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Fast Food, Addiction, and Market Power

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Many attribute the rise in obesity since the early 1980s to the overconsumption of fast food. A dynamic model of a differentiated-product industry equilibrium shows that a firm with market power will price below marginal cost in a steady-state equilibrium. A spatial hedonic pricing model is used to test whether fast food firms set prices in order to exploit their inherent addictiveness. The results show that firms price products dense in addictive nutrients below marginal cost, but price products high in nonaddictive nutrients higher than would be the case in perfect competition.

Key words: addiction, brand loyalty, fast food, generalized method of moments, hedonic pricing, nutrients, shadow values

Introduction

From 1982 to 2003, expenditure on fast food in the U.S. rose from $26.5 billion to $126.7 billion—an annual rate of growth of 6.4%, over 2% higher than the growth rate of at-home food consumption (U.S. Department of Agriculture, 2005). At the same time, the percentage of consumers regarded as obese more than doubled, rising from roughly 14% to 30% (Centers for Disease Control and Prevention, 2005). While there are many other factors that have contributed to the rise in obesity, some regard increasing consumption of fast food as one of the most important (Chou, Grossman, and Saffer, 2004).[1]

Not surprisingly, fast food companies have grown rapidly over this time period and have become highly profitable, despite frequent price wars and the prevalence of low-cost "value" meals. Indeed, the average annual return on equity for the top five fast food firms in the United States from 1999–2004 was 19.4%, versus 15.8% for restaurants more generally.[2] On the surface, it would appear these companies have successfully differentiated themselves from one another through advertising, merchandise promotion, store attributes (play areas, aesthetic decor, attention to cleanliness), and product design. However, others suggest that the rapid growth and high profitability of fast food

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[1] Other explanations in the recent literature include the reduced cost of calorie consumption relative to expenditure (Cutler, Glaeser, and Shapiro, 2003) and a variety of other factors, including anti-smoking laws and increased restaurant density (Rashad, Grossman, and Chou, 2006).

[2] Net profit margin for the top five fast food firms averaged 8.25% versus 6.58% for the restaurant group as a whole. The top five publicly traded firms include McDonalds, Yum! Brands, Wendy's International, Sonic Corporation, and Triarc Companies.

firms is due to their ability to exploit the inherent addictiveness of fast food. Yet, to date, no empirical support has been offered for this assertion. Accordingly, this study seeks to test whether fast food firms price as if their products are addictive in an imperfectly competitive, steady-state equilibrium.

There is evidence from medical research that the nutrients in fast food are inherently addictive (Colantuoni et al., 2002; Grigson, 2002; Del Parigi et al., 2003). Some research suggests fast food firms have learned to exploit this fact in the design and pricing of their products (Drewnowski and Darmon, 2005; White et al., 2002). Because nutrients are not firm-specific, nutrient addictiveness cannot be a source of market power. Rather, any market power fast food firms may have must instead derive from the success of the differentiation strategies described above. When addictiveness is *combined* with market power, however, prices can differ significantly from those set by competitive firms (Villas-Boas, 2006; Driskill and McCafferty, 2001; Showalter, 1999). Namely, if a firm with market power recognizes that it sells an addictive product, then it has an incentive to reduce price—even below marginal cost—in expectation of higher future demand. Without market power, individual firms do not have an incentive to price below marginal cost because they cannot appropriate the future gains from doing so. In this sense, addiction to nutrients is akin to a common property resource—i.e., the size of the pool of addicted consumers is a benefit to all, but none have the incentive to "produce" the benefit by reducing prices.

While both the theoretical (Iannaccone, 1986; Becker and Murphy, 1988) and empirical (Becker, Grossman, and Murphy, 1994; Cawley, 1999) implications of the rational addiction model for firms in competition are well understood, there are few tests of addictive-product pricing by firms with market power. Among empirical studies, Cawley (1999) finds support for the rational addiction model in calories, while Richards and Patterson (2004) fail to reject a rational addiction to macronutrients (protein, fat, and carbohydrates) in a panel-data set of household snack food consumption. Empirically, rational addiction differs from mere habituation in that consumers respond to expected future costs and benefits of consuming the addictive product. Testing for rational addiction, therefore, would seem to require detailed, time-series data on individual consumption behavior. Nevertheless, with only a cross-section of publicly available fast food prices, it is still possible to test indirectly for rational addiction because the implications of addiction for firm behavior are very clear. We test these implications by estimating a steady-state equilibrium model of fast food pricing and demand which explicitly allows for the possibility that the nutrients in fast food are addictive.[3]

Nutrient content, however, is also the primary means by which fast food firms differentiate their products. In a dynamic model, therefore, it is difficult to determine whether firms design their products in order to build brand loyalty through differentiation, or if they instead mimic one another and set prices in order to exploit the addictiveness of fast food in general. In fact, there are four possible combinations of pricing and product design strategies that may describe fast food firm behavior:

[3] The steady-state equilibrium assumption is reasonable given the nature of the fast food industry. Although fast food firms constantly introduce and promote new products, the prices for the products used in this study have not changed in a significant way for several years.

- First, if there is evidence that fast food firms differentiate like products from each other (e.g., hamburgers from firm A are different than hamburgers from firm B) and if they price products high in addictive nutrients (fat and sugar) below marginal cost, then firms are pricing to exploit brand loyalty.[4]

- Second, if firms design foods that imitate rivals' offerings and price foods dense with addictive nutrients below marginal cost, then they implicitly collude in order to expand the total number of addicted consumers in the market. In other words, firms internalize the dynamic externality created by addictiveness in a collective way.

- Third, by allowing for both intra- and inter-firm differentiation, we allow for the case where firms differentiate individual products from those of their competitors', but cluster their own products around a common nutritional strategy. This is a scenario where firms build brand loyalty through differentiation, but then exploit the inherent addictiveness of their products to a cohort of loyal consumers.

- Finally, if firms do not price goods with addictive nutrients any lower than other nutrients, it is clear that the common-property nature of addictiveness dominates and fast foods are priced as they would be in a competitive, albeit differentiated, industry. In this case, the potential future rents to the industry as a whole are not being captured by any of its member firms.

To test among these possible outcomes, we estimate a spatial model of fast food pricing behavior based on the distance metric (DM) approach of Pinkse, Slade, and Brett (2002) and Pinkse and Slade (2004). In the DM model, hamburgers, french fries, chicken sandwiches, and other items offered by fast food chains are arrayed in a multi-dimensional attribute space in which the distance between competing products is readily measurable.[5] With this approach, it is possible to test whether fast food firms price their products collusively in order to take advantage of some common source of demand (addiction), or to exploit any market power that may arise from differentiating themselves in the conventional way (brand loyalty). The methods developed in the spatial econometrics literature are ideally suited for answering questions of this type.

The paper begins by describing a simple model of fast food industry equilibrium where firms compete as oligopolists and demand is linked intertemporally, but depends on nutrient attributes. The second section presents an empirical model of fast food pricing that explicitly incorporates distance between products in attribute space as a

[4] The phrase "pricing below marginal cost" refers to imperfectly competitive firms that may price some nutrients below what they would in perfect competition, but not strictly below marginal cost. This phrase is used in the sense of Pakes (2003) for descriptive purposes only. As Pakes explains, shadow prices for firms with market power are comprised not only of marginal profit due to a particular attribute, but rather consist of a complex interplay of cost, demand, and technological forces. Specifically, he derives the hedonic pricing function $h(x_i)$ for a product with attributes $\mathbf{x}$ as:

$$h(x_i) = E\left(mc(\cdot)\,|\,x_i\right) + E\left(\frac{D_i(\cdot)}{\partial D_i(\cdot)/\partial p}\,\middle|\,x_i\right),$$

where $E(\cdot)$ is the expectation operator, mc is marginal cost, and $D(\cdot)$ is the direct demand function. Therefore, the "price" of any attribute can appear to be above its marginal cost due to market power, or below for other reasons, such as those we identify here.

