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The Demand for Food Away from Home: Do Other Preferences Compete with Our Desire to Eat Healthfully?

Hayden Stewart, Noel Blisard, Dean Jolliffe, and Sanjib Bhuyan

Health-oriented government agencies have had limited success at encouraging Americans to eat a healthful diet. One reason may be that other preferences compete with our desire to eat healthfully. We explore the effect of consumer preferences on the demand for food away from home, including frequency of eating out and choice of outlet type. Preferences for convenience and ambience are found to influence behavior. Furthermore, omitting these variables from econometric models can bias the estimated effect of preferences for a healthful diet.

Key words: convenience, food away from home, nutrition, omitted-variable bias, preferences, social marketing

Introduction

U.S. government agencies are encouraging Americans to eat a balanced, nutritious, and healthful diet, but most Americans do not fully act on this advice. In fact, an estimated 64% of the U.S. population is overweight or obese (Flegal et al., 2002), and only a small fraction of the American population eats the recommended daily quantity of fruits and vegetables (Produce for Better Health Foundation, 2002). One possible explanation for poor dietary habits may be that other preferences, such as the desire for convenience, compete with our desire to eat healthfully. For example, when dining away from home, consumers may be acting on their desire for a convenient meal, if purchasing fast food, or for entertainment and relaxation, if dining at a full-service restaurant.

Preferences for a healthful diet, convenience, and entertainment may be positively or negatively related, or they may be uncorrelated. It may be that people who tend to place a high value on nutrition also tend to place a high value on leisurely sit-down meals. This type of consumer might adjust the number of leisurely meals consumed in a given time period, if leisurely meals appear to conflict with a nutritious and healthful diet. However, it is also possible that another preference, say the desire for convenience,

Hayden Stewart, Noel Blisard, and Dean Jolliffe are economists with the Economic Research Service, U.S. Department of Agriculture, Washington, DC. Sanjib Bhuyan is an associate professor in the Department of Agricultural, Food, and Resource Economics, Rutgers University, New Brunswick, NJ.

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might override the desire for a healthful diet. If these types of preferences are correlated, then models accounting for only a single preference, such as proper nutrition, might suffer from omitted-variable bias. In this study, we explore how competing preferences influence the demand for food away from home, and how omitting a preference may result in biased and misleading estimates.

Analyses of the demand for food away from home often employ the theory of household production to motivate models with a consumer's income and demographic characteristics as independent variables (e.g., McCracken and Brandt, 1987; Nayga and Capps, 1994; Byrne, Capps, and Saha, 1998; Stewart and Yen, 2004). Under this theory, the household is viewed as a production unit that gathers various inputs to produce a final product. For instance, a household could acquire and prepare ingredients from a retail store to produce a complete meal, or obtain a complete meal from a foodservice facility. The household could further select among meals served from different types of restaurants or food outlets. Demographic variables like race, age, and education enter the demand model as exogenous variables, representing proxies of a household's ability to convert raw ingredients into complete meals at home, or the utility derived from foods obtained from different food-away-from-home channels.

However, Senauer (2001) argues that "traditional demographic factors may be of limited importance in explaining differences in consumer preferences and behavior" (p. 12). To better model demand, Senauer contends it is necessary to account for the role of information, attitudes, perceptions, and the other complex psychological factors that shape preferences. As to information, researchers have augmented demand models with measures of a consumer's knowledge of health and nutrition. Applications to the demand for away-from-home foods include Blisard, Variyam, and Cromartie (2003). In the current study, we include measures or proxies of consumer preferences. Specifically, we include the importance placed on a healthful diet and potentially competing preferences, in order to explain the decision to consume food away from home as well as the choices to eat fast food and patronize full-service restaurants.

In estimating such demand models, it might appear natural to estimate the impact of a single preference, such as the desire to eat healthfully, and ignore the impact of desires for entertainment and convenience. However, it is well known that omitting a variable, or in this case a proxy for a preference, can bias the estimated coefficients on included variables, if the omitted and included variables are correlated (e.g., Greene, 1997). Certainly, there could be correlations among the various facets of people's lifestyles and attitudes. As noted above, people who tend to enjoy leisurely sit-down meals may also tend to have concerns related to nutrition and health.

