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RESEARCH ARTICLE

Measuring consumers' demand for nutrition attributes: an application to ready-to-heat meals

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Abstract

This study analyzes consumers' preferences for nutrition and convenience attributes in ready-to-heat meals, using grocery scanner data applied to a Berry, Levinsohn, and Pakes model. Households' preferences for convenience meals stem on saving time. Also, households prefer convenience meals with higher contents of sugar, fat, sodium, cholesterol, and fiber, and lower in calorie content. Results prove that consumption of convenience foods implies a high intake of ingredients with negative consequences on dietary quality and health. Findings showcase the importance of the advancement and adoption of alternative food processing technologies that would circumvent the production of convenient foods high in non-healthy ingredients.

Keywords: BLP model; convenience; nutritional content; ready-to-heat meals

Introduction

Fast-paced modern lifestyles result in households having less time for food preparation at home. As a result, convenience as a food attribute is increasing in importance for consumers (Jabs and Devine 2006; Li et al. 2018). Consumers' expenditures on convenience food have been on the rise in the United States (Funk and Kennedy 2016). In fact, Zhang and Gallardo (2018) analyzed grocery store scanner data for the United States and found that convenient, prepared meal purchases increased by almost 50% between 2008 and 2016.

The main driver for the consumption of ready meals is the saving physical and mental energy in planning, meal preparation, and post-meal activities (Scholderer and Grunert 2005; Scholliers 2015). However, the preference for convenience foods comes at the expense of perceived healthiness and freshness (Amani and Gadde 2015; Cavaliere and Ventura 2018), also nutritional content (Cook et al. 2007; Barnett et al. 2019). It has been argued that increased consumption of, in general, processed foods is the primary driver of increased sodium, fat, and sugar consumption, in many developed countries, leading to increasing obesity rates. In fact, the 2010 Dietary Guidelines for Americans recommends decreasing the consumption of added sugar, saturated fats, and sodium and recognizes that convenient processed foods are the primary source of these dietary components (Okrent and Kumcu 2016). This is aligned with observations in the United Kingdom, where over-reliance on convenience foods, namely ready meals, is suspected to contribute to increases in obesity rates within the population (Remnant and Adams 2015).

There are scant studies analyzing the association between the preference for convenience foods and the intake of unhealthy ingredients. The motivation for this study is to analyze consumers' preferences for the convenience aspect of ready meals along with the preferences for meals' ingredients with a negative impact on health (i.e., sugar content, total fat, sodium, and cholesterol) but that are crucial to ensure an appealable flavor. Ready meals using food processing technologies in its current inception require the addition of unhealthy ingredients to guarantee an appealable flavor (Tang 2015; Barnett et al. 2019). Barnett et al. (2020) point that reducing unhealthy ingredients such as sodium in prepared meals is a challenge that even after extensive reformulation and consumer sensory testing there is no guarantee of consumers' acceptance. Considering that the demand for convenient ready meals has followed an increasing trend, it is important to advance food processing technologies that would not require the addition of large amounts of unhealthy ingredients and yet remain flavorful (Tang 2015; Barnett et al. 2019; Barnett et al. 2020).

The objective of this study is to estimate the marginal prices paid for nutritional content[1] (e.g., sugar, total fat, sodium, calorie, fiber, and cholesterol), along with meal preparation time of ready-to-heat meals. This study uses the Information Resources Inc. (IRI) grocery store scanner data set and applies the Berry, Levinsohn, and Pakes (BLP) random coefficients logit model to estimate the marginal values and distributions for meal preparation time and nutritional content variables mentioned above. This study poses a unique analysis of the values households assign to convenience and nutritional quality when purchasing grocery store ready-to-heat meals produced with current food processing technologies.

Ready-to-heat meals are a type of ready meal requiring only mild heating (less than or equal to 15 minutes on the stovetop, less than or equal to 20 minutes in a conventional oven, or less than or equal to 10 minutes in a microwave oven) before consumption. Examples of these foods are chilled/frozen pizzas, frozen/refrigerated main courses, and shelf-stable soups (Costa et al. 2001). These food meals bought in stores and prepared at home by reheating are considered the prototypical convenience food (Verlegh and Candel 1999).