[5] Note that product design and pricing are, conceptually, different stages in a two-stage game played among fast food vendors. Given the intractability of estimating two-stage games in limited data, however, we focus on the second (pricing) stage and take product design as given.

means of identifying the structure of competitive pricing. Next, we describe the data used to estimate this model and explain the details of our estimation method. The fourth section discusses the estimation results and hypothesis tests regarding the possibility that firms exploit the potential addictiveness of their products and whether this realization leads to higher or lower fast food prices. The final section concludes and offers some implications for potential obesity-control policies that may be directed toward the fast food industry.

A Dynamic Equilibrium Model of Oligopoly Pricing with Addiction

The fact that static and dynamic models of demand have different implications for optimal firm pricing behavior is well understood (Becker and Murphy, 1988; Becker, Grossman, and Murphy, 1994; Showalter, 1999; Driskill and McCafferty, 2001; Villas-Boas, 2006). Yet, there are relatively few empirical studies examining the impact of addictiveness on firm pricing behavior when the addiction is formed over a specific ingredient or attribute of the product itself in a multi-attribute context—particularly when firms have market power. This is somewhat surprising because addiction necessarily forms over a functional attribute and not the product—e.g., smokers are not likely to be addicted to the activity of smoking any more than coffee drinkers can become physically addicted to decaffeinated coffee. Therefore, in this section we review the theoretical results on pricing addictive products in imperfect competition in order to draw a distinction between what we expect to observe in competitive and noncompetitive environments.

Showalter (1999) develops a dynamic model of consumer demand for cigarettes produced by a monopolist manufacturer. Assuming the market consists of a single, representative consumer, he shows that when firms are forward looking it does not matter whether the consumer is rational (forward looking) or myopic, as firms will set their prices in anticipation of expected future demand. More importantly, if consumers are rational, then they understand the firm's incentive to reduce prices initially to build a stock of addicts, only to increase prices in the future. However, assuming firms are able to practice intertemporal price discrimination is not realistic when multiple generations of consumers are likely to coexist and prices do not change over time.[6]

Villas-Boas (2006), on the other hand, develops an overlapping-generations model to show that firms may price either below marginal cost, or above the competitive level. The latter result accrues if potentially addicted consumers recognize that consumption today may lead to higher prices in the future. If so, their demand today can become more inelastic, thus resulting in higher prices in the current period instead of lower. The indeterminacy of this result, however, is not useful for empirical purposes.

Driskill and McCafferty (2001) adopt a definition of utility similar to that of Becker, Grossman, and Murphy (1994), but cast their model instead in a continuous-time, infinite horizon framework and derive a Markov-perfect equilibrium among oligopoly suppliers of an addictive good. As shown by these authors, the optimal price can indeed

[6] As evidence in support of this assumption, compare fast food pricing with haircuts. Fast food vendors do not charge children and adults different prices for the same meals, as hair salons do. Most offer children's meals, but adults are not prevented from buying them, nor are children prevented from buying adult meals. If children and adults paid different prices for the same items, then restaurants could be accused of intertemporal price discrimination.

be below marginal cost in a steady-state equilibrium if marginal cost is rising and the decay rate is not too rapid. Further, like Karp (1996) before them, Driskill and McCafferty conclude market power can be profit-reducing to firms that possess it.[7]

To summarize the theoretical literature, addictiveness alone will not guarantee below-marginal-cost pricing, but addictiveness to specific ingredients or nutrients when combined with market power can cause some of the ingredients to have negative implicit values, thereby contributing to products that are priced below their marginal cost of production. Because ingredient formulation and product design are the central elements of a differentiated strategy intended to yield *higher* prices, evidence of negative implicit ingredient prices is likely due to dynamic pricing strategies by competing firms.

An Empirical Test of Brand Loyalty or Addiction

A Hedonic Model in Fast Food Nutrients

The empirical test is designed to differentiate between pricing behavior consistent with brand loyalty, as defined by a strategy of product differentiation, and pricing intended to exploit nutrient addiction. In time-series data, the distinction between brand loyalty and addiction would be relatively easy to draw given the taxonomy developed by Becker, Grossman, and Murphy (1994). Specifically, brand loyalty, or what Becker and Murphy (1988) refer to as "myopic addiction," is a form of intertemporal demand in which consumers respond only to past prices and consumption levels, whereas a rational addiction reflects expectations of future prices and consumption. With only cross-sectional data on fast food prices, however, we must look elsewhere for a way to distinguish between the two.

Explicit recognition of the spatial nature of fast food characteristics and imperfectly competitive pricing provides a very simple, albeit indirect, alternative. The primary way in which fast food firms establish brand loyalty is through product formulation—taste, texture, aroma, and appearance are all critical variables in food design found to influence preferences and repurchase behavior. Just as the components of a car determine its power, feel, and design, the nutritional elements of fast food comprise a clear, measurable way of comparing food attributes that are otherwise unmeasurable. Hence, by estimating a spatial econometric model in fast food nutrient space, we are able to test whether fast food companies price their products similar to those near in attribute space in order to gain market share (in the sense of Hotelling) or much higher if they are sharply differentiated (distant in attribute space).[8]

[7] Specifically, Driskill and McCafferty (2001) show that when firms producing addictive or durable goods have market power, they price so as to influence future market demand as well as to take advantage of current market power. But because consumers are aware of this fact, they behave under the assumption that the monopolist will likely raise prices in the future. In the absence of the ability to commit to a path of output that guarantees higher future prices, and if marginal costs are rising, monopoly firms will thus overproduce in the Markov-perfect equilibrium and generate lower profits than if the industry were less concentrated.

[8] Hotelling (1929) develops a metaphor for product differentiation wherein a market ("main street") consists of a finite number of heterogeneous consumers whose preferences are uniformly distributed but are not known by firms. If the value to any individual consumer of choosing a product that lies some distance from her location on main street falls in the distance she must travel, then a firm can steal rival business by reducing its price, thus attracting more consumers willing to "travel" a larger distance.

To test for a departure from competitive pricing, we use an equilibrium pricing model under oligopolistic competition that yields a hedonic, or characteristic demand specification (Rosen, 1974; Brown, 1983; Brown and Rosen, 1982; Ekeland, Heckman, and Nesheim, 2004). A characteristic approach is necessary because we only have access to nutritional attribute and price data for a number of differentiated products. Because the traditional model of Rosen (1974) applies only in perfect competition, however, we develop a more general approach using the distance metric (DM) method of Pinkse, Slade, and Brett (2002), Pinkse and Slade (1998, 2004), and Slade (2004) to estimate best-reply functions to account for the dynamic nature of nutrient demand.[9]

By focusing on the supply-side problem, we assume firms compete in prices taking one another's product design (nutrient contents) as given and that fast food vendors sell differentiated menu items to individual consumers (households). Indirect utility is defined over individual fast food items and is assumed to be normalized quadratic (Berndt, Fuss, and Waverman, 1977; McFadden, 1978; Pinkse and Slade, 2004; Slade, 2004). The normalized quadratic represents an appropriate choice of functional form because it is a relatively parsimonious specification which is locally flexible, nonincreasing in prices, symmetric, linearly homogeneous, continuous, and twice differentiable. It is not convex by construction, but the necessary parametric restrictions are easily imposed. Further, aggregate demands are independent of the distribution of consumer heterogeneity or differences in income among households (Slade, 2004). Perhaps most important for this study, it yields linear demands.

While linear demands are not preferred on theoretical grounds, they are necessary given the complexity of the estimation method described below. Households allocate a fixed amount of income $\hat{y}$ among fast food items q_j sold by firms j (where $j = 1, 2, ..., J$) at prices $\hat{p}_j$ and a composite good, Q. Although this assumption is relaxed in the empirical model below, we assume here that each firm sells only one item. Further, each product is comprised of differing proportions of $i = 1, 2, ..., I$ nutritional attributes, so x_{ji} represents one element of the $J \times I$ composition matrix, $\mathbf{x}$. Therefore, utility is ultimately determined by the composition of each product purchased.

