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Measuring Palatability as a Linear Combination of Nutrient Levels in Food Items

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Measuring Palatability as a Linear Combination of Nutrient Levels in Food Items

Abstract

It well known that palatability and nutritional quality of foods and/or diets are viewed as being in tension with one another. While there exist multiple measures of healthiness, there are no such measures for tastiness. This gap limits the degree to which researchers can investigate this tension and its implications for dietary behavior and hence public health and nutrition policy. The scope of future work concerning the dietary behavior of Americans would expand greatly if researchers better understood consumers' willingness to eat certain foods, which matters as much as recommending those foods for them to eat in the first place. Using stepwise selection algorithms, a nutrient profiling model is developed and the resulting estimates are used to compute a numerical measure for the relative palatability of food items. Foods found to be relatively tasty by the measure tend to be relatively lower in nutritional quality, as expected. This implies that policy aimed at altering consumption patterns should emphasize foods that score relatively high in both nutritional quality and tastiness. Tastier foods without the additional benefit of a healthier nutrient composition are candidates for consumption taxes to discourage excess consumption, while healthy foods low in palatability could be subsidized using this tax revenue.

Keywords:

diet choice, nutrient profiling model, NHANES, nutrient composition, palatability, consumption tax

1. INTRODUCTION

1.1 Background

One of the most important aspects of food to consumers is palatability. This is particularly the case for US consumers in recent decades, even to the degree that taste trumps health, convenience, safety, or even cost (Glanz et al., 1998; Blaylock et al., 1999; Malone & Lusk, 2017). Certainly, tastes differ by consumer to some degree, but it is reasonable to say that these tastes tend to follow common patterns and trends. The portfolio of options available to US consumers is vast, and many foods are differentiated further in varieties with respect to nutrient content – for instance, low-sodium, sugar-free, or fat-free. Such differentiations tend to focus on consumer health.

Consider the Thrifty Food Plan (TFP), a USDA-developed portfolio of foods and food groupings that are both low in cost and are considered “healthy” with regards to their adherence to the Dietary Guidelines for Americans (DGA). A problem with the TFP is that it ignores palatability, and little or no research addresses the degree to which the average American will actually eat the foods recommended in the DGA. While many of the foods in the TFP are indeed, cheap and healthy, they may not be very tasty to the typical consumer (Stewart & Blisard, 2006; Drewnowski & Eichelsdoerfer, 2010). This is not a new idea. Stigler (1945) developed an optimal diet for an average American male, minimizing the total expenditure on food subject to his minimum nutritional requirements. This diet included dried navy beans, raw cabbage, raw spinach, wheat flour, and evaporated milk – a combination likely not perceived to be tasty by the typical American adult. Silberberg (1985) observed this and proposed an Engle Curve type of explanation for it. First treating healthiness and tastiness of a diet as substitutable “inputs”, he showed using survey data that as the ratio of actual cost of food to minimal cost of food increases with income, nutrition’s share of expenditure falls with income. His theory proposes that, once an individual’s nutritional requirements are satisfied, any additional money spent on food improves palatability.

The conclusions from Silberberg’s model estimated on survey data continue to appear in more recent studies as well. A diet simulation by Irz et al. (2015) showed that reducing expenditure on a diet of fixed nutritional quality significantly reduces the palatability of that diet. Empirical evidence of this tradeoff has also appeared in studies of grocery purchasing behavior. Binkley & Golub (2011) found a significantly positive relationship between income and

purchases of low fat, reduced sugar, and high fiber groceries after controlling for demographics. That is, they showed consumers with lower income tend to choose the options with higher fat, more sugar, and less fiber, even though the less healthy options of the foods examined cost either the same as or even more than the healthier options. Moreover, the commodities chosen were so simply differentiated (e.g. sugar or calorie content in diet versus regular soft drinks) that lack of knowledge about nutrition was unlikely to be an obstacle to choosing the healthier of two options. A similar conclusion for dietary intake followed in Chen et al. (2012).

1.2 The Role of Taste

Prioritizing the palatability or taste of foods over their healthiness is a well-known pattern of behavior (Berning et al., 2010). A choice experiment conducted by Malone & Lusk (2017) found that, in the case of meat purchasing, American consumers are willing to pay more money to have tastier meat than they are for healthier or even safer meat. This result is consistent with a study by Glanz et al. (1998) finding that US adults tend to place the highest value on the taste of food, followed by cost. In this same vein, Blaylock et al. (1999) write:

In the long run, taste considerations may simply prevail: habits and other forces may be too difficult to overcome. Similarly, the uncertain future benefits of better nutrition—you have to die of something—may outweigh the perceived potential benefits of healthy eating. Put differently, for many people healthy eating is just not worth the effort and sacrifice.... Convincing people of the long-run benefits of good nutrition is clearly made more difficult if immediate gratification is given a higher priority. (p. 275)

This assertion clearly coincides with common observation: for many American adults, there is considerable evidence of a tradeoff between the nutritional quality of a diet and its palatability. If pleasure overrules health, then such a consumer is unwilling to sacrifice taste for improving health – if, indeed, such a sacrifice became necessary – and it is, therefore, no surprise that the tendency of American adults is to value palatability over diet quality. Thus, the scholarly and scientific value of developing new methods of measuring something so important as palatability is without question.

1.3 Measuring Taste for Policy

Without such tools available to researchers, public health and nutrition policies are inevitably designed using only limited information thus far. Just as it is increasingly well known

that many consumers are more concerned with taste than nutrition, it also is increasingly evident that many individuals are perfectly aware that many foods are not healthy, but choose to eat them anyway (Stewart & Blisard, 2006; Binkley & Golub, 2011; Chen et al., 2012; Olstad et al., 2015). Hence, these individuals are not in need of still more nutrition information, and are therefore unlikely to respond to it. However, such consumers may respond to price adjustments. Special efforts may be needed to discourage consumption of highly palatable foods low in health value – since taste has been shown repeatedly to take priority in the absence of such policies. By the same token, special efforts may be needed to increase consumption of less palatable foods of superior nutritional value.

One could argue that analyses combining familiar nutritional quality measures with a palatability index may help determine which foods to emphasize to people who are otherwise unwilling to give up taste in order to eat better. That is, policy aimed at altering consumption patterns should emphasize foods that score relatively higher in both nutritional quality and tastiness. Tastier foods without the additional benefit of a healthier nutrient composition are candidates for consumption taxes to discourage excess intake, while healthy foods low in palatability could be subsidized using that newly generated tax revenue. Such policy intervention would be a much more widely-encompassing variant of the well-known sugar sweetened beverage (SSB) tax and subsequent pilot programs subsidizing fruit and vegetable (FV) purchases that are presently generating extensive discussion among economists.

Any public health and nutrition policies oriented towards a strategy like the above would require first tastiness and healthiness measures – but only the latter has been studied and developed very extensively (examples include Drewnowski & Fulgoni, 2008; Arsenault et al., 2012; Rayner, 2017), which leaves the issue of taste still largely unaddressed, and therefore any relevant policy research only partially informed. The study herein uses detailed individual nutrient intake data from the National Household And Nutrition Examination Survey (NHANES) in conjunction with questions from a survey of those same individuals regarding their preferences of grocery purchases to algorithmize a continuous numeric measure of food items' relative palatability. The methods are straightforward and well-known, the results are intuitive and consistent with the nutrition science literature, and the end product enables new avenues of research regarding food and health economic studies of US consumers.

