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

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1 Introduction

Despite the apparent lack of consensus 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 (Colville 2009; 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 (Mancino, Todd and Lin 2009; Anderson and Matsa 2011), (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. First, eating out represents much more than simply the demand for food consumed somewhere other than the home as restaurant experiences embody the demand for entertainment, convenience, companionship and status as well. Second, while food price and quality are closely related, the quality of a restaurant meal is rarely observable *a priori*. 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.

Multiple discrete / continuous choice problems are not unique to FAFH. 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). Assuming that corner solutions result 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.

FAFH choices and individual attributes are likely to be jointly endogenous. Therefore, we account for the effects of obesity (BMI), level of physical activity (PA) and health status on FAFH demand. Nutritional research finds that such individual factors are of critical importance to food choice and, therefore, whether FAFH is chosen over FAH, and which type of restaurant is chosen within the realm of FAFH (Drewnowski 1997; Nestle et al. 1998; Manore 2004). In a review of the literature regarding taste and food preferences, Drewnowski (1997) finds that "...preferences for higher-fat foods were directly linked to the subjects' own percentage of body fat...suggesting that preferences for fat in foods may carry a familial, and possibly genetic, component (p.243)." Using data from the Behavioral Risk Factor Surveillance System (BRFSS), Simoes et al. (1985) find that men who exercise on a regular basis consume some 30.2% of their daily calories from fat, while sedentary men consume 37.1%. The authors report finding a similar pattern for women: 30.3% of calories from fat for inactive women, and 24.6% for those who exercise. In statistical models of food choice, however, personal factors are likely endogenous as physiological attributes depend on the foods consumed, and the food consumed depends upon the physical state of the individual.

We contribute to the empirical literature on the demand for FAFH in four ways. First, we describe a unique data set on FAFH demand that has been collected for a number of years, but has not yet been exploited for the purpose of analyzing public policy. 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. Fourth, we account for the endogeneity of individual attributes in a model of FAFH demand, and provide empirical estimates of how obesity, physical activity and health status affect FAFH choices.

The empirical approach 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 rest of the paper is structured as follows. The next section provides 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 then discussed, while 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=never, to 5=frequently). Because there is no way of measuring the length or intensity of each session in the data, we create an index of PA by summing exercise frequency and history. For example, if a respondent does aerobics three times per week, swims twice, and has exercised frequently in the past, he or she will have a PA value of 10. This is admittedly a rough measure of actual physical activity, but developing a more complex measure would be imputing false precision into the data. 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. Again, this is also only an approximate measure of actual health status because it does not suggest severity or longevity of any of the conditions, but is likely to be highly correlated with actual health status and does not attempt to infer anything more than the data provides.

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).[1] 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 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:

$$EXP_{ht} = \beta_0 + \sum_i \beta_{1i} F_{iht} + \sum_j \beta_{2j} M_{jht} + \sum_k \beta_{3k} R_{kht} + \sum_l \beta_{4l} T_{lht} + \sum_m \beta_{4m} G_{mht} + \beta_5 WE + \nu_{ht}, \quad (1)$$

where EXP_{ht} is total meal expenditure at occasion t by household h, F_{iht} is a set of binary variables indicating food type i in the meal purchased by consumer h at purchase occasion t (i = burger, side vegetable, hot beverage, etc.), M_{jht} is a set of binary indicators for the meal occasion (j = brunch, lunch, dinner, snack), R_{kht} is a set of binary variables representing the type of restaurant in which the meal was purchased (k = fast food, fast casual, mid-range, or fine dining), T_{lht} is the time of year (l = spring, summer, winter, or fall), G_{mht} is the region (m = New England, Mid Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain and Pacific), WE is a binary indicator for whether the meal was purchased on a weekend, ν_{ht} is an independent, identically distributed (i.i.d.) random error term, and all β_{1i-4l} are parameters that are estimated. Because all of the meal components and restaurant-types are assumed to be exogenous, and the errors homoskedastic equation (1) is estimated with ordinary