Given this preference structure, aggregate indirect utility is written as:

$$V(\hat{\mathbf{p}}, \hat{y}, \mathbf{x}) = \boldsymbol{\alpha}_1(\mathbf{x})\hat{\mathbf{p}} + \alpha_2\hat{y} + \tfrac{1}{2}\left(\hat{\mathbf{p}}^T\boldsymbol{\beta}_1(\mathbf{x})\hat{\mathbf{p}} + \hat{\mathbf{p}}^T\boldsymbol{\beta}_2\hat{y}\right), \tag{1}$$

where all prices and income are normalized by the price of the composite commodity, W, so that $\mathbf{p} = W^{-1}\hat{\mathbf{p}}$ and $y = W^{-1}\hat{y}$, and α_2 is a scalar parameter, $\boldsymbol{\alpha}_1$ and $\boldsymbol{\beta}_2$ are $J \times 1$ parameter vectors, and $\boldsymbol{\beta}_1$ is a $J \times J$ matrix of price-response parameters. Below, we show that $\boldsymbol{\alpha}_1$ and $\boldsymbol{\beta}_1$ are, in turn, functions of the set of nutritional attributes.[10] In cross-sectional data, we set $W = 1$ because the price of the composite commodity is not likely to vary over households (Pinkse, Slade, and Brett, 2002). With this normalization, the indirect utility function then becomes:

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[9] Independent of Pinkse and Slade (1998), Feenstra and Levinsohn (1995) also develop a structural spatial approach to estimating market conduct by oligopolistic firms selling products containing multiple attributes. Their econometric approach, however, also requires data on demand quantities, so does not have a purely hedonic interpretation. With respect to food products, Ladd and Suvannunt (1976) specify a structural hedonic model they use to estimate the marginal value of nutritional attributes.

[10] Note that incorporating product attributes in the indirect utility function in this way is similar to the differentiated-products demand system derived by Davis (1995) which uses the "modifying function" approach of Lewbel (1985) to incorporate demographic scaling factors. Gorman (1976) and Pollak and Wales (1978) originally developed this method of "scaling" demand parameters.

$$V(\mathbf{p}, y, \mathbf{x}) = \boldsymbol{\alpha}_1(\mathbf{x})\mathbf{p} + \alpha_2 y + \tfrac{1}{2}\left(\mathbf{p}^T\boldsymbol{\beta}_1(\mathbf{x})\mathbf{p} + \mathbf{p}^T\boldsymbol{\beta}_2 y\right), \tag{2}$$

By allowing indirect utility to be a function of fast food attributes [equation (2)], the distance metric approach represents a synthesis of traditional demand analysis and hedonic estimation. There are two important points to note in this regard. First, empirical hedonic models typically are not linear in product attributes because this implies shadow values are constant for all nutrient-density levels (Witte, Sumka, and Erekson, 1979). Therefore, the $\boldsymbol{\alpha}_1$ parameter vector in (2) is composed of quadratic functions of food attributes such that each element is written as:

$$\alpha_{1j}(\mathbf{x}_j) = \sum_i \alpha_{10i}x_{ij} + \tfrac{1}{2}\sum_i \alpha_{11i}x_{ij}^2.$$

Second, note that the utility function in (2) is implicitly separable in other goods and strictly concave in nutrients (Cropper et al., 1993; Arguea and Hsiao, 1993). By Roy's theorem, the demand for fast food sold by firm j is found by differentiating (2) with respect to the price, p_j, whereby:

$$q_j = \alpha_{1j}(\mathbf{x}_j) + \sum_k \beta_{1jk}(\mathbf{x}_j)p_k + \beta_{2j}y, \quad \forall j, \tag{3}$$

where $\mathbf{x}_j$ is the jth row of $\mathbf{x}$.[11]

We now turn to the supply side of the model. Given the evidence presented in the introduction regarding the profitability of firms in the industry, and their efforts to develop new products and unique brands, we assume firms compete as differentiated oligopolists. With fast food demands in (3), the firm profit-maximization problem is solved by choosing a price (p_j) to maximize current profit:

$$\Pi_j = \max_{p_j}\,(p_j - c_j)\left(\alpha_{1j}(\mathbf{x}_j) + \sum_k \beta_{1kj}(\mathbf{x}_j)p_k + \beta_{2j}y\right), \tag{4}$$

where c_j is the marginal cost of producing fast food by firm j. Solving the first-order condition to (4) for the optimal price by firm j leads to the best-reply function:

$$p_j = c_j - \frac{1}{\beta_{1jj}}\left(\alpha_{1j}(\mathbf{x}_j) + \sum_{k\neq j} \beta_{1kj}(\mathbf{x}_j)p_k + \beta_{2j}y\right), \quad \forall j, \tag{5}$$

so the price set by firm j depends on marginal cost, the embodied attributes of its product, all other firms' prices, and the distance between its product and all others in attribute space. In this form, however, equation (5) is not estimable in a market with many other products (firms) because the coefficient vector $\boldsymbol{\beta}_{1kj}$ expands directly with the sample size, or the number of firms in the market. Consequently, we follow Pinkse, Slade, and Brett (2002) by allowing each β_{1kj} to be a common function $\beta_{1kj} = g(d_{kj})$ of the distance (in attribute space) between observations k and j, where $g(d_{kj})$ is an element of the spatial weight matrix, $\mathbf{G}$. In fact, we define $g(d_{kj})$ in three different ways, reflecting two of the principal means by which distance can be defined in attribute space: (a) proximity, and (b) contiguity.

[11] As Slade (2004) explains, the marginal utility of income is a price index that varies over observations in the data set, but not over consumers, and thus can be normalized to 1.0. This assumption is valid given our data describe only a cross-section of fast food prices within a single metropolitan market.

First, $g_p(d_{kj})$ is defined as the inverse Euclidean distance between products k and j such that:

$$\beta_{1kj} = \beta_{10p}\left(1 + 2\sum_l (x_{lk} - x_{lj})^2\right)^{-1/2},$$

where β_{10p} is a spatial-autoregressive parameter that captures the importance of "nearness" among all observations. Intuitively, weighting all other observations by the inverse distance from the observation in question in the econometric model reflects the expectation that products closer to each other in attribute space should be stronger substitutes, and vice versa. Analogous to lagging explanatory variables in time-series models, the expectation is that observations further away from each other will exert less of an influence on each other's demand. Euclidean distance, however, implicitly imposes the assumption that the distance in any one direction (any attribute) has the same influence as any other. Because this may not be the case, we define two other contiguity matrices which serve to partition the attribute-distance matrix **G** into elements that measure whether firms are "neighbors" within the same firm ($\mathbf{G}_f$) or belong to the same product class ($\mathbf{G}_g$). Note that there will be one autoregressive parameter, β_{10p}, β_{10f}, or β_{10g}, for each definition of **G**. With these three measures of distance, the cross-price elasticity matrix reflects how "close" a competitor each fast food item is to all others.

The pricing model in (5) differs from a traditional hedonic pricing model in a fundamental way. Specifically, as Pakes (2003), Feenstra (1995), and Feenstra and Levinsohn (1995) suggest, product differentiation allows for nonzero margins in Bertrand rivalry. Therefore, the "shadow values" derived from equation (5) are more accurately interpreted as the marginal-residual value to firm j after allowing for the response of all other firms and all expected future profit. Indeed, the estimated marginal value in this case may be negative, even when the researcher's priors are almost certainly the opposite. After accounting for all other factors that may influence a fast food vendor's price-cost margin, if the residual shadow value remains nonpositive, it must be due to some other factor influencing the firm's pricing behavior. In a static, multi-product model, DeGraba (2006) argues that firms may set prices for loss leaders below marginal cost if buyers of the loss-leader product can be expected to purchase more of all other products in the store. Although this represents a plausible explanation for why turkey prices fall at Thanksgiving (hosts are likely to buy more of all associated products), it does not explain why implicit *nutrient* prices may be negative. Because the vast majority of fast food consumers buy only two or three items per visit (NPD Group), it is unlikely that there is sufficient profit incentive in these other products to warrant a significant loss on the main item. Rather, firms have potentially much more to gain by pricing addictive products such that their consumers have an incentive to buy more fast food over time.