Literature review

The term convenience has been used in the literature with different connotations, but there is consensus that convenience is associated with any aspect of the food that would enable saving physical and mental energy, as well as time, in grocery planning and shopping, meal preparation, consumption, and post-meal activities such as clean up (Scholderer and

[1]We ought to include the generic composition of the macronutrients (i.e., protein, carbohydrates, and fat), calorie count (carbohydrates provide 4 calories per gram, proteins provide 4 calories per gram, and fat provides 9 calories per gram), and micronutrients (e.g., vitamins, iron). We encounter two problems. First, the data set as we have it does not contain observations on protein and micronutrient content for the ready-to-heat meals included in this study. Second, when including carbohydrates, we encounter perfect multicollinearity; therefore, we include sugar instead. The variables included have passed the test for the variance inflation factor and multicollinearity.

Grunert 2005; Scholliers 2015). Of all those activities, meal preparation is the most time-intensive. Okrent and Kumcu (2016) report that between 2003 and 2011, women in the United States spent on average 48 minutes on meal preparation (men spent 18 minutes on average); whereas, in 1920, rural women in the United States spent on average 122 minutes cooking and 68 minutes on meal clearing and clean up.

Several studies have analyzed consumer's demand for ready meals. Capps, Tedford, and Havlicek (1985) found that manufactured convenience foods (e.g., foods with no home-prepared counterparts) were more responsive to own-price changes compared to the non-convenience foods (e.g., the fresh, unprocessed, or home-produced foods) and that basic convenience foods (e.g., food where processing was more related to the preservation method rather than ease of preparation) were more sensitive to own-price changes than complex convenience foods (e.g., multi-ingredient foods with high levels of time-saving and energy inputs). Verlegh and Candel (1999) found that the working status of the person responsible for preparing meals at home had a significant and positive relationship with the consumption of convenience meals. De Boer et al. (2004) found that the importance of freshness negatively affected the purchase of ready meals and that increases in the perceived time pressure positively contributed to the purchase of ready meals. Harris and Shiptsova (2007) found that households with increased disposable incomes, for whom the opportunity cost of time was higher, were positive to expenditures on ready meals. To sum, these studies concur that disposable time and income are positively associated with the purchases of convenience meals, whereas the notion of freshness negatively impacted its purchase.

Consumers' preferences for nutritional content are typically associated with preferences for health-related aspects of consuming a food product. Specific to convenience foods, Binkley (2006) and Burton, Howlett, and Tangari (2009) proved that nutritional content has little impact on the consumption of food away from home. This contrasts with general grocery store food products, like bread, for which nutritional content has a positive impact on consumers' preferences (Ginon et al. 2009). There are no conclusive findings for ready meals. Geeroms, Verbeke, and Van Kenhove (2008) found that health-related statements do not have an impact on consumers' preferences for ready meals. Remnant and Adams (2015) found that ready meals exhibited high contents of saturated fat and salt and low sugars, compared to the nationally recommended UK front-of-pack labeling. Interestingly, they found that the cost of the meals was associated with higher contents of energy, fat, saturated fat, protein, and fiber, and not to healthier ingredients. Kanzler et al. (2015) found similar results to those in Remnant and Adams (2015); in that ready meals were nutritionally imbalanced, being high in fat content and low in carbohydrate levels, with protein content being above dietary recommendations. We extend the previous literature by analyzing the effects of nutritional content, specifically including those ingredients that have a negative health connotation, but that guarantee an appealable flavor on households' demand for ready-to-heat convenience meals sold at grocery stores in the United States.

Data

This study uses the IRI InfoScan retail scanner data. IRI has agreements with retail outlets across the United States, to provide weekly retail sales data including prices and quantities for products with a Universal Product Code (UPC) and perishable products or random weights. Specifically, the data fields include the following: UPC, store ID for store-level or geography key for retailer marketing area, week, number of units sold, and total revenue in dollars and cents. The retail outlets included in the InfoScan data set include grocery stores (>33,000 stores), drug stores (both chain and independent with >42,000 stores), convenience stores with scanning capacity (chain and independent with > 150,000 stores), mass merchandisers, supercenters, traditional neighborhood markets, club stores, dollar stores, defense commissary stores, and exchanges (Muth et al. 2016).

In this study, the InfoScan data are linked to product attributes such as nutrition facts, brands, flavor, meal preparation time, product description, and net weight using the UPC. IRI obtains the scanned image of the nutrition fact label and then codes the information from the package adding it to the database. An example of a nutrition fact label is presented in Figure 1. Note that in some cases, the nutrition data are not complete. IRI codes nutrition data for products with significant sales volume, as the intention is to cover a large portion of the sales and not a large portion of UPCs (Muth et al. 2016).