[1] 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.

least squares.[2] Each of the parameters in (1) thus represents a marginal value of the attribute in question, or the implicit price of each type of food, purchased at each type of restaurant, in each region and time of year. Fitted values for each combination of attributes are then used to calculate prices for each item, p_i, that appear in the NET data, and in the demand model below.[3]

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. 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 calculated 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]

3 Empirical Model of FAFH Demand

In this section, we derive a demand system that reflects multiple discrete / continuous choices among restaurant choices. During each two-week diary period, a 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 maximization 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. Wales and Woodland (1983) describe two ways of estimating

[2] Our implicit assumption in this model is that the restaurant-format and menu-price decsions are made by the restaurant owners and are made in a prior, un-modeled decision stage. As such, they are considered exogenous to the consumer-demand problem considered here. Unlike NET, more detailed demographic variables are not available in CREST so we could not include a more detailed accounting for either observed or unobserved heterogeneity.

[3] The estimates of (1) are extensive and available from the authors upon request.

[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.

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 posses the same utility function. In the latter, utility is instead distributed randomly throughout the population and stochasticity derives directly from consumer heterogeneity. 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. 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 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.[5]

Based on the nutrition literature cited in the introduction, to the extent that all FAFH tends to be more calorically-dense and higher in fat than FAH (French, et al. 2001; Bowman and Vinyard 2004) we expect the demand for all types of FAFH to rise in BMI. Although Drewnowski (1997) suggests that PA should have a negative effect on FAFH demand, the fact that physically active

[5]Bhat (2005, 2008) interprets ϕ_i^h as "baseline utility," or the utility from zero consumption. Because utility is hypothetical for a non-consumed good, we refer to this parameter instead as "perceived quality" as the higher is ϕ_i^h the less likely is zero consumption.

individuals demand higher energy meals leaves this effect uncertain. While we would hope that HS has a negative effect on all types of FAFH demand, once the endogeneity of HS is properly accounted for, it is possible that individuals who have little concern for their health, in fact, consume more FAFH. Within FAFH, we expect to find a stronger positive effect of BMI on fast-food demand. We have no priors on the remaining allocative effects within FAFH of individual attributes.

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).[6]

[6] In the empirical application below, we find, like Bhat (2005, 2008), 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, or estimate the "γ profile" in his terminology. Specifically, 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), which means that α_i is fixed to 0.27 for estimation purposes. In prior estimates of a "hybrid profile" (Bhat 2008) we estimate the value of α_i as 0.27 so this is a logical choice to identify the full γ profile.

[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.[7] 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 not an artifact of the estimation

[7] Accounting for perceived quality with the ϕ_i^h index in this way is well accepted in the literature. When items vary in perceived quality from transaction to transaction in a cross-section, Goldman and Grossman (1978) argue that reported prices must be corrected for unobserved variation in quality to avoid bias in estimation. Our approach in this study is similar to Cox and Wohlgenant (1986) in that we assume different households differ in their preferences for quality. By controlling for the demographic determinants of perceived quality in a direct way, we ensure that as much of the remaining price variation as possible is due to factors specific to the restaurant in question.

procedure. 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:

$$\begin{aligned} \phi_i^h \left(\frac{q_i^h}{\gamma_i} + 1 \right)^{\alpha_i - 1} - \xi^h p_i &= 0, \qquad \text{if } q_i^h > 0, i = 2, 3, ..., I, & (5) \\ \phi_i^h \left(\frac{q_i^h}{\gamma_i} + 1 \right)^{\alpha_i - 1} - \xi^h p_i &< 0, \qquad \text{if } q_i^h = 0, i = 2, 3, ..., I, & (6) \end{aligned}$$

