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Abstract

Widespread obesity in the U.S. is a relatively recent phenomenon, reaching epidemic proportions only in the last 15 years. However, existing research shows that while calorie expenditure through physical activity has not changed appreciably since 1980, calorie consumption has risen dramatically. Consequently, any explanation of obesity must address the reason why consumers tend to overeat in spite of somewhat obvious future health implications. This study tests for an addiction to food nutrients as a potential explanation for the obesity epidemic. Specifically, we use a random coefficients (mixed) logit model applied to household scanner data to test a multi-variate version of the rational addiction model of Becker and Murphy and Chaloupka. We find evidence of a rational addiction to all nutrients – protein, fat and carbohydrates – as well as to sodium, but particularly strong evidence of a forward-looking addiction to carbohydrates. The implication of this finding is that price-based policies – sin taxes or produce subsidies that change the expected future costs and benefits of consuming carbohydrate-intensive foods – may be effective in controlling excessive nutrient intake.

Keywords: addiction, demand, mixed logit, nutrients, obesity.

JEL Codes: D120, I120, C230

Obesity and Nutrient Consumption: A Rational Addiction?

Introduction

The Surgeon General estimates the annual direct and indirect costs of obesity at approximately

$117 billion. Clearly, the search for an appropriate public policy response has gone beyond a

public health interest to a national economic imperative. Existing research on the economic

causes of the national "obesity epidemic" cite technological changes that have reduced the price

of food at the same time that burning food, or expending calories through either work or leisure

activities, has become more expensive (Lackdawalla and Philipson; Philipson and Posner;

Philipson), the proliferation of convenient meal solutions through fast food restaurants, the

effectiveness of anti-smoking campaigns, greater labor market participation and engagement in

low wage jobs and lower real food prices (Chou, Grossman and Saffer), or individuals'

propensity to become addicted to the consumption of food (Cawley). Although these studies

develop comprehensive models that incorporate potential explanations from both sides of the

energy balance equation (ie. weight gain = energy in - energy out), recent evidence on aggregate

energy intake relative to physical activity levels suggest that a more careful analysis of food

consumption is warranted. Consequently, this study investigates whether specific macronutrients

or minerals (protein, carbohydrates, fat or sodium) are indeed addictive, and if so, whether

addiction results from rational economic decisions.[1]

Cutler, Glaeser and Shapiro cite USDA statistics that document a remarkable rise in the

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[1] Although the set of macronutrients includes only protein, carbohydrates and fat, excessive consumption of
sodium may also lead to health problems such as hypertension (high blood pressure), cirrhosis of the liver, kidney
damage, stomach cancer and heart disease (NIH).

total amount of calories consumed since 1980. Further, much of this increase is attributable to a rapid rise in the consumption of refined carbohydrates – from 147 pounds per capita per year in 1980 to 200 pounds in 2000 (USDA 2002). This trend is somewhat alarming as refined carbohydrates are a nutrient that is typically associated with obesity. Over the same period, however, calories used through both work and recreational activities have remained relatively static (Cutler, Glaeser and Shapiro). Significantly, obesity rates increased dramatically, from roughly 12.0% of the adult population in 1991 to over 20.9% in 2001 (CDC).[2] On the surface, therefore, it appears as though the obesity epidemic is largely due to not only food consumption, but consumption of particular types of foods – consumption beyond the point necessary to maintain a healthy lifestyle. If consumers are rational, utility-maximizing agents as economists assume, therefore, how can their demand for food be so clearly sub-optimal from a health perspective? This study is the first to test whether consumers' "rational addiction" to specific macronutrients constitutes a viable explanation for the rising incidence of obesity in the U.S.

To test the rational addiction hypothesis, we use a dynamic random coefficient (mixed) logit (RCL) model similar to Erdem. This approach represents a dynamic extension of the static, attribute-based RCL models used by Berry; Berry, Levinsohn and Pakes; Nevo (2001); Chintagunta (2002) and Chintagunta, Dube and Singh to explain the demand for differentiated products in a high-dimension discrete choice environment. RCL models convey several advantages over traditional, multi-level demand systems (Hausman 1997) for problems such as this. First, they are parsimonious representations of a complex decision process. Second, they

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[2] The Center for Disease Control (CDC) defines obesity as a body mass index (BMI) of over 30.0. BMI is defined as weight (in kilograms) divided by height (in meters) squared. A BMI value over 40.0 is defined as "morbidly obese."

do not suffer from the "independence of irrelevant alternatives" (IIA) problem of traditional logit models, which leads to unrealistic estimates of substitutability among products. Third, viewing different products as bundles of desired attributes allows the modeler to project demand from product space into characteristics space, thus greatly reducing the number of parameters to be estimated. Fourth, RCL models are consistent with consumer utility maximization, so response parameters estimated in an RCL context are assumed to represent optimal, rational economic responses. Further, this approach addresses critical weaknesses of existing empirical tests of the rational addiction hypothesis in that we are able to test for addiction to several nutrients at the same time, it is able to easily incorporate the effect of adjustment costs on addictiveness and it recognizes that addiction is based on the content of products people consume and not on the products themselves. We apply this econometric approach to a highly detailed, household-level scanner data set in which 30 families in a major U.S. metropolitan market report all food purchases over a four-year time period. Our focus in this study lies specifically in sample households' purchases of snack foods because of the diversity of snack foods' nutritional content, the importance of snack foods in modern American diets, the fact that they represent somewhat "discretional" or impulse purchases and a practical necessity to focus on a narrowly defined set of foods for estimation purposes. With these data, we are able to accurately estimate not only purchase dynamics, but consumers' tendency to substitute among alternative foods, based upon differences in their content of key dietary nutrients.

