Promotion and Fast Food Demand

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October 25, 2007

Abstract

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. We study the effect of fast food promotion on market share and total demand by 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
Keywords: consumer demand, discrete choice, fast food, pricing strategy, promotion, spatial modeling

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1 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.

In doing so, we take into account many unique features of fast food demand. First, nutritionists, economists and marketing researchers have shown that fast food consumption is likely to be habitual (Colantuoni, et al., 2002; Del Parigi, et al., 2003). Second, fast food restaurants and the foods they sell are highly differentiated. 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. Richards, Hamilton and Patterson (2007) estimate an attribute-based model of fast food pricing, but without quantity data cannot comment on

[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).

the demand impact of price promotion. Therefore, in this paper we seek to gain a better understanding of fast food demand and menu pricing using a general model of consumer demand for differentiated products.

Prior research has addressed the "category versus brand" question for a number of different products in a variety of ways. Duffy (1995) uses a representative-consumer demand system in which alcohol and tobacco budget shares depend on alcoholic-beverage and cigarette advertising, respectively. Using aggregate data and a share-based model, however, he is unable to separate brand from category demand effects so finds that advertising does not increase aggregate spending on either product. Bucklin, Gupta and Siddarth (1998) estimate a latent-class, nested logit model in retail yogurt data to find that 58% of the impact of the incremental sales due to a price promotion come from brand switching (secondary demand effect) and 42% from increasing the size of the category (primary demand effect). Attempting to generalize results from a large number of studies on this topic, Bell, Chiang and Padmanabhan (1999) conduct a meta-analysis over data from a number of different categories and find an average secondary demand effect of 74% and primary effect of 26%. Reinterpreting the Bell, Chiang and Padmanabhan (1999) results, however, Van Heerde, Gupta and Wittink (2003) report that only 33% is due to brand switching the remainder is due to category effects.

Neither the continuous approach of Duffy (1995) nor the discrete-choice model used by Bucklin, Gupta and Siddarth (1998), however, seem entirely appropriate for answering the category versus brand question with household-level data. Rather, the choice of a fast food restaurant and decision regarding how much to purchase are more appropriately modeled in a three-stage, discrete / continuous choice framework. In the first stage, the consumer decides whether to consume fast food or not. If the consumer chooses fast food, in the second stage he chooses a restaurant 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 third 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, Dube and Chintagunta (2005) each estimate models of discrete / continuous choice based on an approach proposed by Hanneman (1984) and show that it is possible to use the resulting parameter estimates to decompose demand elasticities into purchase incidence, brand choice and purchase quantity. In this study, we develop an extension of this econometric approach that considers restaurant choice and purchase quantity decisions in spatial econometric model of demand.

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.

2 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 were $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 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.

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.

[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.

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.

3 Econometric Model of Fast Food Pricing

3.1 Household Demand for Fast Food

Fast food meal decisions are made in the context of a complex product, demographic and geographic space. We account for this level of complexity by synthesizing the discrete / continuous choice model of Hanneman (1984) with the distance metric (DM) model of Pinkse, Slade and Brett (2002) and Pinkse and Slade (2004). Among other empirical studies, Dubin and McFadden (1984) develop an approach similar to Hanneman (1984) in estimating a model of appliance and electricity-consumption demand. More recently, Chiang (1991), Chintagunta (1993), Arora, Allenby and Ginter (1998), Vaage (2000) and Nair, Dube and Chintagunta (2005) 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. Smith (2004) presents a discrete / continuous model of retail supermarket choice and expenditure, but uses aggregate rather than household data and does not incorporate store-attributes in a spatial sense. Estimating an inherently spatial model allows for more flexible marketing response parameters because the degree of responsiveness depends directly on the distance between observations in attribute space (Pinkse and Slade, 2004). Defining price-reponse 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) distance between choices influences whether promotional strategies have an allocative or expansive effect on demand. Further, 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*. By controlling for unobserved heterogeneity, which often confounds the identification of state-dependent demand, we are able to test whether habits, loyalty or perhaps addiction are important factors in determining fast food demand.