2. METHODS

The end goal of the analysis is to produce a method for measuring food items' tastiness to better inform future work on recommendations about the consumption of foods and food groupings. As argued below, different nutrient compositions can at least to some degree describe taste, so it is reasonable to say that a nutrient profiling model is the optimal approach for achieving that goal. Nutrient profile modeling is a common, well established practice in public health and nutrition research (Quinio et al., 2007; Drewnowski & Fulgoni, 2008; Drewnowski et al., 2009; Hess et al., 2017; Rayner, 2017; Drewnowski, 2018). A simplified explanation of the process is for researchers to use individual-level dietary recommendations with respect to nutrient intake and food group consumption guidelines and translate them down to food items based on the nutrient contents of those foods. These nutrient-specific models also have been applied in recent consumer nutrition and health economic studies (Binkley, 2019; Binkley & Liu, 2019).

The first step in the analysis is to describe the degree to which the variation in nutrient intake for individuals relates to the variation in their stated preferences regarding taste and health. In order to do this, detailed nutrient intake data is required, as well as data on food related preferences and behavior for the same individuals. Once a link is established between consumed nutrients and preferences about relative palatability, that link can then be exploited – using differences in nutrient compositions between foods – to describe the taste value of individual food items.

2.1 *Data*

The data used in this study are from the National Health And Nutrition Examination Survey (NHANES) over the years 2007-2010. This survey, administered by the Centers for Disease Control and Prevention (CDC), collects dietary intake through 24-hour food recalls and nutrient intake data for individuals and includes sampling weights, stratification variables, and sampling units to ensure a representative sample of the US population. A sub-sample of individuals has two days of dietary intake data, to which the sample is restricted¹, along with excluding individuals under the age of 18, giving a remaining sample size of 9,329 adults (4,743 in 2007-2008, 4,856 in 2009-2010) and a total of 5,293 uniquely coded foods. The first day's

¹ Since the majority of individuals are observed for both days, an average pattern of dietary choice can better be represented than those with only one day's worth of data. While two observations per person is small, I know of no other data with such information as NHANES that would allow me to conduct this study in this way.

observation of food intake (more importantly, detailed nutrient intake) is recorded in an in-person interview, and the second via a follow-up telephone interview 4 to 11 days after the in-person interview.

Questionnaires in the 2007-2008 and 2009-2010 NHANES data include the following series of questions: “When you buy food from a grocery store or supermarket, how important is...?” (a) taste, and (b) nutrition, as well as several other characteristics of food. This study makes use specifically of these two questions in order to develop a numerical measure of taste. Each of these is scored on a Likert-type scale² ranging from “not at all important” to “very important”. While the nominal values of these variables are not useful (“very important” may not mean the same thing for two different respondents, since each choice is subject to perception), the difference of taste versus nutrition would speak to the degree of an individual’s relative value placed on food taste: the higher the value of this difference, the greater the prioritization of taste over nutrition. It is to be expected for different combinations of values from these two Likert items to associate with different patterns of individuals’ food choices. That is, eating behaviors are jointly related with “T” and “N”. Simple statistics of the three variables are displayed below in Table 1.

Table 1

Summary Statistics of Consumer Behavior Questionnaire Variables

	Min	Max	Mean	Standard Deviation
Importance of Taste (T)	1.00	4.00	3.74	0.52
Importance of Nutrition (N)	1.00	4.00	3.61	0.60
Difference (T-N)	-3.00	3.00	0.13	0.76

The distribution of possible values of the difference variable, “T-N”, is consistent with literature. That is, the average of the difference of the importance of taste and the importance of nutrition is significantly greater than 0 at an $\alpha = 1\%$ significance level³. One such study finding

² The original scale of these variables as they appeared in NHANES was reversed to make higher scores indicate more importance.

³ This is true for both 2007-2008 and 2009-2010 NHANES samples and for the two samples pooled. Of course, there is little reason to expect preferences to have changed much between the two periods.

evidence of this is Glanz et al. (1998) who found that Americans value food taste significantly more than their nutrition, indicating that these consumers may be particularly reluctant to sacrifice taste in order to achieve better diets (Verbeke, 2006). A similar conclusion appears in Malone & Lusk (2017). Furthermore, a two-sample t-test between individuals classified as obese have slightly greater values of this variable on average (albeit insignificant) – echoing the findings of Hill et al. (2016).

For example, an individual may score the importance of nutrition, “N”, as a 4 and importance of taste, “T”, also a 4. The difference, or relative value of taste, becomes 0 because that individual does not truly prioritize taste over nutrition – they are equally valued. On the other hand, an individual may state “T” = 2 and “N” = 1, making $T - N = 1$, though positive it is not particularly high, but they still prefer taste to nutrition and are, comparatively speaking, a taste-prioritizer. The maximum value of “3” therefore indicates that taste was given the highest possible ranking and nutrition was given the lowest possible ranking ($4 - 1 = 3$). Conversely, a minimum value of “-3” is the exact opposite: health prioritizing individuals who give little if any regard to palatability.

More broadly, any observation falling in the positive range would be an individual who prioritizes taste strictly over nutrition. What is interesting that we would expect patterns of food choice in this range to differ from those outside it. Such a comparison would not be feasible if we were to compare only on the taste importance, “T”, or nutrition importance, “N”, by themselves. Two individuals may place a high premium on tastiness, but have different beliefs regarding dietary quality. Or neither may value taste very much – but place the highest value on something like convenience – while having different beliefs regarding nutrition. In either case, looking at “T” and “N” jointly is required to say anything of value, hence the power of using their arithmetic difference, $T - N$. Figure 1 shows the distribution of the possible values of this variable.

Figure 1

Distribution of Importance of Taste relative to Importance of Nutrition ($T-N$)

It is clear both from Table 1 and from Figure 1 below that the majority of individuals fall into this broader category – nearly twice as many as those falling into the negative range.

Furthermore, it is reasonable to expect there to be some correlation between this taste prioritization variable and individuals' diet compositions. There are obvious factors such as sugar, sodium, and saturated fat content, which can help to signal palatability. The body of literature across disciplines suggesting a positive sign of the relationship between these and the outcome of interest, $T - N$, is quite large (Drewnowski, 1997; Mattes 1997, 2006; Glanz et al., 1998; Yeomans, 1998; Nayga et al., 1999; Griffioen-Roose et al., 2010; Allais et al., 2015; Réquillart et al., 2016). One study by Adelaja et al. (1997) found that individuals who indicated they were more concerned with how their food tastes tended to consume significantly more saturated fat in their diets. Similarly, some suggest that a reasonable proxy for palatability is calorie density in general (Drewnowski & Specter, 2004; Darmon et al., 2005; Drewnowski & Fulgoni, 2008; Binkley & Golub, 2011). Conversely, foods high in vitamins, minerals, and fiber tend to be considered less tasty by consumers – typically grains and whole grain products as well

as fresh fruits and vegetables (Drewnowski & Rock, 1995; Drewnowski, 1997; Glanz et al., 1998; Nayga, 1998; Nayga et al., 1999; Allais et al., 2015). More recently, a survey by Morning Consult revealed that among the top 10 words that US consumers claimed to make groceries less appealing, the words “sugar free” and “fat free” made the top 5 in the list (2018), which implies that because the absence of these nutrients is perceived as less tasty, their inclusion is perceived as more tasty. This is consistent with a similar conclusion reached previously by Nayga et al., (1999) examining demand for food groups. The authors found that, all else (socioeconomics, demographics, behaviors) being constant, there is a positive significant relationship between consumers’ stated importance of taste and their intake of high fat dairy, high fat meat, and sugar and sweets, as well as a negative significant relationship between that same variable and whole grain, fruit, and vegetable intake. A similar conclusion was found later by Aggarwal et al. (2016). Thus, it is to be expected for taste-prioritizing individuals to consume tastier diets, all other things being the same.

