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Promotion and Fast Food Demand: Where's the Beef?

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Many believe that fast food promotion is a significant cause of the obesity epidemic in North America. Industry members argue that promotion only reallocates brand shares and does not increase overall demand. This study weighs into the debate by specifying and estimating a discrete/continuous model of fast food restaurant choice and food expenditure that explicitly accounts for both spatial and temporal determinants of demand. Estimates are obtained using a unique panel of Canadian fast food consumers. The results show that promotion primarily increases demand and has very little effect on restaurant market shares.

JEL Classification: C25, D12, I18, L66, M31

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Introduction

Claims that promotion strategies by fast food companies are at least partly responsible for rising obesity rates are now common (Kuchler, et al, 2005). Although the linkage between fast food consumption and the "obesity epidemic" is far from clear, if such claims are true then the implications for the industry could be far-reaching and pervasive.[1] In a competitive industry, however, promotion may simply constitute a zero sum game in which participants battle over shares of a fixed market and not, in fact, increase the size of the market as a whole. Alcoholic beverage and cigarette companies have used similar arguments to avoid bans on media advertising. Empirical research generally supports their arguments as many studies using aggregate, time-series data have shown that advertising primarily influences market shares and has little effect on aggregate consumption (Duffy, 1995; Dekimpe and Hanssens, 1995; Nelson, 1999 and studies cited therein). In the fast food case, statements regarding the aggregate impact of fast food advertising and promotion have not been verified or refuted by careful academic research. The objective of this paper, therefore, is to determine whether the pricing and promotion strategies of fast food firms increase the overall demand for fast food, or merely allocate market share among competing firms.

To determine the impact of promotion, we take into account many unique features of fast food demand. First, and perhaps most importantly, nutritionists have shown that test subjects exhibit addictive behavior toward some of the nutrients that typify fast food menus (Colantuoni, et al., 2002; Del Parigi, et al., 2003). Addiction, in turn, implies that demand for fast food is intertemporally non-separable (Iannaccone, 1986; Becker and Murphy, 1988), which implies that the demand for fast food is more akin to the demand for durable goods than non-addictive consumer goods. As a result, pricing below marginal cost may be a rational strategy if firms compete as differentiated oligopolists (Karp, 1996; Showalter, 1999; Driskill and McAfferty, 2001). Second, the demand for fast food is spatial, both in a geographic and attribute sense. Kalnins (2003) and Thomadsen (2005) study the geographic dimension of fast food demand while Richards

[1] Although the proportion of food spending away from home has grown rapidly in recent years (30% in 2001, StatsCan), it is still far lower than the equivalent proportion spend away from home in the U.S. (52%, USDA).

and Patterson (2006) estimate a model of fast food demand in which meals from different restaurants occupy unique locations in attribute-space. Without quantity data, however, Richards and Patterson (2006) could not comment on how pricing and promotion strategies influenced where or how much fast food consumers purchased. Given the importance fast food marketers place on product innovation and menu differentiation, an attribute-based approach to modeling the demand for fast food is a logical one. Therefore, in this paper we seek to gain a better understanding of fast food demand and menu pricing using a general model of spatio-temporal differentiation.

There are a number of alternative ways of addressing the question of whether fast food marketing increases the size of the market. Duffy (1995) uses a representative-consumer demand system in which alcohol and tobacco budget shares depend on alcoholic-beverage and cigarette advertising, respectively. With aggregate data, however, he is unable to separate brand from aggregate demand effects. Nor does he explicitly consider the effect of marketing on "upper-level" or non-durable spending. Nijs, et al. (2001), on the other hand, adopt a time-series approach to differentiate between the short- and long-run effects of price promotion on category relative to brand-level demand. In the household-level data used in this study, the joint decisions to purchase fast food and how much to purchase are more appropriately modeled in a two-stage, discrete / continuous choice framework. In the first stage, the consumer decides which restaurant to choose based on a number of factors: location, reputation, food quality (or taste), service quality, facilities for children and a host of other unobservable factors. The second stage, or how much to order, depends on another set of potentially overlapping factors, including the restaurant's marketing strategy and nature of their food. Chiang (1991), Chintagunta (1993) and Nair, Dubé and Chintagunta (2005) each estimate models of discrete / continuous choice based on an approach proposed by Hanneman (1984) to decompose purchased elasticities into purchase incidence, brand choice and purchase quantity. In this study, we develop an extension of this econometric approach that models the fast food restaurant choice and purchase quantity decisions in single, theoretically-grounded model of utility maximization.

Our results show that fast food promotion strategies do indeed have an impact on category demand, and not just restaurant share. In fact, when measured by incremental units sales, and not just contribution to elasticity, a price change or promotion primarily influences fast food demand and has relatively little impact on market share. While members of the fast food industry argue that they are sufficiently competitive that most of the impact is dissipated in competitive rivalry, differentiation from both spatial (food attributes) and temporal (brand loyalty) sources means that consumers tend to substitute very little among restaurants. Therefore, promotion tends to increase the total amount of fast food spending. Clearly, this result has significant implications for the design of potential price-based policies intended to influence fast food consumption as well as proposals for more intrusive policies regulating fast food promotion directly.

We contribute to the literature on discrete / continuous demand by extending existing research into multiple products, by adding explicit spatio-temporal elements in a theoretically consistent way, and by studying an important food-distribution channel that has received little attention in the academic literature. The paper is organized as follows. In the next section, we provide a brief description of the Canadian fast food industry, and the nature of fast food consumption in Canada. In the second section, we develop the econometric model of restaurant choice and meal expenditure. In the third, we describe the household panel data and explain how each of the explanatory and dependent variables are defined. The fourth section contains a detailed explanation of the estimation method, while a presentation and discussion of the estimation results follows. The final section concludes and offers some implications that may be of interest to the many stakeholders who follow the fast food industry.

The Fast Food Industry in Canada

Fast food is an economically important business in Canada. There are over 2,650 firms that sell fast food in Canada, including both chains and independent restaurants (NPD). Fast food purchases, however, are not necessarily restricted to the well-known chains that inhabit most urban street corners or mall food courts. Fast food purchases amounted to some $6.05 billion per year in Canada in 2001, which is 26% of all restaurant spending (StatsCan, 2006). The average fast food outlet does $607,000 in business per year, serving an average of 354 customers per day (CRFA, 2007). Although fast food is generally characterized as being highly caloric and unhealthy, this need not be the case as many companies have created innovative new menus designed to tap into the public concern over dietary quality and health. In fact, the average fast food meal consists of some 681.5 calories, roughly 1/4 of a moderately active adult male's daily requirement.[2] On a per visit basis, however, fast food does represent a relatively low-cost source of energy as some nutritionists suggest (Drewnowski and Darmon, 2005). While full-service restaurant meals average approximately $1.27 per 100 calories, fast food meals average less than $0.41 per 100 calories.[3] This comparison reflects the fact that full-service restaurant meals include a significant premium for the entertainment value of eating out, for the skill of the chef and wait staff, for the higher quality linens and cutlery and generally better quality ingredients. But is there something more? If fast food is addictive as some economists and nutritionists contend, then it may be rational for firms with market power to price below full cost in order to build a cohort of addicted consumers. However, it is not likely that consumers become addicted to one firm's fast food but rather the nutrient profile of fast food in general. If consumers can become addicted to the nutrients in fast food, then the pool of addicted consumers becomes a common property resource. If firms attempt to exploit access to this resource, then promotion and pricing policies intended to be competitive may, in fact, lead to the unintended effect of increasing consumption of fast food in general.

We focus on price-promotion strategies and not mass advertising. First, data on advertising activities by fast food companies is both proprietary and unreliable when measured by third party vendors. Second, as is true of all companies, price promotion is responsible for an increasingly large part of the overall marketing budget. Of the $478 billion in U.S. marketing expenditures in 2004, only 37.5% went toward advertising, while promotion accounted for fully 51.9%. With the reduced importance of television, radio and the printed press as advertising media, a shift in focus to price-based strategies is understandable. Third, if we did include advertising expenditure in the model, it would exhibit a complementary, and not a substitution, effect with promotional activities. Therefore, although our approach provides a look at only one part of the fast food marketing story, it is a critical part that is often overlooked by critics of the industry.

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[2] Based on the sample of NPD diary members used in this study.

[3] Calculations based on survey of ten representative meals from ten full-service restaurants and a similar number of fast food restaurants. Details of the survey can be obtained from the author.