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 a restaurant type is equal to the marginal utility of the numeraire if it is chosen by the consumer, and is less than marginal utility of the numeraire if the type in question is not chosen. 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:

$$\begin{aligned} V_i^h + \varepsilon_i^h &= V_1^h + \varepsilon_1^h \qquad \text{if } q_i^h > 0, i = 2, 3, ..., I & (7) \\ V_i^h + \varepsilon_i^h &< V_1^h + \varepsilon_1^h \qquad \text{if } q_i^h = 0, i = 2, 3, ..., I, & (8) \end{aligned}$$

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 (2008) 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.[8] 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.[9] This expression is convenient as it 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

[8] As Bhat (2005) explains, if one alternative is chosen, the continuous part drops out because the amount of expenditure on the option chosen is equal to the income constraint.

[9] 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).

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. 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. Lewbel (1997) shows that the IV estimator formed in this way is consistent.

Prices are also likely to be endogenous. Because we impute household-level prices using the CREST data, the residuals in the demand model are likely to be correlated with these imputed prices. Therefore, we apply the Lewbel (1997) instrumentation strategy with respect to both the physiological attributes, and FAFH prices.

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's (1994) 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.

With this instrumentation strategy, we estimate the MDCEV model using maximum likelihood with Nlogit 4.0.

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, from the results in table 2, we see that the Godfrey-Hutton $J-$statistic for the fast food equation is 0.887, 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 5.782 while the critical χ^2 value is 14.067, so we fail to reject the null hypothesis of exogeneity for the chosen set of instruments. Third, we find 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 533.541 in the BMI regression to 2,082.804 for the price of Mid-Range restaurants. 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. 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 qualitatively similar, but differ quantitatively in many imporant respects, particularly with respect to the parameters unique to the MDCEV specification (γ_i and τ_i). This finding suggests that the degree of bias in the OLS estimates is considerable. Interpreting the results in the second, IV panel, 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.[10] 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 fast food at the top, to fine dining restaurants, and then mid-range and casual restaurants the least preferred. Because these estimates are driven as much by volume and visitation as price, they are consistent with our prior expectations. In this sense, 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

[10] As suggested by Bhat (2008), the MDCEV model can be estimated in either α-profile, γ-profile, or a hybrid profile in which one α is estimated along with choice-specific γ_i values. In order to examine the robustness of our results, we estimated each of these models and chose the γ-profile version on the basis of goodness of fit. Moreover, the remaining parameters of interst do not vary significantly between specifications so we are confident that our results are robust.

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. In general terms, the price elasticity is derived as the changed in the expected quantity of product i with respect to a change in the price of product j, or:

$$\varepsilon_{ij} = \frac{\partial E(q_i)}{\partial p_j}\frac{p_j}{E(q_i)} = \sum_{i=m}^{M}\left(\frac{\partial P(q_1, I_{2m}q_{2m}, I_{3m}q_{3m}, I_{4m}q_{4m}, I_{5m}q_{5m})}{\partial p_j}\right)\frac{p_j}{E(q_i)},$$

where $I_{lm} = 1$ if $q_{lm} > 0$ and $I_{lm} = 0$ otherwise. The detailed elasticity expressions are available from the authors, while table 4 presents the elasticity estimates. Focusing first on own-price elasticities, the estimates in table 4 show that casual restaurants are the most price elastic, followed by mid-range restaurants. This result is consistent with our prior expectations because visits to these types of restaurants are likely to be regarded as luxuries by a segment of consumers who are particularly price-sensitive. Fine dining restaurants are the least price elastic as consumers of high-end dining experiences are less likely be as price-sensitive as those who frequent lower-priced chain restaurants. Fast food restaurants are also relatively inelastic. Although estimated using data from an earlier period (Feb. 2003 - Feb. 2004) our finding with respect to fast food restaurants is consistent with the industry's recent experience during 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). The elasticity estimates in table 4 also show FAH to be inelastic in demand. Although fast food restaurants are relatively inexpensive among the choices within FAFH, fast food prices still include margins for restaurant chains and an important labor-component of cost. When faced with higher prices, consumers appear to be as reluctant to reduce FAH spending as they are to substitute away from any FAFH category. Again, this is consistent with more recent experience as the 2008 - 2009 recession saw little decline in supermarket sales, but a precipitous fall in particularly casual and mid-range restaurant sales (Jargon 2009). Whether some of this reduction in FAH consumption represents substitution among FAH and FAFH is revealed by the cross-price elasticities. Perhaps not surprisingly, the cross-price elasticities of FAH with respect to all types of FAFH are quite low, ranging from a low of 0.005 for fine dining to 0.062 for fast food restaurants. Among different types of FAFH, the cross-price elasticities are all very low, but fast food substitutes relatively strongly with mid-range restaurants (0.019) and casual restaurants (0.016), but only weakly with fine dining establishments (0.003). 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. Because the cross-price elasticities within FAFH are low, taxing one is not likely to cause consumers to substitute much among different types of venues, but rather reduce their consumption of the FAFH type in question according to the own-price elasticity.

