Demand for Food-Away-From-Home: A Multiple Discrete/Continuous Extreme Value Model

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Abstract

Obesity is a complex problem with many causes, from genetic and behavioral disorders to environmental factors, including access to calorie-dense fast food meals. Economists and epidemiologists disagree on the importance of access to fast food as a causal factor for obesity, but agree that any policy regulating access to fast food will likely use the price system, through taxes or other means to raise the relative cost of buying fast food. Yet, little is known of the structure of demand for food-away-from-home (FAFH). This study provides estimates of the price-elasticity of demand for four different types of FAFH using a novel new dataset from NPD, Inc. By including physiological measures of obesity, physical activity and health status as additional regressors in an instrumental variables framework, we control for important sources of observed heterogeneity. We find that all types of FAFH are price elastic in demand, but fine dining is highly elastic while fast food is nearly unit elastic. Food-at-home (FAH), on the other hand, is relatively elastic. Critically, cross-price elasticities of demand show little willingness to substitute between FAH and any type of FAFH. When prices are rising, consumers prefer to change the type of restaurant they visit, rather than forego the experience entirely. As shown elsewhere in the literature, therefore, taxing fast food is likely to be counterproductive.

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1 Introduction

Despite the apparent lack of concensus on whether food away from home (FAFH) is responsible for the rise in obesity, several jurisdictions nonetheless remain convinced that taxes are an effective means of changing consumers' behavior (Vogel 2011). Indeed,easy access to relatively inexpensive, convenient, well-advertised and calorie-dense restaurant meals is frequently cited as a critical factor in the decline of the quality of the American diet (Binkley and Eales 2000; McCrory, et al. 2000; Gillis and Bar-Or 2003; Chou, Grossman and Saffer 2004; Kuchler, et al. 2005). Although connecting FAFH to obesity seems reasonable, the empirical evidence is mixed. While French, Harnack and Jeffery (2000); Pereira et al. (2005); Niemeier et al. (2006); Davis and Carpenter (2009) and Currie, et al. (2010) find some evidence of a small effect of FAFH, specifically access to fast food, on obesity, Anderson and Matsa (2011) find no evidence at all. Even if FAFH is responsible, empirical research documents the likely failure of taxes in regulating the consumption of fast food (Schroeder, Lusk and Tyner 2008). Taxing FAFH is based on (at least) four assumptions that may not be supported by the data: (i) consumers do not offset high-calorie consumption occasions by eating less at other times (Anderson and Matsa 2011),[1] (ii) that all FAFH is necessarily nutritionally inferior to food at home (FAH), (iii) the own-price elasticity of demand for FAFH is relatively high, and (iv) that the cross-price elasticity of substitution between types of FAFH and FAH is low. In fact, the logic behind taxing FAFH may be predicated on public policy officials' lack of understanding of the structure of FAFH demand. In this study, we investigate consumers' response to changing FAFH prices using a unique dataset and econometric framework.

There are many empirical studies that document different aspects of the demand for FAFH (Sexauer 1979; Kinsey 1983; Lee and Brown 1986; McCracken and Brandt 1987; Yen 1993; Byrne, Capps and Saha 1996, 1998; Jekanowski, Binkley and Eales 2001; Stewart et al 2005). None, however, consider the fundamental question of the structure of demand, namely, how prices affect the demand for FAFH, and how consumers substitute among different types of FAFH and between FAFH and FAH demand. While these studies isolate several important drivers that underlie the rise in FAFH consumption, most notably the demand for convenience in food preparation, price-response is difficult to estimate in FAFH purchase data. Indeed, there are three unique features of FAFH data that must be addressed in estimating the demand for restaurant meals. First, eating out

[1] Mancino, Todd and Lin (2009) find the opposite – that consumers do not fully offset high-calorie meals away-from-home by reducing caloric intake at other times.

represents much more than simply the demand for food consumed somewhere other than the home. Entertainment, convenience, companionship and status are among the utility-generating features consumed with a restaurant meal. Because these other features are generally unobservable we, like others, consider only the demand for the experience itself, in toto. Second, each meal consists of many different foods, only some of which are reported in the data, and not necessarily all of which are consumed. Therefore, we consider the meal as a whole and do not consider the demand for individual meal components. Third, and perhaps most importantly, meals away from home are perhaps the archetypical example of differentiated goods that are consumed in discrete increments, but often in multiples in each time period. Lee and Brown (1986), McCracken and Brandt (1987), Yen (1993), Byrne, Capps and Saha (1996,1998) address part of this problem using various econometric methods of dealing with discrete/continuous choice problems. However, in diary-data such as that used here, and in several of the studies cited above, households often visit many different types of restaurants (which we define as fast food, mid-range, casual and fine dining) during the sample period, and spend various amounts in each. Estimating the structure of FAFH demand is, therefore, a complex problem in that it is not only discrete/continuous, but multiple-discrete/continuous. In this paper, we apply a new method of estimating multiple-discrete/continuous choice problems and show how it can provide valuable policy insights.

Hendel (1999) and Dube (1994) develop a model of multiple-discrete brand choices in personal computers and carbonated soft-drinks, respectively. While a multiple-discrete model captures the restaurant-type-choice aspect of our data well, it does not explain the continuous amounts spent on each restaurant visit. Hanemann (1984) develops a model of discrete-continuous demand that has subsequently been extended to model the demand for variety (Kim, Allenby and Rossi 2002), transportation services (Bhat 2005, 2008; Pinjari and Bhat 2010) and recreational amenities (Phaneuf 1999, von Haefen and Phaneuf 2005). Each of these extensions involves an application of the general Kuhn-Tucker approach of Wales and Woodland (1983).[2] Assuming that corner solutions re-

[2] Wales and Woodland (1983) describe two ways of estimating econometric models of demand in which there are many corner solutions: (1) the Amemiya-Tobin approach, and (2) the Kuhn-Tucker (KT) approach. In the former approach, econometric error terms are interpreted as "errors in measurement" or "errors in optimization," are assumed to be truncated normal and are added to the share equations *ex post* in an ad hoc way. All consumers are assumed to posess the same utility function. In the latter, utility is instead distributed randomly throughout the population and stochasticity derives directly from the utility maximization process. The result is a demand system in which corner solutions are explained and incorporated into the econometric model in a theoretically-consistent way. Estimating corner solutions using censored demand systems essentially uses econometric methods to address a fundamental inconsistency between the theory and the underlying data generating process, whereas KT-based models recognize that discrete/continuous problems require both different theory and consistent econometric methods.

sult naturally from diminishing marginal utility and satiation, Bhat (2005, 2008) develops a model of multiple discrete transportation choices, and a continuous amount of travel demand, which he calls the multiple discrete continuous extreme value (MDCEV) model. During each two-week period, households can visit each type of restaurant multiple times, as well as consume food-at-home (FAH), and then choose continuous quantities of each. Modeling the food-choice decision process in this way is not only more flexible than existing approaches, but is more realistic and, therefore, likely to generate more policy-relevant elasticity estimates.

We contribute to the empirical literature on the demand for FAFH in three ways. First, we demonstrate the value of using data gathered by a private company, for primarily commercial purposes, in analyzing what is primarily a public policy issue. Second, we present a new empirical model, the MDCEV model, that addresses the multiple-discrete / continuous nature of FAFH demand in a single, utility-maximizing framework. Third, we provide estimates of the structure of FAFH demand, including a FAH option, that may prove useful in the design of price-based strategies designed to regulate the consumption of certain types of FAFH, namely fast food.

