Does taste trump health?
Effects of nutritional characteristics on brand-level demand for chips in the U.S.

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Abstract

Recent controversial policy proposals have aimed at creating a healthier food supply by means of taxation, minimum quality standards or nutritional labeling. Yet the outcomes of such policies strongly depend on the competitive structures and thus substitution processes of individual products within categories, which are not well understood. The objective of this paper is to quantify the source and impact of differentiation in ingredient formulation and especially product health attributes on the competitive positioning of brands under heterogeneous consumer preferences. 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 changes in product formulation, pricing and brand attributes. Our results support the unhealthy-tasty intuition hypothesis only to a certain degree with consumers' utility increasing in sodium and saturated fat levels but decreasing in energy and total fat content. Results further suggest strong impacts of price, brand, and flavor effects on band-level market shares. Our analysis underlines the trade-offs involved in food manufacturers' decisions to reformulate products in order to comply with policy and public demands for healthier products options that do not sacrifice taste.

Keywords

Brand-level demand, differentiated products, health-taste trade-off, retail scanner data, product formulation, random-coefficients logit.

1 Introduction

Recent literature has pointed to the important role of the food industry in providing food products with healthier nutrient profiles. Réquillart and Soler (2014) argue that consumers positively associate "unhealthy" attributes like fat, sugar, or sodium with tastiness leading to market outcomes that may present a Prisoner's Dilemma for the food industry. Typically, some firms may market products differentiated by healthy attributes only to target segments of health-conscious consumers willing to pay price premiums. There may, however, be little incentives for food manufacturers to reformulate their entire portfolio in order to comply with U.S. national food-health policy and welfare objectives. Firms deciding to unilaterally

improve the nutritional profiles of their products may risk losing market share to competitors in the face of consumers wary of healthiness coming at the expense of taste.

To overcome such a potential Prisoner's Dilemma, economists generally consider policy interventions to be justified when they lead to superior welfare and public health outcomes. However, the effectiveness and efficiency of regulation aimed at food-health or nutrition outcomes critically depends on substitutive relationships between differentiated, branded food products with respect to prices, as well as potential trade-offs between health and taste attributes. The literature offers plenty empirical evidence on consumers' willingness-to-pay for food-health related ingredients such as (saturated) fat (Øvrum et al. 2012), palm oil (Disdier et al. 2013), omega-3 fatty acids (Marette and Millet 2014), and inulin or fibre (Bitzios et al. 2011, Hellyer et al. 2012). In contrast, few empirical studies employ appropriate econometric techniques to estimate the impact specific product attributes may have on brand-level consumer demand and substitution patterns in retail categories with often oligopolistic structures, pronounced differentiation, and heterogeneous consumer tastes.

Pinkse et al. (2002) and Pinkse and Slade (2004) introduced an econometric approach to demand estimation that included explicit quantitative information on product differentiation. Their distance metric approach (DM) yields semi-parametric estimates of cross-price elasticities as a function of a number of measures of the distance or proximity of brands in a product-characteristic space (e.g. ingredients, attributes). Empirical applications to date are Pofahl and Richards (2009) on fruit juices, Ying and Anders (2013) on soups, and Bonanno (2013, 2015) on functional yogurts. The estimated impact of product formulation, however, remains limited to the role of attribute proximity serving as a modifier for price-competition. In contrast, we are interested in the direct effects of essential health and taste characteristics on consumer choice.

The objective of this paper is to provide empirical evidence of health-taste trade-offs in consumer demand previously raised in the literature (e.g. Raghunathan et al. 2006; Réquillart and Soler 2014). A critical step in achieving this objective is the estimation of direct ingredient and health-attribute elasticities of demand as measures of the underlying consumer substitution patterns.