The objectives of this study are two-fold. We investigate the potential for omitted-variable bias in demand models with measures of consumer preferences, and simultaneously seek to determine whether other preferences compete with the desire to be healthy. To achieve these goals, this analysis employs data from a survey of consumers, and expands upon existing demand models for away-from-home foods. Assuming consumers are rational, we begin by invoking the spirit of Akerlof (1970) and Grossman (1981) to motivate how a consumer's preferences for a healthful diet might affect his or her demand for away-from-home foods. The data collected for the study are then examined, and empirical models incorporating consumer preferences are proposed.

Estimation of the models proceeds in two phases. In the first phase, we fit our demand models with measures of a consumer's preferences for a healthful diet and nutrition.

Then, in the second phase, the models are further complemented with variables capturing other preferences, such as the desire for convenience. This two-phase approach allows us to determine whether other preferences compete with the desire to eat healthfully, and whether unbiased estimates are likely to result when other key variables are omitted from analyses.

How Preferences for Health Could Affect Demand

To motivate how preferences for a healthful diet might affect the demand for restaurant foods, we turn to the models of asymmetric information pioneered by Akerlof (1970) and Grossman (1981). It is assumed restaurants are informed about the healthfulness of their menu items. However, unlike manufacturers of packaged foods,[1] restaurants are not required to reveal this information,[2] although they may voluntarily do so. In Grossman's (1981) model, if consumers prefer menu items with positive health attributes, restaurants providing such foods will be encouraged to impart this information. Restaurants compete for customers by advertising the positive characteristics of their goods. Those not providing information are therefore assumed to provide less healthful foods.

In Akerlof's (1970) model, when only incomplete information is available about product attributes,[3] consumers unable to distinguish among goods with desirable and undesirable attributes will reduce their participation in a market or withdraw.[4] These consumers know when a market contains many sellers offering products with undesirable attributes. However, they still may lack the specific knowledge necessary to evaluate the products sold by a particular vendor. In this study, consumers are assumed to share a very general understanding that meals and snacks consumed away from home are typically less healthful than foods prepared at home (Lin, Frazao, and Guthrie, 1999). Thus, controlling for any specific knowledge about nutrition which might help consumers to evaluate the healthfulness of foods offered by particular restaurants, we hypothesize that consumers with a greater desire for a healthful diet will adjust their behavior by:

- Abstaining from dining out on a frequent basis (for example, they might restrict dining out to special occasions so as to maintain health);
- Limiting the types of restaurants patronized (for example, they may patronize only establishments providing enjoyable foods that they also perceive to be healthful); and
- Purchasing menu items clearly marked at restaurants as healthful.

[1] The Nutrition Labeling and Education Act of 1990 established mandatory labeling for packaged foods. Its cornerstone is the Nutrition Facts Panel, which can be seen on packaged foods, and includes information such as the food's caloric content.

[2] Restaurants are only required to provide nutritional information when making a nutrient content or health claim (see U.S. Food and Drug Administration, 2004).

[3] Although many restaurants do provide information about the nutritional qualities of their foods, Variyam (2005) offers arguments why information might still be imperfect in the market for away-from-home foods.

[4] In an example of the automobile market, Akerlof (1970) assumes individuals to understand when a market includes low-quality cars (i.e., "lemons"). Individuals with the specific knowledge necessary to distinguish between high-quality and low-quality cars (e.g., automobile mechanics) might not only remain in the market, but profit as entrepreneurs.

The last hypothesis has been addressed by the current literature. For example, Patterson et al. (2002) present results from an experimental analysis in which menus at restaurants were adjusted to clearly identify items low in fat and containing more than one serving of fruit and/or vegetables. Simultaneously, restaurant waitstaff recommended these items, while printed fliers and other media devices emphasized the importance of healthy eating. Prior to the experiment, the healthy menu items accounted for 1.89% of all entrees sold at the restaurants. This share increased to 2.68% during the course of the experiment, and yet Patterson et al. conclude that the campaign was unlikely to have had a long-term impact. Efforts to promote healthy eating in one month did not affect behavior in subsequent months.

This study focuses on the first two hypotheses. Furthermore, we adopt a two-phase approach to our demand analysis. In the first phase, the hypotheses are tested by including in the empirical model variables capturing a consumer's preferences just for a healthful diet. In the second phase, these same models are augmented with variables capturing other consumer preferences. If the latter variables are significant in the second phase, then they either compete with or complement health considerations to determine consumer behavior, assuming the health variables were significant in the first phase. This two-phase approach also allows us to evaluate whether the specification from the first phase suffers from omitted-variable bias. Taken together, we can determine whether researchers need to take into account competing preferences when attempting to quantify the impact of health concerns on consumer behavior.