In terms of the empirical model shown in (5), the implicit price of nutrient i is found by differentiating the solution for the price-cost margin so that:

$$(6) \qquad \theta_i = \frac{\partial(p_j - c_j)}{\partial x_{ij}} = -\frac{1}{\beta_{1jj}}\left(\alpha_{10i} + \alpha_{11i}x_{ij} + \sum_{k \neq j}\frac{\partial\beta_{1kj}}{\partial x_{ij}}p_k\right), \quad \forall i,$$

where

$$\frac{\partial\beta_{1kj}}{\partial x_{ij}} = -x_{ij}\beta_{10p}\left(1 + 2\sum_l (x_{lj} - x_{lk})^2\right)^{-3/2}$$

when g is defined in terms of inverse Euclidean distance. Implicit nutrient prices are thus determined by two factors: (a) an autonomous component that changes linearly in the level of the attribute, and (b) a component that depends on the distance between a product and its rivals. If firms compete as differentiated oligopolists, the second term in (6) is greater than zero because differentiation leads to higher margins. On the other hand, if this term is less than zero, then firms reduce margins as they imitate rival products in the expectation of building market share. In terms of the entire expression in (6), the market share effect *reinforces* the autonomous negative implicit price of addictive nutrients (α_{10i}, $\alpha_{11i}x_{ij} < 0$), while the differentiation effect counteracts it. The net effect, therefore, is an empirical question.

In order to identify these competitive effects, it is necessary to estimate the marginal cost of production. Explicitly incorporating the marginal cost of each attribute is, however, problematic as these costs are unobservable. Accordingly, the competitive hedonic pricing model is modified to account for nonzero margins and imperfectly competitive pricing by imposing a solution concept on the game played by fast food vendors and calculating marginal cost from the estimated demand parameters. Assuming Bertrand-Nash rivalry is common in structural models of differentiated-product equilibrium (e.g., Sudhir, 2001; Nevo, 2001), as such, it is relatively uncontroversial. As for the marginal cost estimate, we assume c_j represents the marginal cost of producing each type of fast food item where $c_j = c(\mathbf{r})$, and c is an index constructed from a vector of input prices, $\mathbf{r}$.[12] Nevertheless, including this index of input prices, and all other firms' prices in the estimating equation, introduces a host of econometric issues. We explain how these are addressed in the next section.

Spatial Estimation of the Hedonic Nutrient Model

Based on the above discussion, the empirical strategy is to appropriately control for all possible competitive pricing effects, whether firms differentiate or imitate, so that we can isolate the independent pricing of individual nutrients. Negative nutrient prices will then provide strong evidence of pricing to exploit their inherent addictiveness. In order to estimate equation (5) using spatial methods, we generalize the single-attribute DM method of Pinkse and Slade (2004) to incorporate several nutritional attributes. Relaxing the assumption that each firm produces only one good, assume now that the market consists of $j = 1, 2, ..., J$ items sold by $f = 1, 2, ..., F$ firms so that there are $JF = N$ fast food items in total, indexed as $n = 1, 2, ..., N$. The most general form of the spatial-hedonic pricing model for item n is written as:

$$\text{(7)} \qquad \begin{aligned} \mathbf{p} &= c(\mathbf{r}) - \boldsymbol{\gamma}_{10}\mathbf{x} - \boldsymbol{\gamma}_{11}\mathbf{x}^2 - \gamma_{2m}\mathbf{G}_m\mathbf{p} - \gamma_3 y + \mathbf{u}, \\ \mathbf{u} &= \lambda\mathbf{H}_m\mathbf{u} + \boldsymbol{\varepsilon}, \end{aligned}$$

where a typical element of $\boldsymbol{\gamma}_{10}$ is α_{10i}/β_{1nn}, $\boldsymbol{\gamma}_{11}$ is α_{11i}/β_{1nn}, and γ_{2m} is β_{10m}/β_{1nn} for definition $m = p, f$, or g of spatial distance; $\mathbf{G}_m$ is an $N \times N$ matrix of spatial weights; $\mathbf{x}$ is an $N \times I$ matrix of fast food nutrients; $\mathbf{x}^2$ is $\mathbf{x}$ squared on an element-by-element basis;

[12] Implicitly, we assume constant returns to scale. This assumption is justified based on the empirical results of Hiemstra (2000), who finds only modest returns to scale among a sample of fast food restaurant chains. Hiemstra uses a data set which includes many firms that are smaller, and thus more likely to exhibit unexploited scale economies, compared to those in our data set. Hence, his results overstate the returns to scale among our restaurants.

r is a vector of input prices; λ is the spatial error parameter; and $\boldsymbol{\varepsilon}$ is a vector of i.i.d. error terms.[13] The matrix $\mathbf{H}_m$ is also an $N \times N$ matrix of spatial weights constructed in the same way as $\mathbf{G}_m$, but need not use the same definition of distance for each specification of the system. Similar definitions apply to the firm- and product-class contiguity matrices and spatial autoregressive parameters introduced above.

Notice, however, (7) is a best-response function, so we divide each cross-sectional observation through by its own demand-curve slope. As is true of any spatial model (Anselin, 1988; Pinkse, Slade, and Brett, 2002), because there are as many parameters (N) as observations, β_{1nn} is inherently unidentified. Thus, in our empirical application of the DM model, we follow Pinkse, Slade, and Brett in estimating reduced-form diversion ratios (ratio of the cross-price demand response to own-price response) which are proportional to the distance between products, $g_{mp}(d_{ij})$. Whereas we estimate this factor of proportionality parametrically, Pinkse, Slade, and Brett do so nonparametrically. The autoregressive parameter, γ_{2m}, is the estimate of the effect of distance between a product and all others in the market (multiplication by $\mathbf{G}_m$ creates a spatially weighted average price of all rival products) on pricing strategy in general. One implication of this assumption is that the estimated shadow values are proportionate to the own-price response parameters, reflecting the insight of Pakes (2003) referred to above. Based on specification tests as to whether a spatial autoregressive ($\gamma_{2m} \neq 0$, $\lambda = 0$, SAR) or spatial error ($\gamma_{2m} = 0$, $\lambda \neq 0$, SEM) is more appropriate, we test the primary hypothesis of the paper—whether fast food companies appear to exploit the addictiveness of the nutrients in their food.

Tests of the Addiction–Market Power Hypothesis

By partitioning the spatial weight matrix into firm- and product-specific components, we are able to test specific hypotheses as to whether fast food firms tend to differentiate their menu offerings from others and how they implicitly price nutrient attributes. Specifically, if $\gamma_{2f} < 0$, then each fast food chain differentiates its own products internally, attempting to meet a wide variety of tastes with a single menu. Because utility is assumed to rise in variety (Dixit and Stiglitz, 1977), firms are able to charge higher prices on differentiated menu items. This is the differentiation, or *market power* effect. On the other hand, if it is the case that $\gamma_{2f} > 0$, then individual chains tend to aggressively "cluster" products in terms of nutrients and price in an attempt to gain market share. This is the *market share* effect.

A symmetric argument applies to the product-class weight matrix, $\mathbf{G}_g$. If $\gamma_{2g} < 0$, then firms tend to differentiate each item from others in the product class (i.e., hamburgers, french fries, etc.) offered by other firms. Again, differentiation is achieved through each item's nutritional profile.[14] In contrast, if it is the case that $\gamma_{2g} > 0$, then firms tend to offer products which mimic each other as they attempt to gain market share. To summarize the possible outcomes, we define four joint tests of the spatial-lag and shadow-value parameters:

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[13] Using consistent estimates of **u** above, we test the spatial autoregressive (SAR) null hypothesis that $\lambda = 0$ with a Lagrange multiplier (LM-SAR) test statistic given in LeSage (1998). We also apply Moran, Lagrange multiplier, Wald, and likelihood-ratio tests under the assumption that **u**'s are estimated using OLS instead of the MLE SAR estimates.

[14] Taste is, of course, an important component to design, but tends to vary by individual and therefore is not quantifiable. We allow for differences in taste by including an error term in the price-response function that is individual, rather than product-specific.