The research consists of two stages. In the first stage we use FAFH expenditure data from one dataset (CREST) to impute prices for similar foods in a second dataset (NET) that contains household-level FAFH purchase information. In the second-stage, we develop an empirical model of FAFH and FAH demand, the MDCEV model, in which food consumption choices are derived in a theoretically-consistent, utility-maximizing framework.

The paper begins with a brief description of the FAFH data set. The following section presents the two-stage empirical model used to estimate the demand for FAFH. Estimation results for the food-demand stage are discussed in the third section. A final section concludes and offers some policy implications that follow from the research results.

2 Data Description

The data for this study consist of two survey data sets collected by NPD Group, Inc.: (1) National Eating Trends (NET) and (2) Consumer Reports for Eating Share Trends (CREST). NET data are collected in order to help foodservice researchers (including corporate, government and non-profit clients) understand food purchase behaviors and trends in the foodservice industry. The sample to be used in the proposed research consists of a survey of 4,792 U.S. households. Respondents report all FAH and FAFH consumption occasions over a two-week period, including for FAFH meals the restaurant group (casual dining, fine dining, etc.), restaurant segment (full service or quickservice), restaurant category (Asian, bagel, hamburger, etc.) and restaurant channel (independent, major chain, local chain, etc.). For all meals, respondents report the meal occasion (breakfast, lunch, dinner), and the day and month in which it took place. The respondent file includes demographic and socioeconomic data as well as measures of physical activity, several indicators of health status, and the body mass index (BMI) of all household members. All surveys were conducted between Feb. 24, 2003 and Feb. 29, 2004.

Physical activity (PA) is measured by nine separate fields in the NET data, consisting of self-reported exercise frequency (occasions per week), occasions of seven different types of activity (walking, running / jogging, swimming, bicycling, aerobics, weightlifting and other) and a measure of exercise history (Likert scale defined as 1=frequently, to 5=never). For empirical purposes, we create an index of PA by summing exercise frequency and history. Health status (HS) is measured by the presence or absence (coded as binary 0 / 1 variables) of seven health conditions: diabetes, food allergy, heart disease, high blood pressure, high cholesterol, lactose intolerance, osteoperosis) as well as ten different binary variables indicating whether the respondent is on a diet and, if so, what type of diet is being followed. Because many of the health conditions are likely to be highly correlated with each other, and others are due entirely to genetic and not behavioral causes, we use heart disease, high blood pressure and high cholesterol to form a health status index.

One weakness of the NET data set is that it does not contain food prices or meal expenditures. Data describing firm pricing and meal expenditure is critical to understanding the economic incentives consumers face in their purchase decisions. Therefore, we first develop an estimated price data set using the meal-expenditure data reported in CREST that includes all foods reported in NET. We use a novel statistical estimation procedure to do so. CREST respondents report purchases of the same foods that are reported in NET, but unlike NET, also report the amount paid at each meal. Meal expenditures from CREST (EXP_{ht}) are used to impute prices for similar items purchased in the NET data using the hedonic estimation procedure employed by Richards and Padilla (2009).[3] Based on the characteristic-demand model of Lancaster (1966), hedonic estimation essentially treats all meals as bundles of attributes. With this approach, consumers do not value foods *per se*, but rather the attributes that make up foods and the meals in which they are eaten – food type, the type of restaurant – factors that consumers value when eating out. Therefore, we estimate

[3]Richards and Padilla (2008) use CREST data for Canadian fast food purchases. Specifically, they estimate the impact of fast food promotion (price discounting) on firm market shares and the overall demand for fast food.

the marginal value of meal attributes while controlling for seasonal and regional variation in diet and food choices by specifying the hedonic regression model as:

$$EXP_{ht} = \beta_0 + \sum_i \beta_i F_{iht} + \gamma_1 R_{ht} + \gamma_2 T_{ht} + \gamma_3 G_{ht} + \nu_{ht}, \tag{1}$$

where EXP_{ht} is total meal expenditure at occasion t by household h, F_{iht} is food type i in the meal purchased by consumer h at purchase occasion t (meat, seafood, appetizer, etc.), R_{ht} is the type of restaurant in which the meal was purchased (fast food, fast casual, mid-range, or fine dining), T_{ht} is the time of year (spring, summer, winter, or fall), G_{ht} is the region (Northeast, Southeast, Southcentral, Northcentral, Southwest, Northwest and Pacific), ν_{ht} is an independent, identically distributed (i.i.d.) random error term, and all β_i and γ_k are parameters that will be estimated. Because all of the meal components are assumed to be exogenous, and the errors homoskedastic equation (1) is estimated with ordinary least squares. We then apply the parameter estimates from (1) to each FAFH item reported in the NET data to impute FAFH prices.

FAH is modeled as the numeraire good, or the outside option. As such, it is consumed by all households in the dataset. We include the demand for FAH in the demand model described below by calculating the number of at-home meals as a residual to the total number of meals taken less the number of FAFH meals,. Specifically, we assume that each respondent household faces M total "meal occasions" where $M = 3 * 14 * N_h$ where N_h is the number of household members, each facing 3 meals per day for 14 days. M less the total number of FAFH meals taken over each two-week period is defined as the number of FAH meals. Constructing an outside option in discrete choice models using this approach is well-accepted (Berry, Levinsohn and Pakes 1995). Further, we use a FAH price index from the Bureau of Labor Statistics (USDOL-BLS) matched to each household's region of residence as the numeraire price. The BLS maintains a price index for FAH that is caculated by sampling foods in a representative shopping basket monthly in a large number of markets throughout the U.S. (http://www.bls.gov/cpi/cpi_methods.htm). Although there are well documented weaknesses in their approach (Moulton 1996), the BLS index provides a better regional match with the NPD household locational descriptor that an alternative index from the USDA (USDA-ERS) and is gathered at a greater frequency.[4]

[4] Because the USDA quarterly food-at-home price index (QFAHPI) seems better designed for the purposes at hand, we estimated the model using both and found that the BLS index provided a better fit to the data.

3 Empirical Model of FAFH Demand

A demand system is derived from the expected utility for a household's two-week diary period. During this two-week period, each household is assumed to consider visiting several different restaurant types – fast food, casual, mid-range and fine dining – over the two week period, so the system is defined over restaurant visits. Solving the constrained utility maxmization problem for each household following the general Kuhn-Tucker approach of Wales and Woodland (1983) produces positive demand for a subset of all available restaurant types and FAH as a numeraire or outside option. Following Kim, Allenby and Rossi (2002) and Bhat (2005, 2008), we allow utility to be additive over restaurant visits, and account for satiation and diminishing marginal utility by introducing curvature in the utility function. Therefore, we write the utility function as:

$$u^h(q_i^h, \mathbf{D}^h, \mathbf{Z}^h, \theta) = \frac{1}{\alpha_1}\exp(\varepsilon_1^h)(q_1^h)^{\alpha_i} + \sum_{i=2}^{I}\frac{\gamma_i}{\alpha_i}\left(\phi_i^h\left(\frac{q_i^h}{\gamma_i}+1\right)^{\alpha_i} - 1\right), \quad h = 1, 2, ...H, \tag{2}$$

where q_{ij}^h is the number of visits to restaurant type i by household h, $\mathbf{D}^h$ is a vector of demographic attributes describing household h, the vector $\mathbf{Z}^h$ consists of three physiological measures of the household head: BMI (bmi^h), physical activity level (pa^h) and an index of his or her health status (hs^h), θ is a vector of parameters to be estimated, ε_1^h is a restaurant and household specific random term associated with the outside or numeraire good ($i = 1$, FAH) that reflects unobservable factors driving demand, ϕ_i^h is the perceived quality, or baseline utility, of restaurant type i by household h, α_i are parameters that reflect the curvature of the utility function ($0 < \alpha_i < 1$) and γ_i is the product-specific utility translation parameter.