2 Random-coefficients logit framework

Our choice of methodological framework falls on the established random-coefficients logit demand model proposed by Berry, Levinsohn, and Pakes (BLP) (1995) and further developed by Nevo (2001). The BLP framework provides (own- and cross-) elasticities for prices and product attributes that vary across pairs of products and yield more realistic substitution patterns of brand-level demand. This is achieved by interacting prices and attributes with socio-demographic information, hence, products that are preferred by the same individuals will show stronger substitutive relationships. A particular advantage over the DM approach is the ability to examine direct effects of product characteristics (e.g. health attributes) on utility and demand. Information on how contents of energy, (saturated) fat, or sodium, fat-reductions and flavour types affect consumer utility allows us to derive elasticities and inter-brand substitution patterns as a consequence of product formulation and changes therein. A second advantage is that the framework requires sales data only at the product-level which are increasingly available and socio-economic information can be retrieved from readily accessible census data (BLP, Nevo 2001).

Demand side

The starting point of the model is the indirect utility u_{jit}, that consumer i receives from product j in market t:

$$(1) \qquad u_{ijt} = x_j\beta_i^* - \alpha_i^* p_{jt} + \xi_{jt} + \varepsilon_{ijt}, \quad i = 1, \dots, I_t, \quad j = 1, \dots, J_t, \quad t = 1, \dots, T.$$

In equation (1), indirect utility depends on x_j, a vector of k observable product characteristics, and p_{jt}, product j's price in market t. 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. The individual specific taste parameters (α_i^* β_i^*) are a function of population-wide means, demographic variables, and a standard-normal random term as depicted in equation (2):

$$(2) \qquad \binom{\alpha_i^*}{\beta_i^*} = \binom{\alpha}{\beta} + \Pi D_i + \Sigma v_i, \qquad v_i \sim N(0, I_{K+1}),$$

D_i is a vector of d observed demographic variables (like income, age etc.), v_i are unobserved individual characteristics (like health attitude, health status, illnesses, or overweight) (Nevo 2000). Π is a $(K+1) \times d$ matrix of coefficients for demographic effects on taste parameters, and Σ is a scaling matrix.

The definition of an 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). A basic assumption regarding choice behaviour is that consumers choose only one unit of the good that gives the highest utility. Although households commonly buy more than one brand per shopping trip, the literature defends this assumption that consumers only consume one brand and one serving at a time (e.g. one serving of breakfast cereals every morning). For the case of chips, which are often consumed at parties etc., we follow Nevo (2000) who argues that the framework's proceeding "can be viewed as an approximation of the true choice model" (p. 520) where the one-unit assumption might not hold.

Combining equations (1) and (2) gives:

(3) $$u_{jit} = \delta_{jt}(x_j, p_{jt}, \xi_{jt}; \theta_1) + \mu_{ijt}(x_j, p_{jt}, v_i, D_i, \theta_2) + \varepsilon_{ijt}$$

$$\delta_{jt} = x_j\beta - \alpha p_{jt} + \xi_{jt}, \qquad \mu_{ijt} = [-p_{jt}, x_j]' \cdot (\Pi D_i + \Sigma v_i),$$

$$\theta_1 = (\alpha, \beta), \qquad \theta_2 = (vec(\Pi), vec(\Sigma))$$

In equation (3), indirect utility consists of a part that does not vary across single consumers, named δ_{jt}, which entails observed product characteristics x_j and observed product prices in each market, p_{jt}, evaluated by the population-average taste parameters β and α. A second part, 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 are the random demand shocks ε_{ijt}.

Let the set A_{jt} be the individuals who choose brand j in market t. At given prices, attributes, mean utilities, and parameters for demographic effects, the choice of product j over all other

products $l = 0, 1, \dots, J$ depends on the vector of individual characteristics $(D_i, v_i, \varepsilon_{i0t}, \dots, \varepsilon_{iJt})$ and A_{jt} can be formally written as:

(4) $$A_{jt}(x_{\cdot t}, p_{\cdot t}, \delta_{\cdot t}; \theta_2) = \left\{\left(D_i, v_i, \varepsilon_{i0t}, \dots, \varepsilon_{iJt}\right) \middle| u_{ijt} > u_{ilt} \forall l = 0, 1, \dots, J\right\}$$

