips products is about 3 %, with specific products reaching up to 20 % in certain markets. The average retail price per serving is about US$ 0.19, the lowest price is at US$ 0.13 and the most expensive product sells at US$ 0.40 per ounce.

Table 2 provides disaggregated statistics for the 20 selected chips products on individual market shares and price indicators as well as nutrient contents. Among the top 5 products in terms of market share, three are in the “original” version, i.e. only salted, without a special flavor (Lay’s Classic 9.7 %, Lay’s Wavy Original 6.5 %, Ruffles Original 4.7 %). The other two products, Doritos Nacho Cheese with a market share of 9.2 % and Lay’s KC Masterpiece Barbecue with 4.7 % offer a very strong flavor. With regard to pricing, we observe that different brands have similar gross prices, while discounts and final net prices differ. Strong brands such as Ruffles show only slight and fewer discounts while Lay’s and Lay’s Wavy are subject to more frequent and higher price discounts. Notably, energy content across otherwise differentiated brands shows a rather narrow range mainly between 140 and 160 kcal per serving. Even fat-reduced varieties contain 110 kcal per oz. and are thus to be regarded as energy-dense foods. Levels of saturated fats, ratio of saturated to total fats, and to a lesser degree energy from and total amount of fat per serving vary more strongly. A main contributor to variation in fat content are varietal differences between corn (tortilla) and potato chips, since processing of the latter requires more fat.

Nutrient content as depicted on the nutrition facts panels seems to be subject to a certain degree of rounding. For instance, Tostitos Hint of Lime and Tostitos Restaurant Style both claim 7 g fat per oz. but the former declares 10 kcal more energy from fat per serving. Products also vary in their sodium content. Plain varieties (i.e. the “Originals”) seem to need less sodium for a balanced taste experience in contrast to products with a strong flavor (especially Cheddar and Sour Cream). Also Tostitos show relatively low sodium contents, probably because these are usually eaten together with dips which deliver the main taste experience.

Given the potential trade-offs between health and taste underlying consumers’ food choices, the direction of marginal effects of nutrient levels are not clear a priori. We expect negative signs for energy, fat, or sodium content if consumers predominantly consider the adverse health effects of chips consumption and thus make conscious decisions based on labelled nutritional facts. In contrast, if hedonic utility from chips consumption dominates, nutrition facts may take a backseat and energy, fat, and sodium as contributors to flavor and taste will carry positive signs. Apart from nutrients, we expect brand image and taste profile to play an essential role in consumer choice and utility, which we capture through several sets of dummy variables indicating overarching brands and main flavor categories.

Table 2: Detailed statistics for included chips products

	Market share (%)	Net price ($/oz.)	Gross price ($/oz.)	Discount ($/oz.)	Energy (kcal/oz.)	Energy fat (kcal/oz.)	Tot. fat (g/oz.)	Sat. fat (g/oz.)	Sodium (mg/oz.)	Sat./tot. fat (%)
Baked Lay's Original	2.26	0.336	0.355	0.02	110	15	1.5	0.0	180	0.0
Doritos Cooler Ranch	4.18	0.190	0.261	0.07	150	70	8.0	1.0	180	12.5
Doritos Nacho Cheese	9.20	0.195	0.261	0.07	150	70	8.0	1.5	200	18.8
Doritos Spicier Nacho	1.82	0.194	0.261	0.07	140	60	7.0	1.0	210	14.3
Lay's Cheddar & Sour Cream	1.89	0.174	0.266	0.09	160	90	10.0	3.0	220	30.0
Lay's Classic	9.67	0.174	0.259	0.08	150	90	10.0	3.0	180	30.0
Lay's KC Masterpiece BBQ	4.69	0.173	0.266	0.09	150	90	10.0	3.0	200	30.0
Lay's Sour Cream & Onion	3.37	0.172	0.266	0.09	160	90	10.0	3.0	210	30.0
Lay's Wavy Hickory BBQ	1.23	0.174	0.267	0.09	150	80	9.0	2.0	210	22.2
Lay's Wavy Original	6.53	0.167	0.259	0.09	150	90	10.0	2.5	180	25.0
Lay's Wavy Ranch	1.54	0.170	0.266	0.10	150	80	10.0	3.0	200	30.0
Ruffles Cheddar & Sour Cream	1.72	0.254	0.278	0.02	160	90	10.0	3.0	230	30.0
Ruffles KC Masterpiece BBQ	1.74	0.240	0.277	0.04	150	90	10.0	2.5	190	25.0
Ruffles Original	4.70	0.247	0.268	0.02	160	90	10.0	3.0	160	30.0
Ruffles Reduced	1.38	0.285	0.289	0.00	140	70	7.0	1.0	180	14.3
Ruffles Sour Cream & Onion	1.39	0.251	0.276	0.03	160	90	10.0	3.0	190	30.0
Tostitos Hint of Lime	4.07	0.195	0.252	0.06	150	70	7.0	1.0	125	14.3
Tostitos Restaurant style	4.60	0.189	0.244	0.05	140	60	7.0	1.0	120	14.3
Tostitos Rounds	2.72	0.191	0.244	0.05	140	70	8.0	1.0	110	12.5
Tostitos Scoops	3.81	0.236	0.299	0.06	140	60	7.0	1.0	120	14.3

Source: Own computation.