2.2 Model Selection

Borrowing from the nutrient profiling procedure in Arsenault et al. (2012)⁴, a model of this measurement of an individual’s stated preference for taste relative to nutrition is estimated on the subset of the NHANES data described above. The initial candidate nutrients are selected from the studies cited immediately above, which suggested priors for the signs of their relationships with taste prioritization. These nutrients are added sugars, sodium, saturated fat, dietary fiber, vitamin C, vitamin K, vitamin A, calcium, protein, caffeine, carbohydrates, poly- and monounsaturated fats, moisture, potassium, cholesterol, and natural sugars. The model for the i^{th} individual takes the form

$$y_i = \alpha_i + \mathbf{X}_i \beta_{ij} + \epsilon_i \quad (1)$$

where $y_i = (T - N)_i \in \{-3, -2, -1, 0, 1, 2, 3\}$ is the i^{th} individual’s stated importance of tastiness minus their stated importance of healthiness, and $\mathbf{X}_i$ is a matrix of the i^{th} individual’s intake of the selected nutrients $j = 1, 2, \dots, k$ across the two days recorded. The dependent variable, $T - N$, is used because the interest lies in modeling changes in relative taste prioritization, not absolute⁵.

⁴ The data-driven nutrient profiling model developed Arsenault et al. (2012) is the nutritional quality index used in the studies by Binkley (2019) and Binkley & Liu (2019).

⁵ This would equate to forcing $y = T$. Doing so would fail to capture both pieces of the concept if, indeed, different levels of T and N jointly associate with different nutrient intake patterns.

Because of the ordered discrete nature of the outcome, estimating Equation (1) with an ordered probit or logit model is a reasonable starting point. Beginning in this way ensures that the final product of a palatability index is founded on a consistent model in this first stage of the analysis. In addition to these ordinal models, stepwise selection for an Ordinary Least Squares (OLS) estimation of Equation (1) is also run and compared. The reasoning behind this is straightforward: in order to produce an index that successfully ranks the relative palatability of individual food items – of which there are 5,293 in the data – simply estimating probabilities that link changes in nutrient levels with 7 unique categorical associations is not very helpful. Indeed, foods of different nutrient compositions and therefore palatability may belong to the same category by pure virtue of which category's fitted probability was estimated to be the largest for either food. It should be noted that this limitation is avoided altogether in the context of a linear prediction. Thus, it is reasonable to compare the output and performance of OLS to that of the two ordinal models. If the performance of OLS is comparable, then constructing the palatability index is straightforward. If it is not, then the resulting marginal effects from the ordinal models may still be useful for descriptive purposes.

3. RESULTS

3.1 *Ordered Model Nutrient Weights*

Because some of the pre-selected explanatory nutrients in $\mathbf{X}_i$ from Equation (1) could matter more than others, and with the possibility that some excluded nutrients may be important predictors, the final combination of nutrients is chosen with stepwise regression, minimizing the Akaike Information Criterion (AIC)⁶. This is similar to the method used by Arsenault et al. (2012) who maximized the adjusted R^2 in their OLS regression to the point of minimal variation. Using the “step()” function in conjunction with the “polr()” function in the software R, the Maximum Likelihood Estimation (MLE) results of the ordered models for Equation (1) are shown in Table 2

Table 2

⁶ Backward and forward selection were also employed, for which the results differed very little, other than less desirable AIC values than for stepwise selection.

Ordered Logit/Probit MLE Results

Nutrient	Ordered Logit		Ordered Probit	
	<i>Estimated β</i>	<i>t-statistic</i>	<i>Estimated β</i>	<i>t-statistic</i>
Intercept{-3,-2}	-28.10	-6.54	-15.45	-6.73
Intercept{-2,-1}	-25.87	-6.03	-14.63	-6.38
Intercept{-1,0}	-23.75	-5.53	-13.62	-5.94
Intercept{0,1}	-20.73	-4.83	-11.82	-5.16
Intercept{1,2}	-18.26	-4.26	-10.55	-4.60
Intercept{2,3}	-16.68	-3.89	-9.92	-4.33
Added Sugars	13.49	6.12	6.69	5.45
Sodium	0.28	4.27	0.16	4.29
Saturated Fat	36.91	3.34	18.89	3.09
Moisture	-21.93	-5.09	-12.56	-5.46
Fiber	-34.90	-3.62	-17.48	-3.25
Vitamin C	-1.48	-1.60	-0.97	-1.89
Vitamin A	---	---	-0.08	-1.52
Vitamin K	-0.64	-2.35	-0.27	-1.67
Calcium	-0.34	-1.91	-0.18	-1.82
Monounsaturated Fat	-27.59	-2.54	-14.55	-2.41
Polyunsaturated Fat	-15.99	-1.92	-10.89	-2.38
Protein	-32.85	-6.77	-18.44	-7.05
Caffeine	1.77	4.29	1.00	4.40
Carbohydrates	-22.86	-5.01	-13.03	5.32
Choline	-0.78	-5.08	-0.36	-4.15
Magnesium	-2.68	-2.59	-1.57	-2.73
Natural Sugars	-6.54	-2.35	-2.88	-1.83

Note. The final Pseudo- R^2 is 0.07 for both models. The number of steps was 2 for probit, 3 for logit. A Brant (1990) Wald Test (detailed in Greene, 2012) for proportional odds fails to reject the null hypothesis of parallel regressions or a constant β across the response categories.

As expected, the results between the ordered probit and logit are very similar, the chief exception being the omission of Vitamin A in the logit model. The pseudo- R^2 is not remarkable, but defensible nonetheless – the reasoning for which is explained in more detail below. The marginal effects at the mean for both models are shown in the Appendix. In short, for both models, the marginals of added sugars, saturated fat, sodium, and caffeine are positive and significant for all three categories of $T > N$, but negative and significant for all categories of $T \leq N$. That is, the probability that an individual stated a strict preference for taste over nutrition in the survey significantly increases when that individual's intake of these four nutrients increases.

Conversely, those who prefer nutrition to taste consume significantly less of each of these nutrients. For $T > N$, all other nutrients' marginal effects are either negative or insignificant, and

the opposite is true for $T \leq N$. This robust and intuitive result implies that these nutrients may signal tastiness, as claimed by numerous studies cited in the previous section.

3.2 *OLS Nutrient Weights*

The next step in the analysis is to estimate a stepwise-selected OLS regression using the same starting conditions as for the probit and logit models, and compare the models' results. In this case, the interpretation of β_{ij} from Equation (1) is much more straightforward: it is the change in individual i 's prioritization of palatability over nutrition given a unit increase in their intake of nutrient j per 100g of total intake. The results of the OLS model are listed below in Table 3

Table 3*OLS Estimation Results*

Nutrient	Estimated β	t-statistic
Intercept	8.82	5.73
Added Sugars	4.43	5.39
Sodium	0.10	4.06
Saturated Fat	11.27	2.76
Moisture	-8.74	-5.66
Fiber	-11.28	-3.16
Vitamin C	-0.64	-1.89
Vitamin A	-0.06	-1.59
Vitamin K	-0.17	-1.54
Calcium	-0.12	-1.83
Monounsaturated Fat	-9.63	-2.39
Polyunsaturated Fat	-8.17	-2.68
Protein	-12.43	-7.10
Caffeine	0.67	4.43
Carbohydrates	-8.99	-5.47
Choline	-0.23	-3.92
Magnesium	-1.05	-2.76
Natural Sugars	-1.88	-1.79

Note. The final R^2 is 0.06, and the number of steps was 3.

Unsurprisingly, nutrients generally associated with taste-enhancement (e.g. sodium, saturated fat, and added sugars; all proxies for snacks, deserts, comfort food, etc.) are positively and significantly correlated with an individual increasingly valuing taste over nutrition. Moreover, nutrients whose abundance signals healthier foods like whole grains, fruits, and vegetables (e.g. fiber, vitamin K, magnesium) are negatively and significantly correlated with the dependent variable. While the R^2 is relatively low at 0.06, the degree of variation in the dependent variable itself is small, taking only the 7 possible values indicated in Figure 1. Moreover, R^2 values for models estimated on NHANES data are known to be as low as or even lower than that in Table 3 (Obisesan et al., 2012; Rothenberg & Korrick, 2014; Dhana, 2019; Eicher-Miller et al., 2020).