The results of this study are important for both policy makers and healthcare industry members as they provide critical information as to possible policy responses that may prove valuable in combating the obesity epidemic. Namely, if it is found that nutrients are addictive,

and rationally addictive at that, then this suggests tax policies, which raise consumer expectations

of future prices, may be more effective in reducing demand than previously thought. In the next

section, we describe the rational addiction model and its implications. The third section presents

a new econometric model of the rational addiction hypothesis that overcomes many limitations of

prior tests of the rational addiction theory, while the fourth describes the household panel data set

that is used in estimating the model. A fifth section presents the estimation results, both from

testing the primary addiction hypotheses and the structure of demand for snack foods. The final

section concludes and provides a discussion of the policy implications of our results.

An Economic Model of Nutrient Addiction

Although satiation is a physiological concept, Mela and Rogers cite psychological reasons why

people eat beyond the point of biological optimality. Cawley, on the other hand, considers

obesity the result of an addiction to calories. Wang, *et al.* provide clinical support for this

hypothesis through positron emission tomography (PET) scans of twelve obese sample subjects.

Specifically, when presented with external food stimuli, this experiment found similar brain

responses among obese individuals to that found among cocaine addicts when given doses of the

drug. Nutrition research, however, suggests that dependencies are rather associated with the

unique chemical compositions of particular nutrients, such as fats or simple sugars (Colantuoni,

et al.). Therefore, this study follows Cawley, but extends his analysis by investigating whether

addiction can be attributed to a specific nutrient or set of nutrients.

In terms of the rational addiction model of Becker and Murphy, individuals weigh the

4

current benefit of increased current utility from eating, which is assumed to inherently enjoyable, to the present value of future health implications from overeating. To be a rational addiction, as opposed to myopic, or merely habitual behavior, Becker and Murphy argue that an individual's utility from consuming food must exhibit two characteristics: (1) reinforcement, in which current marginal utility rises in the stock of past consumption, and (2) tolerance, in which the individual must consume more of the addictive product in order to maintain the same level of utility the higher is past consumption. This concept of addiction has met with considerable criticism, however, in that it implies that addicts are somehow "happy" with their situation and would not change it if they could. Suranovic, Goldfarb and Leonard, on the other hand, develop a model of addiction in which adjustment (withdrawl) costs prevent an addict from reducing consumption below harmful levels while Winston develops a theoretical explanation for how former addicts can all too often "fall off the wagon" and resume their old behaviors. Similarly, Oriphanides and Zervos explain how addicts can regret their current situation, but are prevented from changing it due to the high costs of learning how to quit. These arguments are plausible when applied to examples such as cigarettes or alcohol, but they are even more convincing in the case of food because humans can avoid drinking or smoking, but not eating. Although the rational addiction model has met broad acceptance in the economics field due to its agreement with fundamental principles of neoclassical economic analysis, others consider addictive behavior as the result of impulsive, "multiple-self" decisions (Thaler and Shefrin; Schelling), or hyperbolic discounting (Gruber and Kozcegi) that essentially reject rationality as a cause of addiction. Nonetheless, the rational addiction model has met with considerable empirical success.

Empirical Model of Nutrient Addiction

The primary empirical implication of the rational addiction model is that current consumption responds to not only current and past prices, but expected future prices and consumption as well. Numerous empirical tests of the rational addiction model exist in the literature, examining addictions to cigarettes (Becker, Grossman, and Murphy; Chaloupka; Keeler, *et al.*, Douglas), alcohol (Grossman, Murphy and Sirtalan; Waters and Sloan), cocaine (Grossman and Chaloupka caffeine (Olekalns and Bardsley), heroin (Bretteville-Jensen) and calories from food (Cawley 1999, 2000, 2001). These studies show near uniform support for the rational addiction hypothesis, but in very simple, single-equation econometric models. To study the dietary source of obesity, however, it is necessary to account for the fact that "all calories are not equal" or that calories from different sources – fat, protein and carbohydrate – may differ in their addictive properties and, hence, in their contribution to obesity.