[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. Conventional wisdom would lead us to expect higher BMI levels to correspond to more frequent, and expensive, visits to fast food restaurants, but obesity also appears to be strongly related 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. Given that the nutrition literature cited in the introduction shows that higher-BMI individuals tend to demand meals with higher fat contents, and each FAFH category is higher-fat than FAH, BMI should have a positive effect on the demand for each FAFH type. 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 – perhaps because they are the least likely to worry about the caloric-density of their food. 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 casual restaurants and, to a lesser extent, fast food restaurants. With respect to the fast food elasticity, our estimate implies that a 200% change in the HS index (a tripling, or changing from one of the conditions to three) can be expected to result in a 7.2% increase in fast food visits. This is an important result, as it indicates that, *ceteris paribus*, less-healthy people are significantly more likely to frequent fast food restaurants. Clearly, the implication here is that recognition of their own health condition does not stop many consumers from eating fast food.

[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.[11] 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.[12] In the NET data, the Vuong test statistic value is 34.299, 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 with an objective of reducing consumption, the policy would be only moderately successful as demand is inelastic (-0.743). However, taxing fast food specifically would cause a limited amount of substitution into mid-range and casual restaurants as the "spillover effects" of

[11] Alternatives to the MNL model include a nested logit or a mixed-logit alternative. However, both of these models are more flexible versions of the simplest discrete choice model. Pinjari and Bhat (2010) and Bhat (2005) describe flexible analogs using the MDCEV core that are more directly comparable to the nested logit and mixed logit, respectively. We seek to compare the most simple discrete choice and multiple discrete / continuous choice models.

[12] The Vuong test statistic is: $V = n^{-1/2} LR_n(\theta_n, \gamma_n)/\varpi_n$, where $LR_n = L_n^f(\theta_n) - L_n^g(\gamma_n) - (p-q)$ is the difference in log-likelihood values and $\varpi_n = \frac{1}{n}\sum[\log\frac{f}{g}]^2 - [\frac{1}{n}\sum\log\frac{f}{g}]^2$, adjusted for the difference in parameters, p and q, 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.

such a tax are likely to be small. Because the cross-price elasticities are so low, targeted taxation may indeed reduce FAFH consumption as a whole. Although the cross-price elasticity with respect to FAH is also small, a small percentage change in FAH occasions easily absorbs all of the lost fast food visits due to an increase in the tax. We demonstrate this finding numerically by conducting a counterfactual simulation in which we cause fast food prices to rise by 10%, 25% and 50%, and measure the resulting changes in FAH, fast food, casual dining, fine dining and mid-range restaurant demand.[13] Table 6 shows these results. This simulation shows that the own-price effect of a specific tax on fast food is significant, while the cross-effects on other FAFH types and FAH is very small indeed. Note in interpreting these results, however, that the FAH measure is an index so a small change represents a larger number of FAH meals, enough to account for the larger absolute decline in fast food visits.