Econometric Model of Fast Food Pricing

Household Demand for Fast Food

Restaurant meals are excellent examples of differentiated products – whether by geographic location, service attributes, menu types, toy offerings or the name of the head chef, the modes of differentiation are legion. Consequently, we model the demand for meals away from home within a single utility maximization framework in which the consumer makes a discrete choice from among a finite set of restaurant options, and then chooses a continuous amount of expenditure in constructing a restaurant meal. Empirical models of discrete / continuous choice are relatively well understood. Deaton and Muellbauer (1980) show that corner-solutions (discrete choices) are fully consistent with utility maximization when consumers face linear utility functions and, therefore, make choices based on which product has the lowest quality-adjusted price. Hanneman (1984) formalizes this logic in a general empirical framework and describes a number of indirect utility functions that are consistent with discrete first-stage decisions, and continuous second-stage or quantity choices. Dubin and McFadden (1984) follow a similar approach in estimating a model of appliance and electricity-consumption demand. More recently, Chiang (1991), Chintagunta (1993), Arora, Allenby and Ginter (1998) and Vaage (2000) estimate household-level models in which consumers make discrete choices of a logit form and then consume continuous quantities according to demand equation derived from a consistent indirect-utility framework proposed by Hanneman (1984). These household-level models, however, are overly restrictive in that they place unreasonable limits on elasticities of demand for the continuously-purchased meals.[4]

Others have applied discrete / continuous choice models to aggregate, store-scanner data. For example, Nair, Dubé and Chintagunta (2005) estimate a model of orange juice demand in which consumers first choose the specific brand to purchase and then the total quantity, while Smith (2004) presents a similar model applied to competition among retail supermarkets. Nair, Dubé and Chintagunta (2005) develop an

[4] It can also be argued that the demand for restaurant meals is more appropriately modeled as a "multiple discrete" problem as restaurant goers make a discrete choice of restaurants and then choose multiple products from the menu (Hendel, 1999; Dubé, 2004). The variety of options available, however, make estimating such a model intractable for practical purposes. Moreover, there is greater strategic and policy interest in understanding total meal expenditure once in the restaurant.

innovative way of relaxing the restrictive elasticity assumptions that are typical of most discrete / continuous choice models by allowing the price-response parameter to be a general function of chooser attributes. This random-coefficients approach provides a more general substitution matrix among products, even for relatively high-dimension problems, because the demand for each item is essentially projected into a much smaller-dimension attribute space (Berry, Levinsohn and Pakes, 1995; Nevo, 2001). However, aggregate, single-store data does not provide sufficient variation to make best use of this approach. In Smith (2004), consumers first choose a particular retail chain and then decide on how much to spend in their store of first-preference. None of these authors, however, explicitly consider the fact that the consumer's problem is inherently spatial.

Fast food meal decisions are made in the context of complex product, demographic and temporal spaces. Accounting for all three spatial dimensions allows for more flexible marketing response parameters because they depend on the distance between observations in attribute space, or simply attributes for the own-price response parameter (Pinkse and Slade, 2004). Defining price-response in terms of the distance between choices not only affords a degree of flexibility that is absent in traditional discrete / continuous choice models, but also provides a direct test of whether fast food companies tend to differentiate their offerings in order to gain market power, or mimic competitors in a Hotelling market-share battle (Slade, 2004). More important for the purposes of this paper, we are able to test whether spatial (differentiation) or temporal (habit, loyalty or addiction) distance between choices influences whether promotional strategies have an allocative or expansive effect on demand. Further, even in the absence of geographic locations for each we specify and estimate the model at the consumer level and draw implications for aggregate demand by integrating over the distribution of consumer heterogeneity ex post. As in Chiang (1991), Chintagunta (1993) and Arora, Allenby and Ginter (1998), the discrete and continuous choices are made within a single utility maximization framework.

To be more specific, we extend the conventional discrete / continuous demand model in two unique ways. First, we create a continuous quality index that is a function of a series of distance metrics between restaurants and consumers where distance is defined in meal-attribute, household demographic and temporal spaces. Similar to the arguments provided by Anderson, de Palma and Thisse (1992) and Feenstra and Levinsohn (1995), allowing the utility from consuming a particular product to depend on its distance from others is an intuitive and logical way to think about how consumers compare products or services.

Second, the model is explicitly dynamic in that consumers implicitly maximize the present value of all future utility, subject to a lifetime wealth constraint. In recent years, several authors have incorporated dynamic elements of demand in a theoretically-consistent way. Erdem, Imai and Keane (2003) develop a model of household inventory accumulation in order to estimate whether promoting durable goods creates new demand or accelerates existing purchase plans. Similarly, Hendel and Nevo (2004) develop a Markov-perfect equilibrium model of durable good demand that explicitly incorporates firms' optimal price policies with household inventory accumulation. In contrast, fast food demand dynamics do not emanate from stockpiling and inventory-accumulation but from the development of habits or "consumption capital" akin to Becker and Murphy (1988). In this study, we take the solution to an addicted consumers' intertemporal optimization problem as given (Becker, Grossman and Murphy, 1994) and demonstrate a new, more flexible way of implementing an empirical test of the underlying theory. By incorporating both spatial and temporal dimensions into the choice problem, we create a very general, spatio-temporal model of demand in which the distance between observations both in time and in space play a critical role in determining the choice probability and the level of demand. The resulting empirical model then lends itself to estimation techniques developed in the spatial econometrics literature for explicitly spatio-temporal models (Pace, et al 2000).

Empirical Model of Fast Food Demand

In the first stage, a consumer chooses between a fast food restaurant, or some alternative form of quick-service outlet. This alternative form, whether it be a convenience store, cafeteria or coffee shop, forms the outside option in our model.[5] As we show more formally below, a consumer will choose fast food if the value of doing so

[5] Implicitly, we assume the decision to purchase a meal outside the home is exogenous. This assumption is necessary because our survey data does not include non-purchase occasions.

is greater than a threshold or reservation price of a fast food meal. In a second decision, the consumer chooses one restaurant – and, implicitly a meal – that provides the greatest level of utility from among all available choices. Following Deaton and Muellbauer (1980), the direct utility function is additive in quality-adjusted consumption, thus ensuring that a corner solution results. In general notation, consumer $i = 1, 2, \ldots I$ is assumed to choose among $j = 1, 2, \ldots J$ fast food outlets and purchase a continuous quantity of food from the chosen restaurant: q_{ij} or spend his or her remaining income on an outside, or numeraire good, q_{io}, with price normalized to one. The direct utility function that describes the resulting discrete / continuous choice is written:

$$\begin{aligned} \max_{q_{i1},\ldots q_{ij}} U &= U\left(\sum_{j=1}^{J} \phi_{ij} q_{ij}, \phi_{io} q_{io}\right) \qquad (1) \\ s.t.\ y_i &= \sum_{j=1}^{J} p_j q_{ij} + q_{io}, \forall i = 1, 2, \ldots I, \end{aligned}$$

where y_i is the income of consumer i, U is a well-behaved utility function of undefined form, and ϕ_{ij} is a quality index that reflects both choice and chooser attributes. It is common in this literature to choose a flexible functional form for the indirect utility function consistent with (1), so we adhere to this practice and use an indirect translog (Chiang, 1991) defined over household income and quality-adjusted prices of the inside and outside goods:

$$\begin{aligned} V(p_j/\phi_{ij}, y_i) = \alpha_1 \ln(p_j/\phi_{ij}) + \alpha_2 \ln(1/\phi_{io}) + \alpha_3(\ln(p_j/\phi_{ij}))^2 + \\ \alpha_4(\ln(1/\phi_{io}))^2 + \alpha_5 \ln(p_j/\phi_{ij}) \ln(1/\phi_{io}), \qquad (2) \end{aligned}$$

which is assumed to be quasi-convex, non-increasing in prices and non-decreasing in quality. The quality index plays a particularly important role in this model because it embodies the spatial and temporal elements of demand that are unique to fast food. Specifically, the ϕ_{ij} parameter reflects the rather intuitive notion that quality is a relative concept. Therefore, one consumer's perception of the quality of a particular fast food restaurant (meal) depends upon three measures: (1) the meal's distance from others in attribute space –nutritional content, restaurant chain, physical location, etc., (2) the household's distance from others in the chosen sample –whether they are younger or older, the relative level of educational attainment, larger or smaller families, or are a particular race, and (3) the distance between the choice the consumer made during this period and the choice made in previous, and in future, periods. Writing each of these distance metrics in general notation, the quality index is given by:

$$\phi_{ij} = \exp\left(\frac{1}{\eta_j}\left(\gamma_{ij} + \beta d_j + \pi D_i + \lambda_1 f(S_j) + \lambda_2 g(S_i) + \lambda_3 h(T_{ij}) + \lambda_4 k(S_j, S_i, T_{ij}) + \xi_j + \mu_{ij}\right)\right), \quad (3)$$

where η_j is a chain-specific quality parameter for chain j similar to that used by Nair, Dubé and Chintagunta (2005), γ_{ij} is a household-chain specific preference parameter, d_j is a binary variable (or set of binary variables) indicating whether or not a particular meal was purchased on promotion or discount, D_i is a vector of demographic attributes describing the household, the λ_i parameters estimate the spatio-temporal lag associated with each of the distance metrics, and μ_{ij} is an individual and restaurant specific unobservable error term that is assumed to be independent and identically distributed extreme value. To account for other restaurant-specific factors that are unobservable to the researcher and yet likely important to consumers' choice of restaurant, we include an additional iid error term, ξ_j, that becomes the econometric error term in the estimated model below. Such factors may include a highly desirable location, friendliness of the staff, cleanliness or special decor. For the outside option, quality is entirely unobservable, so is given by: $\phi_{io} = \exp(\mu_{io}/\eta_j)$.