Diagnostically, the model results are very good. Nearly every parameter estimate is significant at the 10% level or better. The degree of multicollinearity is also low. The variance inflation factors (VIFs) are all below 10.0 except for moisture (inversely correlated with sodium at -81% and saturated fat at -75%), protein (positively correlated with sodium at 77%, negatively

with moisture at -77%), monounsaturated fat (positively correlated with polyunsaturated fat at 80% and saturated fat at 87%), and carbohydrates (positively correlated with added sugars at 59% and natural sugars at 73%). Furthermore, over half of the VIFs that are below 10.0 are between 1.0 and 5.0. The standardized or studentized residuals tend to be small, with only 5.20% exceeding 2.0 in absolute value. In other words, about 5% of the observations were influential enough to yield a studentized residual either less than -2.0 or greater than 2.0, close to the probability of a Type-1 error – the relative frequency expected as a result of pure chance.

3.3 Model Comparison

All three models generally agree. Regarding nutrient selection: given equivalent initial conditions, the stepwise procedure chose exactly the same nutrients except for Vitamin A, which was excluded from the logit model – and remained only weakly significant at the 15% level in the other two. In terms of sign and significance, marginal effects from OLS almost perfectly align with those of the logit and probit for all $T > N$ outcomes. The fit also is comparable for each model: $R^2 = 0.06$ for OLS and pseudo- $R^2 = 0.07$ for the logit and probit.

Finally, a reasonable point of comparison is the predictive power of the three models. There are 9,329 observations in the data, each with an outcome of some $y = T - N$. Table 4 shows the proportion of correctly predicted outcomes in the data for each of the three models, as well as a 2-proportion z-test between OLS and either of the ordinal models

Table 4

Comparing Predictions: OLS versus Ordered Logit, OLS versus Ordered Probit

Model	% of y-values Correctly Predicted	z-statistic
OLS	60.12%	---
Ordered Logit	60.15%	0.03
Ordered Probit	60.31%	0.25

Note. Statistical significance at the 10%, 5%, and 1% levels indicated by (*), (**), and (***). However, no differences were significant.

It is clear that the performance of OLS does not meaningfully differ from that of the ordered logit or probit, as far as predictive power is concerned (the probit appears to have only a modest advantage in prediction). Moreover, the models have comparable fit, comparable marginal effects at the mean, and virtually the same nutrients chosen in the stepwise selection procedure under equivalent conditions. Hence, it is reasonable to proceed with OLS.

3.4 Estimating Palatability

With these robust results, the next logical step is to utilize the parameter estimates from the first stage to compute an index to measure relative palatability. In the same fashion as Arsenault et al. (2012), the product $\mathbf{X}^* \hat{\beta}$ of the estimated $\hat{\beta}$ values previously shown in Table 3 and the matrix $\mathbf{X}^*$ of each food item's content of the nutrients listed in Table 3 calculates the weighted nutrient density of the food items contained in the data. That is, for palatability T_k of food item k is computed as

$$\begin{aligned}
 T_k = & 8.82 + 4.43(\text{added sugar}_k) + 0.10(\text{sodium}_k) + 11.27(\text{sat fat}_k) - 8.74(\text{moisture}_k) \\
 & - 0.64(\text{Vit. C}_k) - 0.06(\text{Vit. A}_k) - 0.17(\text{Vit. K}_k) - 0.12(\text{calcium}_k) \\
 & - 9.63(\text{M. unsat fat}_k) - 8.17(\text{P. unsat fat}_k) - 12.43(\text{protien}_k) \\
 & + 0.67(\text{caffeine}_k) - 8.99(\text{carbs}_k) - 0.23(\text{choline}_k) - 1.05(\text{magesium}_k) \\
 & - 1.88(\text{nat. sugar}_k)
 \end{aligned} \tag{2}$$

The key difference between this calculation and that shown in Arsenault et al. (2012) is that these estimated weights reflect changes in a consumer's stated preferences of taste versus nutrition. Hence the calculated index $\mathbf{X}^* \hat{\beta}$ from Equation (2) serves as a measure of the tastiness of each uniquely-coded food listed in the sample from NHANES 2007-2010. Table 5 shows some example foods at different levels of the tastiness index, and similarly for the nutritional quality score from Arsenault et al. (2012)

Table 5*Examples of Palatability & Nutritional Quality (foods listed in NHANES 2007-2010)*

Quantile	Examples of Nutritional Quality	Examples of Palatability
2 Std. Dev. Below Mean	--Cheesecake, --Sloppy Joe Sandwich, --Gumdrop Candy	--Bran Cereal, --Dandelion Green Salad, --Cooked Spinach
1 Std. Dev. Below Mean	--Chocolate Frozen Yogurt, --Salad Dressing, --Rice Cereal	--Carrot Juice, --Nonfat Plain Yogurt, --Raw Broccoli
Mean	--Lasagna w/Meat & Spinach, --Turkey & Vegetables w/Cheese, --Egg Omelet	--Egg Omelet, --Meatloaf, --Chicken Noodle Soup
1 Std. Dev. Above Mean	--Raw Avocado, --Bran Cereal, --Cooked Carrots	--Pecan Pie, --Chocolate Ice Cream, --Cheese Quesadilla
2 Std. Dev. Above Mean	--Cooked Broccoli, --Raw Tomato, --Citrus	--Smoked Sausage, --Chocolate Candy, --Beef Ribs

Note. The nutrient levels contained in X^* resulting in the above foods are from the NHANES 2007-2010 data. These are chosen from a set containing 5,293 unique foods items, each with its own combination of nutrient levels.

It is worth noting that some foods appearing in the “high-taste” space resemble, in one form or another, the foods in the “low-health” space, and vice versa. The values of the indices have no meaningful units and are not displayed, although higher values of either index signal tastier or healthier foods. The set of foods scoring high in both nutritional quality and palatability is rather sparse. Some examples include cooked mushrooms, milk, cheese, eggs, okra, several dishes containing poultry, beans, some fruits, a few mixed seafood dishes, and a number of Hispanic dishes. Foods measured as neither tasty nor healthy include canned seaweed in soy sauce, frozen unsweetened rhubarb, and candied sweet potatoes.

The two indices are negatively correlated at -0.41, which is reasonable to expect given the examples in Table 5, and is consistent with findings by previous studies (Drewnowski et al., 2009; Lusk & Briggeman, 2009). An example plot visualizing the tension between these two measures is shown in Figure 2

Figure 2

Scatterplot of Tastiness vs. Healthiness, with Illustrative Quadrants (z-score base; top and bottom 1% of data omitted for easier display)

For a lengthier list of specific food items and their tastiness and healthiness z-scores, see Table A3 in the Appendix.

Concerning foods that measure very high in taste but poor in nutritional quality, the examples provided in Table 5 offer a good starting point. The same is true in the broader sense: high-fat meats, processed and organ meats, desserts, pastries, soft drinks, and candy all offer little to no nutritional benefit, yet score well on the taste index⁷. Similarly, foods in the left tail of this same distribution all tend towards a sense of unappealing taste, but offer desirable (in terms of health) nutrient compositions, such as various greens, whole grains and grain products, kale, spinach, fat free dairy, raw nuts and seeds, and pulses. Similar findings hold for the tails of the distribution of the healthiness measure. While in the anecdotal sense, the example foods either in Table 5 or in the Appendix of extreme healthiness or tastiness certainly coincide with expectations (the also coincide with the literature), and more importantly, the relative scores seem intuitive.