3.2 Empirical Model of Fast Food Demand

In the first decision-stage, a consumer chooses whether to consume fast food. In the second stage, he chooses which restaurant to patronize. As we show more formally below, a consumer will choose fast food if the value of doing so 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 $i = 1, 2, ...I$ is assumed to choose among $j = 1, 2, ...J$ fast food outlets (firms) at each purchase occasion $n = 1, 2, ...N$ and purchase a continuous quantity of food from the chosen restaurant: q_{ijn} or spend his or her remaining income on an outside, or numeraire good, q_{ion},with price normalized to one.[4] The direct utility function that describes the resulting discrete / continuous choice is written:

[4] The outside good consists of all non-fast food expenditure, so category expansion is not constrained by existing food-away-from-home expenditure. This definition is consistent with others in the discrete choice literature (Berry, Levinsohn and Pakes, 1995; Nevo, 2001).

$$\max_{q_{i1n},\dots q_{ijn}} U = U\left(\sum_{j=1}^{J} \phi_{ijn} q_{ijn}, \phi_{ion} q_{ion}\right) \tag{1}$$

$$s.t.\ y_{in} = \sum_{j=1}^{J} p_{jn} q_{ijn} + q_{ion}, \forall i = 1, 2, ...I,$$

where y_{in} is the income of consumer i available to spend on purchase occasion n, U is a well-behaved utility function of undefined form, and ϕ_{ijn} 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:

$$V(p_{jn}/\phi_{ijn}, y_i) = \alpha_1 \ln(p_{jn}/\phi_{ijn}) + \alpha_2 \ln(1/\phi_{ion}) + \alpha_3 (\ln(p_{jn}/\phi_{ijn}))^2 +$$

$$\alpha_4 (\ln(1/\phi_{ion}))^2 + \alpha_5 \ln(p_{jn}/\phi_{ijn}) \ln(1/\phi_{ion}), \tag{2}$$

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_{ijn} parameter reflects the 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.

For each observation, distance is defined relative to all other observations. Therefore, we follow the spatial econometrics literature (Anselin, 1988; Pinkse, Slade and

Brett, 2002) and define distance matrices in which each element represents the distance between meals ($\mathbf{M}$) in attribute space, households ($\mathbf{S}$) in demographic space and time periods ($\mathbf{T}$).[5] To cover the entire sample, each matrix consists of IJN x IJN elements because there are I households, choosing among J restaurants on N purchase occasions. Distance, however, can be defined in a number of ways.[6] When the relevant attributes are continous measures such as the case with nutrient (fat, protein, carbohydrate) content, each element of $\mathbf{M}$ is defined as the inverse Euclidean distance, or proximity, between observation ijn and lkm for each other household (l), restaurant (k) and time period (m). For illustrative purposes, consider the simple case of two attributes (z_1 and z_2). The inverse Euclidean distance between two meals (j and k) at two different time periods (n and m) by the same household is given by the $M_{ijn,ikm}$ element of the $\mathbf{M}$ matrix, which is calculated as: $M_{ijn,ikm} = 1/(1 + 2\sqrt{(z_{1,ijn} - z_{1,ikm})^2 + (z_{2,ijn} - z_{2,ikm})^2})$, and similarly for the household and temporal distance matrices. All distance matrices are row-normalized (row elements are divided by the row sum) so that multiplying any variable vector by a distance matrix creates a vector of weighted-averages. Applying this concept of distance to the quality index defined above, we write the index in general notation as:

$$\phi_{ijn} = \exp\left(\frac{1}{\eta_j}\left(\gamma_{ijn} + \beta d_{jn} + \pi D_i + \lambda_1 f(\mathbf{M}) + \lambda_2 g(\mathbf{S}) + \lambda_3 h(\mathbf{T}) + \lambda_4 e(\mathbf{M}, \mathbf{S}, \mathbf{T}) + \xi_{ijn} + \mu_{ijn}\right)\right), \tag{3}$$

where f, g, h, and e are matrix functions, defined in more detail below, that map the distance between each product and all others into a scalar value representing the degree of differentiation for each product in each dimension. Among other parameters, η_j is a chain-specific quality parameter for chain j similar to that used by Nair, Dube

[5] Kalnins (2003) and Thomadsen (2005) estimate spatial models of fast food demand and competition using a geographic definition of distance. Our data do not contain sufficient detail to calculate geographic distances among the restaurants in our sample.