■ HYPOTHESIS 1. *Differentiation / Pricing Below Marginal Cost:*

$$H_1: \gamma_{2g} < 0, \ \theta_i < 0,$$

where θ_i refers to the shadow value of potentially addictive nutrients from equation (6), which will be negative if firms want to price goods high in this nutrient below marginal cost. In this case, the greater the distance between two products in attribute space, the greater their difference in price. Addictive nutrients, however, have negative shadow values in order to attract as many addicted consumers as possible.

■ HYPOTHESIS 2. *No Differentiation / Pricing Below Marginal Cost:*

$$H_2: \gamma_{2g} = 0, \ \theta_i < 0.$$

In the second case, firms do not differentiate their products, but do price nutrients so as to collectively exploit their addictiveness.

■ HYPOTHESIS 3. *Inter-Firm Differentiation / Intra-Firm Imitation / Pricing Below Marginal Cost:*

$$H_3: \gamma_{2g} < 0, \ \gamma_{2f} > 0, \ \theta_i < 0.$$

Third, firms differentiate like items from those of their competitors, but tend to cluster their own products around a relatively similar nutritional profile. They then exploit any brand loyalty which arises by pricing goods high in addictive nutrients such that the nutrients have negative shadow values.

■ HYPOTHESIS 4. *No Pricing Below Marginal Cost:*

$$H_4: \theta_i \geq 0.$$

Finally, it may instead be the case that firms simply do not recognize the addictiveness of fast food or, if they do, are constrained by competitive pressures from appropriating any rents from building a stock of addicted consumers.

Estimation Method

Clearly, the system described in (7) must be estimated using a method to account for the endogeneity of rival prices. Anselin (1988) and LeSage (1998) describe the alternatives. Typically, maximum likelihood is used to estimate the general model, but this approach is not feasible with multiple spatial-weight matrices (Kalnins, 2003). Therefore, we use a generalized method of moments (GMM) estimator.[15] By choosing the parameter vector in order to minimize the GMM objective function, this method provides parameter estimates that are consistent even when elements of the matrix of explanatory variables, **Z**, are endogenous or measured with error and will be minimum variance if the error terms are normally distributed.

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[15] Kelejian and Prucha (1998, 1999) describe a two-stage GMM estimator for the more general spatial autoregressive/spatial error model, which Bell and Bockstael (2000) apply to residential sales data. However, as discussed below, we fail to reject the null hypothesis that $\lambda = 0$ when firm- and item-specific weight matrices are used. Thus, we use the single-stage GMM estimator described by Anselin (1988), where the GMM weighting matrix is defined as White's (1980) consistent heteroskedastic matrix with weights calculated from variances derived from a first-stage instrumental-variable regression.

Importantly, selecting appropriate instruments for prices is key. In this regard, we follow Pinkse and Slade (2004) in choosing, first, all exogenous indicator variables and firm-specific nutrient values, under the assumption explained above that nutrients are assumed to be predetermined in our model. Second, we create another set of instruments by multiplying rival firm product attributes by different spatial weight matrices, **G**. This is the method suggested by Kelejian and Prucha (1998, 1999), as it is possible to create a number of suitable instruments by using different definitions of **G**, different powers of each element of the weight matrix, and different elements of the rival attribute set. For example, we define one instrument in terms of a "nearest-neighbor" definition of distance, where the neighborhood is defined in terms of attribute space, instead of the firm and product classifications defined above. Each product's nearest neighbor is defined on a minimum-distance basis where distance is Euclidean in the five macronutrients. Of course, each product has only one nearest neighbor, so the matrix simply consists of one binary indicator for the closest product in attribute space. By multiplying the nearest-neighbor distance matrix by the set of rival attributes, the instrument consists of the attributes of the closest product.

This procedure is identical to the approach suggested by Berry, Levinsohn, and Pakes (1995) in the context of a mixed-logit model of demand. Villas-Boas (2003) also adopts a similar procedure and provides a detailed justification for doing so. In addition to the nearest-neighbor instrument, we create instruments using the inverse Euclidean distance and product-class neighbor matrices defined above. Clearly, rival choice variables meet the requirements for good indicators: they are independent of the regression errors in the own-firm's hedonic pricing equation, but likely to be correlated with the price of the own-firm's fast food item.

Data Description

The data for this study consist of prices and nutrient profiles for a cross-section of items offered by the seven most popular fast food chains in the Phoenix, Arizona, metropolitan area: McDonalds, Burger King, Wendy's, Sonic, A&W, Jack-in-the-Box, and Carl's Jr. The set of products includes all hamburgers, chicken sandwiches, chicken nuggets, french fries, milkshakes, desserts, and other side items. For this analysis, it was necessary to drop observations on fish sandwiches, hot dogs, and other specialty items for which there were no comparable offerings at other chains. All prices were gathered by surveying fast food restaurants in the Phoenix metro area. Although Kalnins (2003) documents considerable price variation both within and among chains throughout the entire state of Texas, we observed little price variation within chains in our study area.[16] Therefore, these prices are representative of the competitive landscape in a fairly typical urban market. All prices are expressed on a per gram basis.

Input prices were obtained from the Bureau of Labor Statistics, Producer Price Index (PPI) file. For each product, a small set of input prices was chosen to form an index of relevant prices. For hamburgers, input prices consist of ground beef, white flour, cheese, lettuce, and tomatoes. For chicken sandwiches, we include a price index for young poultry,

[16] If prices were to differ for the same items at other locations, it is not the level of prices that concerns us, but the variability from restaurant to restaurant and product to product. Although the specific prices may differ depending on the location of the restaurant, the way in which they are set does not. In other words, fast food prices are set to reflect cost and competitive conditions as well as considerations of the strength of demand for each product.

including broilers, fryers, and roasters, in addition to the other burger component prices. Chicken nuggets are a function of whole chicken prices, vegetable oil, and flour. French fry prices are a function of frozen potato and vegetable oil prices, while the cost of producing milkshakes depends on price indices for milk and sugar. Similarly, dessert costs include milk and sugar, in addition to flour and oil.

Because the set of inputs varies by product in our cross-sectional data, we cannot estimate a complete, parametric marginal cost function as in Pinske, Slade, and Brett (2002) or Villas-Boas (2003). Rather, we create simple linear sums across the index components that vary by fast food item. While these indices are only proximate, variation among them will capture differences in prices. By specifying the nature of the game being played in (5), we then are able to recover marginal cost by estimating the first-order condition (Berry, 1994). Because the indices do not vary over chains, they provide a measure of product-specific pricing strategy.[17]

Nutrient profiles for all items were constructed from publicly available data sources, whether company websites or Nutritiondata.com, and expressed as nutrient densities, or grams of nutrient per grams of food. Nutrients include the major macronutrients: fat, protein, and carbohydrates, in addition to a specific type of carbohydrate (sugar) and a trace element, sodium. Sugar and sodium are included because they are widely used taste modifiers and have been shown to produce significant sensory responses in consumers, thereby being more likely to be addictive nutrients. Sodium is expressed in terms of milligrams per gram of food, which is a standard metric in the nutritional literature. Total calories are not included because they would be highly collinear with a linear combination of fat, protein, and carbohydrate content. Although using this relatively large set of nutrients results in a large number of firm-specific shadow-value estimates in the nonlinear model, any smaller set would run the risk of missing a critical attribute valued by consumers. All other attributes that influence consumers' preferences for the fast food item are either embodied in the firm-specific coefficient or are included in the regression error term.

Table 1 provides a summary of prices, estimated marginal costs, and nutrient contents by fast food item category, averaged over the sample chains. As expected, burgers are the highest in terms of fat content, but are also high in protein, while french fries are high in terms of both fat and carbohydrates. Desserts and milkshakes are the most sugar-intensive of the products considered here, but provide the least cost per 100g of all the items considered. In fact, these products are also the only two items priced below marginal cost, which leads us to suspect the shadow value of sugar may be a primary factor in this outcome. Although burgers are high in fat, which should cause them to be priced below marginal cost, they also contain high levels of protein—an attribute not likely to have a negative shadow value. Confirmation of this finding requires a more careful analysis of the estimated results reported in the next section.