Measuring Consumer Characteristics and Behavior

Data for this study were collected through a mail survey of consumers. The survey was pre-tested and administered at Rutgers University in Spring 2002, and data collection was completed by June 2002. The sample was drawn from a listing of households supplied by InfoUSA, a private mailing list firm. Surveys were mailed to a random sample of 2,400 households in New Jersey, the target population. Data collection activities included initial and follow-up mailings of questionnaires, with further follow-up to nonrespondents. The total number of responses received was 989, about 41%. Of these surveys, 700 provided complete information on most variables of interest and were usable for this analysis, resulting in an overall response rate of 29%.

A few limitations of the data should be noted. Since the sample consists of residents of only one state (New Jersey), it follows that the empirical results may not necessarily apply to residents of the United States in general. Another limitation of the data stems from inequities in the response rate. In particular, the probability of response was lower among minorities, and increased with a household's income.[5] To address the potential for nonresponse bias, we construct post-stratification weights based on the survey respondent's race/ethnicity and income to match the demographic composition of New Jersey, as identified in the *2000 Census of the Population.* In this adjustment technique, weights are created by comparing estimated sample means to population characteristics (e.g., Levy and Lemeshow, 1999). Table 1 reports characteristics of respondents and their households (weighted and unweighted).

[5] With household survey data, this is a common type of nonresponse bias (e.g., Deaton, 1997).

Table 1. Respondent Characteristics, Weighted and Unweighted Means (N = 700)

	Mean	
Household Characteristic	Unweighted	Weighted
Annual income ($000s per household member)	40.180 (0.993)	29.432 (1.503)
Age of respondent (years)	48.544 (0.468)	51.407 (0.997)
Proportion of respondents with a college education or higher	0.606 (0.018)	0.457 (0.033)
Proportion who are female	0.477 (0.019)	0.560 (0.033)
Proportion employed for wages	0.687 (0.018)	0.623 (0.032)
Proportion of respondents who are Hispanic, any race	0.033 (0.007)	0.105 (0.038)
Proportion of respondents who are Black, non-Hispanic	0.053 (0.008)	0.079 (0.027)
Proportion of respondents who are Asian	0.037 (0.007)	0.043 (0.010)

Note: Values in parentheses are standard errors.

Frequency of Eating Out

Our first hypothesis concerns whether a consumer abstains from eating out frequently due to preferences for health. To allow for such a test, survey recipients were asked how often they "usually" eat out.[6] Respondents could choose among six possible answers: "almost every day" (71 respondents), "every 2–3 days" (178), "once a week" (267), "once every two weeks" (94), "once a month" (86), and "never" (4).

To collect information for explaining a consumer's frequency of eating out, the survey included five-point semantic differential scales (e.g., Osgood, Suci, and Tanenbaum, 1957). Survey recipients were asked to rank, from 1 to 5, the level of importance they place on various attributes of food. Endpoints were coded as 1 for "not at all important" and 5 for "very important." Notably, this question was not directed at away-from-home foods alone. It also applied to foods prepared in the consumer's own kitchen. On average, respondents placed the most importance on taste, with a mean score of 4.52. Nutrition came in second, with a mean importance of 3.85. Ease of preparation (convenience) was close behind, with an average response of 3.49. Ease of digestion and low prices received scores of 3.40 and 3.39, respectively, on average.

The responses to these scaled questions suggest the data are affected by what is sometimes called the "halo effect" (e.g., Nisbett and DeCamp Wilson, 1977). As an illustration, some respondents tended to assign a 4 or 5 to the importance of each attribute, while others tended to assign a score of 3 or 4. According to the halo effect, the mean of

[6] The survey used the words "usually" and "regularly" to capture general behaviors. Thus, if an individual indicated never eating out, we do not interpret that response to suggest the individual has never consumed a meal or snack at a foodservice facility. Rather, that person is understood to eat out only rarely. More detailed aspects of behavior are difficult to capture outside of diary surveys, such as the Continuing Survey of Food Intake by Individuals, administered by the U.S. Department of Agriculture.

an individual's responses on this set of semantic differential scales reflects the importance he or she places on food relative to, say, clothing or entertainment. Because these respondents inflate or deflate the level of importance they place on individual attributes of food, according to the level of importance they place on food in general, there is a positive correlation among the individual responses. For example, the correlation between nutrition and convenience is 0.18, which is statistically different than zero at the 5% level.