The nutrition information available for ready-to-heat meals includes the macronutrients sugar content, calories, total fat, cholesterol, fiber, and sodium. The reason for containing sugar and fiber rather than carbohydrates is to prevent perfect collinearity with the variable calories in the regression, which is an indicator of total energy. We acknowledge that sugar and fiber are listed under the carbohydrates in the nutritional label and that these two components are not the only source of carbohydrates. For fats, we also acknowledge that there are different types of fats (i.e., trans fats, monounsaturated and polyunsaturated fats), and each of them have different impacts on consumers' health. As explained in the preceding paragraph, not all the information in the nutritional label is available for all UPC products, and the nutrition variables included in the study are the ones that are consistently present in the data set, for most ready-to-heat meals. This study does not include micronutrients among the variables used, because the amounts in which micronutrients are present in ready-to-heat meals is negligible.

About the units, the nutrient information is presented on a per-serving-size basis, and we convert these observations to a per ounce unit. The preparation time is available in the data set in minutes.

These data were collected between 2008 and 2017 across all 50 states (plus Washington DC and Puerto Rico) in the country.

Table 1 describes the data used in this study, that is, twenty ready-to-heat meal products with the largest market shares in the entire sample. Also, for each product, the table includes the meal preparation time in minutes, net weight in ounces, and nutritional content including sugar, calories, total fat, cholesterol, fiber, and sodium. The products include pasta, salads, side dishes, and pizza. We found enough variability in terms of the different attributes included, for example time preparation ranges from 2 to 10 minutes, net weight from 4.3 to 24 oz, sugar content from 0.12 to 2.67 g/oz, calories from 22.17 to 80 per oz, total fat 0.10 to 3.90 g/oz, cholesterol 1.33 to 25.80 mg/oz, fiber 0.14 to 1.26 g/oz, and sodium content 72.09 to 326.06 mg/oz.

Table 2 reports the average price in cents per ounce, the standard deviation of the prices, and the average market share of each product in the sample. The prices range from 12.69 to 38.89 cent/oz; the standard deviation for the product bundle prices ranges from 1.53 (pepperoni pizza) to 4.06 cent/oz (salad and pasta box); the average market share ranges from 0.60% (pepperoni pizza) to 2.94% (salad and pasta box). In sum, the products used in this study represent 34% of all ready-to-heat meal sales in the data set.

The observations on the average price and total sale percentage (market share) of each product are included for 52 markets (i.e., each state in the United States plus DC and Puerto Rico) and 522 weeks (i.e., 10 years). In total, the regression sample includes a total of 542,880 observations for 20 ready-to-heat meal products most frequently bought with the largest market shares during 2008–2017 in the IRI grocery scanner data set.

This study uses the InfoScan data set for the empirical modeling and does not use the household-based scanner data, mainly because the ready-to-heat meals are not purchased

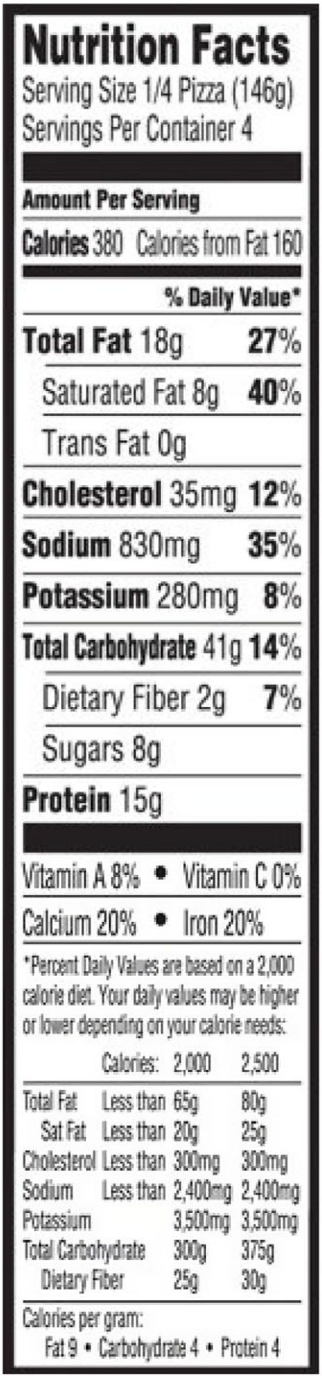

Figure 1. Nutrition fact label for pepperoni pizza.