The market share of product j in market t is then the total share of consumers in the entire market for which the vector of individual characteristics assumes values that make them choose j. BLP (1995, p.864) recommend to obtain these market shares in two steps:

First, assuming D_i and v_i as given and integrating over ε_{it}, yields the choice probabilities for individuals conditional on their characteristics. Assuming ε_{ijt} are distributed type-I extreme value, the individual probabilities/shares can be written as

(5) $$s_{ijt} = Pr_{ijt} = \int_{A_{ijt}} dP(\varepsilon_{it}|D_i, v_i), \quad \text{with} \quad \varepsilon_{it} = (\varepsilon_{i0t}, \dots, \varepsilon_{iJt}) \quad \text{or}$$

(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 D_i and 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) $$s_{jt} = \int_{v_i} \int_{D_i} Pr_{ijt} dP_D(D) dP_v(v)$$

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, 532). It can be approximated by Monte Carlo integration with R random draws of D and v from the distributions $P_D(D)$ and $N(0, I_{K+1})$ (Vincent 2015, 856):

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

The ingredients for simulation and the subsequent estimation algorithm based on eq. (7) are market shares, prices and attributes from product-level sales data, draws from census data for socio-economic characteristics, Halton random draws for the unobserved consumer characteristics, and initial starting values for parameters.

Estimation procedure

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, at a later point, elasticities requires values for v and D. These are retrieved in an initial stage by making R draws from a standard normal distribution and for demographic variables for each market (i.e. for each state-quarter). 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 Π and Σ. Observed market shares $s_{\cdot t}$ are set equal to simulated market shares $s(\delta_{\cdot t}, \theta_2)$ and this system of nonlinear equations is solved for δ_{jt} by the following contraction mapping routine:

(8) $$\delta_{\cdot t}^{h+1} = \delta_{\cdot t}^{h} + \ln s_{\cdot t} - \ln s(\delta_{\cdot t}, \theta_2).$$

Estimates of the mean utilities δ_{jt} allow us to derive the demand-side unobservables ξ_{jt} in a second step, which are given by $\xi_{jt} = \delta_{jt} - x_{jt}\beta + \alpha p_{jt}$. These unobservables are assumed to be correlated with product prices and therefore a potential source of endogeneity. Estimation is based on GMM with the sample moment conditions $\bar{h}(\theta) = T^{-1}\sum_{t=1}^{T} Z_t' \xi_t$, where $Z_t$is a $J \times l$ set of instruments. The GMM objective function is then $Q = \bar{h}(\theta)' A_T \bar{h}(\theta)$, with A_T being a positive-definite weighting matrix (Vincent 2015, p.860). A parameter search retrieves $\theta_1' = (\beta', \alpha)$ and $\theta_2' = (\sigma_1, \dots, \sigma_{K+1}, vec(\Pi))$ where θ_1 is written as a function of θ_2, and the optimization routine solves for the latter (see Nevo 2001, 2000, and Vincent 2015 for more detail).

Elasticities

A main advantage of the BLP model is that it allows for more flexible and, thus, realistic elasticity estimates compared to the standard logit model. The BLP own- and cross-price elasticities are given by:

$$(9) \qquad e_{jkt} = \begin{cases} -\frac{p_{jt}}{s_{jt}} \int_{v_i} \int_{D_i} \alpha_i Pr_{ijt}(1 - Pr_{ijt}) dP_D(D) dP_v(v) \\ \frac{p_{kt}}{s_{jt}} \int_{v_i} \int_{D_i} \alpha_i Pr_{ijt} Pr_{ikt} dP_D(D) dP_v(v) \end{cases}$$

Stronger or weaker substitution patterns between different brands are created by the interaction of attributes with consumer characteristics. For example, when a certain segment of consumers, e.g. Hispanics, have a higher preference for a certain attribute, e.g. tortilla chips, they are more likely to choose any brand of tortilla chips, resulting in stronger substitution between those (Vincent 2015).