Despite the empirical success of the rational addiction model, there are (at least) four reasons why existing empirical methods cannot be used to test for addiction to nutrients: (1) they are all based on single-product models of demand, that do not allow for substitutes, (2) nutrients do not have observable prices, (3) simple multi-product extensions suffer from "overdimensionality" because consumers face too many food choices, even with separability imposed, and (4) they impose severe restrictions on utility and, hence, the resulting demand functions. Because current tests are based on the primal solution to the underlying dynamic optimization problem, they are not sufficiently general to explain addictions in a multi-product context, where the basic need can be filled in a number of ways, yet the consumer chooses one in

which to become addicted. Developing a more general test is essential in testing for addiction to certain food nutrients. While humans can satisfy their basic caloric requirement either through the consumption of protein, fat or carbohydrates, some choose to consume more of one versus the other. Yet when one models the demand for individual foods that contain these nutrients, the substitution matrix quickly becomes too large to estimate with any degree of confidence because there are simply too many foods to choose among. Further, in order to model substitution among nutrients, it is also necessary to have nutrient prices, but nutrient values are only implicit in food prices. Therefore, this study uses a multi-product, dynamic test of whether consumers are rationally addicted to specific nutrients that simultaneously imputes shadow values to otherwise unobservable nutrient types.

As suggested above, the primary empirical problem in estimating addictiveness among particular foods is one of dimensionality – there are simply too many possible foods to hope to estimate a substitution matrix with any degree of confidence. Recent developments in the theory (Berry; McFadden and Train; Nevo 2000) and application (Berry, Levinsohn and Pakes; Nevo 2001; Chintagunta; Chintagunta, Dube and Singh) of the random coefficient (mixed) logit (RCL) model provide a means of estimating substitute relationships among products by projecting their demand into characteristic space, thus greatly reducing the number of estimated parameters. Further, this approach also avoids the unrealistic restrictions on own- and cross-price response elasticities associated with fixed-coefficient logit demand models, and does so in a parsimonious way. Because the data used in this study consists of household-level food choices, however, our model differs substantially from those referred to above. Nonetheless, we retain the key insight that substitution relationships among different food products are driven fundamentally by

7

differences in their nutritional composition.

Formally, the RCL model derives from a random utility framework in which the utility consumer i obtains from consuming product j on purchase occasion t is a function of the product's price (p_{jt}) and mean level of utility, or product-specific preferences, γ_{ijt}, as well as a set of demographic variables (z_{il}):

$$u_{ijt} = \gamma_{ijt} + \alpha_i p_{ijt} + \sum_l \delta_l z_{il} + \epsilon_{ijt}, \qquad (1)$$

where we assume the price-response coefficient is normally distributed so that: $\alpha_i \sim N(\bar{\alpha}, \sigma_\alpha^2)$.

Similar to Erdem; Berry; and Berry, Levinsohn and Pakes, product-specific preferences depend on the attributes (nutrients) of each product (x_{jk}):

$$\gamma_{ijt} = \sum_k \beta_{ik} x_{jk}, \ k = 1,2,3. \qquad (2)$$

Consumers are assumed to differ in their preference for each nutrient so that unobserved consumer heterogeneity is reflected in the distribution of each nutrient's marginal utility:

$$\beta_{ik} = \beta_k + \mu_{ik} \quad \mu_{ik} \sim N(0, \sigma_0^2), \quad \forall \ k = 1,2,3. \qquad (3)$$

Brownstone and Train interpret the elements of (3) in terms of an error-components model of attribute demand. In contrast to the IIA property of a simple logit model, the heterogeneity assumption in (3) creates a general pattern of substitution over alternatives j through the unobserved, random part of the utility function given in (1). The difference between a random-coefficient and simple logit model is easily shown by expressing the partial covariance matrix of

(1) as:

$$E([\boldsymbol{\beta}'\boldsymbol{x}_j + \boldsymbol{\epsilon}_j][\boldsymbol{\beta}'\boldsymbol{x}_m + \boldsymbol{\epsilon}_m]) = \boldsymbol{x}_j' V(\boldsymbol{\beta})\boldsymbol{x}_m, \qquad\qquad (4)$$

which is defined over the vector of nutrients, k, for each food choice. So alternative foods are

correlated according to their nutritional profiles as described by the vector $\boldsymbol{x}_j$. Allowing for non-

IIA substitution among alternatives in this way is key to the objectives of this study as foods that

are similar nutritionally should be closer substitutes for each other, no matter their market share.

In this basic RCL framework, however, utility depends only on current consumption.

Erdem introduces state dependent preferences by allowing utility to reflect both habit persistence

and variety-seeking behavior.[3] With this approach, utility depends on the "distance" of each

attribute acquired during the current purchase occasion from the previous one. If utility rises

with this distance, then the consumer is variety seeking, but if it falls, then the consumer is

habituated. Because distance is measured only in a backward-looking way, however, habits

described by this model are myopic, and not forward-looking, or rational. Therefore, we extend

the dynamic utility model to consider forward-looking decisions. If consumers are rational in the

sense of Becker and Murphy or Chaloupka, then utility falls in the difference between current

and future attribute purchases as well. If this is the case, then the consumer may indeed be

addicted to the attribute, or nutrient in question. To incorporate habituation, variety seeking and

addiction into the utility model, mean utility becomes:

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[3] Unlike Erdem or Chintagunta, Dube and Singh, however, we incorporate observable measures of product attributes, and not latent factors. In these previous studies, the objective was to elicit perceptual "market maps" and not to test for the responses to specific attributes. In this respect, our treatment of observed attributes is more akin to Brownstone and Train.