[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.

and Chintagunta (2005), γ_{ijn} is a household-chain specific preference parameter, d_{jn} 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_k are spatial and temporal lag parameters associated with each of the distance metrics, and μ_{ijn} is an individual and restaurant specific unobservable error term that is assumed to be independent and identically distributed extreme value. To account for other consumer- and 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_{ijn}, 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: $\phi_{ion} = \exp(\mu_{ion}/\eta_j)$.

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_{ijn}) equal zero. Following Hanneman (1984), an expression for this share, in turn, is derived from (2) using Roy's Identity: $w_{ijn}(p_{jn}, \phi_{ijn}, \phi_{ion}) = \alpha_1 - \alpha_3 \ln(p_{jn}/\phi_{ijn}) + \alpha_3 \ln(1/\phi_{ion})$. Solving for $\psi_{ijn} = p_{jn}/\phi_{ijn}$ that makes $w_{ijn} = 0$ gives: $\psi_{ijn} = (1/\phi_{ion}) \exp(-\alpha_1/\alpha_3)$.Therefore, the probability of visiting a fast food restaurant is of a multinomial logit form (Chiang, 1991):

$$P(F_{in} = 1) = P(\psi_{ijn}) \leq \min\{p_{jn}/\phi_{ijn}, j = 1, 2, ..., J\} = \frac{\sum_{j=1}^{J} \exp\{\delta_{ijn}\}}{1 + \sum_{j=1}^{J} \exp\{\delta_{ijn}\}}, \quad (4)$$

where the mean utility from consumer i choosing restaurant j is given by: $\delta_{ijn} = (1/\nu)[(\gamma_{ijn} + \eta_j(\alpha_1/\alpha_3) - \eta_j \ln p_{jn} + \beta d_{jn} + \pi D_i + \lambda_1 f(\mathbf{M}) + \lambda_2 g(\mathbf{S}) + \lambda_3 h(\mathbf{T}) + \lambda_4 e(\mathbf{M}, \mathbf{S}, \mathbf{T}) + \xi_{ijn}], F_{in}$ is a binary indicator that equals one when consumer i purchases fast food and zero when visiting another type of restaurant and ν 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_{jn}) from within the fast food market is: $P(F_{in} = 1, R_{jn} = 1) = \exp\{\delta_{ijn}\}/(1+\sum_{j=1}^{J}\exp\{\delta_{ijn}\})$.This econometric framework completely describes the first two choices. An expression for the third problem – the amount of expenditure in the chosen restaurant – is found by taking the conditional expectation of the share equation over the extreme-value unobservable term. Writing the result in terms of expected expenditure gives:

$$E[q_{ijn}p_{jn}] = \left(\frac{y_{in}}{\eta_j/\nu\alpha_3}\right)\left(\frac{\exp\{\delta_{ijn}\}}{1+\exp\{\delta_{ijn}\}}\right)\left(\ln(1+\sum_j \exp\{\delta_{ijn}\})\right), \qquad (5)$$

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

3.3 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 (5). 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 (4).[7] Applying GMM in this case, however, is problematic because of the fundamental non-linearity of the estimating equation (5). Therefore, we follow Berry (1994), Berry, Levinsohn and Pakes (1995) and Nair, Dube and Chintagunta (2005) by first inverting (5) to