Table 1. Summary of characteristics for each ready-to-heat meal

Product	Preparation time (min)	Net weight (oz)	Sugar (g/oz)	Calories (per oz)	Total fat (g/oz)	Cholesterol (mg/oz)	Fiber (g/oz)	Sodium (mg/oz)
Brand A Ranch salad and bacon pasta	2	14.0	2.01	61.32	1.74	14.98	0.25	125.88
Brand B Salad and pasta lunch	3	7.5	2.67	62.00	1.80	10.78	1.20	198.00
Brand C Cheddar pasta side dish pouch	8	4.4	1.36	80.00	1.33	12.07	0.90	304.54
Brand C Alfredo pasta side dish pouch	7	4.3	0.46	75.50	1.80	10.91	0.93	260.47
Brand D Potato side dish	5	24.0	0.21	31.30	1.50	11.35	0.42	85.41
Brand E Cheddar pasta side dish pouch	2	7.5	1.14	51.16	1.75	21.36	0.70	148.93
Brand F Potato side dish	4	24.0	0.21	31.30	1.35	11.42	0.41	106.35
Brand G Potato side dish	4	20.0	0.40	24.50	1.50	10.70	0.25	95.51
Brand H Chicken salad side dish box	2	8.0	2.17	44.18	0.10	15.52	0.14	127.44
Brand H Potato side dish	2	7.5	2.56	59.18	2.37	16.79	1.26	192.28
Brand I Meat ball spaghetti and potato side dish	10	8.0	0.93	66.79	3.78	25.80	0.46	187.85
Brand I Spaghetti and salad side dish	10	8.0	0.43	24.64	0.94	17.87	0.34	72.09
Brand I Chicken pizza	10	7.0	0.29	67.10	3.25	25.00	0.65	326.05
Brand J Pepperoni pizza	8	10.2	0.67	60.70	1.04	11.33	0.25	299.30
Brand K Chicken pasta side dish box	3	7.5	1.69	50.86	2.33	21.73	0.58	151.80

(*Continued*)

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Table 1. (*Continued*)

Product	Preparation time (min)	Net weight (oz)	Sugar (g/oz)	Calories (per oz)	Total fat (g/oz)	Cholesterol (mg/oz)	Fiber (g/oz)	Sodium (mg/oz)
Brand K Salad and pasta box	3	15.0	2.50	42.90	1.09	13.62	0.30	117.37
Brand L Combination pizza	10	10.2	0.67	60.70	1.04	1.33	0.54	93.33
Brand L Pepperoni pizza	10	20.6	1.55	75.70	3.28	7.76	0.38	161.17
Brand M Chicken pasta box	2	20.0	0.12	22.17	0.52	17.20	0.42	76.26
Brand N Beef pizza	10	7.0	0.29	71.40	3.90	14.29	0.29	105.00

Source: InfoScan data, IRI.

on a frequent basis by a critical mass of households. Thus, there are insufficient observations to provide a stable market share for each time-market combination. Nonetheless, to provide complete information, this study includes a summary of the household-based scanner data set, which is different from the InfoScan data set, to compare the sociodemographic characteristics between households who purchase ready-to-heat meals, at least once during the period of analysis, and those households in the entire data set. The description of the household-based scanner data set is presented in Table 3. One observes that those who purchase ready-to-heat meals exhibit a larger percentage of white, higher educated individuals, are less likely to have both male and female household heads compared to the entire sample, have smaller households in terms of number of individuals, and report higher annual incomes.

Empirical method

This study applies the BLP random coefficients logit model (Berry, Levinsohn, and Pakes 1995; Nevo 2001; Zhang and Palma 2021) to estimate the demand for ready-to-heat meals. Consumer i's utility of consuming product j on period t is given by,

$$U_{ijt} = \alpha_i(y_i - p_{jt}) + \boldsymbol{x_{jt}\beta_i} + \xi_{jt} + \varepsilon_{ijt} \quad (1)$$

where y_i is consumer i's income, p_{jt} is the observed price of product j in time-market combination[2] t. x_{jt}, is a $1 \times$ K dimensional vector and depicts the attributes of product j and includes the convenience variable expressed as preparation time and the nutrition variables: sugar content, calories, total fat, cholesterol, fiber, and sodium content. α_i is the consumer i's marginal utility of income, $\boldsymbol{\beta_i}$ is a K $\times$ 1 dimensional vector and represents the

[2]The time-market combination is a combination of indicator variables for time and state. And if a product was not presented in a time-market combination, the study used the national average price instead.