$$\gamma_{ijt} = \sum_k \beta_{ik} x_{jk} - \sum_k \lambda_{ik1} \left(x_{jk} - \sum_j x_{jk} d_{i,t-1,j} \right)^2 - \sum_k \lambda_{ik2} \left(x_{jk} - \sum_j x_{jk} d_{i,t+1,j} \right)^2, \quad (5)$$

where $d_{itj} = 1$ if consumer i buys product j at time t and 0 otherwise, $\lambda_{ik1} > 0$ implies habit persistence, $\lambda_{ik1} < 0$ variety seeking behavior, and $\lambda_{ik2} > 0$ rational addiction. Because consumers are also assumed to be heterogeneous with respect to their preferences for deviations from past purchases, each λ_{ikm} is assumed to be given by: $\lambda_{ikm} = \lambda_{km} + v_{ikm}$, $v_{ikm} \sim N(0, \sigma_m^2)$, for $m = 1, 2$ and $k = 1, 2, 3$. Further, note that this model also captures the impact of adjustment costs on the likelihood that a consumer becomes addicted to a particular nutrient. If $\lambda_{ik1} > 0$, then withdrawl symptoms or the psychological costs of denying a want cause utility to fall.

By defining the characteristics of foods consumed by a panel of individuals as those that are potentially addictive – fat, carbohydrate, protein, sodium, caffeine, for example – we are able to test not only whether foods are addictive or not, but the source of their addiction. Further, this method is also able to account for the fact that individuals do not have similar tastes. By allowing consumer-specific heterogeneity, we are better able to estimate realistic own- and cross-price elasticities among products. This method also overcomes the failure of existing empirical models of rational addiction to consider the demand for multiple products that may convey the same addictive properties. Accounting for potential complementarities in demand will allow for an even richer description of the nature of addiction.

Data and Estimation

Estimating a RCL model requires data on prices, purchase quantities, and product characteristics, while data on consumer demographics is helpful, but not necessary. While BLP and Nevo (2001) estimate RCL models in data representing differentiated products at an aggregate (US market) level, this study uses household panel data for a number of different snack foods purchased at retail outlets. Specifically, we use A.C. Nielsen, Inc. "HomeScan" data in which 55,000 households throughout the US submit all food purchases each time they visit a store using remote scanning devices. While the entire sample consists of complete purchase information (price, quantity, product description and household demographics) for a geographically and demographically representative sample of U.S. households over the years 1998 - 2001, we use a sub-sample consisting of 30 households from a major Southeast market in order to keep the empirical analysis at a tractable level.[4] Because this data includes foods purchased from a nearly exhaustive list of food categories, we focus on a particular category that is most likely to reveal either habitual or variety seeking behavior. The snack food category is ideal for this purpose, because snacks are commonly purchased on impulse, snacks can vary widely in terms of their nutritional profiles, and are likely to be purchased frequently and regularly. Further, excessive snacking is often blamed for the general rise in obesity among US adults (Chou, Grossman and Saffer).

Nutritional profiles for each snack food are constructed from the USDA food guide database and aggregated according to sample weights from within the A.C. Nielsen data set. We use the A. C. Nielsen definition of what constitutes a "snack food" and augment this list with a

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[4] While 30 households may seem to be a small sample, including all purchase occasions over the four-year time period produces over 73,000 individual observations.

number of others such as cookies and crackers. Table 1 provides a full listing of the chosen foods and some summary statistics regarding their purchase and nutritional content. In the RCL model, nutritional attributes of each food serve the dual role of defining the level of mean utility and the nature of all substitution relationships as foods that are nutritionally similar are likely to be highly correlated through the heterogeneity described in model (1). Because many households purchase several snack foods on each purchase occasion and do so in varying quantities, we define the dependent variable in terms of the share of total snack food expenditures attributable to each particular food. Estimating with shares is necessary in the RCL model and consistent with the approach taken by Berry, Nevo (2000) and others. Implicitly, therefore, we do not standardize purchase quantities on a typical package size as is the case with most studies using panel data.

[table 1 in here]

Assuming the error term in (1) is type I extreme-value distributed, we estimate the complete RCL model using maximum likelihood.[5] With this error assumption, the probability of an individual household i purchasing product j on occasion t is given by:

$$P(f = 1) = \frac{e^{\gamma_{ijt} + \alpha_i p_{ijt} + \sum_l \delta_l z_{il}}}{\sum_j e^{\gamma_{ijt} + \alpha_i p_{ijt} + \sum_l \delta_l z_{il}}}, \tag{7}$$

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[5] Note that (1) does not include the product-specific error term, ξ_j, described in Berry, BLP, Nevo (2000, 2001) and Chintagunta, Dube and Singh. With their approach, this error term captures all attributes of the product that are unobserved to the econometrician, but likely to be correlated with the price. In a retail environment, such attributes may include shelf placing, coupon usage, stock levels or a host of other factors. If these are important, then prices are endogenous and the instrumental-variables procedure described by Berry must be used. In our application, however, it is plausible that prices are instead exogenous, as is commonly assumed in similar studies using panel data (Chintagunta 1994, for example). In future research, however, we incorporate a test for endogeneity in these panel data.