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

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_{ijn}. It is, however, possible to invert (5) numerically using a contraction mapping procedure. Specifically, for a given set of parameter values, Θ, we solve for the vector δ_{ijn} that equates observed with expected purchase quantities by defining a function $m(\delta_{ijn})$:

$$m(\delta_{ijn}) = \delta_{ijn} + \ln(q) - \ln[\widetilde{q}(\delta_{ijn}, \Theta)], \tag{6}$$

and iterating until convergence. This method converts a highly non-linear estimation problem to one that is amenable to more straightforward instrumental variables estimation. Given the definition of mean utility in (4), moment conditions are then formed based upon the econometric error term ξ_{jn} such that $E[\xi_{jn} Z_{ijn} | Z_{ijn}] = 0$ where Z_{ijn} is a vector of instrumental variables that are correlated with mean utility, but not meal prices, which are assumed to be endogenous.

Our identification strategy consists of three parts. First, we follow the usual procedure of instrumenting prices with costs of production. However, in the short panel used here, input prices from public sources vary little so were found to be unsatisfactory. Consequently, we follow Hausman, Leonard and Zona (1994) and Nevo (2001), and many others, in using product attributes and rival prices (in other regions) to instrument for own prices. This is a valid approach in this context because rival prices are likely to reflect aggregate supply shocks that effect own-prices, but not the own-equation unobservables. The second set of instruments includes demographic, lagged promotion, lagged utility and lagged quantity variables and other factors that are exogenous or pre-determined relative to current-period own-prices. Third, Kelejian and Prucha (1998) suggest using distance-weighted averages of all prices in the sample to instrument for own prices. These authors also provide theoretical arguments to support the use of linear and non-linear combinations of weighting matrices in the construction of instruments for spatial GMM estimators.

With the distance metrics defined above, the estimated form of (4) becomes:

$$\delta_{ijn} = (1/\nu)(\gamma_{ijn} + \eta_j(\alpha_1/\alpha_3) - \eta_j \ln p_{jn} \ + \beta d_{jn} + \pi D_i + \lambda_1 M_{ijn}\boldsymbol{\delta} + \lambda_2 S_{ijn}\boldsymbol{\delta}$$

$$+\lambda_3 T_{ijn}\boldsymbol{\delta} + \lambda_4 MT_{ijn}\boldsymbol{\delta} + \lambda_5 ST_{ijn}\boldsymbol{\delta} + \xi_{ijn}), \tag{7}$$

where M_{ijn} is the ijn row of $\mathbf{M}$, MT_{ijn} is the ijn row of the matrix product $\mathbf{MT}$, $\boldsymbol{\delta}$ is a vector of mean utilities, and all other terms are defined in a similar way. Consistent with usual practice in estimating these models (Nair, Dube and Chintagunta, 2005), notice that the scale parameter, ν, 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 (7). 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 (7) such that: $\theta^{-1} = (I - \lambda_1 M_{ijn}\boldsymbol{\delta} + \lambda_2 S_{ijn}\boldsymbol{\delta} + \lambda_3 T_{ijn}\boldsymbol{\delta} + \lambda_4 MT_{ijn}\boldsymbol{\delta} + \lambda_5 ST_{ijn}\boldsymbol{\delta})^{-1}$,and the expression for mean utility becomes:

$$\delta_{ijn} = \theta^{-1}(1/\nu)(\gamma_{ijn} + \eta_j(\alpha_1/\alpha_3) - \eta_j \ln p_{jn} \ + \beta d_{jn} + \pi D_i + \xi_{ijn}). \tag{8}$$

Each of the reduced-form response parameters in (8) 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, Dube 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 (7) 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.