Demographic data

Our data source for individual demographic characteristics is the Current Population Survey's March Supplement for the year 2005 (U.S. Census Bureau 2015). We randomly draw 250 individual observations from the CPS for each state-quarter market to simulate the underlying population characteristics including age, income, sex, ethnicity, education, and subjective health status.

Table 3: Descriptive statistics of demographic variables with variance decomposition over markets

			SD		
Variable	**Definition**	**Mean**	***o*[a)]**	***b***	***w***
Age	Person's age in years	30.64	18.96	0.88	18.95
Male	= 1 if person is male	0.49	0.50	0.02	0.50
Income p.c.	Total income per capita in 1,000 US-$	23.75	25.58	3.47	25.37
Hispanic	= 1 if person is 'Hispanic'	0.22	0.41	0.17	0.38
Black	= 1 if person is 'Black'	0.09	0.28	0.08	0.27
Asian	= 1 if person is 'Asian'	0.04	0.21	0.02	0.21
Child	=1 if person is < 13 years	0.23	0.42	0.03	0.42
Adolescent	= 1 if person is between 13 and 18 years	0.10	0.30	0.01	0.30
Graduate	= 1 if person has university degree	0.19	0.39	0.04	0.39
Poor health	= 1 if person's health is rated ‚fair' or ‚poor'	0.06	0.24	0.01	0.24
Unemployed	= 1 if person is unemployed	0.03	0.16	0.01	0.16
Household size	# of persons in household	3.76	1.63	0.17	1.62

Source: Own computation. **Note**: [a)] o = overall, b = between markets, w = within markets.

Table 3 displays definitions and mean values of major demographic variables as well as measures of overall variation and variation between and within markets. High variation between markets is vital for identifying the effects of individual characteristics on demand behavior. While basic features like age or sex do not offer much variation across states, we find more potential for distinction based on ethnicity, income, unemployment, or household size. A second component of our research objective is to investigate whether and how the effects of product characteristics and price on utility vary along socio-economic lines. For example, we should expect responses to variations in price to be influenced by income, higher demand for tortilla chips in states with a large Hispanic population, different preferences for nutrient profiles along age, education, or subjective health status, as well as heterogeneous preferences for brands and flavors across age groups.

Empirical estimates and elasticities

Following BLP (1995) and Nevo (2001), we first estimate simple logit models by setting $\delta_{0t} = 0$ and writing $\ln S_{jt} - \ln S_{0t} = \delta_{jt} = \boldsymbol{x}'_j\boldsymbol{\beta} - \alpha p_{jt} + \xi_{jt}$. We test and refine different specifications including product price, nutrition characteristics, brand dummies, flavor types, and a full set of product dummies using ordinary least squares (OLS). In order to assess strength and validity of different sets of instruments for prices, we estimate a two-stage least-squares model. The insights from these trials serve to specify more complex random-parameters models subsequently.

Results from simple logit specifications

Table 4 shows results from OLS estimation with a baseline model (A) including only price as explanatory variable without any controls. Adding nutrient characteristics in model (B) considerably shifts the price coefficient downwards. Including brand dummies in model (C) decreases the price coefficient further, while adding flavor type dummies in (D) has only a minor effect on the price coefficient. In model (D), included variables explain up to 43 % of the variation in market shares. Coefficients for nutrient characteristics indicate that higher energy contents affect utility negatively while sodium levels have a positive effect. Products carrying a ‘reduced’ claim are valued less by consumers compared to products without such a claim. Consumers also place a higher value on the plain, unflavored version of products. Among brands, *Ruffles* have the highest marginal utility followed by *Tostitos* and *Doritos*.

Previous literature sometimes included a full set of product dummies to capture also all unobserved effects on mean utility (i.e. ξ_{jt} in eq. (1)) and applied a minimum-distance procedure that regresses product dummy coefficients on product characteristics to retrieve the effects of the latter on mean utility (Nevo 2001; Dubé 2004). In model (E), we present results from a regression including price and a full set of product dummies. Compared to model (D), goodness of fit does not change and the F-statistic decreases. The price coefficient decreases slightly. Given that one main interest of this article is to look at the interdependencies between nutrient characteristics, brand, and flavor, we decided to select model (D) as the basis for further modelling and estimation.