The distance metrics in (3) are written in general form, but can represent the distance between meals (S_j), households (S_i); or time periods (T_{ij}) in a number of different ways.[6] Typically, when the relevant attributes are continuous measures of quality such as macronutrient (fat, protein, carbohydrate) content, the measure S_j is defined as inverse Euclidean distance, or proximity. With this definition, a positive lag parameter suggests that perceived quality rises the more similar a meal is to others that

[6] Pace, et al. (2000) develop a similar spatio-temporal model of residential real estate prices. In their application, they show how filtering in space and time causes an otherwise complicated maximum likelihood estimation problem to collapse into simple least squares.

are available. On the other hand, a negative parameter indicates a demand for variety or differentiation among meal choices. In terms of the S_i variable, or the distance among individuals, a positive effect suggests that individuals of similar taste tend to cluster in their preference for a particular type of meal. Instead of these continuous measures, it is also common to define distance in terms of contiguity, or whether two observations either share a common boundary or are nearest neighbors in the relevant space. For example, two households may differ in nearly every regard (income, education, race, etc) but share the fact that they both have children under 12 years old. A discrete measure of proximity that reflects this will likely be an important indicator of restaurant choice and expenditure level. Similarly, the variable T_{ij} represents distance in time between two observations. Treating this variable as a traditional lag operator means that two observations (*i* and *j*) separated by one unit of time will cause T_{ij} to assume a value of one and zero otherwise. Because this variable is entirely general, however, it can also represent multiple lag periods, or even lead periods if appropriate. Most important for purposes of this study, the T_{ij} variable allows us to define a utility function that is time non-separable. In other words, utility in the current period depends on utility in previous and future periods if the underlying assumptions of the rational addiction model are correct. Addiction, in turn means that a consumer's utility from visiting a fast food restaurant today depends upon his or her cumulative experience with fast food. In the data description below, we provide more details on the specific alternatives chosen for each distance metric in this study.

With this specification of utility, we describe consumers' choice of whether to eat fast food, which restaurant to buy it from, and how much to spend. The reservation price that determines whether a consumer visits a fast food restaurant or the outside option is defined as the quality-adjusted price that makes fast food's budget share (w_{ij}) equal zero. Following Hanneman (1984), an expression for this share, in turn, is derived from (2) using Roy's Identity:

$$w_{ij}(p_j, \phi_{ij}, \phi_{io}) = \alpha_1 - \alpha_3 \ln(p_j/\phi_{ij}) + \alpha_3 \ln(1/\phi_{io}). \tag{4}$$

Solving for $\psi_{ij} = p_j/\phi_{ij}$ that makes $w_{ij} = 0$ gives: $\psi_{ij} = (1/\phi_{io}) \exp(-\alpha_1/\alpha_3)$. Therefore, the probability of visiting a fast food restaurant, conditional on eating out, and given the distributional assumption for the error term described above, is of a multinomial logit form (Chiang, 1991):

$$P(F_i = 1) = P(\psi_{ij}) \leq \min\{p_j/\phi_{ij}, j = 1, 2, ..., J\} = \frac{\sum_{j=1}^{J} \exp\{\delta_{ij}\}}{1 + \sum_{j=1}^{J} \exp\{\delta_{ij}\}}, \qquad (5)$$

where the mean utility from consumer i choosing restaurant j is given by: $\delta_{ij} = (1/\upsilon[\gamma_{ij} + \eta_j(\alpha_1/\alpha_3) - \eta_j \ln p_j + \beta d_j + \pi D_i + \lambda_1 f(S_j) + \lambda_2 g(S_i) + \lambda_3 h(T_{ij}) + \lambda_4 k(S_j, S_i, T_{ij}) + \xi_j]$, F_i is a binary indicator that equals one when consumer i purchases fast food and zero when visiting another type of restaurant and υ is the extreme value scale parameter. Given this result for the probability of purchasing in the category of interest, the joint probability of choosing a particular restaurant (R_j) from within the fast food market is:

$$P(F_i = 1, R_j = 1) = \frac{\exp\{\delta_{ij}\}}{1 + \sum_{j=1}^{J} \exp\{\delta_{ij}\}}. \qquad (6)$$

The first two choices, therefore, are completely described by the multinomial logit framework given in (5) and (6), which are made intertemporally and interspatially inseparable with the specification for utility given above. An expression for the third problem – the amount of expenditure in the chosen restaurant – is found by taking the conditional expectation of (4) over the extreme-value unobservable term. Writing the result in terms of expected expenditure gives:

$$E[q_{ij}p_j] = \left(\frac{y_i}{\eta_j/\nu\alpha_3}\right)\left(\frac{\exp\{\delta_{ij}\}}{1 + \exp\{\delta_{ij}\}}\right)\left(\ln(1 + \sum_j \exp\{\delta_{ij}\})\right), \qquad (7)$$

which can be estimated in a single stage using maximum likelihood (ML) methods (Chiang, 1991; Chintagunta, 1993) or the instrumental variables method described below.

Estimation of the Spatio-Temporal Model

Despite the fact that ML is feasible, it does not address the likely endogeneity of prices and, more importantly, whether the meal is purchased on a promotion. In household panel data, prices are typically assumed to be exogenous. However, Villas-Boas and Winer (1999) present a more nuanced argument that suggests prices are likely to be correlated with the econometric error term embedded in (7). Moreover, they demonstrate the empirical magnitude of the resulting bias in a discrete choice framework similar in nature to the one developed here. Consequently, we use an instrumental variables estimator – generalized method of moments (GMM) – to obtain consistent estimates of the mean-utility parameters described in (5).[7] Applying GMM in this case, however, is problematic because of the fundamental non-linearity of the estimating equation (7). Therefore, we follow Berry (1994), Berry, Levinsohn and Pakes (1995) and Nair, Dubé and Chintagunta (2005) by first inverting (7) to solve for mean utility as a linear function of its arguments and the econometric error term. Unlike the logit or nested logit examples shown in Berry (1994), the discrete/continuous estimating equation cannot be inverted analytically to solve for δ_{ij} : it is, however, possible to invert (7) numerically using a contraction mapping procedure. Specifically, for a given set of parameter values, θ, we solve for the vector δ_{ij} that equates observed with expected purchase quantities by defining a function $m(\delta_{ij})$:

$$m(\delta_{ij}) = \delta_{ij} + \ln(q) - \ln[\widetilde{q}(\delta_{ij}, \Theta)], \tag{8}$$

and iterating until convergence. In this way, we convert a highly non-linear estimation problem to one that is amenable to more straightforward instrumental variables estimation. Given the definition of mean utility in (5), we then form moment conditions based upon the econometric error term ξ_j such that $E[\xi_j Z_{ij} | Z_{ij}] = 0$ where Z_{ij} is a vector of instrumental variables that are correlated with mean utility, but not meal prices, which are assumed to be endogenous. For this application, we follow Kelejian and Prucha (1998) by defining a set of instruments that includes all truly exogenous variables in the system (household demographics, seasonal indicators, regional indicators, indices of fast food

[7] We define the GMM weighting matrix as White's (1980) heteroskedasticity-consistent covariance matrix.

costs (labor, food ingredients and business services) as well as spatial- and temporal-weighted averages of the mean utility from all other observations. Note that, because these measures reflect the distance between one firm's (household's) attributes and all others, the instruments reflect competitive attributes in a manner similar to the strategy used by Berry, Levinsohn and Pakes (1995). This identification strategy has become a standard approach in models with differentiated products.

While there are a number of ways to define the spatial and temporal distance metrics, we adopt a parsimonious linear expansion of each distance term. Not only is this the most straightforward way of introducing a relatively large number of distance terms, by doing so we avoid the temptation to search for the definition of distance that provides the best fit to the data. Further, unlike Pinske, Slade and Brett (2002), each of our distance measures is continuous so Euclidean distance is the most intuitive way to express relative proximity. Third, there are no a priori reason to expect that any measure of contiguity, such as nearest neighbor or shared boundary, should represent a better measure of how close either two restaurants or two households are to each other when considering the demand for fast food. We define meal attributes in terms of their nutritional profile. Whether a particular restaurant attempts to position itself as a "healthy alternative" (Subway) or an "indulgent experience" (Carl's Jr.) is most likely to be reflected in the nutritional profile of their high-volume items. Household attributes include age, size of the household, educational attainment, marital status, income and occupation. Households that are "closer" to each other in terms of this profile, therefore, are expected to demand fast food meals that are relatively similar to each other. For temporal distance, we measure both lead and lag time between purchase occasions. This definition is consistent with the rational addiction literature in that consumers' decisions are assumed to depend upon their cumulative consumption history as well as their expectations of future fast food consumption. Moreover, initial tests of the temporal weight effect found that a "lead and lag" distance performed far better in term of statistical fit than a simple lag variable. This was perhaps to be expected, but does indicate the power of using a flexible distance approach in both space and time.