Instrumental variables

While BLP (1995) model the supply side of the market explicitly and simultaneously with demand, we limit the analysis in this paper to the estimation of demand elasticities and only use supply-side factors in search of adequate instruments to counter potentially endogenous prices following Nevo (2001). A first set of potential instruments are product characteristics and functions thereof, e.g. the sum of characteristics of other products, and second-order-polynomials of characteristics and cost shifters, including squares and interactions terms (see 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 fats, and retail wage labour. The final set are prices of products in neighbouring markets, combined with brand dummies, as suggested by Nevo (2000, 2001) and Hausman (1996).

3 Retail, attribute and consumer demographic data

Savoury snacks and especially fried chips products have been repeatedly cited as a major contributor to excess energy, fat and sodium intake (Barnes et al. 2015; FDA 2003). Moreover, given the attention the retail category of savoury snacks has received in the United States in response to U.S. FDA's 2006 mandatory labeling rule on trans-fats (FDA 2013), we investigate the demand for potato and tortilla chips in the U.S. retail market.

The empirical analysis 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 UPC-level sales quantity, net revenue, gross revenue, and retailer wholesale prices. Weekly store level information for each product is then aggregated to state-quarter observations, which serves as our definition of a "market". From the available category sales data for savoury 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[1] and 20 products yield 2,520 observations in total (with some zero observations).

We retrieve information on relevant product attributes at UPC-level from ShopWell (2015) and Mintel's Global New Products Database (Mintel 2015), manufacturer homepages, and retailer websites. Collected attributes information includes package size (oz.), recommended serving size (oz.), per-serving-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.

Key model variables generated from the scanner data set are product-level market share s_{jt}, which is defined 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 unit net price, computed from product net revenue data after accounting for price discounts and divided by servings sold per quarter and state. To capture the impact of brand, flavor and product form-specific differentiation we generated 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).

Definitions and summary statistics for product-related variables are given in Table 1. 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.

[1] 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.

Table 1: Variable definitions and summary statistics

Variable	Definition	Median	SD	Min	Max	CV
Market share	Share of net revenues (total revenues per state-quarter)	0.027	0.03	0.00	0.19	0.81
Price	Net price per serving (net revenues/number of servings sold)	0.192	0.05	0.13	0.40	0.24
Energy	Energy per serving (kcal/oz.)	150	11.60	110	160	0.08
Energy from fat	Energy from fat per serving (kcal/oz.)	80	18.49	15	90	0.24
Total fat	Total fat per serving (g/oz.)	10	2.11	1.5	10	0.25
Saturated fat	Saturated fat per serving (g/oz.)	2.5	1.00	0	3	0.50
Sodium	Sodium per serving (mg/oz.)	190	31.67	110	230	0.17
Carbohydrates	Carbohydrates per serving (g/oz.)	16	2.19	14	23	0.13
Vitamin C	Vitamin C per serving (% of GDA)	10	4.63	0	10	0.71
Fat ratio	Ratio of saturated/total fats	0.25	0.09	0	0.3	0.40
Package size	Package size (oz)	11.5	1.56	4.25	16	0.13

Source: Own computation.

Notable features among product characteristics are a rather uniform energy content across otherwise differentiated brands, flavors and product forms. Even fat-reduced varieties contain 110 kcal per oz. and are thus to be regarded as energy-dense foods. While levels of sodium and carbohydrates, and package sizes do not vary much, levels of saturated fats, ratios of saturated to total fats, and to a lesser degree energy from and total amount of fat per serving reveal a higher degree of variation. A main contributor to variation in fat content are varietal differences between corn (tortilla) and potato chips, since processing of the latter obviously requires more fat.