Table 4: Results of OLS regressions for $\ln S_{jt} - \ln S_{0t}$

	(A)	(B)	(C)	(D)	(E)
Price	-7.002***	-10.950***	-14.967***	-14.010***	-16.491***
	(0.474)	(0.866)	(1.426)	(1.210)	(1.284)
Energy	---	8.355**	13.900***	-43.322***	---
		(4.202)	(4.636)	(10.173)	
Total fat	---	-0.131***	-0.301***	-0.078	---
		(0.024)	(0.034)	(0.053)	
Sodium	---	-5.340***	-23.865***	39.031***	---
		(0.787)	(2.042)	(5.222)	
Reduced	---	0.342***	-0.557***	-2.180***	---
		(0.104)	(0.106)	(0.151)	
Doritos	---	---	0.410***	1.740***	---
			(0.101)	(0.133)	
Tostitos	---	---	-1.563***	1.854***	---
			(0.201)	(0.326)	
Ruffles	---	---	0.810***	2.000***	---
			(0.160)	(0.166)	
Lay's	---	---	0.867***	1.389***	---
			(0.089)	(0.095)	
BBQ	---	---	---	-0.774***	---
				(0.164)	
Cheddar & Cream	---	---	---	-2.064***	---
				(0.149)	
Plain	---	---	---	1.651***	---
				(0.239)	
Lime	---	---	---	1.982***	---
				(0.208)	
Ranch	---	---	---	-0.011	---
				(0.133)	
Cream & Onion	---	---	---	-0.715***	---
				(0.139)	
Spicy	---	---	---	-2.471***	---
				(0.123)	
Product dummies	---	---	---	---	Yes
Constant	-1.069***	0.613	5.467***	0.344	1.523***
	(0.100)	(0.548)	(0.790)	(1.543)	(0.309)
R^2	0.08	0.14	0.25	0.43	0.44
F (p-value)	218 (.000)	99 (.000)	102 (.000)	186 (.000)	164 (.000)
N	2,520	2,520	2,520	2,520	2,520

Source: Own computation. **Note:** * p<0.1; ** p<0.05; *** p<0.01. Robust standard errors in parentheses. Product dummies refer to specific products such as "Lay's Originals" or "Doritos Nachos Cheese". Reference categories for sets of dummy variables: *Wavy Lay's* for brands and *Cheese* for flavors. *Energy* expressed in Kcal/oz and *Sodium* in g/oz for numerical reasons. All variables enter in demeaned form.

Table 5: Results of two-stage least squares regressions for $\ln S_{jt} - \ln S_{0t}$

	(1) Neighbor price (NP)	(2) NP, states & time	(3) NP & time	(4) NP & states	(5) NP*brands	(6) NP*brands, time & state
Price	-17.152***	-16.664***	-16.719***	-17.073***	-17.754***	-16.874***
	(1.310)	(1.283)	(1.309)	(1.285)	(1.273)	(1.244)
R^2	0.43	0.43	0.43	0.43	0.43	0.43
N	2,520	2,520	2,520	2,520	2,520	2,520
First-stage indicators:						
R^2	0.94	0.94	0.94	0.95	0.94	0.95
F	2994	176	226	380	762	201
Prob >F	0.000	0.000	0.000	0.000	0.000	0.000
Robust score test (p-value) (Wooldridge)	0.008	0.023	0.023	0.008	0.001	0.007

Source: Own computation. **Note**: * p<0.1; ** p<0.05; *** p<0.01. Robust Standard errors in parentheses. All models include same controls as model (D) in Table 4.

Table 5 presents results of two-stage least squares estimations based on model (D) that include different sets of instruments, namely the average prices for the product in the region (i.e. neighboring states; Nevo 2001, Hausman 1996) in model (1), combinations of neighbor prices with state and time indicators in models (2)-(4), as well as interactions of these neighbor prices with brand dummies (Villas Boas 2007) in models (5) and (6). A comparison of models reveals that price coefficients are only slightly sensitive to the choice of instruments. Otherwise, goodness of fit of first-stage regressions exceeds 90 % in nearly all cases and F-tests indicate a highly significant joint effect of included instruments. A robust score test (Wooldridge, 1995) generally rejects exogeneity of prices indicating necessity of instrumentation. We also tested further instruments such as cost shifters (i.e. electricity and gas prices, prices for potatoes, corn, and sunflower oil, and average weekly wage in retailing), (BLP 1995, Nevo 2001). However, these perform poorly in the first-stage regression, most likely because there is basically no variation in costs over different chips products regarding these basic raw materials and inputs.