With the definition of mean utility in (8), a positive autoregressive (lag) parameter in attribute space (λ_1) suggests that perceived quality rises the more similar a meal is to others that are available. On the other hand, a negative parameter indicates a demand for variety or differentiation among meal choices. In terms of the $S_{ijn}\boldsymbol{\delta}$ term, or the weighted-average distance from individual i, choosing a meal in restaurant j at purchase occasion n and all other observations, a positive effect suggests that individuals of similar taste tend to cluster in their preference for a particular type of meal. Similarly, the term $T_{ijn}\boldsymbol{\delta}$ represents the weighted average distance in time between an observation and all others. This term is equivalent to a combination of the traditional lead and lag operators in that the current observation is influenced by all those in the past and future, but with geometrically declining weight. By definition, this construct is entirely general as it represents multiple lead and lag periods in a single function. Most important for purposes of this study, the $T_{ijn}\boldsymbol{\delta}$ variable allows us to define a utility function that is time non-separable. Habits, loyalty or addiction all mean that a consumer's utility from visiting a fast food restaurant today depends upon his or her cumulative experience with fast food.[8]

[8] Our treatment of intertemporal demand linkages is more general than Hendel and Nevo (2004) and Erdem, Imai and Keane (2005) in that we consider the entire future and past purchase histories.

As is well known, however, state dependence in demand is difficult to separate empirically from unobserved heterogeneity. Unobserved hetergeneity refers to components of the error term that are specific to an individual household, are unobserved to the econometrician, and may explain patterns in consumption that are otherwise attributed to observed explanatory variables (Heckman and Singer, 1984; Wedel, et al., 1999). Persistence in demand may simply be due to an unobserved attribute of the household that is not measured, and not due to habits, loyalty or some other behavioral cause. We control for heterogeneity in two ways. First, the effect of observed heteroeneity is addressed by including the vector of demographic variables for each household (πD_i). Second, we account for unobserved heterogeneity by allowing the taste parameter γ_{ijn} to consist of a mean that varies over restaurants, and a random component that reflects the heterogeneity of households: $\gamma_{ijn} = \gamma_j + \epsilon_{in}$ where $\epsilon_{in}\tilde{} MVN(0, \Sigma)$. We estimate the resulting error-component model using a variant of the two-stage method originally conceived by Balestra and Nerlove (1966). In this way, the temporal-lag parameter λ_3 will reflect any true state-dependence in demand.

3.4 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. In general, 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 the fast food case, this insight implies 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 defintion 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 and n purchase occasions such that:

$$
\begin{aligned}
\varepsilon_j^R &= \sum_i \sum_n \left((\partial PR_{ijn}/\partial p_{jn})(p_{jn}/PR_{ijn}) \right) / IN \\
&= \sum_i \sum_n (\theta^{-1} \eta_j p_{jn} \left(1 - PR_{ijn}\right))/IN, \qquad (9)
\end{aligned}
$$

where $PR_{ijn} = P(F_{in} = 1, R_{jn} = 1) = \exp\{\delta_{ijn}\}/(1 + \sum_{j=1}^{J} \exp\{\delta_{ijn}\})$ is the probabilty that consumer i selects restaurant j at purchase occasion n. The choice elasticity, therefore, 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. 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 and purchase occasions, the conditional quantity elasticity is given by:

$$
\begin{aligned}
\varepsilon_j^Q &= \sum_i \sum_n ((\partial E[Q_{ijn}]/\partial p_{jn})(p_{jn}/E[Q_{ijn}]))/IN \\
&= \sum_i \sum_n (-1 + \theta^{-1} \eta_j p_{jn}[(1 - PR_{ijn}) + PR_{ijn}/(\ln(P(F_{in} = 0)))])/IN, \qquad (10)
\end{aligned}
$$

for the own-restaurant choice.[9] While these price elasticities show how the demand response for each restaurant is decomposed into brand-switching and quantity-increasing components in the conventional way, the aggregate effect on fast food spending is 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, 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

[9] Equivalent expressions for the cross-price elasticities are available from the authors.

of the discrete / continuous choice model, the proportion of the rise in unit-sales due to the primary-demand effect is given by:

$$\Delta_U^P = \sum_i \sum_n (1 + \theta^{-1}\eta_j (1 - \sum_j (p_{jn}/p_{kn})\Phi_{in}))/ \big(1 + \theta^{-1}\eta_j (1 - \Phi_{in}\big)))/IN, \quad (11)$$

where $\Phi_{in} = P(F_{in} = 1|R_{jn} = 1) + P(F_{in} = 1, R_{jn} = 1)/\ln[P(F_{in} = 0)]$ 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.