Results and Discussion

In this section, we present the results obtained from estimating the distance metric model in fast food prices and nutrient attributes. Prior to discussing the tests of hypotheses 1–4 outlined above, however, it is first necessary to establish the appropriate form

[17] Because we are only interested in marginal costs of producing fast food, labor, capital, and energy are not included in the set of input prices comprising the indices.

Table 1. Summary Statistics for Fast Food Pricing: Mean Values by Item

Item	Price ($/100g)	Marginal Cost ($/100g)	Weight (gms)	Fat (gms/gm)	Carbo-hydrates (gms/gm)	Protein (gms/gm)	Sodium (gms/gm)	Sugar (gms/gm)
Burger	1.000	0.660	267.004	0.149	0.180	0.124	4.819	0.037
Chicken Sandwich	1.298	0.813	249.900	0.099	0.209	0.122	5.099	0.028
Chicken Nuggets	1.718	0.842	184.773	0.135	0.180	0.147	7.376	0.007
Fries	1.076	0.766	145.400	0.139	0.364	0.037	4.147	0.007
Sides	0.985	0.753	214.793	0.111	0.241	0.042	5.490	0.020
Milkshake	0.500	0.712	455.463	0.064	0.221	0.032	0.936	0.203
Dessert	0.592	0.789	338.642	0.059	0.205	0.026	1.057	0.180

Notes: All nutrient values are expressed on a per gram of serving weight basis. Data are averages calculated over all chains in the sample. Marginal costs are estimated based on the parameters in table 3.

Table 2. Spatial Specification Tests: Spatial Autoregression versus Spatial Autocorrelation

Alternative Model			
1. Nonspatial Regression Model		**2. Spatial Autoregressive Model**	
Test	Test Statistic	Model	Test Statistic
Moran Test	0.136	$\mathbf{G}_p$	4.982*
LM Test	0.465	$\mathbf{G}_g$	0.018
Wald Test	1.279	$\mathbf{G}_f$	0.229
LR Test	0.809	$\mathbf{G}_f$, $\mathbf{G}_g$	0.076
		$\mathbf{G}_p$, $\mathbf{G}_f$, $\mathbf{G}_g$	0.014

Notes: A single asterisk (*) denotes rejection of the null hypothesis at the 5% level. In each case, the null hypothesis is H_0: $\lambda = 0$, where λ is the spatial autocorrelation parameter described in the text. In the first set of tests, the alternative model is a simple, nonspatial regression model. In the second set of tests, the alternative model is a spatial autoregressive model with one of five alternative spatial-weight definitions: $\mathbf{G}_p$ consists of elements that are inverse Euclidean distances in attributes across firms and items, $\mathbf{G}_f$ consists of inverse Euclidean distances in attributes across firms, and $\mathbf{G}_g$ consists of distances across items. All tests in column 1 are based on simulated maximum-likelihood estimation, and those in column 2 on generalized method of moments (GMM) estimates. All test statistics are χ^2 distributed with one degree of freedom, except for the Moran test statistic, which is asymptotically normal.

of the econometric model. Given the number of alternative ways of defining the structure of the spatial model, the first set of results presented in this section consists of a series of specification tests—i.e., whether it should be a spatial autoregressive, spatial error model, or one that combines elements of both. With the preferred form of the model, we then proceed to test the primary hypotheses of the paper, namely, whether fast food prices exhibit evidence of differentiation and nutrient-specific addictiveness. Based on these results, we offer some important implications for industry conduct and possible policy designs to counter fast-food-related obesity issues.

Table 2 reports the results obtained from testing the null hypothesis (H_0: $\lambda = 0$) using the battery of tests described in LeSage (1998) and the alternative weight specifications discussed above. The test statistics in the first column compare a nonspatial model under the null hypothesis to a spatial error model, or SEM. None of these tests suggest rejection of the null hypothesis. The test statistics in the second column refer to the same null, but the alternative consists of various forms of the spatial autoregressive (SAR) model. These results are interesting because they suggest that simple application of a single spatial weight matrix can lead to incorrect conclusions regarding the appropriate structure of the model. Specifically, when only a single, attribute-based weight matrix is used ($\mathbf{G}_p$), the LM-SAR test suggests that a general spatial autocorrelation (SAC model in LeSage's terminology) is required. However, when firm and item contiguity is included, λ is no longer significant and the appropriate model is a relatively simple SAR specification.

Quasi-likelihood ratio (QLR) tests are used to select among the SAR variants (Gallant and Jorgenson, 1979). A QLR test compares the value of the GMM objective function from an unrestricted model to a restricted alternative. The difference is χ^2 distributed with degrees of freedom equal to the number of restrictions. According to the results in table 2, the QLR test suggests the preferred model is the all-inclusive spatial model, or the one that includes attribute weights, firm-specific weights, and item-specific weights. Finding that the most comprehensive definition of distance dominates the others is consistent with the results reported by Pinkse, Slade, and Brett (2002), and Kalnins (2003), who also use multiple spatial weight specifications to describe distance and contiguity with rival firms. Anticipating the results presented in table 3, this model also provides a high percentage of significant coefficients, plausible parameter estimates, and a broad agreement with the other model results reported in this table. Hence, we use the most comprehensive spatial model to test hypotheses regarding brand loyalty and nutrient-specific pricing.

To evaluate the robustness of the hedonic price estimates across model specification, table 3 includes the GMM parameter estimates from each of the alternative SAR models. In these results, brand loyalty has two dimensions. First, table 3 includes estimates of firm-specific price premia—the coefficients on the firm-binary variables. As discussed above, to control for product-specific pricing and pricing above marginal cost, we include an index of input prices for each product. Firm-level indicator variables allow for variations in product prices due to advertising, reputation, in-store marketing, and other unobservable, firm-specific effects likely to be correlated with price.

Assuming firms are competitive in all nonprice marketing strategies, the most important determinant of firm-specific price premiums is likely to be brand loyalty. Although not all of the firm-specific coefficients in table 3 are significantly different from zero in the preferred model specification, the premia are relatively robust across models and they are jointly different from zero. We therefore interpret this finding as evidence that each firm does indeed have some brand loyalty. The degree of brand loyalty, however, varies widely among sample firms. For example, in table 3, A&W represents the excluded firm-specific indicator variable, so each of the other firms (except firm 6) receives a lower margin than A&W on each equivalent product. Interestingly, A&W represents an example of a firm with a uniquely loyal following, arguably attracted by a signature item (root beer and root beer floats) not offered by any other firm. On the other hand, with respect to hamburgers, McDonalds earns a margin that is \$0.082 less than A&W.[18] Nonetheless, each margin is still positive.

[18] It is also important to note that, as a subsidiary of Yum! Brands, Inc., A&W plays a critical role as the flagship brand of a major fast food market participant in the most important submarket—hamburgers. Consequently, it is backed by more financial, marketing, and operational capital than other chains of similar size would be.