Results from models without demographic interactions

Table 6 shows results for different BLP model specifications utilizing the Stata code by Vincent (2015) without demographic interactions. All models use neighbor prices and time and state dummies as instrumental variables for price. The main purpose of these specifications is to investigate correlations and interdependencies between different types of product attributes. Model (I) contains only product prices and nutritional characteristics, while models (II) and (III) add brand effects and flavor dummies. Models (IV)-(VI) investigate interdependencies between energy- and fat-related variables in more detail.

The coefficient estimates for mean utility levels across variables are, with a few exceptions, significant and their signs and magnitudes provide valuable insights on consumer preferences regarding nutrients and other product attributes. Price coefficients are consistently negative and significant across specifications and including brand effects increases their magnitude. The major effect of consecutively adding brand effects in (II) and especially flavor effects in (III) is that coefficients of energy, sodium, and the ‘reduced’ dummy switch their signs. As shown in Table 2, the successful ‘plain’ varieties typically contain lower amounts of sodium than other flavors types. When flavors are not explicitly controlled for, the positive impact of ‘plain’ on demand is absorbed by the sodium coefficient. Controlling for flavors isolates the pure effect of sodium which shows a positive sign suggesting that higher levels of sodium contribute to taste and utility. We observe a similar effect for the coefficient of the ‘reduced’ dummy, which increases its magnitude considerably in model (III).

Estimated coefficients for energy, total fat content, and ‘reduced’ varieties in (III) have a negative effect on consumer utility. We interpret this finding in that consumers evaluate fat and energy content on nutrition facts panels from a health perspective, while the visible positioning of products as ‘low fat’ such as in *Baked Lay’s* and *Ruffles Reduced* is perceived from a taste perspective by the average consumer. Models (IV) to (VI) show that it is important to control for all three variables at the same time. When we omit the ‘reduced’ dummy in (IV), the coefficient of fat content turns positive, now representing a net effect of health and taste considerations. Further omitting the fat content in (V) decreases the magnitude of the energy effect, which is now also to be interpreted as a net effect. Model (VI), including the ‘reduced’ dummy again, shows a very high energy coefficient, indicating that energy and fat may have different effects on health considerations. These findings are perfectly in line with the results discussed in Kiesel and Villas-Boas (2013) who found that making ‘low calorie’ attributes more salient increases sales for microwave popcorn, while highlighting ‘low fat’ characteristics decreases sales. These results suggest that consumers infer product taste particularly based on fat content.

Table 6: Estimates for population-average coefficients of price and product characteristics

	(I)	(II)	(III)	(IV)	(V)	(VI)
Price	-11.230***	-17.067***	-16.664***	-13.628***	-14.306***	-15.434***
	(0.798)	(1.310)	(1.204)	(1.227)	(1.146)	(1.106)
Energy	8.828*	13.375**	-45.845***	-21.080***	-7.904*	-62.470***
	(4.905)	(5.339)	(8.894)	(9.030)	(4.692)	(5.983)
Total fat	-0.134***	-0.342***	-0.124***	0.081*	---	---
	(0.026)	(0.041)	(0.049)	(0.048)		
Sodium	-5.362***	-24.034***	38.431***	25.053***	24.732***	38.206***
	(0.773)	(1.378)	(3.187)	(3.153)	(3.149)	(3.185)
Reduced	0.373***	-0.603***	-2.250***	---	---	-2.129***
	(0.133)	(0.161)	(0.160)			(0.152)
Doritos	---	0.364***	1.699***	1.736***	1.599***	1.891***
		(0.102)	(0.157)	(0.162)	(0.141)	(0.137)
Tostitos	---	-1.610***	1.770***	1.660***	1.627***	1.814***
		(0.152)	(0.222)	(0.230)	(0.229)	(0.222)
Ruffles	---	0.992***	2.222***	1.314***	1.336***	2.134***
		(0.136)	(0.135)	(0.123)	(0.122)	(0.131)
Lay's	---	0.899***	1.415***	1.191***	1.206***	1.382***
		(0.073)	(0.077)	(0.078)	(0.077)	(0.075)
BBQ	---	---	-0.772***	-0.951***	-0.887***	-0.869***
			(0.169)	(0.175)	(0.171)	(0.165)
Cheddar & Cream	---	---	-2.000***	-1.971***	-1.994***	-1.969***
			(0.182)	(0.188)	(0.188)	(0.181)
Plain	---	---	1.661***	0.841***	0.876***	1.570***
			(0.206)	(0.204)	(0.203)	(0.202)
Lime	---	---	1.980***	1.123***	0.995***	2.111***
			(0.226)	(0.225)	(0.212)	(0.219)
Ranch	---	---	0.009	-0.447***	-0.376***	-0.113
			(0.136)	(0.137)	(0.130)	(0.127)
Cream & Onion	---	---	-0.668***	-1.028***	-1.051***	-0.659***
			(0.177)	(0.182)	(0.181)	(0.177)
Spicy	---	---	-2.494***	-2.109***	-1.975***	-2.657***
			(0.145)	(0.147)	(0.124)	(0.130)
Constant	-0.177	1.054***	0.969***	0.329	0.472*	0.709***
	(0.180)	(0.283)	(0.259)	(0.264)	(0.248)	(0.239)
Price x Std. Dev.	0.019	0.019	0.019	0.019	0.019	0.019
	(105.93)	(99.00)	(86.63)	(89.70)	(89.73)	(86.58)