Table 2. Market share and average prices for each ready-to-heat meal

Product	Average price (cent/oz)	Price standard deviation (cent/oz)	Average market share (%)
Brand A Ranch salad and bacon pasta	21.94	3.19	2.45
Brand B Salad and pasta lunch	23.65	3.38	1.13
Brand C Cheddar pasta side dish pouch	35.05	2.16	1.62
Brand C Alfredo pasta side dish pouch	37.22	1.99	1.06
Brand D Potato side dish	14.28	2.97	1.75
Brand E Cheddar pasta side dish pouch	33.46	2.43	2.00
Brand F Potato side dish	12.69	2.52	1.98
Brand G Potato side dish	14.29	3.76	1.94
Brand H Chicken salad side dish box	38.89	2.12	1.24
Brand H Potato side dish	19.30	3.26	2.90
Brand I Meat ball spaghetti and potato side dish	33.71	2.91	2.50
Brand I Spaghetti and salad side dish	35.91	2.72	1.65
Brand I Chicken pizza	21.66	2.35	2.39
Brand J Pepperoni pizza	25.77	1.53	1.19
Brand K Chicken pasta side dish box	22.61	3.66	1.09
Brand K Salad and pasta box	28.40	4.06	2.94
Brand L Combination pizza	29.10	2.86	0.85
Brand L Pepperoni pizza	21.71	3.72	0.60
Brand M Chicken pasta box	35.09	2.88	1.86
Brand N Beef pizza	21.34	2.72	1.82

Source: InfoScan data, IRI.

consumer i's marginal utility of product attributes, ξ_{jt} captures the unobserved product-specific shock in each market, and ε_{ijt} is the error term.

Equation 1 assumes both α_i and β_i have a constant and a random component. Randomness stems from standard normal distributions, which are used to represent the heterogeneity of parameters. The parameters are composed by a mean and a variance-covariance matrix, following,

$$\begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} = \begin{bmatrix} \alpha \\ \beta \end{bmatrix} + \boldsymbol{v_i}, \;\; \boldsymbol{v_i} \sim P_v(v) \tag{2}$$

where $\boldsymbol{v_i}$ is the K by 1 dimensional vector of taste parameters for consumer i. The distribution of $\boldsymbol{v_i}$ is denoted by $P_v(v)$.

$\boldsymbol{x_{jt}}$ denotes the attributes capturing heterogeneity and has two parts coefficients: random $\boldsymbol{v_i}$ and non-random $\boldsymbol{\beta_0}$; in other words, $\boldsymbol{\beta_i}$ consists of two vectors: $\boldsymbol{\beta_0}$ and $\boldsymbol{v_i}$, which yields,

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Table 3. Description of household sociodemographic characteristics

Sociodemographic variables	All household sample		Households who purchase ready-to-heat meals	
	Frequency	Percentage	Frequency	Percentage
Household head race				
All white not Hispanic	291,047	61.83	53,723	68.31
All black not Hispanic	41,514	8.82	7,270	9.25
All Hispanic	49,816	10.58	5,771	7.34
Others	88,348	18.77	12,878	16.38
Household head highest education				
High school degree or less	163,755	34.79	21,946	27.91
Some college	141,902	30.15	21,649	27.53
Bachelor's degree or higher	165,068	35.07	35,047	44.56
Household head gender				
Both	337,109	71.61	44,090	56.06
Only female	99,805	21.20	18,576	23.62
Only male	33,811	7.18	15,977	20.32
Household region				
Northeast	77,676	16.50	15,128	19.24
Midwest	92,603	19.67	15,740	20.01
South	184,919	39.28	34,759	44.20
West	115,527	24.54	13,014	16.55
Household size				
1	67,775	14.40	21,054	26.77
2	144,738	30.75	29,137	37.05
3	90,062	19.13	10,247	13.03
4 and above	168,150	35.72	18,205	23.15
Weighted average (number of individuals)	2.9		2.7	
Household income				
Under $14,999	36,534	7.76	7,311	9.30
$15,000–$24,999	43,146	9.17	4,078	5.19
$25,000–$34,999	57,529	12.22	10,675	13.57
$35,000–$44,999	55,345	11.76	13,196	16.78
$45,000–$59,999	75,033	15.94	14,928	18.98
$60,000–$99,999	130,480	27.72	14,870	18.91

(*Continued*)

Table 3. (*Continued*)

Sociodemographic variables	All household sample		Households who purchase ready-to-heat meals	
	Frequency	Percentage	Frequency	Percentage
$100,000 and above	72,658	15.44	13,584	17.27
Weighted average (dollars)	57,353		60,754	

Source: IRI household scanner data.

$$\begin{aligned} u_{ijt} &= \alpha_i(y_i - p_{jt}) + \boldsymbol{x_{jt}\beta_i} + \xi_{jt} + \varepsilon_{ijt} \\ &= \alpha_i y_i - \alpha_i p_{jt} + \boldsymbol{x_{jt}\beta_0} + \boldsymbol{x_{jt}v_i} + \xi_{jt} + \varepsilon_{ijt} \\ &= \alpha_i y_i + (-\alpha_0 p_{jt} + \boldsymbol{x_{jt}\beta_0} + \xi_{jt}) + \boldsymbol{x_{jt}v_i} + \varepsilon_{ijt} \end{aligned} \tag{3}$$