The parameters α_i and γ_i are largely what separate the MDCEV model from others in the class of discrete, multiple-discrete, or discrete-continuous models. In mathematical terms, γ_i is a translation parameter that determines where the indifference curve between q_1 and q_2 becomes asymptotic to the q_1 or q_2 axis, and thereby where the indifference curve intersects the axes. For example, if $\gamma_1 = 2$, then the indifference curve becomes asymptotic to the q_1 axis at $q_2 = -2$. Because the value of q_2 is less than zero, the indifference curve necessarily defines a corner solution at some positive value of q_1. Moreover, as Bhat (2008) explains, γ_i is, in more intuitive economic terms, a satiation parameter in that higher values of γ_i imply a stronger preference for q_i. Because γ_i governs the slope of the indifference curve between the two restaurant types, higher values of γ_1 imply a higher marginal rate of substitution of restaurant-type 2 for restaurant-type 1, meaning that the consumer is willing to give up more visits to restaurant-type 2 for a given number of visits to restaurant-type 1. The parameter α_i, on the other hand, is also interpreted as a satiation parameter in that it determines how the marginal utility of restaurant-type i changes as q_i rises. If $\alpha_i = 1$, then the marginal utility of i is constant, indifference curves are linear, and the consumer allocates all income to the restaurant with the lowest quality-adjusted price (Deaton and Muellbauer 1980). As the value of α_i falls, satiation rises, the utility function in restaurant i becomes more concave, and satiation occurs at a lower value of q_i. Figures 1 and 2 demonstrate numerically how $\gamma_i \neq 0$ leads to corner solutions in which at least one of the restaurants is not visited, and how different values of α_i affect the shape of the utility function. Importantly, if the values of ϕ_i^h are approximately equal across all types, and if the individual has relatively low values of α_i, then he or she can be described as "variety seeking" and visit some of all choices, while the opposite will be the case if α_i are relatively high (close to 1.0) and the perceived qualities differ (Bhat 2005).

[Insert figures 1 and 2 here]

The sub-utility function described in (2) is additive in quality-adjusted visit-numbers. Therefore, the consumer chooses the specific items and adjusted number of visits that provide the highest utility on each meal out, subject to the satiation effects captured by α_i and γ_i. Consequently, the perceived quality index is critically important in determining which restaurants are chosen. Perceived quality is written as:

$$\phi_i^h = \exp\left(\tau_i + \sum_{k\epsilon K} \beta_k D_k^h + \sum_{m\in M} \alpha_m Z_m^h + \varepsilon_i^h\right), \tag{3}$$

where τ_i is an item-specific preference parameter, $\mathbf{D}^h$ includes income (inc^h), education (ed^h), age (age^h), household size (hsz^h), marital status (mar^h), whether the household has a child below twelve years of age (cld^h), and a set of four regional indicators (rg_l^h); k indexes the number of demographic variables, m the number of physiological variables, and ε_{ij}^h is an iid error term designed to account for any unobserved heterogeneity that may remain in the quality function associated with product i. We separate the demographic and physiological variables, because it is likely that the elements of $\mathbf{Z}^h$ are endogenous. While not simultaneously determined in cross-sectional data, its is probable that each of these measures are correlated with unobservable factors that are important to restaurant choice decisions: loyalty to a certain restaurant, proximity or even a preference for eating out. Below, we explain how we instrument for each of these effects, and how we test the validity of our instrumentation strategy.

The Kuhn-Tucker approach to solving for discrete / continuous demand systems is a structural framework, meaning that it is derived from a constrained utility maximization problem, as opposed to the empirical approach developed by Amemiya (1974). The Kuhn-Tucker method is appropriate for our restaurant-choice application because it allows for the derivation of multiple discrete-continuous demand functions that explicitly take into account the stochastic nature of the underlying utility functions. By solving the Kuhn-Tucker conditions for the constrained utility maximization problem, we derive demand functions that consist of a mixture of corner and interior solutions that are a product of the underlying utility structure, and are not simply imposed during econometric estimation. The constrained utility maximization problem is solved for all I restaurant types, recognizing that M will be visited during each two-week period and $I - M$ will not. The Lagrangian for the MDCEV problem is given by:

$$L^h = u^h(q_i^h, \phi_i^h, \mathbf{D}^h, \theta) + \xi^h \left(y^h - \sum_{i=1}^{I} p_i q_i^h \right), \tag{4}$$

if the total amount of expenditure for household h is given by y^h,and ξ^h is the Lagrange multiplier, so the Kuhn-Tucker first order conditions require:

$$\phi_i^h \left(\frac{q_i^h}{\gamma_i} + 1 \right)^{\alpha_i - 1} - \xi^h p_i \;=\; 0, \qquad \text{if } q_i^h > 0, i = 2, 3, ..., I, \tag{5}$$

$$\phi_i^h \left(\frac{q_i^h}{\gamma_i} + 1 \right)^{\alpha_i - 1} - \xi^h p_i \;<\; 0, \qquad \text{if } q_i^h = 0, i = 2, 3, ..., I, \tag{6}$$

and, if $i = 1$, then $\phi_1^h(q_1^h/\gamma_1 + 1)^{\alpha_1 - 1} = \xi^h p_1$as the outside good is always consumed (no one in the dataset ate FAFH exclusively). Intuitively, the first order conditions imply that the marginal utility of all restaurant types are equal if the restaurant type is visited, and is less than the other types if not consumed. We then use the expression for ξ^h from the first-order condition for the outside good to eliminate the Lagrange multiplier value from the other first-order conditions so the interior and corner solutions can be written, respectively, as:

$$V_i^h + \varepsilon_i^h \;=\; V_1^h + \varepsilon_1^h \qquad \text{if } q_i^h > 0, i = 2, 3, ..., I \tag{7}$$

$$V_i^h + \varepsilon_i^h \;<\; V_1^h + \varepsilon_1^h \qquad \text{if } q_i^h = 0, i = 2, 3, ..., I, \tag{8}$$

where $V_1^h = (\alpha_1 - 1)\ln(q_1^h/\gamma_1 + 1) - \ln(p_1)$ for the numeraire type, $V_i^h = \overset{\sim h}{\phi_i} + (\alpha_i - 1)\ln(q_1^h/\gamma_1 +$

1) $- \ln p_i, i = 2, ..., I$, for the others, and $\overset{\sim h}{\phi_i} = \ln \phi_i^h - \varepsilon_i^h$. Notice that this structure implies $\varepsilon_i^h = V_1^h - V_i^h + \varepsilon_1^h$.