4 Data Description

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 summarizes all variables used in this study. [table 1 in here]

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 qualitative (restaurant name, promotion type, demographic variables) and quantitative attribute values (grams of fat, protein, carbohydrate and water) and use the resulting parameter estimates to calculate implicit prices for specific foods.[10] 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 price variation in a theoretically consistent way. In order to infer a nutrient content for each part of the meal, we 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 participating 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 household expenditure on goods other than fast food. By defining the outside option this way,

[10] Nutrient contents for each food item were taken from the USDA Nutrition Guide (USDA). This hedonic regression generated an R^2 value of 47.0%, which is acceptable in a short panel data set.

fast food pricing and promotion strategies may lead to category expansion by either drawing consumers from other types of restaurants, from at-home food spending, or from other goods entirely.

5 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. 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.[11] 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 173.076 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

[11] The test statistic is calculated as: $(\beta_1 - \beta_0)'(V_1 - V_0)^{-1}(\beta_1 - \beta_0)\tilde{\ }\chi^2_k$, where $\beta_1$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.

– the price parameter estimated with OLS is -1.736, while the GMM estimates is -1.722. However, each of the GMM promotion parameters differ significantly from their OLS counterparts. The practical import of this error is likely to be much more significant than mis-estimating the base-price elasticity. [table 2 in here]

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 matrices are defined as inverse distance in: (1) nutrient-attribute space, (2) household demographic-attribute space, (3) time, and (4) product- and household-attribute space interacted with time. 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 (Q_0) and restricted (Q_1) 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 89.709, so we reject the non-spatial in favor of the spatial model.

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 61.715 with critical value also 3.84). Unlike the spatial-lag parameter in the nutrient-distance case, however, the more similar a household is 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. [table 3a in here]

In table 3b, we extend the model to include temporal proximity between observations. Note that this variable captures more general dynamic behavior than a simple lagged-consumption effect because it includes distance between both past and *future* observations for each household.[12] In this regard, our specification is similar to the rational addiction model of Becker, Grossman and Murphy (1994) while not entirely ruling out other possible explanations for dynamic behavior. Again applying the D-test (test value is 4.755 with critical value 3.84), 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. Consequently, the accumulation of consumption experience leads to "adjacent complementarity" in which positive consumption experiences are self-reinforcing and

[12] As in Becker, Grossman and Murphy (1994), we assume consumers hold rational expectations regarding future prices and their own consumption paths.

lead to ever greater consumption, and more frequent visits. 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, such habituated consumers 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 in here]

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 (D-test value of 12.210 with critical value 3.84). In the preferred model, the estimated price- and promotion-response parameters are significantly lower relative to the non-spatial model in table 3a, 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. Moreover, the meal-attribute distance parameter is negative in the preferred model. This suggests 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.[13] The significance of the interaction parameters mean that variety-preference tends to diminish with the temporal proximity of other consumption occasions, while the household-attribute results are accentuated. This means that households tend to prefer variety in the long-run, but predictability in the short-run. In terms of demographics, positive interaction with temporal proximity suggests that the target market segment described above becomes more similar over time. This observation is consistent with both prior expectations and marketing practice.

In order to address the objective of this paper, we present and discuss the es-

[13]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.

timated price 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 of the top ten firms' pricing strategies are shown in tables 4a and 4b, respectively.[14] 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. 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. Although brand-switching is apparently important, only by considering the unit-sales impact will we obtain and accurate decomposition of the primary and secondary-demand effects.[tables 4a and 4b in here]

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 27.9% while the average secondary, brand-switching response is 72.1%. 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 reponse is 67.3% and the secondary 32.7%. 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

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

restaurants is relatively small, then it is to be expected that the aggregate effect of any price-based promotion will dominate. [table 5 in here]

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 fast food consumption tends to be habitual, then pricing strategies that would otherwise appear to be self destructive (ie., pricing below marginal cost) can be rationalized by their dynamic effects. This raises a third, more subtle implication for firms' marketing strategies. Because fast food promotion increases the size of the aggregate market, and consumers are habitual fast food consumers and not necessarily loyal to specific 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.