Source: Own computation. **Note**: *** p <.001; ** p < .01; * p < .05. Robust standard errors in parentheses. Reference categories for sets of dummy variables: *Wavy Lay's* for brands and *Cheese* for flavors. All models use neighbor prices and time and state dummies as instrumental variables for price. *Energy* expressed in Mcal/oz and *Sodium* in g/oz for numerical reasons. All variables enter in demeaned form.

On the basis of mModel (III), we see that *Ruffles* stand out as the brand which consumers value the most, followed by *Doritos*, *Tostitos*, and *Lay's* on approximately the same level, and *Wavy Lay's* way behind. Another important insight from model (IV) is that brand coefficients change significantly once flavor dummies are included and differences between brands are not as pronounced as in the previous models. Among flavors, we find *Plain* and *Lime* to be consumers' favorites while *Spicy* and *Cheddar & Cream* are least preferred.

Results from models with random-parameters and elasticities

Table 7 depicts results of the final random-parameters logit specification that include interactions of independent variables and unobserved individual characteristics. Most coefficients appear to be robust compared to the population-average model (III) in Table 6, however, introducing random parameters apparently causes a loss in precision. Consumer preferences seem to be most heterogeneous regarding 'reduced' products and the brand *Tostitos*. Among flavors, we find the largest random parameters for *Cream and Onion* and *Cheddar and Sour Cream*.

Table 8 shows the median values of simulated own- and cross-price elasticities across markets based on RPL coefficients. An elasticity ε_{ij} is to be interpreted as the percent change in market share of the product in the i^{th} row resulting from a one percent change in the price of the product in the j^{th} column. Own-price elasticities are all negative and range from -2.1 (*Tostitos Hint of Lime*) to -4.9 (*Baked Lay's Original*). The values are quite high in absolute terms, but remain well within the range of elasticities for differentiated food products reported in literature (Nevo 2001, Dubé 2005, Bonanno 2013, Meza and Sudhir 2010). There are a couple of plausible and insightful patterns of demand and substitution behavior that emerge from the set of price elasticities and substitution patterns that we will describe in the following.

Own-price elasticities across brands

Across brands, *Tostitos* products (especially *Restaurant Style* and *Hint of Lime*) have the lowest own-price elasticities, probably, because they represent a subcategory of basic products bought on a regular basis, especially in regions with a large Hispanic population[3].

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[3] Trials of specifications including sociodemographic interactions indicated highly significant effects of Tostitos interacted with the share of Hispanics.

Lay's, *Lay's Wavy,* and *Doritos* products have own-price elasticities in the medium range, while market shares of *Ruffles* are most sensitive to price changes. *Ruffles* as a strong brand with relatively high per-unit prices may be perceived as luxury products by consumers for which price changes (e.g. through discounts) spark much stronger demand reactions. Lopez and Lopez (2009) and Meza and Sudhir (2010) report similar findings for specialty milk products and national brands of ready-to-eat cereals compared to private labels.

'Reduced' varieties as separate subcategory

Elasticities of the 'reduced' varieties *Baked Lay's* and *Ruffles Reduced* allow highly interesting insights from a health perspective. First, both have the highest own-price elasticities indicating that they are not treated as standard products by the majority of consumers. Second, cross-price effects between both products are much stronger than towards all other products. This finding strongly suggests that 'reduced' versions form a separate subcategory addressing consumers who explicitly look for low calorie / low fat options. Hence, reduced options do not represent strong alternatives within the groups of other *Lay's* or *Ruffles* products. This notion is also supported by results of Lopez and Lopez (2009), who report stronger substitution among milk products with the same fat content, and by Rojas and Peterson (2008) who find stronger substitution between beers of the same alcohol content in the U.S. beer market.

Tostitos as separate subcategory

A second subcategory with very pronounced substitutional ties are the four *Tostitos* products. Cross-price elasticities among them are considerably higher than towards every other product, hence, they can be regarded as a subcategory in their own respect. Their unique differentiation characteristic is that they are usually consumed together with dips and sauces that build the basis for product differentiation and variety seeking. Interestingly, they are only weak substitutes for *Doritos*, the other tortilla chips brand, which come with strong flavors and aim at different consumer segments.