Purely discrete-choice models of demand maintain that the probability any particular alternative is chosen is the probability that the random utility associated with that alternative is greater than all others. The equivalent assumption in the MDCEV case is that the probability a particular set of restaurant visits is chosen is given by the first order condition (7). Specifically, it is the probability that the marginal utility from M of the choices are equal to the marginal utility available from the numeraire, and the marginal utility from the others is less than the numeraire. Because each portfolio of restaurant choices over a two-week period potentially consists of many different restaurants, the solution for the choice probability necessarily involves the joint distribution of the error terms, ε_i^h, that capture the distribution of tastes among households. In the MDCEV model, the probability that any M of the I alternatives is chosen is, therefore, given by the expectation:

$$P(q_1^h, q_2^h, ..., q_m^h, 0, 0...0) = |J| \int_{\varepsilon_1^h} \int_{\varepsilon_M^h} .. \int_{\varepsilon_{I-M,}^h} \int_{\varepsilon_I^h} f(\varepsilon_1^h, ..\varepsilon_M^h, ..., \varepsilon_{I-M,}^h, ..., \varepsilon_I^h) d\varepsilon_1^h ... d\varepsilon_M^h ... d\varepsilon_{I-M,}^h ... d\varepsilon_I^h, \quad (9)$$

where $|J|$ is the determinant of the Jacobian of the transformation from ε_i^h to q_i^h with typical element: $J_{lk} = \partial \varepsilon_{l+1}^h / \partial q_{k+1}^h$. Bhat (2005) shows that the Jacobian determinant is written as: $|J| = \prod_{k=1}^{M} g_k \sum_{k=1}^{M} \frac{p_k}{g_k}$ where $g_k = \left(\frac{1-\alpha_i}{q_i^h + \gamma_i} \right)$. The econometric model assumes a more concrete form by assuming further that the error terms are distributed iid extreme value so that the multivariate integral above collapses to a relatively simple form:

$$P(q_1^h, q_2^h, ..., q_m^h, 0, 0...0) = \frac{1}{\sigma^{M-1}} \left(\prod_{k=1}^{M} g_k \right) \left(\sum_{k=1}^{M} \frac{p_k}{g_k} \right) \left(\frac{\prod_{k=1}^{M} e^{V_k^h/\sigma}}{(\sum_{i=1}^{I} e^{V_i^h/\sigma})^M} \right) (M-1)!, \quad (10)$$

where M varieties are chosen out of I available choices.

In this estimating equation, $\sigma$is the logit scale parameter. In fact, when $M = 1$, or only one alternative is purchased, the MDCEV model becomes a simple logit. Therefore, (10) is appropriately described as a multiple-choice version of a simple logit model that also allows for continuous purchase decisions. Below, we present results from a non-nested testing procedure to compare the fit of the MDCEV model relative to a simple logit alternative.[5] This expression is convenient as it

[5] We compare the MDCEV to a logit, rather than a censored demand system, alternative because both the MDCEV and logit model are derived from the same underlying theoretical model (random utility).

represents a closed form that is easily estimated using maximum likelihood methods.

4 Estimation Method and Identification Strategy

The physiological attributes included in $\mathbf{Z}^h$ are likely to be endogenous in that many of the same unobservable factors that lead NET respondents to be obese, have low levels of physical activity, or obesity-related health problems are the same factors that cause them to consume high levels of FAFH. Without correcting for this possibility, therefore, least squares estimates of (10) will be unreliable. Although obtaining consistent estimates of the BMI, PA and HS effects is not our primary objective, if these parameters are biased and inconsistent, the price-effects of interest will be as well. In using the cross-sectional NET data, we face a problem similar to that encountered by Park and Davis (2001) who explain that "...if available instruments are not highly correlated with the endogenous or mismeasured variable, then the IV [instrumental variables] estimator is biased in the same direction as the ordinary least squares (OLS) estimator and the IV loss of efficiency relative to OLS can be substantial, even in large samples" (p. 841). Indeed, in cross-section datasets such as ours, demand theory does not suggest a set of valid instruments that are available in the data, so an alternative must be found. Our approach in addressing endogeneity follows the framework outlined in Park and Davis (2001) in that we use the method of moments approach developed by Lewbel (1997) to select a set of appropriate instruments. Lewbel's (1997) method of moments circumvents the problems associated with traditional IV analysis in the absence of theoretically-consistent instruments by using the second and third moments of the exogenous variables, and in the included endogenous variable, as instruments. In our application, we calculate covariance terms between each of the exogenous variables and the included endogenous variable, covariance between the FAFH demand variables and the included endogenous variables, in addition to the entire set of exogenous variables. Lewbel (1997) shows that the IV estimator formed in this way is consistent.

We then test the exogeneity and relevancy of our chosen instruments using the testing procedure suggested by Godfrey and Hutton (1994) and Shea (1997). Godfrey and Hutton (1994) develop a nested test for the relevance of instrumental variables. Specifically, they recognize the weaknesses inherent in simply applying a traditional Hausman (1978) $H-$test for exogeneity (and errors in variables) and adopting an IV estimator if the null hypothesis of exogeneity is rejected because the IV solution is predicated on the assumption, not always true, that endogeneity (or errors in variables) is indeed the source of the problem. Therefore, their two stage test proceeds as follows: in the first stage, a J-test is developed to determine whether endogeneity or errors-in-variables are the source of misspecification. If the J statistic is large, then the validity of the chosen set of instruments is in question, and alternatives should be considered. If the J statistic is small, then the second stage test is carried out. In the second stage, the null hypothesis is that the variables thought to be endogenous are, in fact, exogenous, consistent with the Hausman (1978) general specification test. If the H statistic for this test is large, then exogeneity is rejected and the IV estimator is used, whereas if the H statistic associated with the Hausman (1978) test is small, then OLS is appropriate. Further, Shea (1997) argues that traditional tests of instrument validity, or the "weak instrument" problem (Staiger and Stock, 1997) are misleading because they are based on the total explanatory power of the instruments, and not their partial explanatory power. Rather, to be truly valid, instruments must contribute a significant amount of explanatory power to the endogenous variable in question above the usual set of exogenous variables already included in the model. However, Shea (1997) does not suggest a value for the partial R^2 that would form a threshold for being "too low" to suggest the chosen instruments are invalid. Therefore, we follow Staiger and Stock (1997) and interpret an $F-$statistic in the partial regressions lower than 10 as indicating weak instruments. We also present Shea's (1997) partial R^2 statistic for each suspected endogenous variable for completeness.

5 Results and Discussion

Prior to presenting the results obtained from estimating both stages of the econometric model, we first provide a brief description of the sample data. Table 1 provides a summary of the NET panel data used in this study, including the quantity (defined as number of meals) of each type of FAFH, the price per meal and the full set of physiological metrics and demographic descriptors. Perhaps as expected, the price per visit and number of visits to each type of restaurant are inversely related, with fast food the least expensive and the most frequently visited, and fine-dining by far the most expensive, but least visited. The average respondent in the NET survey has a BMI of nearly 26, which is not obese, but yet several points above what is considered healthy. Despite the relatively high BMI value, however, the typical respondent does not have any of the health problems included in the HS index (diabetes, heart disease, high blood pressure, or high cholesterol) as the mean HS index score is 0.279. Although not presented in the table, the strongest partial correlations among the variables of interest are between age and HS (0.38) and BMI and HS (0.29). These findings are suggestive of the fundamental relationships that may exist in the data, but await confirmation upon taking all relevant factors into account.