where utility from one of the $j = 1, 2, 3, \ldots m$ foods is normalized to zero in order to facilitate estimation. It is widely understood in the literature that estimation of (7) requires the evaluation of multiple integrals – one for each source of heterogeneity that is assumed. Consequently, there is no closed-form solution for the maximization procedure proposed in (7). To address this problem, we follow the literature by estimating the RCL model using the method of simulated maximum likelihood (MSL), which involves drawing random samples from each of the heterogeneity distributions, evaluating the resulting likelihood function at each draw, and maximizing over the distribution of joint outcomes. The simulated likelihood function for this procedure is as follows:

$$\log L(x_{ij}, p_{ij}, z_{il} | \Theta) = \sum_{i=1}^{N} \sum_{t=1}^{T} \log \frac{1}{R} \left(\sum_{r=1}^{R} \frac{e^{\gamma_{ijtr} + \alpha_i p_{ijt} + \sum_l \delta_l z_{il}}}{\sum_j e^{\gamma_{ijtr} + \alpha_i p_{ijt} + \sum_l \delta_l z_{il}}} \right), \tag{8}$$

for the set of parameters $\Theta = (\gamma, \alpha, \delta, \beta, \lambda)$, defined over N panel members, with T purchase occasions each and R draws from the random distributions that define the parameters that comprise mean utility, γ_{ijt}. Alternatives to this method include the method of simulated moments (MSM). Nevo (2001) discusses the relative merits of this method compared to MSL. Hypotheses to be tested with the estimates include the significance of all own- and cross-price elasticities in addition to the core rational addiction hypotheses. In this regard, rational addiction involves the parameters of the mean utility function. Because our objective concerns the addictiveness of individual nutrients, we test for rational addiction using t-tests for each nutrient as opposed to a joint test of all nutrient dynamics together. The results of this testing procedure

13

are presented in the next section.

Results and Discussion

Before interpreting the parameters of the RCL model, it is first necessary to establish the validity

of this estimation approach relative to more parsimonious alternatives. Because the RCL model

is a generalization of a non-random coefficient discrete choice approach, the most direct test

between these two alternatives involves comparing the log-likelihood function value of the

estimated, random coefficient model with one in which all parameters are held constant. Using

the log-likelihood values reported in table 2, a likelihood ratio test statistic for the null hypothesis

that all coefficients are constant is 4,517.01, while the critical value for 5 degrees of freedom at a

5% level of significance is 11.07. Therefore, we are led to reject the null hypothesis and

conclude that the RCL represents a better description of the household scanner data than a

constant coefficient logit model. A second set of specification tests examine the statistical

significance of the standard deviations for each of the maintained-random coefficients in table 2

using standard t-test statistics. According to this approach, it is evident that all of the random

parameters have standard deviations that are significantly different from zero.[6] Therefore, the

RCL approach again represents a better description of the underlying data than a constant-

parameter alternative.

[table 2 in here]

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[6] Although the empirical model description above included random product preference and nutrient-distance weights as well, this more general model would not converge in a meaningful way.

In the RCL model, each food is defined in terms of its attributes, including both price and nutrient content. Therefore, the parameter estimates presented in table 2 show the sample-average marginal utility associated with variations in price, each nutrient, and the lagged and lead nutrient distance measures defined above. Interestingly, at current consumption levels, the marginal utility associated with fat content is negative. In the terminology of Becker and Murphy, this suggests that, if found to be addictive, fat constitutes a "harmful addiction." Whether or not each nutrient can indeed be defined as addictive in the sense of Becker and Murphy involves examining the sign and significance of each of the nutrient distance measures. As defined by Erdem, a positive "habit persistence" parameter suggests that the average household consumes the nutrient in a habitual way. If this parameter is negative, then households are more prone to variety seeking, because their utility rises the more dissimilar the current purchase is from the last. From the lagged-distance parameter estimates in table 2, it is apparent that consumers tend to purchase snack foods that are relatively similar from one shopping trip to the next, except with respect to their sodium content. Although the lagged distance parameter is not significantly different from zero, consumers obtain higher utility from consuming low-sodium snacks, *ceteris paribus*, if they expect the next to be salty. This result is interesting in that the other food attributes are all macronutrients, the consumption of which provides food energy, while sodium conveys taste and other, perhaps less sensory, functions within the body. Therefore, if energy is a primary human need that drives addiction, then the demand for salt may indeed be more of a "want" than a "need." Finding that consumers tend to form habits in their food purchases is not new (Heien and Durham), but isolating a possible cause in nutritional dependence is. Habits, however, may reflect myopic decision making rather than

15

rational, forward-looking addiction if there is not further evidence that consumers consider future consumption plans when deciding what to purchase today.