6 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 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 and distance metric methods. 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.

Our results 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 temporal proximity of fast food purchases, we find evidence of habitual fast food consumption. 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.

Highly detailed, panel-survey data on fast food consumption provides a real opportunity for future research. A natural extension of this study would extend our analysis to consider a full structural model of strategic pricing behavior on the part of fast food firms. If fast food consumption is indeed habitual, then firms may price below marginal cost in order to build up a cohort of habitual consumers. Second, we consider only mesurable 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 / habituation / obesity relationship.

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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	1.306	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 reported in '000 of units. Price is in $/100 gram. All values per meal. Marital status is defined 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.

Table 2. Non-Spatial Estimates: Fast Food Restaurants

	OLS		GMM	
Variable	**Estimate**	**t-ratio**	**Estimate**	**t-ratio**
Age	-0.002	-0.974	0.008*	2.602
Household Size	0.066*	4.090	0.063*	2.424
Marital Status	-0.317*	-7.128	-0.403*	-5.899
Education	-0.036*	-2.787	-0.055*	-3.165
Occupation	-0.301*	-8.211	-0.456*	-7.879
Minutes	0.002*	3.180	0.001	1.340
Combo	4.871*	11.342	2.152*	7.967
Buy One, Get One	3.932*	4.944	8.180*	6.322
Special	-0.851	-0.241	-0.803*	-4.029
Constant	-5.024*	-40.354	-5.406*	-27.050
Log(Price)	-1.736*	-109.721	-1.722*	-67.413
Hausman χ^2	173.076			
LLF/Q	6,888.632		598.862	

[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, LLF is the log-likelihood function value from the OLS regression.

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

	Product Attribute[a]		Household Attribute	
Variable	**Estimate**	**t-ratio**	**Estimate**	**t-ratio**
Age	-0.002	-0.602	-0.006*	-2.958
Household Size	-0.102*	-5.158	-0.138*	-7.177
Marital Status	-0.064	-1.276	0.079	1.586
Education	0.031*	2.186	0.082*	5.753
Occupation	-0.279*	-6.215	-0.198*	-4.500
Minutes	0.001	1.774	0.002	1.527
Combo	1.908*	9.490	1.834*	9.432
Buy One, Get One	3.618*	4.419	3.084*	4.016
Special	-1.217*	-8.328	-1.089*	-7.730
Constant	-3.229*	-18.460	8.245*	8.053
Log(Price)	-1.649*	-73.296	-1.687*	-76.809
M	-0.059*	-26.549	-0.042*	-15.807
S			0.238*	11.359
Q	509.153		447.438	

[a] In this table, a single asterisk indicates significance at a 5.0% level. The GMM objective function value is denoted by Q. **M** is a spatial distance matrix (inverse Euclidean distance) in meal attributes, **S** is a spatial distance matrix in household attributes.

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

	Temporal Distance[a]		Spatio-Temporal	
Variable	**Estimate**	**t-ratio**	**Estimate**	**t-ratio**
Age	-0.007*	-2.987	-0.007*	-2.888
Household Size	-0.141*	-7.194	-0.132*	-6.268
Marital Status	0.079	1.584	0.061	1.113
Education	0.081*	5.681	0.082*	5.244
Occupation	-0.197*	-4.460	-0.182*	-3.871
Minutes	0.002	1.554	0.002	1.766
Combo	1.841*	9.443	1.676*	8.378
Buy One, Get One	3.139*	4.054	2.501*	3.286
Special	-1.104*	-7.796	-1.010*	-6.879
Constant	8.196*	7.976	12.442*	3.537
Log(Price)	-1.687*	-76.528	-1.713*	-79.899
M	-0.044*	-13.857	-0.033*	-3.798
S	0.238*	11.332	0.328*	4.493
T	0.723*	2.279	0.799*	2.278
MT			-0.022*	-3.314
ST			0.188	1.376
Q	442.683		430.473	

[a] In this table, a single asterisk indicates significance at a 5.0% level.**T** is a temporal distance matrix (lead and lag).