With the distance metrics defined this way, the estimated form of (5) becomes:

$$\delta_{ij} = (1/\nu)(\gamma_{ij} + \eta_j(\alpha_1/\alpha_3) - \eta_j \ln p_j \ + \beta d_j + \pi D_i + \lambda_1 S_j \delta_{ij} + \lambda_2 S_i \delta_{ij}$$
$$+\lambda_3 T_{ij}\delta_{ij} + \lambda_4 S_j T_{ij} \delta_{ij} + \lambda_5 S_i T_{ij} \delta_{ij} \ + \xi_j), \tag{9}$$

where the spatial and temporal weight matrices are defined above. Consistent with usual practice in estimating these models (Nair, Dubé and Chintagunta, 2005), notice that the scale parameter, υ, is not identified so we normalize it to 1.0 without loss of generality. Further, α_1 and α_3 are not separately identified so we also normalize α_3 to 1.0 in the final specification. By including interactions between spatial and temporal distance, the distance metric model also reflects the insight of Pace, et al. (2000) that spatial effects are likely to depend on how far apart observations are in time. For example, a household that seeks variety may regard two restaurants with similar nutrient profiles to be close competitors at one point in time, but not on the next purchase occasion. Similarly, two households that are alike in terms of their demographic profile may make choices over time that differ based upon their preference for restaurant attributes, or their own purchase history. Our model allows for both types of eventuality.

Notice that mean utility appears on both the right and left sides of (9).Writing the expression for mean utility as a reduced-form yields response parameters that reflect spatial (attribute and demographic) as well as temporal distance. Specifically, define θ^{-1} as the inverse of the spatio-temporal component of (9):

$$\theta^{-1} = (I - \lambda_1 S_j \delta_{ij} + \lambda_2 S_i \delta ij + \lambda_3 T_{ij} \delta_{ij} + \lambda_4 S_j T_{ij} \delta_{ij} + \lambda_5 S_i T_{ij} \delta_{ij})^{-1}, \tag{10}$$

then the expression for mean utility becomes:

$$\delta_{ij} = \theta^{-1}(1/\nu)(\gamma_{ij} + \eta_j(\alpha_1/\alpha_3) - \eta_j \ln p_j \ + \beta d_j + \pi D_i + \xi_j). \tag{11}$$

So, each of the reduced-form response parameters in (11) implicitly reflect the weighted average distance to all other observations. This equation also shows how accounting for distance – measured in attribute space between products and households and in temporal space between purchase occasions – produces a general pattern of substitution among restaurants. Whereas the cross-price elasticities in Nair, Dubé and Chintagunta (2005) reflect differences in household composition through the distribution of unobserved heterogeneity in a random-coefficients framework, we achieve a similar effect by first expressing the solution for mean utility in (9) in reduced form and deriving the entire matrix of price elasticities. In this way, the own- and cross-price responses embody the distance between restaurants in attribute, demographic and temporal space. A distance metric approach not only allows for a richer explanation of the competitive relationships between restaurants compared to a non-attribute-based model, but also incorporates the primatives of the theoretical model derived above in way that is more intuitive than in a random coefficients model.

Decomposition of the Promotion Effect

In order to address the question posed at the outset – whether fast food promotion increases the demand for fast food in general or merely reallocates market share – it is necessary to decompose the promotion effect into components that reflect brand choice, category choice and purchase quantity. In a discrete choice (or discrete/continuous) context, the sum of the latter two effects is referred to as the "primary demand" impact, while the former is "secondary demand" (Bell, Chiang and Padmanabhan, 1999). Using this terminology, the relative magnitudes of the primary and secondary effects determine the extent to which fast food promotion increases the demand for fast food in general, as opposed to simply changing market share.

There are two ways to express the primary versus secondary promotion effect. Gupta (1988); Chiang (1991); Bell, Chiang and Padmanabhan (1999), and others since, define the primary demand effect as the proportion of the total demand elasticity attributable to the response of category choice and purchase quantity, while the secondary effect is the share due to brand switching. These studies find that approximately 75% of the elasticity is due to brand switching and only 25% due to purchase incidence or quantity effects. However, Van Heerde, Gupta and Wittink (2002) show that the secondary-effect definition used in previous research implicitly assumes that the size of the category remains constant. In order to isolate the true volume effect, they demonstrate that the unit sales effect with respect to a relative price change can be decomposed into additive components that reflect the response of category purchase probability, brand choice probability and purchase quantity. Allowing for the fact that promotion increases the purchase incidence of non-promoted brands, they show that a 75% secondary effect calculated the traditional way implies a 33% secondary effect calculated in terms of the actual unit quantity response (and, hence, a much larger – 67% – primary unit sales response). For current purposes, the aggregate demand response for fast food is more appropriately defined in terms of the unit sales responses, although both are of interest. Consequently, we present and interpret both the elasticity decomposition and the unit value impact of price changes and promotional response.

In a discrete / continuous choice model similar to the one used here, Nair, Dubé and Chintagunta (2005) demonstrate the marked difference between results obtained using an elasticity versus a unit sales promotion decomposition.[8] Beginning with the traditional definition of the secondary demand effect, Van Heerde, Gupta and Wittink (2003) show that the proportion of total unit-sales response due to a promotion is equal to the elasticity-proportion less an amount that reflects the purchase-incidence probability. Measured in terms of unit-sales response, therefore, the true brand-switching proportion is always smaller than when measured using an elasticity decomposition, and the primary demand effect always larger. In terms of the issue at hand, this means that focusing solely on brand-switching and quantity elasticities would understate the likely impact of fast food promotion on aggregate consumption. More formally, if we define ε_j^D as the total demand elasticity, ε_j^Q as the primary-response elasticity and ε_j^R as the secondary, or restaurant-share response, then the proportion due to secondary response with the elasticity-based definition is given by $\Delta_E^S = \varepsilon_j^R / \varepsilon_j^D$ and the primary effect by $\Delta_E^P = \varepsilon_j^Q / \varepsilon_j^D = 1 - \Delta_E^S$. Including the distance effect, the total price-elasticity of demand for each restaurant is ε_j^D, so we write the elasticity as the sum of the unconditional restaurant choice elasticity and the expected quantity elasticity: $\varepsilon_j^D = \varepsilon_j^R + \varepsilon_j^Q$. In terms of the discrete/continuous choice demand model derived above, the choice elasticity is the average over all *i* households of:

[8] Applying the method developed by Van Heerde, Gupta and Wittink (2002) they find that, although an average 35.0% of the response elasticity is due to purchase incidence and quantity response, this primary effect accounts for over 92.0% of the change in unit sales for each brand of orange juice.

$$\varepsilon_j^R = (\partial PR_{ij}/\partial p_j)(p_j/PR_{ij}) = \theta^{-1}\eta_j p_j\,(1 - PR_{ij})\,, \tag{12}$$

where $PR_{ij} = P(F_i = 1, R_j = 1) = \exp\{\delta_{ij}\}/(1+\sum_{j=1}^{J}\exp\{\delta_{ij}\})$ is the probabilty that consumer i selects restaurant j. Each choice elasticity thus depends on each restaurant's distance from all others in attribute space and the distance of each choice from others in demographic and temporal space through the θ^{-1} function. Similarly, the cross-price elasticity of restaurant choice is written as: $\varepsilon_{jk}^R = (\partial PR_{ij}/\partial p_k)(p_k/PR_{ij}) = \theta^{-1}\eta p_k PR_{ik} PR_{ij}$. By allowing each response elasticity to vary with distance our approach produces choice elasticities that are more flexible than in the traditional discrete / continuous choice model of Hanneman (1984) or Chintagunta (1993).

The conditional quantity elasticity, on the other hand, measures the sensitivity of the average household to changes in price given that they have already chosen to visit a fast food restaurant and have chosen the particular restaurant. Again expressing the elasticity in terms of the average over all sample households, the conditional quantity elasticity is given by:

$$\varepsilon_j^Q = (\partial E[Q_{ij}]/\partial p_j)(p_j/E[Q_{ij}]) = -1 + \theta^{-1}\eta_j p_j[(1 - PR_{ij}) + PR_{ij}/(\ln(P(F_i = 0)))], \tag{13}$$

for the own-restaurant choice and:

$$\varepsilon_{jk}^Q = (\partial E[Q_{ij}]/\partial p_k)(p_k/E[Q_{ij}]) = y_k/(\theta^{-1}\eta_j Q_{ij})[PR_{ij}PR_{ik}(\ln(1 + \sum_j \exp(\delta_{ij})))] \tag{14}$$

for the cross-price quantity elasticity. While these equations show how the demand elasticities for each restaurant are decomposed into brand-switching and quantity-increasing components in the conventional way, the aggregate effect on fast food spending is perhaps better understood by breaking the change in unit-sales into brand-choice and quantity-purchase parts. To do so, we need to include the impact of promotion on the probability of purchasing fast food, or some other type of food entirely, or the outside option.