⁷ This further evidence is expected. For example, an individual may enjoy the taste of raw cauliflower, but it is difficult to argue that a person ate a slice of pecan pie because they thought it was healthy.

An important note to make is that analyses using the tastiness values of foods should not focus entirely on the specific scores of the food items, but more on how they compare. That is, the reader should place more onus on the relative values than absolute. For instance, looking again to Table 5, smoked sausage scores higher in palatability than cooked spinach (it lies “further to the right” on the tastiness scale), but lower in nutritional value (it lies “further to the left” on the healthiness scale). Similarly, a carbonated citrus-flavored drink may or may not be tastier than chocolate cake or beer to an individual, but such a pedantic argument is not interesting; what is interesting is that the carbonated citrus-flavored drink’s taste value is indisputable when compared with raw broccoli or bran cereal – as well as its health value or lack thereof.

4. DISCUSSION

4.1 *Concluding Observations*

The first-stage models finding the associated weights for each nutrient were of acceptable and even expected fit, given the noise in the data. As a plus, nearly every slope estimate was significant at the 10% level or better, and there was very little evidence of influential observations or of multicollinearity between the nutrients selected in the stepwise procedure. Furthermore, beginning the selection procedure in the first stage of the analysis using the appropriate ordinal models did not change the sign or significance of any one of the average marginal effects (see Tables A1 and A2 in the Appendix). This allowed for the use of OLS to compute a tangible measure of taste to analyze and describe. The outcome of this computed index seemed realistic in light of prior expectations. It is reasonable to expect that palatability and nutritional quality are negatively correlated (Raghunathan et al., 2006; Drewnowski et al., 2009; Noel & Dando, 2015). This holds up empirically: the nutritional quality score developed by Arsenault et al. (2012) and the palatability score developed here are, indeed, negatively correlated at -0.41. Put differently, many foods in the right tail of the distribution of one variable were found in the left tail of the other variable’s distribution, as illustrated by Table 5. Example values of the z-scores for each of these measures can be found in Table A3 of the Appendix for a sampling of food items in the data.

The relative palatability measure developed in this study is the first of its kind to the author’s present knowledge, and undoubtedly leaves room for improvement. But it does appear

to capture reasonable forms of palatability, at least in a general sense (Drewnowski, 1997; Mattes 1997, 2006; Yeomans, 1998; Nayga et al., 1999; Chen et al., 2012). Further value of this procedure is its speed and low cost. There is much work surveying individuals about their tastes and preferences with regards to food groups, or occasionally food items (Lusk, 2011; Jo et al., 2016; de Bruijn et al., 2017; Monteleone et al., 2017; Jo & Lusk, 2018). The limitations to that approach are obvious: surveys are very costly, they take a long time to complete (much less process, analyze, and publish findings), they often end up with mediocre sample sizes, have yet to provide any discernable quantification of tastiness – usually an averaged ranking system of a small, arbitrarily handpicked list of foods or food groups – and like any other such study of individuals’ tastes and preferences, require periodic updating. Computing a simple linear combination of nutrient intakes from publicly available data is not only fast and cheap, it is easy to update whenever a researcher desires (conditional on data availability). Relative to consumer surveys⁸, the palatability index is more sustainable, feasible, and cost effective.

4.2 *Policy Implications*

Previous work has confirmed or elaborated either on the more granular concepts of palatability and nutrient composition, or on general diet composition and nutrient intake questions (Liem & De Graaf, 2004; Ren et al., 2010; Degliare et al., 2012; van Dongen et al., 2012; van Langeveld et al., 2017), although some studies were able to offer descriptive statistics and correlations between individual foods and very general taste sensations such as sweetness, saltiness, and bitterness (Cox et al., 2016; Cornelis et al., 2017). There also is much work surveying individuals about their tastes and preferences with regards to food groups, or occasionally food items (Lusk, 2011; Jo et al., 2016; de Bruijn et al., 2017; Monteleone et al., 2017; Jo & Lusk, 2018). There remains, however, a shortfall in the resources needed for more complete analyses in the design of future health policies.

The chief contribution of this study is its pioneering a method to obtain a numerical measure of relative palatability for specific food items. This procedure clears new paths of food and nutrition policy research: the lack of such a measure up to present is a longstanding gap in food and nutrition research. Indeed, providing insight and policy recommendations about what

⁸ The same argument goes for other time-consuming, costly, and small sample methods such as lab experiments and taste testing studies.

people should be encouraged to eat is only part of the issue. It also matters a great deal that researchers gain a clearer understanding of people's willingness to eat the foods recommended.

Generally speaking, to the average American consumer, there is clear a tension between the healthiness and tastiness of foods (Berning et al., 2010). Moreover, it is reasonable to say this tension is a primary factor in the widespread dietary deficiency in US consumers' behavior (Blaylock et al., 1999; Binkley & Golub, 2011; Chen et al., 2012; Fisher, 2018). This deficiency does not appear to have responded to the growing mass of nutrition information, at least not at an adequately swift rate (Stewart & Blisard, 2006; Olstad et al., 2015). Hence, other efforts besides providing more information are necessary to curb consumption patterns. One possibility mentioned in the introduction is price adjustments. It is clear that foods can be identified on a basis of tastiness and healthiness, two of the most important food attributes to consumers (Lusk & Briggeman, 2009; Arsenault et al., 2012; Jo et al., 2016).

The new capability of food analysis offered herein facilitates and guides any needed price adjustments, and enhances related policy work overall. For example, individuals consuming more highly palatable foods with little to no nutritional value, and fewer healthy foods of reduced palatability could, perhaps, be induced to change their present pattern of consumption for the better. An immediately tangible example is the case of sugar-sweetened beverages (SSB) and fruits and vegetables (FV). As seen in Table A3 in the Appendix, the currently most recognized candidate for consumption taxes, SSB, scores very low on the nutrition index and around the mean on the tastiness index. The opposite is true for FV. But a tax-subsidy effort need not be so narrow in its scope (Nordström & Thunström, 2009): a tax could reduce the presently high consumption levels of multiple tasty foods of inferior health value⁹. In turn, the revenue from that tax can, in one instance, be reallocated as a subsidy to encourage consumption of multiple healthy foods which do not score well on the tastiness scale.

A very recent example of studying this idea of combining consumption taxes and subsidies – though it is constrained only to the scope of SSB and FV – comes from Valizadeh & Ng (2021). The authors find that, conditional on the pass-through rates from SSB to FV and relevant subsidy rates, it is possible for the FV subsidies to offset the SSB taxes. This is consistent with some prior work finding that when the FV subsidies along with SSB restrictions

⁹ The use of nutrient profiling models for the purpose of proposing consumption taxes is not new. For two fairly recent examples, see Mendoza et al. (2017) and Rayner (2017).

or taxes were targeted towards SNAP-enrolled households, the average dietary quality of those households improved (French et al., 2017; Mozaffarian et al., 2018; Lacko et al., 2019). However, this type of policy intervention comes with its share of underlying assumptions and nuances (Epstein et al., 2015; Cremer et al., 2016; Lin et al., 2017; Cawley et al., 2019; Xiang et al., 2020).

A clear benefit of developing and introducing a palatability index into the conversation is that consumption taxes on unhealthy foods (nearly always restricted to SSB in recent work) can be expanded much more broadly as a direct result, even optimized. As a result of this expansion, the impact of any potential healthy food subsidies may grow as well.