[table 1 in here]

Next, we present the results of the Godfrey-Hutton-Shea IV selection and validation procedure. These results are presented in table 2. First, the Godfrey-Hutton $J-$statistic is chi-square distributed with $p-k$ degrees of freedom, where p is the number of instrumental variables and k is the number of explanatory variables in the model. In our application the critical chi-square value is 43.773. From the results in table 2, we see that the $J-$statistic for the fast food equation is 0.943, for casual dining is 0.992, for mid-range restaurants is 1.381 and for fine-dining establishments is 1.034. Therefore, we fail to reject the null hypothesis in each case that endogeneity is indeed the problem and conclude that our set of IV are likely to be valid. Second, the Hausman $H-$statistic obtained with this set of instruments is 4.303 while the critical χ^2 value is 7.814, so we fail to reject the null hypothesis of exogeneity for the chosen set of instruments. Third, we calculate the partial-R^2 statistic suggested by Shea (1997) in order to determine the partial explanatory power of our instruments. In table 2, we report both total F-statistics and R^2 and partial values for comparison purposes. Again from the results reported in table 2, we see that the total explanatory power of the chosen instrument set is very good in each case (for cross-sectional data), ranging from a $F-$statistic of 19.923 for the PA index to 80.156 for HS. Applying the partial-regression procedure of Shea (1997), however, we see that the $F-$statistics vary from 576.991 in the BMI regression to 1,413.591 for HS. Clearly, the chosen instruments have a high degree of partial explanatory power, and cannot be described as "weak instruments" in the sense of Staiger and Stock (1997).

[table 2 in here]

Based on the validation procedure described above, we interpret the results of the MDCEV model obtain using Lewbel's (1997) method of moments. The results obtained from estimating the MDCEV-MOM model are found in table 3 below. First, following the pragmatic suggestion of Nakamura and Nakamura (1986), when there is some question regarding the quality of instruments used we show both the OLS and IV estimates. Note that the estimates are very similar, which suggests that the degree of bias in the OLS estimates is small. Second, like Bhat (2005, 2008), we find that the curvature parameters α_i and γ_i are not separately identified. Therefore, we follow

Bhat (2008) and fix α_i for all equations and allow γ_i to vary.[6] In doing so, we find that all four curvature, or satiation parameters, are significantly different from zero. Comparing these values to the range of γ_i shown in figure 1 illustrates a notion that some public health experts regard is at the core of the obesity problem – that the satiation level for fast food is much higher than for other types of FAFH and is indeed high in absolute terms. Further, while not a formal statistical test of the specification (we conduct non-nested model selection tests below) the fact that all four parameters are statistically significant suggests that the fundamental assumption of the MDCEV model – that corner solutions are a feature of the data and consumer decision process – cannot be rejected. Third, the τ_i estimates, which are interpreted as restaurant-type specific preference parameters, suggest a rank-ordering of preferences from fine dining at the top, to casual restaurants, and then mid-range and fast food restaurants the least preferred. Because these estimates are consistent with our prior expectations, at least in terms of the implied ranking, they lend further support to the validity of the MDCEV model. Based on these results, therefore, the MDCEV model should produce reliable price-elasticity estimates.

[table 3 in here]

Price response, which is the focus of this study, is implicitly estimated in the highly non-linear structure of the MDCEV. Therefore, to compare price elasticities across FAFH types, it is necessary to derive the matrix of own and cross-price elasticities. The elasticity expressions are shown in the appendix, while table 4 presents the elasticity estimates. Focusing first on own-price elasticities, the estimates in table 4 show that fine dining restaurants are the most price elastic, followed by mid-range restaurants. This result is consistent with our prior expectations because visits to fine dining restaurants are luxury items and, as such, are more sensitive to higher prices. On the other hand, fast food restaurants are the least price elastic. This is also consistent with the industry's recent experience in the commodity price spike during 2008, and again in 2010. While all restaurants were forced to raise prices, fast food restaurants continued to do relatively well as they still represented a better-value option to most households (MXyMag 2011). Interestingly, the second-most elastic choice represented in table 4 is FAH. When faced with higher prices, consumers reduce FAH expenditures at twice the rate they do for fast food restaurants. Higher prices for FAH clearly cause households to economize in ways that they are not willing or able to do with respect to their fast food habits. Whether some of this reduction in FAH consumption represents substitution

[6] As explained by Bhat (2005, 2008) α_{ik} is not separately identified from γ_{ik} so we are only able to interpret the latter. The value of α_{ik} is restricted to $\alpha_{ik} = 1/(1 + \exp(\delta))$, where $\delta = 1$ for all i, k as suggested by Bhat (2008).

among FAH and FAFH is revealed by the cross-price elasticities. Perhaps not surprisingly, the cross-price elasticity of FAH with respect to all types of FAFH is quite low, ranging from a low of 0.034 for fine dining to 0.087 for mid-range restaurants. Note, however, that the data period covered by our sample (Feb. 2003 - Feb. 2004) does not include a period of either rapid food price increases (2008) or economic slowdowns (2009). Particularly during the 2009 period, restaurant operators witnessed a significant drop in visits, while supermarket sales rose in response to higher FAH consumption (Jargon 2009). That said, our results describe what can be expected in "normal" times. Among different types of FAFH, our results are as expected. Fast food substitutes relatively strongly with mid-range restaurants (0.401) and casual restaurants (0.286), but only weakly with fine dining establishments (0.140). In fact, the cross-price elasticity between fine dining and all restaurant formats is uniformly low. Considering all FAFH types in the NPD data, the demand for fine dining is likely to be driven by attributes of the experience not captured in our data: ambience, service quality, food quality and the other aesthetic factors not associated with food volume and price.

[table 4 in here]

The NET data are somewhat unique among commercial datasets as they contain physiological measures of consumers' well-being: BMI, physical activity and health. Previous research finds that such chooser-attributes are important determinants of a consumer's demand for FAFH (Stewart et al 2005), but do not differentiate between the relative effect of each on the demand for different types of FAFH using comparable, elasticity measures. Therefore, we use the MDCEV model to calculate elasticities of each type of FAFH demand with respect to BMI, physical activity and health (see table 5). These estimates are potentially important for policy purposes because, after appropriately controlling for the endogeneity of each measure, they can provide more specific information on the type of individual that frequents each restaurant-type than was previously available. For example, the "BMI" row in table 5 shows the elasticity of demand for each FAFH type with respect to variation in obesity. While conventional wisdom would lead us to expect higher BMI levels to correspond to more frequent, and expensive, visits to fast food restaurants, obesity appears to be related more strongly to the demand for fine dining. Notice also that all BMI elasticities are positive. Relative to FAH, therefore, the demand for any type of FAFH rises in the level of obesity. Similarly for physical activity. Consumers who tend to exercise more frequently tend to consume more of each type of FAFH. Among the different types of FAFH, the demand for fast food appears to be most closely related to physical activity – consumers who tend to exercise more also visit fast food restaurants more frequently. Finally, recall that the HS index is calculated such that higher values imply more health problems. A positive elasticity with respect to each FAFH type, therefore, means that people with more heart-related health problems tend to eat out more, particularly mid-range restaurants and, to a lesser extent, fast food restaurants.

[table 5 in here]

As a final model-validation test, we conduct a non-nested test comparing the MDCEV model to the most logical discrete-choice alternative: a multinomial logit (MNL) model of FAFH-type choice. However, the dependent variable in a MNL model is fundamentally different from the MDCEV model. Although the MDCEV collapses to the simple logit in the case of $M = 1$, that is not a feature of our data. Therefore, we treat multiple-discrete observations as truly discrete in defining the alternative model. Rather than simply exclude multiple-purchase observations, we choose the restaurant-type with the highest implied utility for each observation and deem that to be the discrete choice. We then apply a simple logit model to the resulting dataset and conduct a Vuong (1989) test for non-nested alternatives. In general, the Vuong test compares two models $f(\theta)$ and $g(\gamma)$; if the Vuong test statistic, V, is greater than the critical standard-normal test value, $V > c$, then we reject the null hypothesis that the two models are equivalent in favor of the hypothesis that $f(\theta)$ is preferred. If $V < -c$, then we conclude the opposite, and if V lies between $-c$ and c then we cannot reject the null that the models are, in fact, the same.[7] In the NET data, the Vuong test statistic value is 6.624, easily rejecting the null hypothesis that the two models are the same, and supporting the MDCEV model.