The expression above is composed of the utility from income, the mean utility from the product attributes, consumer heterogeneity, and the independently and identically distributed (iid) error term. The mean utility from the product attributes and consumer heterogeneity is defined by,

$$\delta_{jt} \equiv -\alpha_0 p_{jt} + \boldsymbol{x_{jt}\beta_0} + \xi_{jt} \tag{4}$$

$$\mu_{ijt} \equiv \boldsymbol{x_{jt}v_i} \tag{5}$$

Then, the utility function can be expressed as,

$$u_{ijt} = \alpha_i y_i + \delta_{jt} + \mu_{ijt} + \varepsilon_{ijt} \tag{6}$$

where δ_{jt} is the mean utility from a consumer's choice of product j that is homogeneous across all consumers, μ_{ijt} is the heteroskedastic disturbance term that shows consumer heterogeneity, and ε_{ijt} is the homoscedastic iid error term.

Each consumer purchases one product unit at a time that gives the highest utility compared to all others, including the outside product. Conditional on the product attributes $(\boldsymbol{x}, \boldsymbol{\xi})$ and market prices p, a consumer i chooses product j if,

$$u_{ijt} \geq u_{ikt} \text{ for all } j, k \in \{0, , 1, 2, \ldots, J\} \tag{7}$$

Further, if q_{jt} represents the quantity of the product j sold in market t, then the observed probability of a consumer i choosing the product j over other products is given by,

$$\begin{aligned} \Pr(u_{ijt} > u_{ikt}) &= \Pr(\alpha_i y_i + \delta_{ijt} + \mu_{ijt} + \varepsilon_{ijt} > \alpha_i y_i + \delta_{ikt} + \mu_{ikt} + \varepsilon_{ikt}) \\ &= \Pr(\varepsilon_{ikt} - \varepsilon_{ijt} < \delta_{ijt} - \delta_{ikt} + \mu_{ijt} - \mu_{ikt}) \\ &= \int_\varepsilon I(\delta_{ijt} - \delta_{ikt} + \mu_{ijt} - \mu_{ikt}) f(\varepsilon | v_i) d\varepsilon \\ &= s_{ijt} \quad \forall\, j \neq k\# \end{aligned} \tag{8}$$

Equation 8 is integrated over the density of unobserved preference to obtain the theoretical share of product j in market t, resulting in Equation 9,

$$s_{jt}(p, \boldsymbol{x}) = \int_v s_{ijt} dP_v^*(v)\# \tag{9}$$

The study uses the STATA BLP package to analytically estimate the coefficients using Monte Carlo integration. The package uses 200 draws for the Monte Carlo simulation,

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the tolerance level used to define the convergence of the contraction mapping algorithm is 10^{e-15}, and the starting value for the standard deviations of the random coefficients is 0.5 (Vincent 2015). Considering that price is endogenous to the market share, this study uses as an instrumental variable, the average price of the same product in other markets[3] (Hausman 1996). The instrument was tested, and results of the first-stage F-test larger showed this was not a weak instrumental variable (Nevo 2001).

To capture the effect of convenience, expressed in terms of preparation time, and nutritional content, as the demand for ready-to-heat meals, product j is depicted by 20 ready-to-heat meal products j ($j = 1,2 \ldots ,20$). The time-market combination[4] (t) includes 50 states plus Washington DC and Puerto Rico, over 522 weeks (from 2008 to 2017 or 10 years): $t = 1, 2, \ldots, 27144$. We include the net weight of each ready meal to control for different weights per package that could result in different prices per unit as control variables. The net weight is an important control variable for two reasons, as discussed by Cohen (2008). First, with respect to sales strategy, large packages could be used for the strategy bundling selling for price discrimination. Second, the net weight of a product is related to the packaging cost (although it is not a large cost). Thus, weights per package could result in different prices per unit.