4.3 *Present Limitations and Opportunities for Future Work*

Since this study is, under present knowledge, the first attempt to quantify relative palatability for specific food items, the procedure in its current form undoubtedly leaves room for improvement. For instance, the effect and role of unobservable variables is not clear. There is some work using dietary recall data and finding the role of socioeconomic and demographic variables to be important in a Marshallian demand framework when evaluating the impact of the importance of taste (and separately, nutrition) on the quantity demanded for multiple food groups (Nayga et al., 1998; 1999). While including more variables could enhance the R^2 of the model, their inclusion arguably creates more complexity than it does value. For one, not all potential lurking variables can be accounted for in the NHANES data, and the resulting measures of palatability must be assumed to average out resulting shifts in the distribution of the dependent variable, $y = T - N$. For another, developing a conditional tastiness index by controlling for something like race or household size does not adequately address the gap in the literature detailed at the outset of this paper¹⁰. Indeed, evaluating the effect of, say, household size would better be carried out first by estimating a separate household size equation to examine differences in nutrient intake levels. Not only is it difficult to say why that would be interesting, but it is perhaps a case of over controlling: the association of sugar intake and taste prioritization should already include any effect of differences in household size. In other words, this would undoubtedly dilute the effects of interest. Separating the effects of the socioeconomic and

¹⁰ For example, consider the association between either age or impulsive tendencies and taste prioritization. This is already studied (see Feeny et al., 2011; Giesen et al., 2012) and offers no progress in developing a way to measure palatability – the goal of the work herein.

demographic variables contained in NHANES through estimating multiple equations adds questionable value at best, at least in the context of this study.

Another area of potential improvement is the final selection of nutrients. The selection of which nutrients best predict US consumers' taste prioritization was carried out with stepwise regression. The stepwise procedure is accessible, understandable, requires little computing power, and is included in most standard statistical software. Moreover, it is familiar and has been utilized repeatedly by applied economists. But the palatability formula offered herein, being the first of its kind, stands to benefit from further development on the computational and algorithmic front. For instance, modern machine learning methods may be of some value in developing a better-fitting combination of nutrients, as well as in the evaluation of any nonlinear and interacting terms. These are empirical and technical questions suited for further study.

There are two obvious opportunities for future work regarding the application of the taste measure. The first is evaluating the present palatability formula in the context of other nutrient-specific data, even data from more recent years than those used to estimate the parameter values herein. Examining the tastiness values of sample foods and comparing them to findings from existing surveys – academic or otherwise – asking people to rank their food choices based on taste undoubtedly has value. A corollary question would be to empirically test the assumptions of the tastiness index against micro-studies within and between households. The second branch of future study would be to revisit some of the work evaluating SSB taxes and their interaction with FV subsidies, but in a better-informed light of having measures for palatability at the disposal of the researchers. For instance, a study or series of studies could propose and evaluate the impacts of imposing consumption taxes on multiple tasty and unhealthy foods other than SSB alone and using that augmented tax revenue for targeted FV subsidies.

It is also worth noting that speaking to the association between the cost of food in general and its healthiness and tastiness (e.g. examining the implications from Binkley & Golub, 2011; Chen et al., 2012) is beyond the scope of this work. However, any initial analyses of designing special efforts meant to shape dietary behavior are now more feasible in light of the ability to measure palatability. But one thing remains clear: with the ability to design better health and nutrition policy comes improved public health, an indisputably desirable outcome.

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Appendix

Table A1

Marginal Effects for Ordered Logit (t-statistics listed in parentheses below)

Nutrient	Marginal Effect						
	$y = -3$	$y = -2$	$y = -1$	$y = 0$	$y = 1$	$y = 2$	$y = 3$
Added Sugars	-0.03*** (-3.63)	-0.20*** (-5.59)	-1.28*** (-6.09)	-1.01*** (-5.82)	2.16*** (6.10)	0.28*** (5.75)	0.08*** (4.87)
Sodium	-0.00*** (-3.11)	0.00*** (-4.08)	-0.03*** (-4.26)	-0.02*** (-4.17)	0.04*** (4.27)	0.01*** (4.14)	0.00*** (3.77)
Saturated Fat	-0.07*** (-2.68)	-0.56*** (-3.24)	-3.50*** (-3.33)	-2.76*** (-3.29)	5.91*** (3.34)	0.77*** (3.27)	0.21*** (3.08)
Moisture	0.04*** (3.38)	0.33*** (4.77)	2.08*** (5.08)	1.64*** (4.91)	-3.51*** (-5.08)	-0.46*** (-4.87)	-0.13*** (-4.30)
Fiber	0.07*** (2.82)	0.53*** (3.50)	3.31*** (3.61)	2.61*** (3.55)	-5.59*** (-3.61)	-0.73*** (-3.53)	-0.20*** (-3.29)
Vitamin C	0.00 (1.51)	0.02 (1.59)	0.14 (1.60)	0.11 (1.60)	-0.24 (-1.61)	-0.03 (-1.59)	-0.01 (-1.57)
Vitamin K	0.00** (2.08)	0.01** (2.31)	0.06** (2.34)	0.05** (2.33)	-0.10** (-2.34)	-0.01** (-2.32)	0.00** (-2.25)
Calcium	0.00* (1.76)	0.01* (1.89)	0.03* (1.91)	0.03* (1.90)	-0.05* (-1.91)	-0.01* (-1.90)	0.00* (-1.86)
Monounsaturated Fat	0.05** (2.22)	0.42** (2.50)	2.62** (2.54)	2.07** (2.52)	-4.42** (-2.54)	-0.57** (-2.51)	-0.16** (-2.42)
Polyunsaturated Fat	0.03* (1.77)	0.24* (1.90)	1.52* (1.92)	1.20* (1.91)	-2.56* (-1.92)	-0.33* (-1.91)	-0.09* (-1.87)
Protein	0.06*** (3.76)	0.50*** (6.06)	3.12*** (6.73)	2.46*** (6.38)	-5.26*** (-6.74)	-0.68*** (-6.26)	-0.19*** (-5.18)
Caffeine	-0.00*** (-3.11)	-0.03*** (-4.10)	-0.17*** (-4.28)	-0.13*** (-4.19)	0.28*** (4.29)	0.04*** (4.16)	0.01*** (3.79)
Carbohydrates	0.04*** (3.35)	0.35*** (4.70)	2.17*** (4.99)	1.71*** (4.84)	-3.66*** (-5.00)	-0.48*** (-4.79)	-0.13*** (-4.25)
Choline	0.02*** (3.38)	0.01*** (4.76)	0.07*** (5.06)	0.06*** (4.91)	-0.12*** (-5.07)	-0.02*** (-4.86)	0.00*** (-4.29)
Magnesium	0.01** (2.25)	0.04** (2.55)	0.25** (2.59)	0.20** (2.57)	-0.43** (-2.59)	-0.06** (-2.56)	-0.02** (-2.46)
Natural Sugars	0.01** (2.08)	0.10** (2.31)	0.62** (2.34)	0.49** (2.33)	-1.05** (-2.35)	-0.14** (-2.32)	-0.04** (-2.25)

Note. The final Pseudo- R^2 is 0.07, and the number of selection steps was 3. Statistical significance at the 10%, 5%, and 1% levels indicated by (*), (**), and (***).