Plain varieties as primary substitutes of all other products

Within groups of brands, we find the plain varieties (i.e. "Originals", "Classic") to be the primary substitutes of all other products showing the highest cross-price elasticities. This result is intuitive in that plain versions are closer (or less specific) to other flavors than specific flavors to each other. Additionally, they hold the largest market share which may be allocated to other products in the case of price changes. Close substitutional ties between products with the same flavor but from different brands or chips types are not pronounced at all. Our results clearly indicate, that consumer decide first for eating style (i.e. tortilla chips with dip vs. just (flavored) chips), then for a specific brand (*Lay's* vs. *Ruffles* vs. *Doritos*) and then for the flavor type.

Socio-demographic interactions

Models including interaction effects between product characteristics and consumer demographic variables indicate some significant and interesting results. For example, the marginal utility of Doritos corn chips (a strong brand known for exotic flavors) is significantly higher for adolescents compared to other age groups. Likewise, people of Hispanic origin receive a higher marginal utility from tortilla chips. Standard interactions of price and per-capita income as well as of package size and household size indicate significant differences in marginal utility, too. Despite significant coefficients, these interactions do not translate into cross-price and cross-attribute elasticities that clearly indicate groups of more or less close substitutes.

This result is no surprise given that the relevant consumer characteristics and specific product attributes determining the choice of chips are less obvious and easily measurable than those employed in previous BLP applications for cars or breakfast cereals. Undoubtedly, income plays a much more significant role in the choice decisions of buying an automobile (BLP 1995). Likewise, families with children are clearly more likely to buy cereals targeted at children (Nevo 2001). The choice of chips appears to depend much more on the combination of flavor and brand preferences that cannot be operationalized as easily given the limited availability of more specific data on consumer characteristics.

Table 7: Estimates for random-parameters logit specification

	Mean utility		***Std. Dev.***	
Price	-17.126	***	0.000	
	(5.282)		(11.054)	
Energy (Mcal)	-45.514	***		
	(15.878)			
Total fat (g)	-0.140	*		
	(0.085)			
Sodium (g)	40.661	***	0.252	
	(4.946)		(13.023)	
Reduced	-4.010		2.219	
	(5.700)		(4.543)	
Doritos	1.539		0.743	
	(4.828)		(13.589)	
Tostitos	-1.311		4.666	***
	(1.475)		(1.437)	
Ruffles	2.217		0.585	
	(2.230)		(8.174)	
Lay's	1.433		0.195	
	(0.962)		(16.108)	
BBQ	-0.771	***	0.000	
	(0.231)		(30.671)	
Cheddar and Sour Cream	-2.194		0.520	
	(10.736)		(25.095)	
Plain	1.707	***	0.074	
	(0.313)		(13.404)	
Lime	1.307	*	0.036	
	(0.669)		(17.514)	
Ranch	0.068		0.000	
	(0.180)		(52.403)	
Cream and Onion	-0.733		0.330	
	(8.946)		(33.641)	
Spicy	-2.514	***	0.000	
	(0.375)		(86.463)	
Constant	0.671		0.000	
	(2.136)		(3.223)	
No. of observations		*2520*		
No. of markets		*140*		
No. of random draws		*1000*		

Source: Own computation. **Note**: *** p <.001; ** p < .01; * p < .05. Robust standard errors in parentheses. Reference categories for sets of dummy variables: *Wavy Lay's* for brands and *Cheese* for flavors. All models use neighbor prices and time and state dummies as instrumental variables for price. *Energy* expressed in Mcal/oz and *Sodium* in g/oz for numerical reasons. All variables enter in demeaned form.

Table 8: Own- and cross price elasticities based on random-parameters logit estimates.