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	-2.924	0.056	0.061	0.047	0.055	0.049	0.024	0.025	0.019	0.010
A&W	0.066	-4.233	0.021	0.016	0.019	0.017	0.008	0.009	0.006	0.004
SUB	0.084	0.024	-4.800	0.020	0.024	0.021	0.010	0.011	0.008	0.005
BK	0.042	0.012	0.013	-3.173	0.012	0.010	0.005	0.005	0.004	0.002
WEN	0.058	0.017	0.018	0.014	-3.765	0.015	0.007	0.008	0.006	0.003
KFC	0.089	0.025	0.028	0.021	0.025	-6.458	0.011	0.011	0.008	0.005
DQ	0.059	0.017	0.019	0.014	0.017	0.015	-9.043	0.008	0.006	0.003
PH	0.070	0.020	0.022	0.017	0.020	0.018	0.009	-9.257	0.007	0.004
HRV	0.025	0.007	0.008	0.006	0.007	0.006	0.003	0.003	-5.085	0.001
ARB	0.014	0.004	0.004	0.003	0.004	0.003	0.002	0.002	0.001	-4.930

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	-1.879	0.033	0.036	0.028	0.032	0.029	0.014	0.015	0.011	0.006
A&W	0.034	-1.809	0.011	0.008	0.009	0.009	0.004	0.004	0.003	0.002
SUB	0.051	0.014	-1.936	0.012	0.014	0.013	0.006	0.007	0.005	0.003
BK	0.027	0.008	0.009	-1.589	0.008	0.007	0.003	0.003	0.003	0.001
WEN	0.031	0.009	0.010	0.008	-1.717	0.008	0.004	0.004	0.003	0.002
KFC	0.024	0.007	0.007	0.006	0.007	-2.207	0.003	0.003	0.002	0.001
DQ	0.020	0.006	0.006	0.005	0.006	0.005	-2.550	0.003	0.002	0.001
PH	0.011	0.003	0.004	0.003	0.003	0.003	0.001	-2.765	0.001	0.001
HRV	0.015	0.004	0.005	0.004	0.004	0.004	0.002	0.002	-1.855	0.001
ARB	0.006	0.002	0.002	0.001	0.002	0.002	0.001	0.001	0.001	-1.805

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

	Elasticity		**Unit Sales**	
Restaurant[a]	**Primary**	**Secondary**	**Primary**	**Secondary**
McDonalds	0.422	0.578	0.845	0.155
A&W	0.327	0.673	0.823	0.177
Subway	0.315	0.685	0.797	0.203
Burger King	0.360	0.639	0.869	0.131
Wendy's	0.340	0.659	0.842	0.158
KFC	0.282	0.718	0.732	0.268
Dairy Queen	0.246	0.754	0.639	0.361
Pizza Hut	0.238	0.762	0.589	0.410
Harvey's	0.293	0.707	0.798	0.201
Arby's	0.294	0.706	0.807	0.193
Other Fast Food	0.273	0.727	0.764	0.236
Mr. Submarine	0.268	0.732	0.754	0.246
Pizza Pizza	0.202	0.797	0.317	0.683
La Belle Province	0.320	0.680	0.849	0.151
Little Caesar's	0.209	0.790	0.419	0.581
Taco Bell	0.192	0.808	0.014	0.986
Dominos'	0.210	0.789	0.407	0.593
Cultures	0.237	0.762	0.658	0.342
Taco Time	0.301	0.698	0.823	0.176
Pizza Delight	0.251	0.749	0.703	0.296
Average	0.279	0.721	0.673	0.327

[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.