Table A2*Marginal Effects for Ordered Probit (t-statistics listed in parentheses below)*

Nutrient	Marginal Effect						
	$y = -3$	$y = -2$	$y = -1$	$y = 0$	$y = 1$	$y = 2$	$y = 3$
Added Sugars	-0.03*** (-3.55)	-0.24*** (-3.10)	-1.15*** (-5.42)	-0.70*** (-5.22)	1.73*** (5.42)	0.30*** (5.21)	0.10*** (4.61)
Sodium	0.00*** (-3.18)	-0.01*** (-4.13)	-0.03*** (-4.28)	-0.02*** (-4.18)	0.04*** (4.29)	0.01*** (4.17)	0.00*** (3.82)
Saturated Fat	-0.10** (-2.59)	-0.69*** (-3.03)	-3.24*** (-3.09)	-1.97*** (-3.05)	4.88*** (3.09)	0.85*** (3.04)	0.27*** (2.90)
Moisture	0.07*** (3.56)	0.46*** (5.11)	2.16*** (5.43)	1.31*** (5.24)	-3.24*** (-5.43)	-0.57*** (-5.21)	-0.18*** (-4.64)
Fiber	0.09** (2.68)	0.64*** (3.17)	3.00*** (3.24)	1.82*** (3.20)	-4.51*** (-3.25)	-0.79*** (-3.20)	-0.25*** (-3.04)
Vitamin C	0.01* (1.76)	0.04* (1.88)	0.17* (1.89)	0.10* (1.88)	-0.25* (-1.89)	-0.04* (-1.88)	-0.01* (-1.85)
Vitamin A	0.00 (1.45)	0.00 (1.51)	0.01 (1.52)	0.01 (1.51)	-0.02 (-1.52)	0.00 (-1.51)	0.00 (-1.49)
Vitamin K	0.00 (1.57)	0.01 (1.66)	0.05* (1.67)	0.03 (1.67)	-0.07* (-1.67)	-0.01 (-1.66)	0.00 (-1.64)
Calcium	0.00* (1.70)	0.01* (1.80)	0.03* (1.81)	0.02* (1.81)	-0.05* (-1.82)	-0.01* (-1.81)	0.00* (-1.78)
Monounsaturated Fat	0.08** (2.15)	0.53** (2.38)	2.50** (2.41)	1.52** (2.39)	-3.76** (-2.41)	-0.66** (-2.39)	-0.21** (-2.32)
Polyunsaturated Fat	0.06** (2.12)	0.40** (2.35)	1.87** (2.38)	1.14** (2.36)	-2.81** (-2.38)	-0.49** (-2.36)	-0.15** (-2.31)
Protein	0.10*** (3.91)	0.67*** (6.36)	3.16*** (6.98)	1.92*** (6.59)	-4.76*** (-7.00)	-0.83*** (-6.55)	-0.26*** (-5.48)
Caffeine	-0.01*** (-3.23)	-0.04*** (-4.22)	-0.17*** (-4.38)	-0.10*** (-4.28)	0.26*** (4.39)	0.05*** (4.27)	0.01*** (3.91)
Carbohydrates	0.07*** (3.52)	0.47*** (4.99)	2.24*** (5.29)	1.36*** (5.11)	-3.36*** (-5.29)	-0.59*** (-5.09)	-0.18*** (-4.55)
Choline	0.00*** (3.12)	0.01*** (3.99)	0.06*** (4.14)	0.04*** (4.05)	-0.09*** (-4.14)	-0.02*** (-4.04)	-0.01*** (-3.72)
Magnesium	0.01** (2.37)	0.06** (2.69)	0.27** (2.73)	0.16** (2.70)	-0.40** (-2.73)	-0.07** (-2.70)	-0.02** (-2.60)
Natural Sugars	0.02* (1.71)	0.10* (1.82)	0.50* (1.83)	0.30* (1.83)	-0.74* (-1.83)	-0.13* (-1.82)	-0.04* (-1.79)

Note. The final Pseudo- R^2 is 0.07, and the number of selection steps was 2. Statistical significance at the 10%, 5%, and 1% levels indicated by (*), (**), and (***).

Table A3

Example Foods with Healthiness Index z-scores (nutrient profiling model from Arsenault et al., 2012) and Tastiness Index z-scores.

Food	<i>Nutritional Quality</i>	<i>Relative Palatability</i>
Almonds, unroasted	0.91	-3.23
Apple, raw	0.79	-0.67
Asparagus, cooked, from canned, fat not added in cooking	1.41	-0.37
Asparagus, raw	2.55	0.43
Baby Ruth	-0.85	2.65
Bacon cheeseburger, 1/4 lb. meat, with mayonnaise or salad dressing and tomatoes, on bun	-0.61	0.65
Beans, string, green, raw	2.09	-0.71
Beef curry	0.21	0.03
Beef stroganoff soup, chunky style	-0.47	0.08
Blackberries, raw	2.70	-0.91
Bologna, beef	-0.61	2.32
Brussels sprouts, cooked, from fresh, fat not added in cooking	2.46	-0.92
Broccoli, raw	3.88	-0.99
Butterscotch hard candy	-0.65	3.00
Cake, chocolate, devil's food, or fudge, pudding-type mix (oil, eggs, and water added to dry mix), with icing, coating, or filling	-1.33	1.26
Cake, yellow, standard-type mix (eggs and water added to dry mix), with icing	-1.67	0.92
Carbonated citrus juice drink	-3.95	-0.40

Carbonated non-citrus juice drink	-7.02	-0.21
Carrot juice	0.48	-0.96
Carrots, raw	1.26	-0.37
Cauliflower, raw	3.17	-0.41
Chalupa with beef, cheese, lettuce, tomato and sour cream	-0.10	0.33
Cheerios	0.56	-2.35
Cheese spread, cream cheese, regular	-1.15	2.98
Cheesecake, chocolate	-0.90	1.60
Chewing gum, sugared	-0.23	2.82
Chewing gum, sugarless	0.00	1.70
Chicken and vegetable entree with noodles and cream sauce (frozen meal)	0.17	-0.52
Chicken fricassee, Puerto Rican style (Fricase de pollo)	0.13	0.09
Churros	-0.35	1.48
Cocoa Puffs	-0.34	0.93
Coconut candy, chocolate covered	-1.27	4.21
Coleslaw	0.01	2.59
Collards, cooked, from canned, fat not added in cooking	2.58	-1.34
Cookie, chocolate chip	-0.70	2.42
Croissant, chocolate	-0.55	1.70
Double bacon cheeseburger (2 patties, 1/4 lb meat each), with mayonnaise or salad dressing and tomatoes, on bun	-0.46	0.69
Doughnut, cake type, chocolate covered	-0.77	2.18

Eggplant, raw	2.83	0.02
Energy drink	-6.68	0.17
Flounder, baked or broiled w/o fat	0.26	-0.38
Frankfurter or hot dog, beef	-0.59	2.25
Fudge, caramel and nut, chocolate-coated candy	-0.85	2.46
Garlic, cooked	0.54	2.53
Granola bar, high fiber, coated with non-chocolate yogurt coating	0.30	-1.46
Granola bar, with coconut, chocolate-coated	-0.82	3.20
Grapefruit, raw	1.52	-0.71
Green or yellow split peas, dry, cooked, fat not added in cooking	1.24	-1.20
Greens, cooked, from fresh, fat added in cooking w/ vegetable oil, no further details	1.62	-1.43
Greens, cooked, from fresh, fat not added in cooking	3.19	-1.57
Ham on biscuit	-0.69	1.90
Honeydew melon, raw	0.73	-0.49
Ice cream bar or stick, rich ice cream, thick chocolate covering	-0.98	1.62
Imitation cheese, American or cheddar type	-0.56	1.36
Italian sausage	-0.36	1.61
Puffed cereal (Kashi)	0.41	-2.10
Kit Kat	-0.87	3.23
Kiwi fruit, raw	2.21	-1.19
Kumquat, raw	2.25	-1.07