	%-change of market share	**1-% change in price**									
		Baked Lays Original	*Doritos Cooler Ranch*	*Doritos Nacho Cheese*	*Doritos Spicier Nacho*	*Lays Cheddar & Sour Cream*	*Lays Classic*	*Lays KC Masterpiece BBQ*	*Lays Sour Cream & Onion*	*Lays Wavy Hickory BBQ*	*Lays Wavy Original*
1	*Baked Lays Original*	**-4.855**	0.098	0.212	0.043	0.043	0.230	0.119	0.085	0.030	0.143
2	*Doritos Cooler Ranch*	0.089	**-2.999**	0.444	0.089	0.059	0.289	0.162	0.109	0.040	0.199
3	*Doritos Nacho Cheese*	0.089	0.205	**-2.849**	0.089	0.059	0.289	0.162	0.109	0.040	0.199
4	*Doritos Spicier Nacho*	0.089	0.205	0.444	**-3.171**	0.059	0.289	0.162	0.109	0.040	0.199
5	*Lays Cheddar & Sour Cream*	0.097	0.140	0.305	0.061	**-2.850**	0.329	0.182	0.123	0.044	0.220
6	*Lays Classic*	0.099	0.142	0.310	0.063	0.070	**-2.609**	0.186	0.125	0.045	0.226
7	*Lays KC Masterpiece BBQ*	0.099	0.143	0.311	0.063	0.070	0.336	**-2.778**	0.125	0.045	0.226
8	*Lays Sour Cream & Onion*	0.098	0.141	0.308	0.062	0.069	0.332	0.184	**-2.781**	0.045	0.224
9	*Lays Wavy Hickory BBQ*	0.096	0.141	0.312	0.063	0.069	0.331	0.184	0.125	**-2.888**	0.229
10	*Lays Wavy Original*	0.098	0.144	0.314	0.063	0.068	0.329	0.182	0.122	0.046	**-2.609**
11	*Lays Wavy Ranch*	0.091	0.130	0.320	0.059	0.074	0.370	0.198	0.133	0.054	0.236
12	*Ruffles Cheddar & Sour Cream*	0.087	0.131	0.294	0.059	0.083	0.297	0.169	0.114	0.042	0.209
13	*Ruffles KC Masterpiece BBQ*	0.084	0.122	0.300	0.056	0.068	0.344	0.184	0.123	0.050	0.220
14	*Ruffles Original*	0.089	0.135	0.296	0.060	0.065	0.304	0.169	0.115	0.042	0.215
15	*Ruffles Reduced*	0.817	0.092	0.202	0.040	0.039	0.207	0.110	0.077	0.028	0.135
16	*Ruffles Sour Cream & Onion*	0.087	0.132	0.295	0.059	0.065	0.302	0.171	0.128	0.043	0.210
17	*Tostitos Hint of Lime*	0.027	0.035	0.077	0.016	0.015	0.081	0.045	0.030	0.011	0.051
18	*Tostitos Restaurant style*	0.024	0.028	0.069	0.013	0.009	0.073	0.040	0.029	0.009	0.044
19	*Tostitos Rounds*	0.024	0.028	0.069	0.013	0.009	0.073	0.040	0.029	0.009	0.044
20	*Tostitos Scoops*	0.024	0.028	0.069	0.013	0.009	0.073	0.040	0.029	0.009	0.044

Source: Own computation.

Table 8 (continued)

	%-change in market share	Lays Wavy Ranch	Ruffles Cheddar & Sour Cream	Ruffles KC Masterpiece BBQ	Ruffles Original	Ruffles Reduced	Ruffles Sour Cream & Onion	Tostitos Hint of Lime	Tostitos Restaurant style	Tostitos Rounds	Tostitos Scoops
		1-% change in price									
1	*Baked Lays Original*	0.034	0.058	0.048	0.156	0.438	0.045	0.030	0.032	0.018	0.030
2	*Doritos Cooler Ranch*	0.046	0.079	0.065	0.218	0.042	0.062	0.036	0.038	0.021	0.040
3	*Doritos Nacho Cheese*	0.046	0.079	0.065	0.218	0.042	0.062	0.036	0.038	0.021	0.040
4	*Doritos Spicier Nacho*	0.046	0.079	0.065	0.218	0.042	0.062	0.036	0.038	0.021	0.040
5	*Lays Cheddar & Sour Cream*	0.050	0.111	0.071	0.237	0.045	0.067	0.037	0.038	0.022	0.038
6	*Lays Classic*	0.051	0.088	0.072	0.246	0.046	0.068	0.038	0.038	0.022	0.038
7	*Lays KC Masterpiece BBQ*	0.051	0.088	0.072	0.245	0.046	0.068	0.038	0.038	0.022	0.038
8	*Lays Sour Cream & Onion*	0.051	0.087	0.071	0.241	0.045	0.075	0.037	0.038	0.022	0.038
9	*Lays Wavy Hickory BBQ*	0.052	0.091	0.073	0.252	0.046	0.072	0.038	0.038	0.022	0.039
10	*Lays Wavy Original*	0.052	0.089	0.072	0.249	0.046	0.069	0.038	0.038	0.022	0.039
11	*Lays Wavy Ranch*	**-2.847**	0.102	0.073	0.271	0.052	0.080	0.032	0.036	0.018	0.036
12	*Ruffles Cheddar & Sour Cream*	0.047	**-4.232**	0.090	0.306	0.057	0.089	0.035	0.035	0.020	0.035
13	*Ruffles KC Masterpiece BBQ*	0.049	0.128	**-4.019**	0.352	0.064	0.101	0.032	0.036	0.018	0.034
14	*Ruffles Original*	0.049	0.113	0.092	**-3.973**	0.059	0.090	0.036	0.037	0.021	0.037
15	*Ruffles Reduced*	0.032	0.074	0.060	0.206	**-4.338**	0.059	0.031	0.032	0.018	0.031
16	*Ruffles Sour Cream & Onion*	0.048	0.114	0.091	0.315	0.055	**-4.217**	0.035	0.037	0.021	0.037
17	*Tostitos Hint of Lime*	0.013	0.022	0.019	0.061	0.014	0.018	**-2.126**	0.649	0.415	0.628
18	*Tostitos Restaurant style*	0.012	0.023	0.020	0.061	0.012	0.017	0.520	**-2.579**	0.415	0.628
19	*Tostitos Rounds*	0.012	0.023	0.020	0.061	0.012	0.017	0.520	0.650	**-2.918**	0.628
20	*Tostitos Scoops*	0.012	0.023	0.020	0.061	0.012	0.017	0.520	0.650	0.415	**-3.393**