Data on demographics are sampled from the Current Population Survey's March Supplement for the years 2004 through 2007 (U.S. Census Bureau 2015). We perform 250 random draws for each market to simulate the underlying population characteristics including age, income, gender, ethnicity, education, and subjective health status. Table 2 displays definitions and mean values of major demographic variables as well as measures of overall variation and variation between and within markets. Since different frequencies of demographic attributes across markets is vital for identifying the effects of individual characteristics on demand behaviour, a high variation between markets is desirable. In this regard, basic features like age or sex do not differ much across states, while ethnicity, income, unemployment, or household size vary more between markets.

Table 2: Descriptive statistics of demographic variables with variance decomposition over markets

Variable	Definition	Mean	SD			CV		
			o[a)]	*b*	*w*	*o*	*b*	*w*
Age	Person's age in years	33.52	21.61	1.77	21.53	0.64	0.05	0.64
Male	= 1 if person is male	0.49	0.50	0.03	0.50	1.03	0.06	1.03
Income p.c.	Total income per capita in 1,000 US-$	22.48	25.28	30.74	25.10	1.12	0.14	1.12
Hispanic	= 1 if person is ‚hispanic'	0.22	0.41	0.15	0.38	1.90	0.69	1.77
Adolescent	= 1 if person is between 13 and 18 years	0.10	0.30	0.02	0.30	2.95	0.18	2.94
Graduate	= 1 if person has university degree	0.18	0.38	0.04	0.38	2.14	0.20	2.13
Poor health	= 1 if person's health is rated ‚fair' or ‚poor'	0.09	0.29	0.02	0.29	3.14	0.21	3.13
Unemployed	= 1 if person is unemployed	0.03	0.16	0.01	0.16	5.95	0.40	5.93
Household size	# of persons in household	3.61	1.65	0.17	1.64	0.46	0.05	0.45

[a)] o = overall, b = between markets, w = within markets.

Source: Own computation.

4 Empirical analysis

Hypotheses

Given the unsolved question about potential trade-offs consumers may make between health and taste, our ex ante hypotheses regarding the effects of product characteristics are not unambiguous. Especially the coefficients of nutrients can have signs in either direction. We would expect negative signs for energy, fat, fat-ratio, 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 indulgence utility from chips consumption dominates, nutrition facts may take a backseat and energy, fat, fat-ratio, and sodium as contributors to flavor and taste will carry positive signs.

Apart from nutrients, we expect brand image and taste profile (as the unique combination of ingredients that creates their "addictive potential" making us grave chips) to play an essential important role in consumer choice and utility. Nevo (2001) makes a similar argument for the case of ready-to-eat breakfast cereals, which he nests by consumer segments (e.g. children). We capture such distinctions through a set of several dummy variables indicating overarching brands and main flavor categories. 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.

Results from models without interactions

Estimation results obtained from the BLP model specification utilizing the Stata code developed by Vincent (2015) produces a number of interesting results. The coefficient estimates for mean utility levels across variables are, with a few exceptions, significant and their signs and magnitude provide valuable insights on consumer preferences. Regarding the suitability of instrumental variables, models that included product prices in neighbouring markets yield the strongest and most robust results.

Results for different model specifications are shown in Table 3. Model (I) contains only product prices and characteristics and models (II) to (IV) are extensions by brand effects. Models (V) and (VI) further add common flavor-type effects to control for unobservable taste profiles that may be correlated with certain ingredients. Price coefficients are consistently negative and significant across specifications. Adding brand and flavour effects increases their magnitude. Once mostly invariant relative prices between brands and/or flavors are controlled for, pure variations in price effects are emphasized. The observed elastic price patterns can be explained by a high frequency of price promotions in the savoury snacks category.

Coefficient estimates for energy and total fat content also exhibit negative and significant signs, regardless of whether they are included individually or as a group. We therefore conclude that energy and fat, per se, do not contribute to consumer utility, lending no support to Réquillart and Soler's (2014) Prisoner's Dilemma hypothesis regarding barriers to health-oriented product formulation in the face of adverse consumer preferences. Results for the fat ratio variable however differ revealing a significant and positive coefficient across models. A higher share of saturated fats seems to contribute to utility by increasing taste, texture, and/or product stability as has been previously argued by Unnevehr and Jagmanaite (2008).