Lentils, dry, cooked, fat not added in cooking	1.25	-1.27
Lettuce, Boston, raw	2.43	-0.55
Licorice	-1.36	2.43
Lobster creole, Puerto Rican style (Langosta a la criolla)	0.22	-0.15
Long Island iced tea	-4.00	0.62
Luncheon meat, no further details	-0.54	2.43
M&M's Peanut Chocolate Candies	-0.49	1.61
M&M's Plain Chocolate Candies	-1.00	2.95
Macadamia nuts, unroasted	0.43	-0.22
Macaroni, creamed, with cheese w/butter, no further details	-0.29	0.24
Margarita	-1.26	1.82
Marinated fish (Ceviche)	0.74	-0.74
Marshmallow	-1.58	2.94
Meat pie, Puerto Rican style (Pastelon de carne)	-0.34	1.97
Milk chocolate candy, plain	-0.72	3.03
Milk, cow's, fluid, skim or nonfat, 0.5% or less butterfat	0.64	-0.49
Milk, cow's, fluid, whole	-0.21	-0.14
Milky Way Bar	-1.26	3.23
Mixed salad greens, raw	3.15	-0.99
Mung beans, fat not added in cooking	0.84	-1.05
Mushrooms, raw	1.30	0.16

Naan, Indian flatbread	-0.34	0.51
Noodle soup, made with milk	-0.07	-0.26
Oat bran cereal, cooked, fat not added in cooking	1.20	-0.65
Oat cereal, no further details	0.38	-1.72
Octopus, steamed	0.17	-0.44
Okra, cooked, from fresh, fat not added in cooking	2.78	-0.78
Orange juice, no further details	0.84	-0.71
Parsley, cooked (assume fat not added in cooking)	4.46	-3.14
Pasta with carbonara sauce	-0.18	-0.03
Peanuts, yogurt covered	-0.31	1.56
Pear, dried, uncooked	0.45	-2.25
Pear, Japanese, raw	1.51	-0.75
Peas and carrots, cooked, from fresh, fat not added in cooking	1.23	-0.70
Peas, green, raw	1.69	-1.34
Pecans	0.72	-0.59
Pepperoni	-0.48	3.36
Peppers, green, cooked, fat added in cooking w/vegetable shortening	1.39	-0.01
Pie, coconut cream	-1.74	1.36
Pig in a blanket (frankfurter or hot dog wrapped in dough)	-0.34	1.51
Pina Colada	-2.36	0.70
Pina Colada, nonalcoholic	-3.13	0.02

Pineapple, dried	0.61	-2.36
Pineapple, raw	1.26	-0.79
Pizza with meat and vegetables, thin crust	-0.15	0.48
Polish sausage	-0.40	1.67
Popcorn, popped in oil, lowfat, low sodium	0.49	-1.53
Popcorn, sugar syrup or caramel-coated	-0.69	1.19
Pork and beef sausage	-0.39	2.24
Pork bacon, smoked or cured, cooked	-0.36	3.19
Pork bacon, smoked or cured, lower sodium	-0.18	2.88
Pork chop, battered, fried	0.00	0.04
Puffed wheat cereal	0.52	2.00
Quesadilla with meat and cheese	-0.24	0.72
Raisin Bran, Total	0.90	-2.56
Raspberries, red, raw	2.69	-0.90
Reese's Pieces	-0.75	4.37
Rice-vegetable medley w/o fat	0.02	-0.02
Rice and potato soup, Puerto Rican style	-0.12	-0.09
Rice Krispies Treats Cereal (Kellogg's)	-0.45	0.71
Rice with chicken, Puerto Rican style (Arroz con Pollo)	-0.07	0.27
Roast beef sandwich with cheese	-0.39	0.82
Roll, sweet, cinnamon bun, frosted	-0.91	1.58

Roll, white, soft, toasted	-0.43	0.35
Roll, whole wheat, 100%	0.39	-1.11
Salami, dry or hard	-0.49	2.59
Salisbury steak with gravy, whipped potatoes, vegetable, dessert (frozen meal)	-0.45	0.21
Salmon, steamed or poached	0.43	-0.78
Salsa, red, cooked, homemade	0.30	0.35
Sausage on biscuit	-0.30	1.30
Scone, with fruit	-0.09	0.13
Seafood paella, Puerto Rican style (Paella a la marinera)	0.22	-0.45
Shredded wheat, plain (Includes: Shredded Wheat, 100%)	0.65	-2.58
Shrimp-egg patty (Torta de Cameron seco)	0.11	-0.11
Shrimp and vegetables (including carrots, broccoli, and/or dark-green leafy (no potatoes)), soy-based sauce (mixture)	0.49	-0.60
Shrimp, no further details	0.35	0.11
Shrimp, floured, breaded, or battered, fried w/vegetable oil, no further details	0.06	0.32
Snickers Bar	-0.64	2.19
Snowpeas (pea pod), raw	2.52	-0.80
Soft drink, fruit-flavored, caffeine free	-8.36	-0.09
Soft taco with beef, cheese, and lettuce	-0.11	0.23
Sopa de Fideo Aguada, Mexican style noodle soup	0.15	-0.28
Spaghetti sauce with meat, canned, no extra meat added	-0.56	0.09
Spinach, raw	3.40	-1.56

Spinach, cooked, from frozen, with cheese sauce	0.44	-0.86
Stewed, seasoned, ground beef with potatoes, Mexican style (Picadillo de carne de rez con papas)	-0.07	0.01
Strawberries, raw	2.71	-0.77
Sweet and sour chicken or turkey	-0.31	-0.16
Taco or tostada salad with beef and cheese, corn chips	0.04	-0.11
Tamale with chicken	-0.06	0.03
Toffee, plain	-0.72	2.00
Tomatoes, cooked	1.18	-0.15
Trout, baked or broiled w/o fat	0.31	-0.70
Turkey sandwich, with spread	-0.17	-0.51
Turkey, no further details	0.36	0.03
Turkey, wing, cooked	0.19	-0.01
Twix Cookie Bars	-1.03	3.55
Vegetable beef soup, canned, undiluted	-0.25	0.04
Vegetable soup, home recipe	0.21	-0.25
Vegetarian stew	0.42	-1.34
Whipped topping, dairy based, fat free, pressurized container	-0.25	1.79
White potato, baked, peel eaten, no details as to fat added in cooking	0.15	0.10
White potato, stuffed, baked, peel not eaten, stuffed with sour cream	-0.45	0.23
Zucchini with tomato sauce, cooked, fat not added in cooking	0.46	-0.28

Note. Total count of example foods is 163. Indices are standardized to z-scores, magnitudes should be interpreted as standard deviations away from the base of 0.00.

Figure A1. Locally-linear smoothed plot of fitted probabilities from ordered logit model for the aggregated case, $T < N$. Shaded areas depict bootstrapped 95% confidence intervals.

Figure A2. Locally-linear smoothed plot of fitted probabilities from ordered logit model for the aggregated case, $T > N$. Shaded areas depict bootstrapped 95% confidence intervals.

Figure A3. Locally-linear smoothed plot of fitted probabilities from ordered logit model (marginal effect of dietary fiber intake) for three aggregated cases, $T < N$ (“prefers health”), $T > N$ (“prefers taste”), and $T = N$ (“prefers neither”). Shaded areas depict bootstrapped 95% confidence intervals.

Figure A4. Locally-linear smoothed plot of fitted probabilities from ordered logit model (marginal effect of magnesium intake) for three aggregated cases, $T < N$ (“prefers health”), $T > N$ (“prefers taste”), and $T = N$ (“prefers neither”). Shaded areas depict bootstrapped 95% confidence intervals.

Figure A5. Locally-linear smoothed plot of fitted probabilities from ordered logit model (marginal effect of saturated fat intake) for three aggregated cases, $T < N$ (“prefers health”), $T > N$ (“prefers taste”), and $T = N$ (“prefers neither”). Shaded areas depict bootstrapped 95% confidence intervals.

Figure A6. Locally-linear smoothed plot of fitted probabilities from ordered logit model (marginal effect of added sugar intake) for three aggregated cases, $T < N$ (“prefers health”), $T > N$ (“prefers taste”), and $T = N$ (“prefers neither”). Shaded areas depict bootstrapped 95% confidence intervals.