We also include binary primary ingredient indicators to control product heterogeneity: pizza, pasta, potato, and salad. For example, the binary variable pizza equals one if the observation is a pizza product, zero otherwise. This information is given by the data set. State fixed effect (FE) and week FE variables are also included to control for state heterogeneity and time seasonality. That is, these variables control variations over place (states within the United States) and time. For example, households might have greater supply of salads in lower latitude states such as California or Florida, compared to states such as Minnesota. Also, there might be a larger supply of salads during the summer season weeks. A White test for heteroscedasticity shows evidence of heteroscedastic error terms. Therefore, the model uses the robust standard error to control for heteroscedasticity, given that the time and geographic range is broad (White 1980; Vincent 2015).We also apply the variance inflation factor (VIF) method to test for multicollinearity. Results indicate no multicollinearity (VIF > 10) in the set of independent variables included in the

[3]As mentioned in Dubois et al. (2014), the combination of $\xi_{jt} + \mu_{ijt} + \varepsilon_{ijt}$ depicts elements of preferences and the environment. For example, preferences for different ready meals could vary across households depicted by μ_{ijt}. ξ_{jt} and ε_{ijt} would capture other elements of preferences. It is possible that ε_{ijt} includes unobserved characteristics of the goods that will likely impact the choice of quantities raising the concern about endogeneity of nutrient content. Therefore, Dubois et al. (2014) use instrumental variables for nutrient content. However, Dubois et al. (2014) explain that the use of instrumental variables for nutrient content is challenging because researchers can only observe the products that are actually purchased by some households in the data. We do not see the complete set of available products. The strategy is to "approximate the nutrients of products available to each household by computing the unweighted average nutrient content of products purchased, in that category and quarter, by household in a reference group." They are able to identify a reference group for each household by category and then compute the average nutrient content of products bought by members of the reference group and assume this is the average nutritional content of the products in the household's choice set. We claim that the Dubois et al. (2014) approach to address this issue is feasible because the set of products included in their study is by far more comprehensive, and they have enough variability across reference households. This approach might not be feasible to apply to our case, because our data set of interest is only limited to a set of ready-to-heat meals. Therefore, we limit the use of instrumental variables to prices, as is the approach used in the seminal papers by Berry, Levinsohn, and Pakes (1995) and Nevo (2001).

[4]These data ordered as 1-522 coincide with the first state 522-week periods, 523-1,044 for the second state, etc. And the 52 jurisdictions are listed in alphabetical order.

model. Further, when presenting the results, we include the proportion of households who have a positive (negative) marginal utility parameter for each nutritional attributes. Because we assume a normal distribution for the marginal utility parameters, and we can observe the mean and the standard deviation for each marginal utility parameters, we calculate the share of households with a positive/negative marginal utility for a given nutritional variable.

A limitation of this approach is that when using grocery store scanner data, the researcher observes choices, or households' actual purchases, leaving out the opt-outs. That is, the researcher does not observe the entire choice setting, as this information is not available in the data set. This study offers one mitigation strategy. Because not all the 20 convenience food options were available to every household in every time-market combination, this study uses the national average price for the ready-to-heat meal, when it was not available in a specific time-market combination. This caveat is discussed in Nevo (2001), who argues that not having the entire choice set results in an overestimated unobservable taste heterogeneity. For future research, we hope for improvements in the data collection, by including observations of those products not purchased or the entire choice set faced by households.

Results

Table 4 presents the parameter estimates for the BLP model, including the negative utility share.[5] The mean coefficient estimates are presented in column 2, and the coefficients for taste heterogeneity by means of random draws from known distributions are presented in column 3. The table also reports the first-stage regression F-value (equal to 131.47), implying that the instrumental variables used are strong.

The mean marginal utility of income was negative and statistically significant, indicating the negative effect of price on the utility derived from consuming ready-to-heat meals. In relation to the convenience attributes, the mean marginal utility of preparation time is negative and statistically significant, implying that longer preparation times are detrimental to the utility derived from consuming these meals. The proportion of households that have a negative marginal utility for preparation time is 99.91%. This is aligned with previous literature that the main driver of ready meal consumption is the time savings from the meal preparation time (Verlegh and Candel 1999; De Boer et al. 2004; Harris and Shiptsova 2007; Okrent and Kumcu 2016).

In relation to nutritional attributes, sugar, total fat, sodium, cholesterol, and fiber exhibit a positive mean marginal utility; that is, household's utility increases with higher contents of the previously mentioned attributes. Additionally, 74.49% (100–25.51) of households display a positive marginal utility for sugar, 90.78% display a positive marginal utility for total fat, 74.75% display a positive marginal utility for sodium, 69.57% display a positive marginal utility for cholesterol, and 78.81% display a positive marginal utility for fiber. These results imply that, except for fiber content, households in this data set prefer convenience products with higher content of ingredients contributing to taste that could be detrimental to health if overconsumed. This finding coincides with Malone and Lusk (2017) who concluded that consumers derive the most utility out of how they perceive a product's taste, rather than how healthy or safe they believe the product to be. These

[5]The study assumed a normal distribution for the marginal utility parameters and thus has the cumulative distribution function of the parameter estimates, given that the mean and standard deviation of the marginal utility parameters are given by the STATA output, the table includes the share of participants that have a positive (negative) marginal utility for the nutrition variables and the mean preparation time.