While the tax propositions considered in Schroeter, Lusk and Tyner (2008) and Richards, Patterson and Tegene (2007) show that substitution opportunities thwart the intent of targeted taxes so that calories consumed actually increase, our results show the opposite. If consumers are not willing to substitute away from one type of FAFH, then targeted taxes may indeed be effective. However, 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 both fast food and fine dining restaurants alike tend to attract consumers who are more obese, and those who visit fine dining restaurants tend to be less likely to be physically active than average. Tax effectiveness, therefore, depends on both the type of restaurant, and the type of individual paying the tax.

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,

[13] We conduct this simulation using the algorithm developed in Pinjari and Bhat (2011) that ensures the solution at each new price point is consistent with the Kuhn-Tucker conditions and the budget constraint facing each consumer.

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, particularly fine dining while FAH is still elastic, but less so. FAH, is relatively inelastic as consumers have a limited ability to substitute away from home meals 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, and among different types of FAFH. When prices are rising, consumers prefer to forego the experience entirely rather than substitute some other type of FAFH. In that regard, our cross-price elasticity estimates show that consumers will not readily substitute between fast food, casual, mid-range and fast food restaurants, and that fine dining establishments are even more 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, fast food and 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, supported by a simulation exercise, suggest that a tax targeted to fast food restaurants is likely to be successful in reducing FAFH consumption more generally when consumers' unwillingness 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 only small increases in demand for food from casual or mid-range restaurants. Rather than visit fast food restaurants, consumers in our data prefer to eat at home.

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

Variable	Mean	Units	Std. Dev.	Min	Max
Cost	80.313	$	93.660	1.247	1031.800
Price of Fast Food	4.475	$ / visit	1.080	1.247	8.683
Price of Mid-Range	5.931	$ / visit	0.646	3.270	10.391
Price of Casual Dining	9.374	$ / visit	0.495	6.536	13.181
Price of Fine Dining	19.981	$ / visit	0.337	16.498	23.399
Quantity of Fast Food	6.370	# visits	6.763	0.000	86.000
Quantity of Mid-Range	3.423	# visits	7.063	0.000	82.000
Quantity of Casual Dining	1.526	# visits	3.565	0.000	50.000
Quantity of Fine Dining	0.937	# visits	2.985	0.000	34.000
Income	45.902	$,000	34.965	0.000	300.000
Age	44.988	years	14.202	0.000	70.000
Education	14.006	years	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	2.241	#	0.417	0.000	1.000
Marital Status	0.780	% married	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	Index	7.309	4.900	99.500
Physical Activity	5.561	Index	4.135	0.000	12.000
Health Status	0.379	Index	0.742	0.000	4.000

N=3036

Table 2: Specification Test Results: MDCEV Model

Godfrey-Hutton J-Test

	J	Critical J
Fast Food	0.887	43.773
Casual	1.296	43.773
Mid-Range	1.578	43.773
Fine Dining	1.419	43.773

Instrument Validity

	Total		Partial	
	R^2	F	R^2	F
BMI	0.301	32.641*	0.119	533.541*
PA	0.207	19.923*	0.196	956.463
HS	0.513	80.156*	0.265	1,413.807
Fast Food Price	0.222	21.671*	0.189	913.128
Casual Price	0.357	42.239*	0.317	1,827.176
Mid-Range Price	0.349	42.276*	0.347	2,082.804
Fine Dining Price	0.381	46.883*	0.322	1,868.159