Decomposing promotion response using a unit-sales definition, Van Heerde, Gupta and Wittink (2002) show that unit-sales secondary (brand switching) effect is given by the difference between the elasticity-based secondary effect and a term that reflects the impact of a price change on purchase incidence and quantity decisions. In terms of the discrete/continuous choice model, Nair, Dubé and Chintagunta (2005) show that the proportion of the rise in unit-sales due to the primary-demand effect is given by:

$$\Delta_U^P = \left(1 + \theta^{-1}\eta_j(1 - \sum_j (p_j/p_k)\Phi)\right) / \left(1 + \theta^{-1}\eta_j(1 - \Phi)\right), \qquad (15)$$

where $\Delta_U^P = P(F_i = 1|R_j = 1) + P(F_i = 1, R_j = 1)/ \ln[P(F_i = 0)]$ so that the secondary, brand-switching effct as $\Delta_U^S = 1 - \Delta_U^P$. With this expression, we are able to determine whether fast food promotion mainly reallocates spending among restaurants, or if it generates more fast food spending overall.

<u>Data Description</u>

The data used in this study was drawn from a large-scale survey of Canadian households by the NPD Group (NPD). Although the complete sample consists of 12,000 households who report all food purchased away from home for a period of 6 years (2000 - 2005), we focus on visits to fast food restaurants by those households who report consistently over the entire 6 year sample period. Given that households make an average of 40.69 restaurant visits over the sample period, we choose a random sample of 139 households in order to create a more tractable data set while maintaining its representative nature. The resulting data set consists of 5,657 restaurant visits. The data include a full set of demographic and socioeconomic descriptors (region of residence, education of household head, race, income classification, number of children, ages of children), as well as the type of food purchased and how many guests accompanying the bill payer. Specific restaurant classifications and names are also included.

Table 1. Summary of Household and Fast Food Data

Variable[a]	N	Mean	Std. Dev.	Min.	Max.
Age	5,657	48.937	12.319	21.000	86.000
Household Size	5,657	2.773	1.3069	1.000	6.000
Marital Status	5,657	0.744	0.437	0.000	1.000
Education	5,657	3.248	1.451	0.000	6.000
Occupation	5,657	0.489	0.500	0.000	1.000
Income	5,657	53.419	23.885	7.500	80.000
Combo	5,657	0.146	0.353	0.000	1.000
Buy One, Get One	5,657	0.022	0.148	0.000	1.000
Special	5,657	0.345	0.475	0.000	1.000
Spending per Trip	5,657	$1.015	$1.004	$0.052	$34.500
Price	5,657	$1.457	$2.165	$0.043	$57.500
Grams	5,657	1.008	0.841	0.022	7.857
Calories	5,657	1.342	1.151	0.000	10.440
Protein Grams	5,657	0.053	0.036	0.000	0.273
Fat Grams	5,657	0.065	0.041	0.000	0.271
Carbo Grams	5,657	0.165	0.088	0.000	0.728
Water Grams	5,657	0.716	0.165	0.040	1.087

[a] Income, grams, and calories are report in '000 of units. Price is in $/gram. All values per meal. Marital status is definede as 0=single, 1=married; Education is from 0=no high school, to 6=post-graduate degree; Occupation is 0=blue collar, 1=white collar; Combo, BOGO and Special are defined as 0=no promotion and 1=promotion.

Respondents to the NPD diary survey, however, report on a "single check" basis, meaning that there are no individual product prices appearing on the bill for each meal. Rather, the "price" of a meal includes the total expenditure all items ordered by the primary eater and all of his or her guests on a single outing. Because our interest lies in estimating the price elasticity of demand, it is necessary to impute a per-item price so that we can work with independent series of price and quantity data. Theoretically, it would be possible to recover prices for individual items by estimating a hedonic regression model that specifies meal expenditure as a function of a set of product-item binary variables, restaurant name, year, region and other factors important to the firm's pricing decision. However, with 262 individual foods chosen over the five year sample period, this approach is not feasible. Rather, we project the demand for fast food into a smaller attribute space spanned by binary indicators (year purchased, region, restaurant) and continuous attribute variables (grams of fat, protein, carbohydrate and water) and use the resulting parameter estimates to calculate implicit prices for specific foods.[9] We then use these implicit component prices to infer the price of each meal component and, hence, the quantity purchased. With this approach, we are able to measure restaurant-specific meal

[9] Nutrient contents for each food item were taken from the USDA Nutrition Guide (USDA).

price variation in a theoretically consistent way. In order to infer a nutrient content for each part of the meal, we had to assume standard serving sizes for each food item. For this purpose, we used gram weights of reference products within each category from dominant suppliers. For example, a "small hamburger" is a McDonalds regular hamburger, while a "large hamburger" is a quarter-pounder. To the extent that each restaurant's offerings differ from these reference items, our product weights and nutrient contents will be measured with error. To compensate for this measurement error, we use an instrumental variables approach that also accounts for the expected endogeneity of meal prices.

Over the sample period, the sample households visited over 2,600 unique restaurants. Therefore, we focus our analysis on the top 20 restaurant choices by market share and aggregate all other visits into an "other fast food" choice category. Because of the dominance of the major fast food chains, "other fast food" accounts for only 20% of all fast food visits. The outside option is defined as all quick-service food purchases not made from a fast food outlet. While it would seem intuitive to define the outside option as all non-fast food restaurant visits, doing so would be misattributing the potential demand for fast food. When consumers visit a fine-dining restaurant, for example, they do so for entirely different reasons than when they go to a fast food restaurant. To consider a fine-dining experience as an alternative to fast food, therefore, would be an error. Therefore, by defining the outside option this way, we consider the relevant market to be all purchases of "convenient foods," including purchases of fast food-type items from convenience stores, coffee shops and other non-restaurant environments. Because this choice of outside option is relatively unconstrained by theory, we test several alternative definitions for the outside option and found that the results were qualitatively similar no matter the choice.

Results and Discussion

Prior to discussing the structural demand estimates, it is first necessary to establish the validity of the ITL discrete/continuous choice model and the spatio-temporal extensions introduced here. We do so through a number of specification tests that are commonly used in the literature for such purposes.

First, Villas-Boas and Winer (1999) describe the circumstances under which prices may be correlated with the econometric error term in the mean utility equation introduced above. Although prices are typically regarded as exogenous in household data, fast food vendors may set prices based on factors that are common to the sample households here, but not measured in our data. If this is the case, our estimates will suffer from simultaneous equations bias. Therefore, we use a Hausman (1978) test of the endogeneity of fast food prices. This test compares the weighted distance between estimates obtained using an estimator that is consistent under both the null (no endogeneity) and alternative (endogeneity) hypotheses with estimates obtained with one that is efficient under the null hypothesis.[10] The resulting test statistic is chi-square distributed with degrees of freedom equal to the number of potentially endogenous variables. The test statistic reported in table 2 is 105.786 while the critical value at a 5.0% level and 35 degrees of freedom is 49.802 so we reject the null hypothesis and conclude that prices are endogenous. Consequently, subsequent results are reported using an instrumental variables (GMM) estimator. As a more qualitative analysis of the practical impact of ignoring endogeneity, we compare the parameter estimates obtained using both OLS and the maintained GMM estimator. At first glance, the results in table 2 suggest that the extent of the bias is not large in an economic sense – the price parameter estimated with OLS is -1.857, while the GMM estimates is -1.809. However, each of the GMM promotion parameters differ from between 10.0% and 30.0% from their OLS counterparts. The practical import of this error is likely to be much more significant than mis-estimating the base-price elasticity.

[10] The test statistic is calculated as: $(\beta_1 - \beta_0)'(V_1 - V_0)^{-1}(\beta_1 - \beta_0) \sim \chi^2_k$, where β_1 is the vector of GMM parameters, β_0 is the vector of OLS parameters, V_1 is the GMM covariance matrix, V_0 is the OLS covariance matrix, and there are K degrees of freedom, where K is the number of parameters in the model.