The policy implications of our findings are readily apparent. If local jurisdictions were to place a tax on fast food, the reduction in fast food consumption would be only moderate as the price elasticity of demand is near to -1.0. However, taxing fast food specifically would cause a rather strong substitution into mid-range and casual restaurants, which may indeed thwart the intent of the original tax. Because casual and mid-range restaurant operators have more diverse menus, and greater opportunities to market differrent offerings to customers as they wait for table service, meals tend to be more calorie-dense than even fast food meals. If the intent is to drive a substitution instead toward FAH, our results suggest that this is not likely to happen as the

[7] The Vuong test statistic is: $V = n^{-1/2} LR_n(\theta_n, \gamma_n)/\varpi_n$, where $LR_n = L_n^f(\theta_n) - L_n^g(\gamma_n)$ is the difference in log-likelihood values and $\varpi_n = \frac{1}{n}\sum[\log \frac{f}{g}]^2 - [\frac{1}{n}\sum \log \frac{f}{g}]^2$ where n is the number of observations, f is the density of the maintained model, g is the density of the alternative and θ and γ are parameter vectors.

cross-price elasticity between fast food and FAH is very low. This result is similar to that expected from the tax propositions considered in Schroeter, Lusk and Tyner (2008) and Richards, Patterson and Tegene (2007), namely that substitution opportunities mean that targeted taxes are not likely to achieve their intended goals. Even if a tax were to change consumer behavior with respect to fast food, it is not necessarily true that obese people – ostensibly the target of any tax on fast food – would be affected. Rather, our results show that fine dining restaurants tend to attract consumers who are both more obese, and less likely to be physically active than average.

6 Conclusion

Nutritionists, public health officials and economists typically place blame for the obesity epidemic on excessive consumption of restaurant meals, or FAFH more generally. Even casual observation of the data show that FAFH consumption and obesity have both been moving upward over time so the apparent statistical association between the two cannot be denied. Uncovering the true structural factors underlying FAFH demand, however, is a much more complicated problem. In this study, therefore, we use a detailed, household-level data set to estimate the structure of FAFH demand, and how physiological attributes – obesity, physical activity and BMI – are associated with the demand for different types of FAFH. Our data consist of two survey data sets collected by NPD, Inc. that are commonly used by firms in the foodservice industry to track restaurant demand and to better understand their key market segments. For the purposes of this study, however, we use one data set – CREST – to impute prices for foods consumed away from home by respondents to a second NPD survey – National Eating Trends (NET).

In the NET data, we observe consumers visiting many different types of restaurants during each two-week period, and consuming various amounts of food each time. For that reason we estimate a multiple discrete continuous extreme value (MDCEV) model of demand that accounts for satiation effects and multiple corner solutions in a structural way. Our model is structural in the sense that all decisions, including the demand for FAH as an outside option or numeraire, are derived from a single utility-maximization model. Validation tests show that the MDCEV model performs well in an absolute sense, and in comparison to the most plausible, discrete-choice alternative.

We find that all types of FAFH are price elastic in demand, but fine dining is highly elastic while fast food is nearly unit elastic. FAH, on the other hand, is relatively elastic as consumers tend to economize on food spending during times of rising food prices. In terms of the cross-price elasticities of demand, we find little willingness to substitute between FAH and any type of FAFH. When prices are rising, consumers prefer to change the type of restaurant they visit, rather than forego the experience entirely. In that regard, our cross-price elasticity estimates show that consumers will readily substitute between casual, mid-range and fast food restaurants, but fine dining establishments are relatively independent in demand. This result is likely due to the fact that many non-price variables enter into the decision to visit fine dining establishments. We also find that the demand for different types of FAFH varies according to the physiological profile of the consumer, measured by their BMI, level of physical activity and health status. While all FAFH response elasticities are positive with respect to BMI, fine dining establishments appear to be the primary beneficiaries of the obesity epidemic. Perhaps contrary to the received wisdom, this result suggests that the destructive cycle of consumers habitually consuming fast food, growing more obese, and demanding more fast food as a result, is at best an overstatement of the truth and may, in fact, be misleading.

Market-based policies designed to control the spread of obesity are often targeted toward specific foods (the "twinkie tax") or food suppliers (restrictions on fast food marketing). Our results, like others before us, suggest that a tax targeted to fast food restaurants is likely to fail when consumers' ability to substitute other types of meals is taken into account. Taxes or regulations that target fast food, or the restaurants that sell fast food, are likely to result in greater demand for food from casual or mid-range restaurants. There is little evidence to suggest, however, that meals from these outlets is substantially lower-calorie or inherently more healthy than from fast food restaurants, so the ultimate goal of the policy will not be achieved.

7 Appendix: Elasticity Expressions

In this appendix, we provide expressions for all own- and cross-price elasticities for the MDCEV model. The elasticities are defined as the percentage change in the expected quantity of each FAFH type with respect to the percentage change in each price. Note that P_i is the marginal probability of choosing type i, in any combination with other restaurant types, so the expected quantity is the probability multiplied by the quantity implied by the continuous part of the model, and E_{ij} is the price-elasticity of type i with respect to the price of type j. Define $D = \sum_{i=1}^{4} V_i$.

1. Own-price elasticity of numeraire type:

$$
\begin{aligned}
E_{11}/p_1 = \frac{\partial P_1}{\partial p_1} &= \left(\frac{e^{V_1/\sigma}}{D} \left[1 - \frac{1}{\sigma}(1 - \frac{e^{V_1/\sigma}}{D}) \right] \right) \\
&+ \frac{g_2 e^{V_1/\sigma} e^{V_2/\sigma}}{\sigma D^2} \left[1 - \frac{g_1(\frac{p_1}{g_1} + \frac{p_2}{g_2})}{\sigma p_1}(1 - \frac{2e^{V_1/\sigma}}{D}) \right] \\
&+ \frac{g_3 e^{V_1/\sigma} e^{V_3/\sigma}}{\sigma D^2} \left[1 - \frac{g_1(\frac{p_1}{g_1} + \frac{p_3}{g_3})}{\sigma p_1}(1 - \frac{2e^{V_1/\sigma}}{D}) \right] \\
&+ \frac{g_4 e^{V_1/\sigma} e^{V_4/\sigma}}{\sigma D^2} \left[1 - \frac{g_1(\frac{p_1}{g_1} + \frac{p_4}{g_4})}{\sigma p_1}(1 - \frac{2e^{V_1/\sigma}}{D}) \right] \\
&+ \frac{2 g_2 g_3 e^{V_1/\sigma} e^{V_2/\sigma} e^{V_3/\sigma}}{\sigma^2 D^3} \left[1 - \frac{g_1(\frac{p_1}{g_1} + \frac{p_2}{g_2} + \frac{p_3}{g_3})}{\sigma p_1}(1 - \frac{3e^{V_1/\sigma}}{D}) \right] \\
&+ \frac{2 g_2 g_4 e^{V_1/\sigma} e^{V_2/\sigma} e^{V_4/\sigma}}{\sigma^2 D^3} \left[1 - \frac{g_1(\frac{p_1}{g_1} + \frac{p_2}{g_2} + \frac{p_4}{g_4})}{\sigma p_1}(1 - \frac{3e^{V_1/\sigma}}{D}) \right] \\
&+ \frac{2 g_3 g_4 e^{V_1/\sigma} e^{V_3/\sigma} e^{V_4/\sigma}}{\sigma^2 D^3} \left[1 - \frac{g_1(\frac{p_1}{g_1} + \frac{p_3}{g_3} + \frac{p_4}{g_4})}{\sigma p_1}(1 - \frac{3e^{V_1/\sigma}}{D}) \right] \\
&+ \frac{6 g_2 g_3 g_4 \Pi e^{V_i/\sigma}}{\sigma^3 D^4} \left[1 - \frac{g_1(\frac{p_1}{g_1} + \frac{p_2}{g_2} \frac{p_3}{g_3} + \frac{p_4}{g_4})}{\sigma p_1}(1 - \frac{4e^{V_1/\sigma}}{D}) \right].
\end{aligned}
$$