In fact, the rational addiction model implies that the "habit formation" parameter, or the parameter on the lead distance measure, is positive and significant for households that are not merely myopically habitual consumers of a particular nutrient, but form habits in a rational, forward-looking way. In other words, they are rationally addicted. According to the estimates in table 2, the distance weight on each future nutrient value is positive and significant (again, with the exception of sodium), which suggests that consumers are indeed rationally addicted to each of the macronutrients considered here. Because the same general conclusion applies to all nutrients, however, the relative magnitude of each parameter is a better measure of a nutrient's comparative addictiveness. By this reasoning, the results in table 2 show that protein is the least addictive of all nutrients followed by fats, while carbohydrates are slightly more addictive than the others. Consequently, despite the fact that much media attention and public debate has centered on "high fat" fast food as a likely culprit in the obesity epidemic, our finding suggests a focus rather on increased consumption of high-carbohydrate foods. Drawing such a conclusion would be questionable if there were only marginal differences in the nutrient content of the foods included in the model. However, our analysis considers snack foods – a category which includes intensive sources of dietary fat (potato chips) as well other others that are very high in carbohydrate (pretzels, cookies) and protein (snack meats).

If consumers are indeed addicted to specific nutrients, but their addiction is part of a rational, dynamic utility maximization process in the sense of Becker and Murphy, then this suggests that conventional economic tools (price-based taxes or subsidies) can be effective in

modifying behavior. However, because foods are ultimately the medium by which consumers obtain nutrients, the effectiveness of any price-based policy depends on the preferences and demand elasticities of demand for specific foods. The value of the RCL method in this regard lies in the fact that food elasticities are driven by their nutritional profiles and relative preference orderings are estimated directly from the data. Therefore, the information demands of policy makers or public health officials are directly reflected in the econometric method used here. In other words, when considering ways to ameliorate any nutrient-addictive behavior that may contribute to obesity, policy makers or public health officials are equally as interested in the structure of the demand for the products that deliver nutrients (ie., foods) as they are with the demand for nutrients themselves.

Results concerning the intensity and observed heterogeneity of demand, as determined by households' demographic characteristics, are provided in table 2 while the matrix of demand elasticities is in table 3. Defining carrots as the numeraire commodity, table 2 shows that the sample households express a preference for cookies, puffed cheese and popcorn, while they show a comparative dislike for products such as pork rinds, corn chips and tortilla chips. Holding mean preferences constant, these results also show that larger households have a relative dislike for popcorn and snack meats, while, perhaps surprisingly, favoring no other snack foods to carrots in a statistically significant way. Higher income households, on the other hand, appear to prefer snack meats, low-fat potato chips, nuts, corn chips and puffed cheese while showing less of a preference for popcorn and tortilla chips. In terms of other "healthy" snacks, apple preferences rise only slightly in income relative to the other products. Combining these two results, it appears as though rising incomes may not increase the demand for the most healthy

17

snacks (fruit), but it is associated with a preference for some foods that are consistent with

current popular diets (Atkins, South Beach, or traditional low fat).

As suggested above, any consumption-based response to the obesity epidemic is likely to

address specific foods or classes of foods rather than specific nutrients. Therefore, the structure

of snack food demand may become of considerable practical importance. To this end, we present

the matrix of own- and cross-price substitution elasticities in table 3. Before interpreting

individual elasticity estimates, it is important to provide some observations on the value of the

RCL approach. In fact, these estimates demonstrate the true value of using an RCL approach

relative to a continuous alternative such as an AIDS or Rotterdam model. First, continuous

alternatives are not likely to be able to provide precise, plausible elasticity estimates in a high

dimensional problem such as this. Second, while continuous demand models often produce

seemingly anomalistic cross-price elasticity estimates, the results in this table indicate that all

products are gross substitutes for each other – a highly plausible outcome in a category of largely

discretionary, or impulse purchases. Third, because the cross-price elasticities are driven by

correlations among random nutrient marginal utilities, products that are "similar" to each other in

a nutritional sense represent closer substitutes than those that are fundamentally different

products. For example, it is very plausible to expect popcorn and pretzels to be close substitutes,

while popcorn and pork rinds are likely to satisfy quite different needs. Further, the two fresh

produce snacks are closer substitutes for each other and similar low-fat alternatives such as

reduced-fat potato chips and pretzels rather than more fatty snacks. More importantly, apples

and carrots are also the only two snacks that are inelastic in demand while the two meat-based

snacks are far more elastic than the other foods. This suggests that any tax applied to snack

meats or pork rinds is likely to significantly reduce consumption, while efforts to increase fruit

and vegetable snacking through price-based policies is likely to be ineffective. Moreover, regular

potato chips are significantly less elastic in demand than reduced-fat alternatives so any "sin tax"

that targets "potato chips" in an indiscriminate way is likely to alter consumption toward the high

fat option. Rather, if the desire is to reduce the intake of foods high in addictive content, then

taxes should be targeted more toward corn chips, puffed cheese and tortilla chips – each of which

is relatively elastic and carbohydrate-dense. Because of the likely political difficulty in enacting

such legislation, however, several other practical implications of this research may prove more

useful.