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	1.172*	37.740	1.747*	15.466	3.236*	7.413	0.712*	23.982
BMI	0.067*	6.105	0.219*	12.056	0.255*	10.645	0.282*	18.666
PA	0.119*	3.512	0.303*	5.224	0.244*	2.569	0.029	0.583
HS	0.272	2.686	0.213	1.295	0.257	1.244	0.156	1.138
Income	-0.111*	-10.825	0.011*	4.956	-0.156*	-7.324	-0.085*	-6.053
Age	-0.124	-33.205	-0.043*	-6.791	-0.005*	-0.547	-0.047*	-9.645
Education	0.202*	9.298	0.232	5.881	0.496*	7.565	0.171*	5.231
Household Size	-0.012*	-3.618	0.078*	13.895	0.086*	10.516	0.045*	10.389
Child $<$ 12	0.163*	15.217	-0.010*	-0.587	0.161*	6.029	0.094*	6.266
Marital Status	0.010*	1.056	0.064*	3.738	0.101*	3.743	0.092*	6.590
Region 1	-0.097*	-7.429	0.067*	2.836	-0.186*	-4.801	-0.099*	-5.860
Region 2	0.073*	4.859	0.091*	3.632	0.137*	4.428	0.051*	2.851
Region 4	-0.016	-1.202	-0.082*	-3.362	-0.114*	-3.412	-0.107*	-6.143
τ_i	0.779	15.259	0.613	6.779	0.729	5.294	0.464	6.126
σ	0.177*	99.882						
γ_0	1.445	37.103						
LLF	8,909.963							

Instrumental Variables Estimator								
	Fast Food		Casual		Fine Dining		Mid-Range	
γ	0.887*	34.276	0.552*	18.872	2.563*	10.388	0.473*	23.742
BMI	0.131*	9.488	0.096*	4.437	0.279*	12.112	0.262*	16.481
PA	0.194*	4.545	0.300	5.240	0.222	2.920	0.141*	2.665
HS	0.170	1.273	0.270	1.518	0.374	1.938	0.198	1.403
Income	-0.344*	-25.270	-0.059*	-3.550	0.013*	1.919	-0.186*	-11.698
Age	-0.115	-25.943	0.056*	8.292	0.067*	9.061	-0.077*	-13.757
Education	-0.069*	-2.382	0.253	6.066	0.478*	9.266	0.139*	4.000
Household Size	0.063*	13.816	0.129	20.067	0.207*	30.732	0.009*	1.751
Child $<$ 12	-0.007	-0.553	0.010*	0.551	-0.142*	-6.791	-0.156*	-9.421
Marital Status	-0.123*	-9.065	0.122*	6.272	0.102*	4.214	0.298*	18.312
Region 1	-0.125*	-7.760	-0.524*	-25.440	-0.191*	-8.535	-0.186*	-10.237
Region 2	-0.153*	-9.325	-0.178*	-9.315	-0.259*	-11.972	-0.117*	-6.585
Region 4	-0.211*	-14.531	-0.229*	-12.718	-0.145*	-6.635	-0.059*	-3.564
τ_i	1.051	15.944	0.437	4.604	0.515	4.571	0.461	5.624
σ	0.212*	215.656						
γ_0	1.025	37.927						
LLF	9,315.905							

Table 4: FAFH Elasticity Matrix

	FAH	Fast Food	Casual	Fine Dining	Mid-Range
FAH	-0.829	0.095	0.097	0.061	0.104
Fast Food	0.062	-0.743	0.049	0.035	0.047
Casual	0.009	0.016	-0.917	0.028	0.042
Fine Dining	0.005	0.003	0.003	-0.577	0.026
Mid-Range	0.029	0.019	0.017	0.023	-0.790

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	0.2076	0.0092	0.1066	0.0562
Physical Activity	0.2631	0.0284	0.0088	0.0377
Health Status	0.0361	0.0532	0.0191	0.0098

Note: Elasticities are calculated at the mean of observations.

Table 6: Response of FAH and FAFH to a Fast Food Tax

	FAH	Fast Food	Casual	Fine Dining	Mid-Range
Base Case	1.11835	0.46755	0.17480	0.10169	0.29655
10% Tax	1.11856	0.42661	0.17485	0.10173	0.29671
25% Tax	1.11914	0.34503	0.17498	0.10178	0.29690
50% Tax	1.11963	0.26908	0.17509	0.10184	0.29712

Note: Simulations conducted using the Pinjari and Bhat (2011) algorithm.