Table 2. Non-Spatial Estimates: Fast Food Restaurants

	OLS		GMM	
Variable	**Estimate**	**t-ratio**	**Estimate**	**t-ratio**
Age	0.012*	7.343	0.012*	4.268
Household Size	0.014	1.022	0.079*	2.988
Marital Status	-0.372*	10.108	-0.448*	-6.499
Education	-0.020*	-1.976	-0.063*	-3.615
Occupation	-0.614*	-18.337	-0.595*	-9.582
Combo	3.454*	21.802	3.154*	10.453
Buy One, Get One	10.830*	16.954	13.703*	7.835
Special	-1.070*	-9.424	-1.299*	-5.489
Constant	-5.237*	-45.540	-5.347*	-26.027
Log (Price)	-1.857	-81.873	-1.809*	-48.358
Hausman (1978) χ^2	105.786			
Q	2,875.777		690.481	

[a]A single asterisk indicates significance at a 5.0% level. Restaurant dummy variables are suppressed due their number. Estimates are available from the authors. Instruments for the GMM procedure include all exogenous and spatially-weighted endogenous variables. Q is the GMM objective function value.

Next, we conduct specification tests of several alternative spatial models. The four models reported in tables 3a and 3b successively add distance-weighted mean utility terms where the distance matrix is defined as: (1) inverse Euclidean distance in nutrient-attribute space, (2) inverse Euclidean distance in household demographic-attribute space, (3) temporal distance, and (4) inverse product- and household-attribute distance interacted with temporal distance. The spatio-temporal filtering in (4) is expected to reveal any time-dependent preference for either similar fast-food meals or variety from one visit to the next. To select among these models, we use a variant of the D-test (Newey and West, 1987). Logically analogous to a likelihood ratio test, the D-test compares unrestricted (Q0) and restricted (Q1) values of the GMM objective function where the difference is chi-square distributed with degrees of freedom equal to the number of implied restrictions in the maintained model. Using the Q-values reported in table 2 for the non-spatial model and in table 3a for the simplest spatial specification, we find that accounting for distance between meals in attribute space creates a significant improvement in fit. At a 5.0% level, the critical chi-square value for the D-test is 3.84 while the estimated value is 11.717, so we reject the non-spatial in favor of the spatial model. Moreover, the estimated price- and promotion-response parameters are significantly lower in the spatial relative to the non-spatial model, indicating that a failure to account for nutritional-attribute differences between meals results in a potentially serious over-estimate of the response to marketing variables. In a spatial model, the lag parameter also conveys important information. Because this parameter is negative (and statistically significant) the results in table 3a suggest that the more similar a meal is to others in a nutritional sense, mean utility falls. Households, therefore, appear to seek variety both in their choice of restaurant and fast food meal. From the firms' perspective, this result also reflects the fact that firms tend to differentiate their menus from others given their understanding that consumers will respond in a positive way.[11]

Table 3a also shows the parameters obtained by estimating a model with both nutrient and household demographic distance metrics. Using the same test to compare the nutrient-distance model to the household-distance model, we find that the promotional response parameters are again lower in the more comprehensive model, but the price-response is higher. More importantly, however, the model that includes household attributes provides a better fit to the data (D-test value is 107.183 with critical value also 3.84). Unlike the spatial-lag parameter in the nutrient-distance case, however, the more similar a household to the others in the sample data, the higher is mean utility from purchasing fast food and, hence, the more often they purchase. This result is important on a number of levels. First, it reflects the fact that fast food firms know and exploit a common demographic that is likely to become heavy fast food consumers. Based on our results, this household is likely to be headed by a male or female who is slightly younger than average, more educated, less likely to have a professional occupation, with a family that is smaller than others. Second, our finding shows that marketing strategies targeted toward dominant market segments are more likely to increase the frequency and quantity of fast food purchases. A third implication follows from the second. By targeting households that are similar to each other, fast food firms apparently cluster around a demographic that for some consumes fast food heavily and frequently.

[11] The estimated model includes a set of restaurant-specific fixed effects so the variety effect is true even when the same restaurant is visited on multiple trips. The fixed-effects estimates are not reported in tables 3a - 3b, but are available from the authors.

Table 3a. Spatial Estimates: GMM, Fast Food Restaurants

	Product Attribute[a]		Household Attribute	
Variable	**Estimate**	**t-ratio**	**Estimate**	**t-ratio**
Age	-0.002	-0.972	-0.007	-0.643
Household Size	-0.096*	-6.426	-0.143*	-5.429
Marital Status	-0.070*	-1.884	-0.103*	-2.817
Education	0.022*	2.133	0.075*	7.323
Occupation	-0.300*	-8.566	-0.211*	-6.251
Minutes	0.002	1.748	0.001	1.366
Combo	1.912*	11.503	1.906*	12.014
Buy One, Get One	4.503*	5.993	3.775*	5.534
Special	-1.194*	-10.087	-1.122*	-9.938
Constant	-3.231*	-23.651	-8.832*	-11.278
Log (Price)	-1.495*	-63.766	-1.575*	-69.216
$\mathbf{S}_j$	-0.061*	-37.048	-0.043*	-22.470
$\mathbf{S}_i$			0.239*	15.911
Q	678.764		571.581	

[a]In this table, a single asterisk indicates significance at a 5.0% level. The GMM objective function value is denoted by Q.

In table 3b, we extend the model to include temporal proximity between observations. Note that this variable captures more than a simple lagged-consumption or habituation effect because it includes distance between both past and future observations for each household. In this regard, our specification represents a single parameter test of the rational addiction model of Becker, Grossman and Murphy (1994). Rational addiction, according to Becker, Grossman and Murphy, follows from a rejection of the joint hypothesis that consumers do not respond to either lagged nor lead prices. Again applying the D-test, we find that a model with temporal-distance is preferred to a purely spatial alternative, suggesting that consumers' fast food purchasing behavior is significantly influenced by both their entire consumption history, and their expectation of future purchase occasions. Interpreting the temporal "lag" parameter, however, is fundamentally different from the more usual case of a simple, single-period lag structure. Recall that the temporal weighting matrix is defined in terms of inverse distance (proximity) normalized across all purchase occasions. Thus, a positive temporal lag parameter indicates that utility rises the greater the increment in utility from previous, and expected future, fast food purchases. In terms of the rational addiction model, the accumulation of consumption experience, or capital, leads to "adjacent complementarity" in which positive consumption experiences are self-reinforcing and lead to ever greater consumption, and more frequent visits. This is a direct, and unique, implication of the rational addiction model. The practical implication of this result are clear. Namely, heavy fast food users are more likely to be heavy consumers both in the current and future periods. More important from a policy perspective, rational addicts are likely to be more responsive to expected future price increases because they anticipate having to pay more for their habit in the future. Thus, taxes on fast food consumption are likely to be more effective than previously believed.

Table 3b. Spatio-Temporal Estimates: GMM, Fast Food Restaurants

	Temporal Distance[a]		Spatio-Temporal	
Variable	**Estimate**	**t-ratio**	**Estimate**	**t-ratio**
Age	-0.007*	-4.055	-0.007*	-4.251
Household Size	-0.144*	-9.931	-0.139*	-9.625
Marital Status	-0.102*	-2.290	-0.125*	-3.341
Education	0.074*	7.237	0.077*	7.603
Occupation	-0.211*	-6.235	-0.206*	-6.118
Minutes	0.001	1.340	0.001	1.535
Combo	1.927*	12.056	1.831*	11.842
Buy One, Get One	3.859*	5.602	3.554*	5.180
Special	-1.138*	-9.911	-1.092*	-9.631
Constant	-8.299*	-11.199	-12.849*	-4.045
Log (Price)	-1.575*	-69.078	-1.570*	-68.901
S_j	-0.045*	-17.400	-0.061*	-6.496
S_i	0.240*	15.891	0.375*	4.891
T	0.919*	2.115	0.949*	3.389
S_jT			0.031*	2.523
S_iT			0.166*	2.994
Q	565.055		541.637	

[a] In this table, a single asterisk indicates significance at a 5.0% level. The GMM objective function value is denoted by *Q*.

In the final column of table 3b, we present results obtained by interacting spatial and temporal distance. Based on the D-test results, the most comprehensive model is the preferred specification. While the other parameters do not change qualitatively, the significance of the interaction parameters suggest that the spatial behaviors described above do indeed vary according to a household's purchase history. Specifically, the product-attribute estimates described above tend to diminish with the temporal proximity of other consumption occasions, while the household-attribute results are accentuated. In terms of nutrient space, this means that the variety-seeking behavior described above is attenuated for purchase occasions that are closer in time, whether in the past or in the future. In other words, households' preference for variety is a long-term phenomenon while their short-term decision making tends towards meals that are relatively similar from one visit to the next. With respect to demographic space, a positive interaction with temporal proximity suggests that the target market segment described above becomes more similar over time – likely a reflection of marketing strategies designed to exploit the most lucrative segments. This observation is consistent with both prior expectations and marketing practice. While these results provide important insights into the structure of fast food demand, the main purpose behind accounting for spatio-temporal distance in this way is to obtain more accurate estimates of the pricing and promotional elasticities for each firm.