[table 3 in here]

 In fact, given that our results show consumers to be addicted to carbohydrates to a greater

extent than to fats or protein, then existing USDA dietary guidelines, as outlined in the

controversial "food pyramid" may need to be modified somewhat. Rather than emphasizing

limited consumption of fats and oils, perhaps a more effective strategy to stem the obesity

epidemic should recommend limiting carbohydrate intake. This recommendation would also be

consistent with current trends in the weight loss industry wherein low-carbohydrate diets such as

Atkins and South Beach are becoming increasingly popular. While proponents of these diets

have sought scientific support for their validity in the nutritional science literature, this study

provides at least indirect support from the economic analysis of consumption data. More

importantly, finding that both nutrients often associated with overconsumption and obesity – fats

and carbohydrates – can be addictive suggests public policy oriented toward controlling obesity

should be directed at the addiction and not necessarily current consumption. Because addicted

consumers do indeed take the future economic implications of their behavior into account, price-based policies may be more effective than previous behavior-based models of obesity would have led us to believe.

Our findings also have important implications for producers of apparently less-addictive commodities, such as fruits and vegetables or even protein-dense meats and dairy products. For retailers or commodity groups charged with marketing these products, the optimal marketing solution may not lie in price-promotion or discounting as is appears to be with the rationally addictive products, but rather advertising or public relations. If fresh produce is indeed on the "wrong side" of an addictive process that is based in otherwise rational, price-based economic decision making, then continued investment in information and advertising programs that emphasize the sweetness and flavor of fresh snacks may be more successful. Price-promotion, discounting or couponing may be effective in changing the demand for high-fat and high-carbohydrate snacks, but discounting produce is not likely to change the forward-looking cost-benefit calculus that drives addictive behaviors.

Conclusions

This study provides a test of the rational addiction hypothesis as a potential explanation for the current "obesity epidemic." Because calorie expenditure among Americans has been relatively static over the past twenty years, while calorie consumption has risen dramatically, obesity is now widely thought to be predominantly a consumption-phenomenon. Addiction to food, or more precisely the most harmful macronutrients in food, presents a logical explanation for why

consumers persist in purchasing and consuming more food than is necessary for survival.

Our test considers potential addiction to three macronutrients and one key mineral – fat, protein, carbohydrates and sodium – in the case of snack foods purchased from retail outlets. Due to the large number of snack foods available to consumers, the demand estimation problem is made tractable through the use of random coefficients logit (RCL) model in which the coefficients on each price and nutrient attribute are allowed to vary. In this way, we not only reduce the dimensionality of the problem, but solve the independence of irrelevant alternatives criticism of logit demand estimation by allowing the correlation among demand errors to be driven by nutrient content. The RCL model is applied to a highly detailed, disaggregate household panel scanner dataset gathered by the A.C. Nielsen Company (HomeScan) for thirty households over four years in a major Southeastern metropolitan market.

The estimation results provide broad support for the rational addiction hypothesis for each macronutrient. However, it is also apparent that the addiction to carbohydrates is far stronger than to other nutrients. Importantly, the form of addiction in this model is an inherently rational one, so consumers purchase (and presumably consume) nutrients in amounts that are likely harmful to their health only through a reasoned process of comparing current marginal utility to the discounted future costs of any negative health consequences. Because consumers take costs and benefits into account and do not overeat out of some pathological obsession, price-based policies designed to address the obesity epidemic are likely to be more effective than once thought to be the case. Consequently, existing information-based policies may need to be re-thought and "sin-taxes" considered anew.

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Table 1. Summary Statistics of Snack Food Nutrient Contents

Food	Share	Amount (100Gms)	Energy (Kcal)	Fat (Grams)	Protein (Grams)	Carbo (Grams)	Sodium (Mg)
Popcorn	0.044	0.614	500.345	28.101	9.124	57.223	884.532
Corn Chips	0.036	0.238	536.453	33.289	6.664	56.789	651.172
Low Fat Potato Chips	0.022	0.101	432.336	12.311	8.167	73.986	555.460
Reg. Potato Chips	0.160	0.880	526.508	34.053	7.341	52.613	624.714
Pretzels	0.030	0.244	388.902	4.830	9.030	78.200	1621.304
Puffed Cheese	0.029	0.153	552.524	34.130	7.611	54.024	1052.843
Tortilla Chips	0.053	0.375	495.077	25.110	7.431	63.415	596.925
Pork Rinds	0.005	0.018	542.157	31.503	59.919	0.650	2174.663
Snack Meats	0.005	0.007	331.409	26.651	17.891	4.119	1345.295
Cookies	0.264	2.240	466.820	20.860	5.220	66.820	409.310
Crackers	0.121	1.058	476.974	20.284	8.714	64.232	1051.400
Nuts	0.072	0.606	595.879	52.198	19.253	22.675	508.776
Carrots	0.088	1.827	52.196	0.170	0.260	13.810	1.094
Apples	0.071	0.884	145.392	0.130	0.640	8.243	78.221

Table 2. Demand for Snack Foods: Random-Coefficients Logit Model Parameter Estimates - Simulated Maximium Likelihood