2. Cross-price elasticity of numeraire type:

$$
\begin{aligned}
E_{12}/p_2 = \frac{\partial P_1}{\partial p_2} &= \left(\frac{e^{V_1/\sigma} e^{V_2/\sigma}}{\sigma D^2} \left[g_1 + \frac{p_1}{p_2} - \frac{g_1 g_2(\frac{p_1}{g_1} + \frac{p_2}{g_2})}{p_2 \sigma} \left(1 + \frac{2e^{V_2/\sigma}}{D} \right) \right] \right) \\
&+ \frac{2 g_1 g_3 e^{V_1/\sigma} e^{V_2/\sigma} e^{V_3/\sigma}}{\sigma^2 D^3} \left[1 + \frac{(\frac{p_1}{g_1} + \frac{p_3}{g_3})}{p_2} - \frac{g_2(\frac{p_1}{g_1} + \frac{p_2}{g_2} + \frac{p_3}{g_3})}{p_2 \sigma} \left(1 - \frac{3e^{V_2/\sigma}}{D} \right) \right] \\
&+ \frac{2 g_1 g_4 e^{V_1/\sigma} e^{V_2/\sigma} e^{V_4/\sigma}}{\sigma^2 D^3} \left[1 + \frac{(\frac{p_1}{g_1} + \frac{p_4}{g_4})}{p_2} - \frac{g_2(\frac{p_1}{g_1} + \frac{p_2}{g_2} + \frac{p_4}{g_4})}{p_2 \sigma} \left(1 - \frac{3e^{V_2/\sigma}}{D} \right) \right] \\
&+ \frac{6 g_1 g_3 g_4 \Pi e^{V_i/\sigma}}{\sigma^3 D^4} \left[1 + \frac{(\frac{p_1}{g_1} + \frac{p_3}{g_3} + \frac{p_4}{g_4})}{p_2} - \frac{g_2(\frac{p_1}{g_1} + \frac{p_2}{g_2} + \frac{p_3}{g_3} + \frac{p_4}{g_4})}{p_2 \sigma} \left(1 - \frac{3e^{V_2/\sigma}}{D} \right) \right]
\end{aligned}
$$

3. Own-price elasticity of non-numeraire type:

$$E_{22}/p_2 = \frac{\partial P_2}{\partial p_2} = \left(\frac{g_1 e^{V_1/\sigma} e^{V_2/\sigma}}{\sigma D^2} \left[1 - \frac{g_2(\frac{p_1}{g_1} + \frac{p_2}{g_2})}{p_2 \sigma} \left(1 - \frac{2e^{V_2/\sigma}}{D} \right) \right] \right)$$
$$+ \frac{2 g_1 g_3 e^{V_1/\sigma} e^{V_2/\sigma} e^{V_3/\sigma}}{\sigma^2 D^3} \left[1 - \frac{g_2(\frac{p_1}{g_1} + \frac{p_2}{g_2} + \frac{p_3}{g_3})}{p_2 \sigma} \left(1 - \frac{3e^{V_2/\sigma}}{D} \right) \right]$$
$$+ \frac{2 g_1 g_4 e^{V_1/\sigma} e^{V_2/\sigma} e^{V_4/\sigma}}{\sigma^2 D^3} \left[1 - \frac{g_2(\frac{p_1}{g_1} + \frac{p_2}{g_2} + \frac{p_4}{g_4})}{p_2 \sigma} \left(1 - \frac{3e^{V_2/\sigma}}{D} \right) \right]$$
$$+ \frac{6 g_1 g_3 g_4 \Pi e^{V_i/\sigma}}{\sigma^3 D^4} \left[1 - \frac{g_2(\frac{p_1}{g_1} + \frac{p_2}{g_2} + \frac{p_3}{g_3} + \frac{p_4}{g_4})}{p_2 \sigma} \left(1 - \frac{4e^{V_2/\sigma}}{D} \right) \right]$$

4. Cross-price elasticity of non-numeraire type:

$$E_{23}/p_3 = \frac{\partial P_2}{\partial p_3} = \left(\frac{2 g_1 g_2 e^{V_1/\sigma} e^{V_2/\sigma} e^{V_3/\sigma}}{\sigma^2 D^3} \left[1 + \frac{(\frac{p_1}{g_1} + \frac{p_2}{g_2})}{p_3} - \frac{g_3(\frac{p_1}{g_1} + \frac{p_2}{g_2} + \frac{p_3}{g_3})}{p_3 \sigma} + \frac{3 g_3 e^{V_3/\sigma} (\frac{p_1}{g_1} + \frac{p_2}{g_2} + \frac{p_3}{g^3})}{p_3 \sigma D} \right] \right)$$
$$+ \frac{6 g_1 g_2 g_4 \Pi e^{V_i/\sigma}}{p_1 \sigma^3 D^4} \left[1 + \frac{(\frac{p_1}{g_1} + \frac{p_2}{g_2} + \frac{p_4}{g^4})}{p_3} - \frac{g_3(\frac{p_1}{g_1} + \frac{p_2}{g_2} + \frac{p_3}{g_3} + \frac{p_4}{g_4})}{p_3 \sigma} + \frac{4 g_3 e^{V_3/\sigma} (\frac{p_1}{g_1} + \frac{p_2}{g_2} + \frac{p_3}{g_3} + \frac{p_4}{g_4})}{p_3 \sigma D} \right]$$

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Table 1: Summary of NET Data: FAFH Demand and Respondent Demographics.

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Cost	80.313	93.660	1.247	1031.800
Price of Fast Food	4.475	1.080	1.247	8.683
Price of Mid-Range	5.931	0.646	3.270	10.391
Price of Casual Dining	9.374	0.495	6.536	13.181
Price of Fine Dining	19.981	0.337	16.498	23.399
Quantity of Fast Food	6.370	6.763	0.000	86.000
Quantity of Mid-Range	3.423	7.063	0.000	82.000
Quantity of Casual Dining	1.526	3.565	0.000	50.000
Quantity of Fine Dining	0.937	2.985	0.000	34.000
Income	45.902	34.965	0.000	300.000
Age	44.988	14.202	0.000	70.000
Education	14.006	2.179	0.000	16.000
HH Size	3.196	1.483	0.000	8.000
% White	0.874	0.332	0.000	1.000
% Black	0.078	0.268	0.000	1.000
% Asian	0.016	0.126	0.000	1.000
Children	0.224	0.417	0.000	1.000
Marital Status	0.780	0.414	0.000	1.000
Employed Full-Time	0.065	0.246	0.000	1.000
Employed Part-Time	0.707	0.455	0.000	1.000
Not Employed	0.222	0.415	0.000	1.000
New England	0.039	0.193	0.000	1.000
Mid Atlantic	0.141	0.348	0.000	1.000
East North Central	0.184	0.388	0.000	1.000
West North Central	0.079	0.270	0.000	1.000
South Atlantic	0.177	0.382	0.000	1.000
East South Central	0.067	0.249	0.000	1.000
West South Central	0.103	0.304	0.000	1.000
Mountain	0.071	0.258	0.000	1.000
BMI	25.739	7.309	4.900	99.500
Physical Activity	5.561	4.135	0.000	12.000
Health Status	0.379	0.742	0.000	4.000

N=3036

Table 2: Specification Test Results: MDCEV Model

Godfrey-Hutton J-Test		
	J	Critical J
Fast Food	0.943	43.773
Casual	0.992	43.773
Mid-Range	1.381	43.773
Fine Dining	1.034	43.773

Instrument Validity				
	Total		Partial	
	R^2	F	R^2	F
BMI	0.301	32.641*	0.128	576.991*
PA	0.207	19.923*	0.196	955.153*
HS	0.513	80.156*	0.264	1,413.59*

Note: In all tables, a single asterisk indicates significance at a 5% level.