In order to address the objective of this paper, we present and discuss these elasticities in terms of their implications for primary, or aggregate quantity, and secondary, or brand switching effects. The primary and secondary demand effects of each firm's pricing strategy are shown in tables 4a and 4b, respectively.[12] Clearly, price changes have significant impacts on both brand-switching and quantity purchased. These effects, however, vary by restaurant and the nature of its products. For example, McDonalds, the restaurant with the largest market share, has the most inelastic demand with respect to brand choice, but once in the store consumers appear to be equally responsive among all restaurants with regards to the amount they purchase. The value of using a distance-metric approach, however, is most apparent in the cross-price responses

[12] These tables show only the top 10 restaurants for clarity purposes. The other 10 are similar and are available from the authors.

as the competitive structure of the fast food market reflects the relative proximity of each restaurant's menu and target demographic to its competitors'. Accounting for the distance between restaurants in attribute and demographic space, McDonalds appears to substitute most strongly not with hamburger-based restaurants as expected, but non-hamburger-based sandwich, chicken and pizza choices. Based on these results, consumers appear to prefer a specific restaurant within each sub-category (hamburger, sandwich, chicken, etc.), but substitute more freely among sub-categories. Although the magnitude of these elasticities suggests that brand-switching is more important than the purchase-quantity effect of a price change, accurately decomposing the two effects requires a consideration of the unit-sales impact.

Table 4a. Partial Price Elasticity Matrix: Unconditional Brand Choice - Top 10

	With Respect to:									
	McD	**A&W**	**SUB**	**BK**	**WEN**	**KFC**	**DQ**	**PH**	**HRV**	**ARB**
McD	-1.831	0.035	0.038	0.029	0.034	0.031	0.015	0.016	0.012	0.007
A&W	0.047	-2.650	0.013	0.010	0.012	0.010	0.005	0.005	0.004	0.002
SUB	0.053	0.015	-3.005	0.013	0.015	0.013	0.006	0.007	0.005	0.003
BK	0.026	0.007	0.008	-1.987	0.007	0.007	0.003	0.003	0.002	0.001
WEN	0.036	0.010	0.011	0.009	-2.357	0.009	0.004	0.005	0.033	0.002
KFC	0.056	0.016	0.018	0.013	0.016	-4.043	0.007	0.007	0.005	0.003
DQ	0.037	0.011	0.012	0.009	0.010	0.009	-5.662	0.005	0.004	0.002
PH	0.044	0.005	0.006	0.004	0.004	0.004	0.002	-6.472	0.004	0.001
HRV	0.016	0.005	0.006	0.004	0.004	0.004	0.002	0.002	-3.183	0.008
ARB	0.009	0.022	0.003	0.002	0.002	0.002	0.001	0.001	0.001	-3.086

Table 4b. Partial Price Elasticity Matrix: Conditional Quantity Purchase - Top 10

	With Respect to:									
	McD	**A&W**	**SUB**	**BK**	**WEN**	**KFC**	**DQ**	**PH**	**HRV**	**ARB**
McD	-1.112	0.236	0.261	0.199	0.232	0.208	0.102	0.107	0.079	0.044
A&W	0.244	-1.122	0.077	0.059	0.068	0.068	0.030	0.032	0.023	0.013
SUB	0.364	0.104	-1.130	0.088	0.102	0.091	0.045	0.047	0.035	0.021
BK	0.195	0.056	0.061	-1.092	0.055	0.049	0.020	0.025	0.019	0.010
WEN	0.227	0.065	0.072	0.055	-1.092	0.057	0.028	0.029	0.022	0.012
KFC	0.171	0.049	0.054	0.041	0.048	-1.167	0.021	0.022	0.016	0.009
DQ	0.145	0.041	0.046	0.035	0.041	0.036	-1.215	0.019	0.014	0.008
PH	0.082	0.023	0.026	0.020	0.073	0.021	0.010	-1.245	0.088	0.004
HRV	0.110	0.031	0.035	0.026	0.031	0.028	0.014	0.014	-1.119	0.006
ARB	0.042	0.012	0.013	0.010	0.012	0.011	0.005	0.005	0.004	-1.112

A comparison of the elasticity and unit-sales decompositions is provided in table 5. If measured by the share of total elasticity, the average primary response is 22.9% while the average secondary, brand-switching response is 77.1%. According to this measure, we are lead to believe that nearly all of a promotional response comes from consumers moving among restaurants and very little from purchase incidence and quantity effects. However, if we measure the response according to unit-sales, the average primary response is fully 93.5% and the secondary 6.5%. Because the unit-sales decomposition is a more accurate indication of the total consumption-effect of a promotion, this result provides evidence that fast food promotion has relatively large impact on total fast food expenditure and a relatively minor impact on restaurant-switching. This result, while damaging to the argument that fast food marketing has only competitive, market-share effects, is nonetheless consistent with the structure of demand shown in tables 4a and 4b. Specifically, if the cross-price response among restaurants is relatively small, then it is to be expected that the aggregate effect of any price-based promotion will dominate.

Table 5. Primary and Secondary Demand Impacts: Elasticity and Unit Sales

	Elasticity		**Unit Sales**	
Restaurant[a]	**Primary**	**Secondary**	**Primary**	**Secondary**
McDonalds	0.380	0.620	0.971	0.029
A & W	0.296	0.704	0.965	0.035
Subway	0.273	0.727	0.960	0.040
Burger King	0.353	0.647	0.974	0.026
Wendy's	0.318	0.682	0.969	0.031
KFC	0.224	0.776	0.947	0.053
Dairy Queen	0.177	0.823	0.929	0.071
Pizza Hut	0.162	0.838	0.919	0.081
Harvey's	0.260	0.740	0.960	0.040
Arby's	0.265	0.735	0.962	0.038
Other Fast Food	0.231	0.769	0.953	0.047
Mr. Submarine	0.225	0.775	0.951	0.049
Pizza Pizza	0.112	0.888	0.864	0.136
La Belle Province	0.309	0.691	0.970	0.030
Little Caesar's	0.125	0.875	0.885	0.115
Taco Bell	0.090	0.910	0.804	0.196
Dominos'	0.124	0.894	0.882	0.118
Cultures	0.177	0.823	0.932	0.068
Taco Time	0.229	0.721	0.965	0.035
Pizza Delight	0.197	0.803	0.941	0.059
Average	0.229	0.771	0.935	0.065

[a] Elasticity and unit-sales decomposition calculated using the equations given in the text. Primary demand refers to purchase incidence and quantity demand effects, while secondary demand refers to brand-switching.

The practical implications of this result are clear. First, and most obviously, if overconsumption of fast food is indeed a fundamental cause of the obesity epidemic as some suggest, then regulating fast food marketing strategies does have some empirical support. Second, to the extent that the nutrients in fast food can be addictive, then pricing and promotional strategies that would otherwise appear to be self destructive (ie., pricing below marginal cost) can be rationalized by their dynamic effects on the size of the addicted cohort. This raises a third, more subtle implication for firms' marketing strategies. Because fast food promotion increases the size of the aggregate market, and consumers can become addicted to nutrients and not restaurants, firms are likely to overinvesting in promotional strategies that are expected to have significant, long-term, firm-specific demand effects. To the extent that they understand this outcome, however, they nonetheless underinvest relative to the industry-optimal promotion level.

Conclusions and Implications

This paper addresses a question that is often raised in public policy and in the media: does fast food marketing cause consumption to rise? While to many the answer to this problem is obvious, in a competitive industry the aggregate effects of strategic marketing may, in fact, be minimal. Although this question is typically raised with respect to advertising, price-promotion is a more common and pervasive way of raising demand. Consequently, we focus specifically on the aggregate versus market share effects of fast food-firms promotional activities.

Beyond the obvious policy implications of our findings, this paper contributes to the methodological literature on estimating the demand for differentiated products. Differentiated products are typically modeled in a discrete-choice framework. While the logit model (McFadden, 1973) is typically used to model demand in discrete-choice environments, variants either suffer from inflexible patterns of substitution (conditional logit), or from a reliance on second-order or covariance relationships to identify relationships among products (mixed logit). Further, a discrete choice model is inappropriate when consumers purchase a variable amount of their chosen product. To address both of these issues, we develop a synthesis of the discrete/continuous choice approach (Hanneman, 1984) and the distance metric (Pinkse, Slade and Brett, 2002) method. The distance metric approach is valuable for this purpose because it explicitly allows substitution patterns among restaurants to depend directly on the distance between them in attribute, demographic and temporal space.

In this paper, we show that promotional activity by fast food vendors is effective in both increasing the market share of the promoting firm, and in expanding the demand for fast food in general. More importantly, however, we find that the proportion of any unit-sales increase caused by price-promotion due to an expansion in demand is far greater than that due to brand-switching. Therefore, industry arguments that such marketing expenditures are necessary in a competitive industry are not entirely credible. Rather, the principal effect is to cause fast food consumers to purchase more often, or buy more on each visit. While this is likely viewed as a welcome outcome by marketing managers in the fast food industry, from a public policy perspective it provides support for those who argue in favor of regulating the marketing of fast food to groups at risk of obesity. Further, by accounting for the nutritional, demographic and temporal proximity of fast food purchase occasions, we find that the sample households behave in a way that is consistent with a rational addiction. Consequently, tax policy is likely to be more effective than previously believed, given the common assumption that the demand for fast food is highly inelastic.