Utility Parameters			Product Preferences						
				Constant		Household Size		Household Income	
	Estimate	t-ratio		Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Price[a]	-0.273	-127.548	Popcorn	0.737	2.211	-0.854	-7.024	-0.029	-3.144
Protein	0.045	7.073	Corn Chips	-0.843	-3.510	-0.054	-0.438	0.042	5.162
Fat	-0.010	-4.911	Low Fat Potato Chips	-0.652	-2.245	-0.068	-0.593	0.053	7.600
Carbo	0.010	21.367	Puffed Cheese	1.140	3.270	-0.147	-2.133	0.041	8.854
Sodium	0.007	2.510	Tortilla Chips	-0.719	-4.212	-0.297	-2.059	-0.016	-1.789
$^{-}\Delta$Protein	3.504	4.311	Regular Potato Chips	-0.337	-2.607	-0.200	-1.589	0.025	2.924
$^{-}\Delta$Fat	5.475	4.210	Pretzels	-0.176	-7.368	-0.225	-2.264	0.039	5.537
$^{-}\Delta$Carbo	7.914	16.601	Pork Rinds	-1.936	-4.795	0.092	0.104	0.006	0.151
$^{-}\Delta$Sodium	-0.001	-0.805	Snack Meats	-0.625	-3.018	-0.910	-3.177	0.086	6.078
$^{+}\Delta$Protein	1.042	2.502	Cookies	1.246	3.730	-0.280	-4.308	0.020	4.426
$^{+}\Delta$Fat	6.019	4.329	Crackers	-0.185	-4.466	-0.085	-1.140	0.026	4.595
$^{+}\Delta$Carbo	8.813	10.175	Nuts	-0.195	-2.406	-0.051	-0.425	0.045	6.066
$^{+}\Delta$Sodium	-0.004	-2.787	Apples	0.673	5.714	-0.079	-1.023	0.014	2.388

Random Coeff. Std. Dev.			Model Statistics	
Price	0.017	2.367	N	5,155
Protein	0.126	64.387	LLF	-6,431.661
Fat	0.033	81.814	LLF (Const. Params.)	-8,690.165
Carbo	0.004	19.871	LLF (Null Model)	-13,604.328
Sodium	0.001	52.953		

[a] In this table, all parameters but the standard deviations for Fat and Carbo are significant at a 5% level. For each nutrient deviation, $^{-}\Delta$ indicates the difference between the implicit quantity purchased on this occasion relative to the previous occasion, while $^{+}\Delta$ is the difference between the current occasion and the next. A chi-square test statistic comparing the null and estimated models consists of 73 degrees of freedom, so the critical value is 90.53 at a 5% level. The chi-square test statistic is calculated as twice the difference between the estimated and null (all coefficients restricted to zero) log-likelihood function values.

Table 3. Snack Food Own-Price and Cross-Price Elasticities

	PPC	CCH	RFPC	RPC	PTZ	PFC	TTC	PKR	SNM	COK	CRK	NTS	APP	CAR
PPC	-1.653	0.099	0.161	0.422	0.027	0.049	0.113	0.003	0.018	0.231	0.124	0.138	0.196	0.072
CCH	0.011	-2.179	0.143	0.429	0.013	0.049	0.114	0.003	0.016	0.245	0.119	0.140	0.203	0.074
RFPC	0.019	0.103	-2.971	0.437	0.025	0.050	0.118	0.003	0.013	0.246	0.117	0.145	0.206	0.083
RPC	0.015	0.086	0.121	-1.779	0.011	0.042	0.102	0.003	0.008	0.265	0.109	0.122	0.176	0.063
PTZ	0.022	0.101	0.147	0.427	-1.363	0.049	0.116	0.005	0.019	0.241	0.115	0.142	0.201	0.094
PFC	0.019	0.102	0.146	0.431	0.012	-2.005	0.116	0.003	0.014	0.247	0.116	0.141	0.203	0.074
TTC	0.011	0.100	0.142	0.423	0.090	0.048	-1.999	0.003	0.009	0.245	0.114	0.139	0.199	0.073
PKR	0.009	0.102	0.149	0.433	0.011	0.050	0.117	-5.061	0.023	0.234	0.111	0.141	0.194	0.075
SNM	0.005	0.082	0.123	0.344	0.008	0.039	0.090	0.001	-5.011	0.176	0.078	0.106	0.152	0.056
COK	0.012	0.081	0.115	0.360	0.010	0.040	0.096	0.003	0.008	-1.566	0.108	0.113	0.164	0.059
CRK	0.013	0.091	0.130	0.392	0.012	0.045	0.105	0.003	0.016	0.240	-1.681	0.130	0.180	0.067
NTS	0.019	0.094	0.135	0.399	0.011	0.046	0.107	0.003	0.012	0.236	0.102	-2.700	0.190	0.070
APP	0.021	0.105	0.151	0.321	0.023	0.056	0.131	0.003	0.003	0.218	0.134	0.154	-0.766	0.091
CAR	0.024	0.104	0.151	0.314	0.031	0.059	0.121	0.003	0.005	0.204	0.131	0.161	0.281	-0.752

[a] In this table, each column represents the elasticity of the column product with respect to the price of the row product. Elasticity values are sample averages. All elasticities are significant at a 5% level. The variables are defined as follows: PPC = popcorn, CCH = corn chips, RFPC = reduced-fat potato chips, RPC = regular potato chips, PTZ = pretzels, PFC = puffed cheese, TTC = tortilla chips, PKR = pork rinds, SNM = snack meat, COK = cookies, CRK = crackers, NTS = nuts, APP = apples, CAR = carrots.