Table 3: FAFH MDCEV Model Estimates: OLS and IV Estimator

OLS

	Fast Food		Casual		Fine Dining		Mid-Range	
Variable	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
γ	0.005	0.812	0.136*	5.422	0.134*	2.962	0.155*	5.633
BMI	0.051*	4.619	0.131*	5.967	0.098*	3.288	0.126*	8.488
PA	0.159*	5.099	0.219*	3.936	0.194*	2.758	0.188*	4.737
HS	0.185	1.283	0.149	0.660	0.132	0.521	0.244	1.357
Income	0.171*	7.904	0.164*	4.956	0.103*	3.245	0.136*	6.013
Age	0.009	1.410	0.092*	7.528	0.186*	13.520	0.025*	2.863
Education	0.158*	3.589	0.166	1.880	0.209*	2.073	0.172*	2.869
Household Size	0.043*	6.815	0.052*	3.830	0.188*	14.935	0.039*	4.932
Child < 12	0.265*	12.964	0.202*	4.771	0.172*	3.189	0.193*	7.170
Marital Status	0.136*	7.139	0.181*	5.021	0.088*	1.989	0.169*	6.498
Region 1	0.114*	4.580	0.156*	3.584	0.174*	2.951	0.269*	8.090
Region 2	0.182*	8.631	0.229*	5.848	0.241*	4.744	0.215*	6.499
Region 4	0.163*	7.769	0.141*	3.360	0.222*	4.625	0.271*	8.793
τ_i	0.135	1.670	0.188	1.143	0.226	1.221	0.136	1.149
σ	0.271*	80.682						
γ_0	0.049	1.236						
LLF	368.375							

Instrumental Variables Estimator

	Fast Food		Casual		Fine Dining		Mid-Range	
γ	0.006*	2.001	0.137*	5.394	0.134*	2.981	0.156*	5.572
BMI	0.052*	2.489	0.138*	3.118	0.097*	2.044	0.136*	4.584
PA	0.163*	2.343	0.221	1.630	0.194	1.344	0.188*	2.039
HS	0.186	0.853	0.149	0.450	0.132	0.391	0.244	0.863
Income	0.171*	7.946	0.164*	4.796	0.103*	3.312	0.136*	6.041
Age	0.009	1.314	0.091*	6.935	0.186*	12.970	0.022*	2.422
Education	0.157*	3.563	0.166	1.842	0.211*	2.076	0.171*	2.773
Household Size	0.043*	6.511	0.051*	3.598	0.189*	14.342	0.039*	4.611
Child < 12	0.265*	12.974	0.201*	4.710	0.172*	3.222	0.193*	6.919
Marital Status	0.136*	7.148	0.181*	4.891	0.088*	2.001	0.169*	6.449
Region 1	0.114*	4.597	0.156*	3.497	0.174*	2.971	0.269*	8.019
Region 2	0.182*	8.575	0.229*	5.670	0.239*	4.768	0.215*	6.403
Region 4	0.163*	7.781	0.141*	3.306	0.222*	4.644	0.271*	8.620
τ_i	0.135	1.402	0.188	0.914	0.226	0.988	0.135	0.981
σ	0.269*	80.602						
γ_0	0.051	1.247						
LLF	390.789							

Table 4: FAFH Elasticity Matrix

	FAH	Fast Food	Casual	Fine Dining	Mid-Range
FAH	-2.475	0.058	0.074	0.034	0.087
Fast Food	0.058	-1.209	0.286	0.140	0.401
Casual	0.074	0.286	-1.768	0.068	0.016
Fine Dining	0.034	0.140	0.068	-3.314	0.109
Mid-Range	0.087	0.401	0.016	0.109	-1.915

Note: Elasticities are of the column variable with respect to the row variable.

Table 5: BMI, Physical Activity, Health Status Elasticities

	Fast Food	Casual	Fine Dining	Mid-Range
BMI	0.159	0.139	0.829	0.175
Physical Activity	0.215	0.152	0.120	0.181
Health Status	0.023	0.019	0.015	0.031

Note: Elasticities are calculated at the mean of observations.

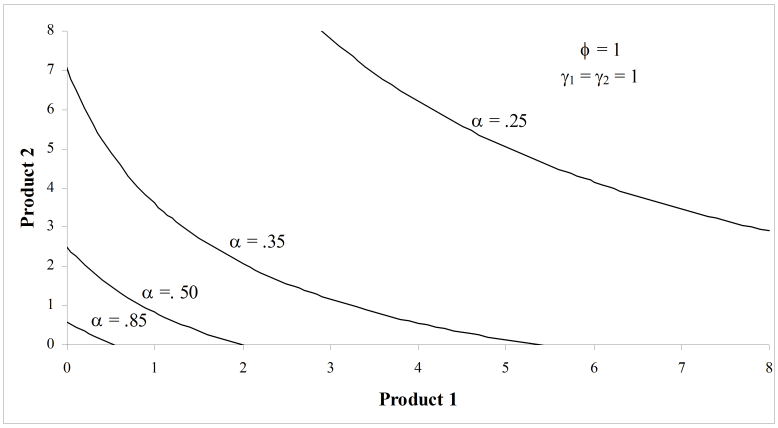

Figure 1: Effect of Varying α on Utility

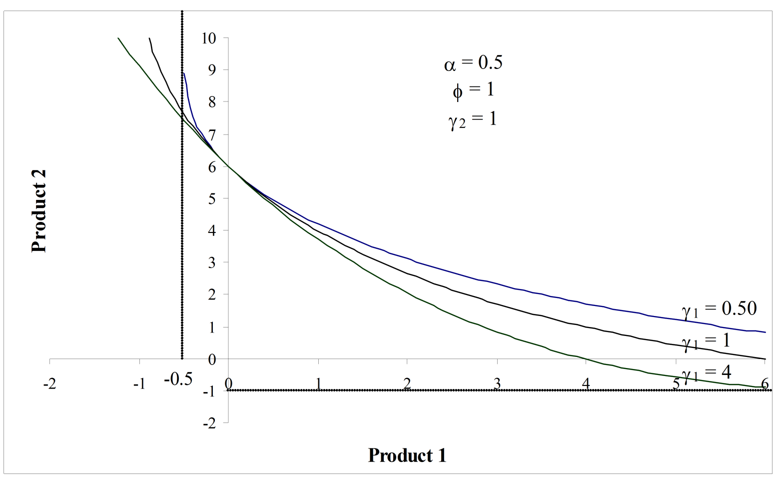

Figure 2: Effect of Varying γ on Utility