Results for sodium and the reduced dummy are more ambiguous, with switching signs after including flavour dummies. We suppose a high correlation of both sodium and reduced varieties with different flavour profiles as the underlying reason for this effect. Most prominently, the successful “plain” varieties come in a reduced version and have lower contents of sodium than other flavors types. When flavors are not explicitly controlled for, the positive impact of “plain” on demand is absorbed by the coefficients for reduced and sodium. Controlling for flavors isolates the pure effect of sodium which is positive suggesting that higher levels of sodium contribute to taste and utility.

Brand effects in the final model (VI) indicate the largest brand value for Doritos corn chips followed by Ruffles, another brand. Tostitos corn chips (the reference brand) and Lay’s chips share third rank. In comparison to the previous model specifications results in model (VI) show some correlation between brands and flavor profiles. As mentioned, most flavor variations provide less utility than simple plain chips, the reference category. Lime-flavored chips are the only exception. Evaluated at mean utility levels these result appear to be reasonable and realistic as some consumer segments prefer specific flavors while others dislike them. Plain potato or corn chips represent a category of good compromise, especially since many U.S. consumers eat chips in combination with dipping sauces. For example, there appears to be no Superbowl social viewing party without chips, salsa and/or guacamole.

Table 3: Estimates for population-average coefficients of price and product characteristics

	(I)		(II)		(III)		(IV)		(V)		(VI)	
Price	-9.414	***	-10.073	***	-14.764	***	-14.828	***	-16.138	***	-16.787	***
	(2.334)		(1.526)		(2.095)		(2.118)		(1.871)		(1.935)	
Constant	5.584	***	5.478	***	5.986	***	7.148	***	9.784	***	9.323	***
	(1.048)		(0.658)		(0.712)		(0.984)		(1.744)		(1.752)	
Energy	-0.026	***	-0.041	***	---		-0.011	*	-0.085	***	-0.078	***
	(0.005)		(0.005)				(0.006)		(0.012)		(0.012)	
Total fat	---		---		-0.456	***	-0.421	***	---		-0.232	***
					(0.050)		(0.053)				(0.064)	
Sodium	-0.027	***	-0.007	***	-0.031	***	-0.030	***	0.020	***	0.020	***
	(0.001)		(0.001)		(0.001)		(0.001)		(0.005)		(0.005)	
Potatoes	---		-1.027	***	---		---		---		---	
			(0.122)									
Reduced	0.741	***	1.397	***	0.541	***	0.539	***	-1.510	***	-1.379	***
	(0.173)		(0.171)		(0.174)		(0.174)		(0.270)		(0.273)	
Fat ratio	6.442	***	9.163	***	11.549	***	12.089	***	4.610	**	9.652	***
	(1.017)		(0.999)		(1.186)		(1.219)		(2.165)		(2.533)	
Package size	---		---		---		---		---		0.051	***
											(0.016)	
Lay's	1.459	***	---		1.764	***	1.643	***	0.138		-0.113	
	(0.173)				(0.161)		(0.172)		(0.276)		(0.282)	
Ruffles	0.978	***	---		1.695	***	1.625	***	0.869	***	0.712	**
	(0.203)				(0.217)		(0.218)		(0.286)		(0.283)	
Doritos	2.233	***	---		2.571	***	2.527	***	1.396	***	1.708	***
	(0.127)				(0.128)		(0.130)		(0.419)		(0.427)	
Wavy Lay's	0.785	***	---		1.292	***	1.160	***	-0.943	***	-0.994	***
	(0.156)				(0.145)		(0.160)		(0.281)		(0.279)	
BBQ	---		---		---		---		-1.961	***	-1.879	***
									(0.151)		(0.153)	
Cheddar & Sour Cream	---		---		---		---		-2.359	***	-2.408	***
									(0.294)		(0.293)	
Spicy	---		---		---		---		-3.860	***	-4.285	***
									(0.321)		(0.332)	
Cheese	---		---		---		---		-1.367	***	-1.856	***
									(0.299)		(0.316)	
Lime	---		---		---		---		0.887	***	0.663	***
									(0.156)		(0.163)	
Ranch	---		---		---		---		-1.563	***	-1.744	***
									(0.169)		(0.172)	
Sour Cream & Onion	---		---		---		---		-1.605	***	-1.657	***
									(0.192)		(0.191)	