Table 3. Fast Food Spatial Characteristics Model Estimates: GMM

Variable	Nonspatial Est./(t-Ratio)	$\mathbf{G}_p$ only Est./(t-Ratio)	$\mathbf{G}_g$ and $\mathbf{G}_f$ Est./(t-Ratio)	$\mathbf{G}_g$ only Est./(t-Ratio)	$\mathbf{G}_p$, $\mathbf{G}_f$, and $\mathbf{G}_g$ Est./(t-Ratio)
$\mathbf{G}_p$	NA	0.576*	NA	NA	0.782
		(7.413)			(1.902)
$\mathbf{G}_f$	NA	NA	0.665*	NA	0.696*
			(3.112)		(2.926)
$\mathbf{G}_g$	NA	NA	-0.221	0.459*	-0.836
			(-0.764)	(6.434)	(-1.873)
Firm 1	-0.092	-0.091	-0.083	-0.097	-0.082
	(-1.223)	(-1.194)	(-1.089)	(-1.282)	(-1.070)
Firm 2	-0.177*	-0.154*	-0.176*	-0.158*	-0.190*
	(-3.222)	(-2.713)	(-3.137)	(-2.863)	(-3.275)
Firm 3	-0.128*	-0.121*	-0.116*	-0.130*	-0.102
	(-2.153)	(-2.132)	(-2.061)	(-2.306)	(-1.809)
Firm 4	-0.077	-0.066	-0.064	-0.086	-0.031
	(-1.210)	(-1.077)	(-1.032)	(-1.415)	(-0.546)
Firm 5	-0.147*	-0.122	-0.102	-0.122	-0.087
	(-2.148)	(-1.875)	(-1.548)	(-1.881)	(-1.298)
Firm 6	0.019	0.043	0.052	0.024	0.081
	(0.346)	(0.846)	(1.014)	(0.478)	(1.548)
MC 1	-0.129*	-0.112*	-0.132*	-0.117*	-0.125*
	(-3.643)	(-3.624)	(-4.249)	(-3.841)	(-4.001)
MC 2	0.024	0.043	0.007	0.048	-0.008
	(0.414)	(0.857)	(0.143)	(0.960)	(-1.298)
MC 3	0.053	0.058	0.037	0.059	0.035
	(0.937)	(1.206)	(0.730)	(1.229)	(0.701)
MC 4	-0.023	-0.058	-0.078	-0.037	-0.106*
	(-0.052)	(-1.481)	(-1.955)	(-1.732)	(-2.549)
MC 5	-0.036	-0.053	-0.088*	-0.034	-0.116*
	(-0.698)	(-1.233)	(-1.973)	(-1.871)	(-2.577)
MC 6	-0.077*	-0.061*	-0.059*	-0.045	-0.078*
	(-3.072)	(-2.665)	(-2.508)	(-1.924)	(-3.196)
Fat	0.118	0.016	-0.045	0.062	-0.205
	(0.775)	(0.111)	(-0.293)	(0.429)	(-1.223)
Carbo	0.667*	0.546*	0.501*	0.453*	0.633*
	(3.622)	(3.097)	(2.720)	(2.511)	(3.476)
Protein	0.310*	0.021	0.160	0.108	0.085
	(2.331)	(0.149)	(1.136)	(0.790)	(0.562)
Sodium	0.381*	0.301*	0.454*	0.288*	0.471*
	(4.375)	(3.704)	(4.394)	(3.726)	(3.981)
Sugar	-0.035	-0.206*	-0.309*	-0.157	-0.376*
	(-0.317)	(-1.994)	(-3.025)	(-1.532)	(-3.497)
Fat^2	0.135	0.167*	0.182*	0.168*	0.208*
	(1.825)	(2.262)	(2.520)	(2.328)	(2.724)
Carbo^2	-0.233*	-0.200*	-0.143*	-0.159*	-0.189*
	(-3.157)	(-2.929)	(-1.956)	(-2.234)	(-2.660)

(continued . . .)

Table 3. Continued

Variable	Nonspatial Est./(*t*-Ratio)	G_p only Est./(*t*-Ratio)	G_g and G_f Est./(*t*-Ratio)	G_g only Est./(*t*-Ratio)	G_p, G_f, and G_g Est./(*t*-Ratio)
Protein^2	-0.004	0.110	0.059	0.076	0.083
	(-0.644)	(1.735)	(0.937)	(1.245)	(1.201)
Sodium^2	-0.127*	-0.152*	-0.140*	-0.124*	-0.170*
	(-3.149)	(-3.863)	(-3.795)	(-3.413)	(-3.492)
Sugar^2	-0.003	0.117*	0.128*	0.090	0.158*
	(-0.653)	(2.032)	(2.281)	(1.581)	(2.707)
GMM	119.231	100.147	97.646	104.576	91.264
QLR		19.084	21.585	14.655	27.967

Notes: A single asterisk (*) denotes statistical significance at the 5% level. *Firm 1* = McDonalds, *Firm 2* = Wendy's, *Firm 3* = Burger King, *Firm 4* = Carl's Jr., *Firm 5* = Jack-in-the-Box, and *Firm 6* = Sonic. *MC* refers to the marginal cost of producing item 1 = hamburger, item 2 = chicken sandwich, item 3 = chicken nuggets, item 4 = french fries, item 5 = side dish, and item 6 = milkshake (item 7 = dessert, and is defined as the base case). The QLR statistic is a quasi-likelihood-ratio statistic defined as $QLR = (GMM_R - GMM_U)$, where GMM_R is the restricted value of the GMM criterion function (*GMM*) and GMM_U is the unrestricted value. The resulting test statistic is χ^2 distributed with degrees of freedom equal to the number of implied restrictions. In this table, all models are general cases of the nonspatial model. The critical χ^2 value with one restriction at the 5% level of significance is 3.841, with two restrictions is 5.991, and with three restrictions is 7.815.

Second, the firm-specific spatial autoregressive parameters indicate whether firms differentiate their foods from one another ($\gamma_{2g} < 0$), thereby earning brand loyalty through differentiation, or if they tend to mimic one another ($\gamma_{2g} > 0$) in an attempt to earn market share by moving to the middle ground. When $\mathbf{G}_g$ enters the model on its own, the results in table 3 suggest firms tend to choose similar nutritional profiles for like items. However, the fit of this model is significantly worse than the preferred model which includes $\mathbf{G}_p$ and $\mathbf{G}_f$. Indeed, comparing the autoregressive parameters from the preferred model to the other, partial models indicates that firms tend to cluster their own menus and tend to follow other firms in a general way, but differentiate individual items. Although not significant in a two-tailed test at a 5% level, γ_{2g} is significant in a one-tailed test, so we are led to conclude that firms do indeed differentiate their menus by altering nutritional profiles for specific items. Consequently, of the two effects measured by the distance metric model—market share or market power—the latter appears to dominate the former. Thus, it appears we can rule out hypothesis 2.

Whether firms price below marginal cost, however, depends upon the nutrient shadow values. These values, which are point estimates calculated over the entire sample, appear in table 4. Of the potentially addictive nutrients, the estimates for the preferred model (row 5 in the table) suggest that both fat and sugar indeed have negative implicit prices. Although this result is robust among the alternative spatial models in the case of sugar, the estimated shadow value is positive for fat in three of the five models. Among the other nutrients, carbohydrates and proteins have positive implicit prices—both in an economic and a statistical sense. Sodium, on the other hand, has a negative implicit price over all five models, but never in a statistically significant way. Consequently, combining the results from tables 3 and 4, our findings suggest that fast food companies recognize both the value in differentiating products and in exploiting the potential addictiveness of the nutrients in fast food in order to build a cohort of loyal, addicted customers.

Table 4. Nutrient Shadow Value Estimates for Alternative Spatial Models

Model	θ_{Fat}	θ_{Carb}	$\theta_{Protein}$	θ_{Sodium}	θ_{Sugar}
1. Nonspatial	0.144*	0.563*	0.309*	-0.451	-0.035*
	(0.014)	(0.042)	(0.004)	(0.646)	(0.006)
2. $\mathbf{G}_p$	0.049*	0.456*	0.035*	-0.697	-0.182*
	(0.017)	(0.036)	(0.011)	(0.775)	(0.021)
3. $\mathbf{G}_g$	0.096*	0.382*	0.118*	-0.527	-0.139*
	(0.017)	(0.029)	(0.007)	(0.633)	(0.017)
4. $\mathbf{G}_f$, $\mathbf{G}_g$	-0.083*	0.437*	0.167*	-0.465	-0.283*
	(0.019)	(0.026)	(0.006)	(0.714)	(0.023)
5. $\mathbf{G}_p$, $\mathbf{G}_f$, $\mathbf{G}_g$	-0.163*	0.549*	0.096*	-0.646	-0.345*
	(0.022)	(0.034)	(0.008)	(0.867)	(0.029)

Notes: A single asterisk (*) denotes statistical significance at the 5% level. All shadow values (θ_i) are generated from the GMM estimation procedure. Values in parentheses are standard errors, calculated using a Wald test statistic evaluated at the sample mean.