Source: Own computation.

Discussion and Conclusion

This article's objective was to investigate product-level substitution patterns triggered by differences in product formulation with a specific focus on the nutritional characteristics of potato and corn chips products in the U.S. retail market. Our study aimed at providing insights on the ambiguous role that basic nutrients such as fat or sodium play for consumers' taste and health evaluation of food products. Information on the effects of nutrient levels on consumer utility, market shares, and substitution patterns is crucial for product (re)formulation by manufacturers and retailers as well as for policymaking with respect to taxes on unhealthy nutrients.

We selected and estimated Berry, Levinsohn and Pakes (1995)' random-coefficients logit demand model to obtain price, nutrient, flavor, and brand effects on consumer utility and market shares for the top 20 potato and corn chips products in the United States and derived a set of own- and cross-price elasticities. The analysis employed retail scanner sales data for a large North American retail chain, demographic characteristics from the U.S. Census March Supplement of the Current Population Survey, and product attribute information from online searches and consumer retail product databases at the UPC level.

A key result of this analysis is that coefficient estimates for nutrients indicate that consumers' utility and demand depends on whether a specific item is directly related to taste or not. Consumers seem to evaluate energy and total fat content as indicated by the nutrition facts panel from a rational and health-oriented perspective suggested by significantly negative signs for both of them. In line with previous research, a 'fat-reduced' claim decreases consumer utility, since consumers infer products carrying such a claim to be less tasty. The content of sodium which is vital for taste, mouthfeel, and product stability reveals significant and positive coefficients. Prices and unobserved brand image or brand-taste profiles as proxied by brand and flavor effects were found to exhibit more consistent effects in determining consumer choices and thus retail market shares.

Substitution patterns indicate that available 'low fat' options form a distinct segment within the chips market and are no viable alternative for the large majority of consumers. These findings underline the importance of taste-relevant attributes for consumer choice. If changes in product formulation to a healthier nutrient profile ignore the impact of sodium or other nutrients on sensory characteristics, consumers will decrease their demand and/or switch to rival brands.

Another main finding - and inherent strength and weakness of the BLP approach - is the fact that the quality of empirical results is highly dependent on available product characteristics and consumer demographics data, which in our case seemed to be insufficient to uncover more diverse brand substitution patterns and elasticities. Despite a higher sampling rate for consumer characteristics than Nevo (2001), 250 over 50 per market, the case of chips may require more subtle and complex information on the underlying consumer population in order to uncover distinct segmentation, needed to address the unhealthy-tasty intuition hypothesis. Also whether and to what degree consumers react along health or taste concerns still remains an open question. While we interpreted a positive coefficient of sodium and a negative one for the reduced dummy as supportive of a stronger taste effect, their magnitude are likely to be an aggregate of both health and taste effects.

An assignment for policy-makers and also economists that arises from this discussion is to consider the relative advantage of subsidising public research and development of modified ingredients over more restrictive measures like taxes or minimum quality standards to alleviate a Prisoner’s Dilemma situation. Findings on the balance of ingredients or nutrients within a product such as for the correlation of plain varieties with sodium content point to interesting new research questions and the need to employ more advanced methodology and data. Future work should thus be directed to a deeper and probably interdisciplinary study of the nutritional and sensory attributes of consumer products through the integration of formal econometric modelling and complementary experimental and/or survey approaches. A potential gain from such approaches would allow to separate taste-effects from health-effects that a specific ingredient may have on consumers’ utility. Ideally, such information would also enable the econometrician to observe changes in product formulation over time, which could play a critical role in isolating the causal effects of nutrient changes and reformulation on market share and propensity to substitute.

Finally, data on consumer product choices should also include attitudes and actual eating behavior, including stated taste preferences, individual health attitudes or health status, which would make for better determinants of product choice compared to the basic U.S. Census variables available to us in this study. Alternatively additional information could be obtained via nutritional panel surveys such as U.S. NHANES or household panel data from major providers of market research (e.g. Nielsen, GfK).

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