The availability of highly detailed, panel-survey data on fast food consumption has created a rich area for future research. While we focus on the demand response by consumers to fast food vendors' promotional activity, future research in this area would benefit from extending our analysis to consider a full structural model of strategic pricing behavior on the part of fast food firms. If fast food consumption does indeed exhibit addictive properties as our results suggest, then firms can be expected to price below marginal cost in order to build up the cohort of addicted consumers. Second, we consider only measurable attributes of fast food – nutritional profiles, vendor identity or the distance from a consumer's home. However, a more detailed experimental analysis would be able to determine the effect of perceptual attributes on consumer demand as well. Specific qualities of taste, consumer self-esteem, the reputation of each restaurant and other non-measurables may be relevant to a comprehensive treatment of an attribute-based fast food model. Third, more recent data collection efforts include body mass index (BMI) scores in addition to restaurant and food choices. While these data are not yet widely available for research purposes, they would allow for the estimation of a more complete model of the fast-food/addiction /obesity relationship.

References

Andersen, S.P., A. de Palma and J.-F. Thisse. 1992. *Discrete choice theory of product differentiation*. Cambridge, MA: MIT Press.

Arora, N., G. Allenby, and J.L. Ginter. 1998. A hierarchical Bayes model of primary and secondary demand. *Marketing Science* 17:29-44.

Becker, G.S. and K.M. Murphy. 1988. A theory of rational addiction. *Journal of Political Economy* 96:675-700.

Becker, G., M. Grossman, and K.M. Murphy. 1994. An empirical analysis of cigarette addiction. *American Economic Review* 84:396-418.

Bell, D.R., J. Chiang, and V. Padmanabhan. 1999. The decomposition of promotional response: An Empirical Generalization. *Marketing Science* 18:504-526.

Berry, S. 1994. Estimating discrete-choice models of product differentiation. *Rand Journal of Economics* 25:242-262.

Berry, S., J. Levinsohn, and A. Pakes. 1995. Automobile prices in market equilibrium. *Econometrica* 63:841-890.

Canadian Restaurant and Foodservices Association. 2007. *Economic impact of Canada's foodservice industry*. http://www.crfa.ca/research/factsand-stats.asp#consumer.

Chiang, J. 1991. The simultaneous approach to the whether, what, and how much to buy questions. *Marketing Science* 10:297-315.

Chintagunta, P.K. 1993. Investigating purchase incidence, brand choice and purchase quantity decisions of households. *Marketing Science* 12:184-208.

Colantuoni, C., P. Rada, J. McCarthy, C. Patten, N.M. Avena, A. Chadeayne, and B.G. Hoebel. 2002. Evidence that intermittent, excessive sugar intake causes endogenous opioid dependence. *Obesity Research* 10:478-488.

Deaton, A. and J. Muellbauer. 1980. *Economics and consumer behavior*. Cambridge: Cambridge University Press.

Dekimpe, M. G. and D. Hanssens. 1995. Empirical generalizations about market evolution and stationarity. *Marketing Science* 14:G109-21.

Del Parigi, A., K. Chen, A.D. Salbe, E.M. Reiman, and P.A. Tataranni. 2003. Are we addicted to food? *Obesity Research* 11:493-495.

Drewnowski, A. and N. Darmon. 2005. Food choices and diet costs: An economic analysis. *Journal of Nutrition* 135:900-904.

Driskill, R. and S. McCafferty. 2001. Monopoly and oligopoly provision of addictive goods. *International Economic Review* 42:43-72.

Dubé, J.-P. 2004. Multiple discreteness and product differentiation: Demand for carbonated soft drinks. *Marketing Science* 23:66-81.

Dubin, J. A. and D.L. McFadden. 1984. An econometric analysis of residential appliance holdings and consumption. *Econometrica* 54:345-362.

Duffy, M. 1995. Advertising in demand systems for alcoholic drinks and tobacco: A comparative study. *Journal of Policy Modeling* 17:557-577.

Erdem, T., S. Imai, and M.P. Keane. 2003. A model of consumer brand and quantity choice dynamics under price uncertainty. *Quantitative Marketing and Economics* 1:5-64.

Feenstra, R.C. and J.A. Levinsohn. 1995. Estimating markups and market conduct with multidimensional product attributes. *Review of Economic Studies* 62:19-52.

Gupta, S. 1988. Impact of sales promotions on when, what, and how much to buy. *Journal of Marketing Research* 25:342-355.

Hanemann, W.M. 1984. Discrete/continuous models of consumer demand. *Econometrica* 52:541-561.

Hausman, J.A. 1978. Specification tests in econometrics. *Econometrica* 46:1251-1271.

Hendel, I. and A. Nevo. 2004. Intertemporal substitution and storable products. *Journal of the European Economic Association* 2:536-547.

Iannaccone, L. R. 1986. Addiction and satiation. *Economics Letters* 21:95-99.

Kalnins, A. 2003. Hamburger prices and spatial econometrics. *Journal of Economics and Management Strategy* 12:591-616.

Karp, L. 1996. Monopoly power can be disadvantageous in the extraction of a durable nonrenewable resource. *International Economic Review* 37:825-849.

Kelejian, H. and K.R. Prucha. 1998. A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances. *Journal of Real Estate and Finance Economics* 17:99-121.

Kuchler, F., E. Golan, J.N. Variyam, and S.R. Crutchfield. 2005. Obesity policy and the law of unintended consequences. *Amber Waves* 3:26-33.

McFadden, D. 1973. Conditional logit analysis of qualitative choice behavior. In *Frontiers of econometrics*, ed. P. Zarembka. New York: Academic Press.

Nair, H., J.-P. Dubé and P. Chintagunta. 2005. Accounting for primary and secondary demand effects with aggregate data. *Marketing Science* 24: 444-460.

Nelson, J. P. 1999. Broadcast advertising and the U.S. demand for alcoholic beverages. *Southern Economic Journal* 66:774-790.

Newey, W.K. and K.D. West. 1987. Hypothesis testing with efficient method of moments estimation. *International Economic Review* 28:777-787.

Nevo, A. 2001. Measuring market power in the ready-to-eat cereal industry. *Econometrica* 69:307-342.

Nijs, V.R., M.G. Dekimpe, J.-B.E.M. Steenkamp, and D.M. Hanssens. 2001. The category-demand effects of price promotions. *Marketing Science* 20:1-22.

NPD Group. 2005. *CREST survey*. North York, Ontario, Canada.

Pace, R.K., R. Barry, O.W. Gilley, and C.F. Sirmans. 2000. A method for spatial-temporal forecasting with an application to real estate prices. *International Journal of Forecasting* 16:229-246.

Pinkse, J. and M.E. Slade. 1998. Contracting in space: An application of spatial statistics to discrete-choice models. *Journal of Econometrics* 85:125-154.

Pinkse, J., M.E. Slade and C. Brett. 2002. Spatial price competition: A semiparametric approach. *Econometrica* 70:1111-1153.

Pinkse, J. and M. Slade. 2004. Mergers, brand competition and the price of a pint. *European Economic Review* 48:617-643.

Richards, T.J., and P.M. Patterson. 2006. Fast food, addiction and obesity. Working paper, Morrison School of Management and Agribusiness, Arizona State University.

Showalter, M. 1999. Firm behavior in a market with addiction: The case of cigarettes. *Journal of Health Economics* 18:409-427.

Slade, M. 2004. The role of economic space in decision making. Working paper, Department of Economics, University of Warwick, Warwick, UK.

Smith, H. 2004. Supermarket choice and supermarket competition in market equilibrium. *Review of Economic Studies* 71:235-263.

Statistics Canada. 2003. Food expenditure in Canada, 2001. Ottawa, Ontario, Canada.

Thomadsen, R. 2005. The effect of ownership structure on prices in geographically differentiated industries. *RAND Journal of Economics* 36:908-929.

U.S. Department of Agriculture, Agricultural Research Service. 2006. USDA National Nutrient Database for Standard Reference, Release 19. Nutrient Data Laboratory Home Page. http://www.ars.usda.gov/ba/bhnrc/ndl.

Vaage, K. 2002. Heating technology and energy use: A Discrete/continuous choice approach to Norwegian household energy demand. *Energy Economics* 22:649-666.

Van Heerde, H.J., S. Gupta, and D.R. Wittink. 2002. Is 75% of the sales promotion bump due to brand switching? No, only 33% Is. *Journal of Marketing Research* 40: 481-491.

Villas-Boas, J.M. and R.S. Winer. 1999. Endogeneity in brand choice models. *Management Science* 45:1324-1338.

White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica* 48:817-838.