*** p <.001; ** p < .01; * p < .05.

Source: Own computation

Results from models with interactions and elasticities

Interaction effects between product characteristics and consumer demographic variables indicate some significant and interesting results. For example, the interactions of Doritos corn chips and age cohort of adolescent, price and per-capita income, potato-chips dummy and Hispanic ethnicity, as well as package size and household size indicate significant preference heterogeneity for these product features amongst U.S. consumers. However, these interactions are not pronounced enough to obtain cross-elasticity estimates that clearly translate attribute proximity between products to substitution patterns. Importantly, we do not find significant interactions between subjective health perceptions or education and levels of health-adverse nutrients.

Due to the large number of coefficient estimates and space limitations we only provide a summary of elasticities estimates for selected variables of interest in Table 4. Generally, own-effects are of large magnitude. The median of own-price elasticities comes in at around three in absolute value, roughly comparable to the elasticities for breakfast cereals published by Nevo (2001), which shares the high frequency of retail price promotions found in the savoury snacks category.

Table 4: Summary of selected price- and attribute elasticities

	Own			Cross		
	Median	**Min**	**Max**	**Median**	**Min**	**Max**
Price	-3.092	-5.874	-2.624	0.099	0.012	0.317
Total Fat	-1.960	-2.173	-0.324	0.051	0.006	0.210
Sodium	3.257	1.911	4.065	-0.081	-0.313	-0.018
Fat Ratio	2.134	0.000	2.784	-0.048	-0.269	0.000

Source: Own computation.

Cross-elasticities are much lower in magnitude and there is only little variation in cross-elasticities emerging from a change in an attribute of one product. We conclude from these preliminary results that overall consumer preferences and specific product characteristics that determine the choice of a specific brand and flavor profile may be less obvious, or in other words directly observed, for chips than previous BLP applications have uncovered 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 consumer characteristics data available to us and the majority of empirical studies using large scale sets of scanner data.

5 Discussion and Conclusion

This paper'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 is motivated by the recent attention and empirical evidence on the unhealthy-tasty intuition that is suspected to underlie many Western consumers' food choice decisions. We selected and estimated Berry, Levinsohn and Pakes (1995)' random-coefficients logit demand model to obtain price, nutrient, and brand effects on consumer utility and market shares for the top 20 potato and corn chips products in the United States and derived elasticity estimates of nutritional characteristics. 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 we do not find strong evidence for consumer behaviour that would support the prisoner's dilemma hypothesis put forward by Réquillart and Soler (2014). In other words, habitual consumer preferences appear to not act as a barrier to savoury snacks manufacturers wanting to unilaterally reformulate chips products in order to comply with public demands for healthier processed food (e.g. snacks) options. Although many estimates effects of nutritional characteristics were significant, their signs remained either negative (e.g. energy, fat content) or ambiguous (e.g. sodium, reduced fat) indicating a weak impact of product formulation on consumer brand-switching behavior. Only the ratio of saturated to total fat affected utility positively, supporting its role in shaping taste and texture of chips products. In contrast, 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.

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.

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. Ideally, such information would also allow the econometrician to observe changes in product formulation over time, which could play a critical role in the context of the objective in this paper. Hence, data on consumer product choices that include attitudes and actual eating behavior, including stated taste preferences, individual health attitudes or health status, 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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