A formal test of hypotheses 1–4 consists of a joint Wald chi-squared test of the restrictions implied by each. To test these hypotheses, however, it is first necessary to rephrase each in terms of a testable null. Thus, the first hypothesis becomes H_0: $\gamma_{2g} \geq 0$, $\theta_i \geq 0$, and rejection of this null with a one-tailed test implies firms do not cluster products around common nutritional profiles, nor do addictive nutrients have positive shadow prices. Each of the other hypotheses are constructed similarly. Because the nutritional research cited in the introduction indicates that fat and sugar are the most likely nutrients to produce addictive responses in consumers, the joint tests consist of the item-specific autoregressive parameter, as well as the shadow value for both fat and sugar. For hypothesis 1, the χ^2 value is 14.106, while the critical χ^2 value at a 5% level of significance and three restrictions is 9.35 (for a one-tailed test). Consequently, we can reject the first null. Rejecting a null hypothesis, however, provides only indirect support for the alternative, so we can only tentatively conclude that firms in this sample differentiate their menus from their competitors using nutrient profiles. If firms differentiate their products in nutrient space, then doing so generates a measure of market power, thus exploiting the addictiveness of fat and sugar by pricing each below their implied marginal cost.

Due to the arguments outlined above regarding the statistical significance of the shadow values for fat and sugar, H_2 and H_4 are ruled out immediately because they are dominated by H_1 and H_3. For H_3, the null hypothesis is H_0: $\gamma_{2g} \geq 0$, $\gamma_{2f} \geq 0$, $\theta_i \geq 0$, which is again evaluated using a one-tailed test. In this case, the critical value with four restrictions is 11.143, while the calculated value is 19.157. Rejection of this null again provides indirect support for the assertion that firms not only differentiate specific items from their competitors, but offer menus which are relatively homogeneous. Catering to their target market in this way, fast food companies build a further dimension of brand loyalty and add to their ability to price addictive products without fear of losing their customers to other fast food firms. Note, however, that the sample used here describes only one segment of the fast food market (hamburger vendors), while a wider sample of quick service firms including sandwich chains (Subway, Quiznos), Mexican food (Taco Bell, Del Taco), or Chinese (Panda Express) would be necessary to generate stronger support for this result.

Importantly, the shadow value functions for fat and sugar are convex. In other words, the implied shadow values rise for higher densities of each nutrient. While the results described to this point explain 99¢ hamburgers and inexpensive, jumbo-size soft drinks, convexity also explains why some of the recently introduced items such as the "Monster Thick Burger" or premium cookies sell for high prices despite the fact that they are loaded with fat and sugar. Specifically, the more fat or sugar a product has, the "less negative" is the shadow value of those nutritional components. Convex shadow value functions for some nutrients are, in turn, explained by the knife's-edge solution to the dynamic pricing game under addiction. In particular, recall the learning mechanism described by Villas-Boas (2006). If the marginal forward-looking consumer understands that by purchasing a fast food item this period she will face higher prices next period, she is likely to become less price sensitive in the current period. As a result, equilibrium prices rise in the current period with the degree of learning, or addiction in this case. On the other hand, if firms believe that the market-building effect of pricing fat- and sugar-laden products below marginal cost is more important than capitalizing on current profit opportunities, then high-fat and high-sugar foods will be priced below cost in order to build up the cohort of addicted consumers. Therefore, products with moderate levels of fat and sugar are likely to be priced below marginal cost, while products which are very high in either will command premium prices.

This result has significant implications for anti-obesity policy. Indeed, proposals for nutrient-specific policies have circulated within political circles for some time now. "Fat taxes" or "protein subsidies" are two examples of the wide range of price-based policies used by policy makers to induce individuals to change their behavior, and firms to change their pricing practices. If fast food companies price below marginal cost with the intention of creating a new set of addicts, then such a tax would be effective in countering this particular strategy.[19]

What does a convex nutrient-value function mean for anti-obesity policy? Consider another side of the learning dynamic cited above. According to the logic of Becker and Murphy (1988), pricing items with moderate sugar content below marginal cost and high-sugar items above marginal cost could be due to a "tolerance effect" wherein fat-addicted consumers require more and more to achieve the same level of utility as they previously enjoyed with relatively low-fat foods. Firms increase the price of high-fat items as consumers' addiction becomes more severe, and prevalent in aggregate.[20] Consequently, and somewhat counterintuitively, the optimal nutrient tax should be highly nonlinear—zero at low nutrient density levels, higher for moderate levels of fat or sugar, but then lower still as firms raise prices to exploit current-period addiction rents. By raising the price of moderately high fat- and sugar-content items, consumers will be induced to pay the full cost or choose a healthier option.

The implications for product design are also clear and suggestive of future work in this area. Implicitly, fast food companies understand what products attract customers due to their inherent taste or addictive qualities—high-sugar items such as milkshakes and dessert treats—and price them accordingly. Future research, should price and consumption data become available, could endogenize food nutrient content in a structural

[19] As a reviewer suggests, it is important to note the fundamentally regressive nature of a fat tax. Therefore, although it may be effective in reducing fat consumption, a fat tax is likely to fall on lower income groups in an inequitable way.

[20] Note that this finding is also consistent with casual industry observation—most "value deal" meals consist primarily of a hamburger, one side, an order of fries, and a drink, but it is the hamburger that is the loss leader among this group.

framework similar to Cropper et al. (1993) or Ekeland, Heckman, and Nesheim (2004). In this way, researchers could not only address the problem of nutrient endogeneity in a more complete way, but also provide better answers to questions surrounding the strategic nature of fast food product design. Given this type of data, important questions regarding the role of advertising and marketing strategies could be addressed as well.

Conclusions and Implications

This study investigates pricing behavior by fast food companies on a product and nutrient level. Prior theoretical work on optimal pricing by firms with market power when demand is linked intertemporally, either through brand loyalty or nutrient addiction, shows firms may have an incentive to price below marginal cost in order to build a group of addicted consumers. If addiction is not firm-specific, however, this incentive disappears as the habitual consumption of nutrients becomes more akin to a common property resource than a source of monopoly rents. In contrast, if consumers are forward-looking, their demand in the current period may become more inelastic if they suspect their addiction will lead to higher prices in the future. Thus, prices for products containing addictive nutrients may instead be higher than would otherwise be the case.

We test for which of these two effects dominates using an equilibrium distance metric model for fast food in the Phoenix market. Unlike traditional hedonic pricing models, the distance metric approach allows for imperfectly competitive pricing where market power derives from nutrient-based product differentiation strategies. In order to test which pricing strategy best describes fast food seller conduct, we estimate the distance metric model using spatial econometric methods where products lie at different points in a multi-dimensional attribute (nutrient) space. Estimating firm- and item-specific autoregression parameters reveals whether firms tend to differentiate their products from one another, or offer relatively homogeneous items. The spatial attribute model is estimated using a generalized method of moments procedure that accounts for the likely endogeneity of rival prices.

Based on our estimation results, fast food companies tend to differentiate their products from rival offerings on an item-by-item basis. In other words, the price for a particular item will rise the farther it is from the others in attribute space. Additionally, and more importantly, we find that the average steady-state shadow prices for fat and sugar are significantly below zero. We interpret this result as consistent with a strategy of pricing items high in potentially addictive nutrients below marginal cost, thereby building a community of consumers who are not just loyal to a particular firm's offerings, but addicted to them. Although firms price fat- and sugar-filled products below marginal cost, they tend to price high carbohydrate- and protein-content foods significantly above, suggesting these items may bear the burden of differentiating the restaurant from others. Moreover, the shadow values for fat and sugar are highly convex, so prices for the most fat- and sugar-dense foods are likely to be relatively high due to the inherent attractiveness of these nutrients.

Future research will investigate the deeper implications of these results for product design by formally endogenizing nutrient content in a structural model of price and nutrient rivalry. It is expected that competition in nutrients will provide important insight into how nonprice marketing strategies impact price outcomes in the fast food market. These results will also help policy makers design programs to combat an important cause of the obesity epidemic. In particular, our results suggest a somewhat counterintuitive fat-tax policy—raising taxes for moderately fat- or sugar-intensive foods in order to reduce the incentive for firms to exploit the potential addictiveness of their products.

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