Table 4. Parameter estimates for the Berry-Levisohn-Pakes Demand Model for ready-to-heat meals

	Mean	Standard error	Negative utility share
Price	−0.051***[1]		
	(0.003)[2]		
Convenience attributes			
Meal preparation time	−0.097***	0.031***	99.91%
	(0.017)	(0.009)	
Nutritional attributes			
Sugar	0.027***	0.041***	25.51%
	(0.004)	(0.002)	
Total fat	0.077***	0.058***	9.22%
	(0.004)	(0.009)	
Sodium	0.002***	0.003***	25.25%
	(0.000)	(0.000)	
Calories	−0.017***	0.034***	69.15%
	(0.003)	(0.005)	
Cholesterol	0.021***	0.041***	30.43%
	(0.005)	(0.008)	
Fiber	0.012***	0.015***	21.19%
	(0.004)	(0.004)	
Control variables			
Net weight	−0.056***		
	(0.000)		
Pizza	0.010***		
	(0.000)		
Pasta	−0.006***		
	(0.003)		
Potato	−0.013***		
	(0.001)		
Salad	0.024***		
	(0.001)		
State FE[3]	Included		
Week FE	Included		
Observations	542,880		
First-stage F statistics	131.47		

[1]Single, double, and triple asterisks (*,**,***) indicate [statistical] significance at the 10%, 5%, and 1% level, respectively.
[2]Standard errors between parentheses.
[3]Instead of including each binary variable for state (52) and week (522), for ease of presentation, we mention that these variables were included.

results are also aligned with the claims of Remnant and Adams (2015), Kanzler et al. (2015) and Okrent and Kumcu (2016); in that increased consumption of processed convenience foods is the primary driver of increased sugar, fat, and sodium intake.

Calorie content is the only variable in the model with a negative sign for the marginal utility. Also, 30.85% of the households in the data set derive a negative marginal utility. Considering that proteins, carbohydrates, and fat contribute to the calorie content, it is possible that the combination of these elements altogether implies a negative effect on the demand for ready-to-heat meals and that fat content alone would imply a positive effect, as fat content is more related to flavor.

On the control variables, net weight exhibits a negative marginal utility, indicating that larger sizes of ready-to-heat meals imply less prices per oz. The mean marginal utility for pizza and salad is positive, whereas the mean marginal utility for pasta and potato is negative.

Conclusions

This study analyzes consumers' preferences for nutrition and convenience attributes in ready-to-heat meals. We used InfoScan IRI scanner data for 50 states in the United States, plus Washington DC and Puerto Rico, for the period 2008–2017. This study applies a BLP model to estimate the marginal utility derived from nutritional (expressed in terms of sugar, calories, total fat, cholesterol, fiber, and sodium content) and convenience attributes (expressed in terms of meal preparation time).

Households whose purchases have been recorded in InfoScan prefer shorter meal preparation times, emphasizing the notion that households' preferences for these convenience foods stem on saving time. For nutritional content, results indicate that households prefer convenience meals with higher contents of sugar, fat, sodium, cholesterol, and fiber. These results confirm the claims that the consumption of processed convenience foods implies a high intake of sugar, fat, sodium, and cholesterol components in the diet, which denotes a negative consequence on dietary quality and health. Because demand for convenience foods is likely to remain or increase at least for a population segment, it is important to consider alternative measures to prevent the production of processed foods high in unhealthy components. The findings in this study signals that the unhealthy ingredients with the highest marginal values are those that are added to ensure flavor and palatability. Reducing the amount of unhealthy ingredients in processed foods is challenging with current food processing technologies, such as sterilization in retort, because they damage aromatic and flavor components naturally present in the food, making it necessary to add extra quantities of salt and sugar to ensure palatable flavor. Therefore, to improve the nutrition quality of convenience foods, it is important to advance the development and adoption of new food processing technologies that would preserve the natural flavor and aromatic components of the ingredients and reduce the need to add unhealthy ingredients to processed convenient foods.

Data availability statement. Data were obtained via a third-party agreement with the United States Department of Agriculture and NORC (National Opinion Research Center) at the University of Chicago.

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Conflicts of interest. The authors declare no conflicts of interest.

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