To remove correlation due to the halo effect, and to measure the relative importance placed by a consumer on say, nutrition versus convenience, survey responses were standardized by calculating z-scores.[7] Among z-scores for level of importance placed on nutrition, taste, convenience, price, and ease of digestion, many share a negative correlation. For example, the z-score between nutrition and convenience is -0.42, which is again statistically different than zero at the 5% level.

Outlet Choice

Our second hypothesis concerns whether a consumer restricts his or her choice of outlet type in search of healthful meals. Thus, in the survey, consumers were asked whether they tend to "regularly" patronize each of several establishment types.[8] Respondents could (and often did) respond to more than one option. Types of establishments included restaurants offering fast food[9] (415 respondents) and fine dining (443 respondents).

Survey participants were further asked to clarify their reasons for regularly dining at the types of establishments identified. More than one reason could be selected from a list of possibilities provided in the survey. This list included the enjoyment derived from the dining experience[10] (468 respondents), the convenience of the location (433), and the healthfulness of the food (128).

The respondents' reasons for regularly soliciting a type of restaurant are correlated. For example, the correlation between soliciting a restaurant for the healthfulness of its food and the enjoyment derived from the dining experience is 0.21. By contrast, the correlation between selecting a place for the healthfulness of its food and the convenience of its location is -0.08. Both correlation coefficients differ from zero at the 5% level.

Nutritional Knowledge

The existing literature reveals that dietary knowledge is an important determinant of consumer behavior, and we attempt to control for this when testing both hypotheses (e.g., Gould and Lin, 1994; Variyam, Blaylock, and Smallwood, 1996; Kim, Nayga, and Capps, 2001; Blisard, Variyam, and Cromartie, 2003). Blisard, Variyam, and Cromartie

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[7] The standardized variables are centered on each respondent's average score over the various food attributes. Specifically, we first calculated each individual's average response to all five semantic differential scales. The respondent's evaluations of individual attributes, such as nutrition, were then measured against their average response in number of standard deviations.

[8] Refer to footnote 6.

[9] Fast food includes Mexican food, sandwiches, burgers, and chicken-type facilities.

[10] This variable was defined by the authors to include respondents who identified the taste of the food, the quality of the service, the atmosphere, or any combination of these three.

(2003), for example, report that consumers with less knowledge of diet and health issues consume away-from-home foods less often. As noted earlier, consumers least able to ascertain the quality of a good are the ones most apt to withdraw from the market.

To control for nutritional knowledge, the survey listed several chronic diseases that can be caused by poor eating habits. It then asked respondents whether they believe each of these ailments can be caused by diet. The responses were diabetes (60%), heart disease (72%), high blood pressure (63%), and liver disease (31%). The authors interpret a respondent's ability to answer these questions correctly as a proxy for that person's nutritional knowledge, similar to the approach of Kim, Nayga, and Capps (2001), and Blisard, Variyam, and Cromartie (2003).

Income, Demographics, and Lifestyle

Previous research on the demand for food away from home suggests the need to control for consumer income and demographics (e.g., Byrne, Capps, and Saha, 1998; Stewart and Yen, 2004). Thus, the survey included questions designed to measure the income of the respondent's household, the age of the respondent, the gender of the respondent, whether the respondent had completed college, whether the respondent worked for wages, and the race/ethnicity of the respondent.[11]

Although such data were not available to past researchers to the best of the authors' knowledge, we sought to control for certain aspects of a consumer's lifestyle. First, an important factor which may influence a person's demand for food away from home is whether that individual exercises. Of the 700 surveys comprising the sample for this analysis, 365 respondents reported exercising "more than once a week," 110 claimed to work out "once a week," 57 stated they do so "once a month," 153 reported they exercise "less than once a month," and 14 indicated they did not exercise at all. Also potentially important is whether a consumer tended to dine primarily with business associates or family and friends. Only 60 of the 700 respondents primarily dined with business associates.

The Empirical Model

In the first phase of our analysis, the set of independent variables includes income, demographic characteristics, and nutrition knowledge, as well as measures of the importance placed on a healthful diet and nutrition. In the second phase, this list of variables is further augmented to include the importance placed on other attributes of foods, such as convenience. Detailed below are the empirical specifications of the models used in the first phase.

Frequency of Eating Out

To test our hypothesis about whether a person's concern for a healthful diet drives him or her to abstain from eating out frequently, the binary response variable *FREQUENT* was created. This variable equals 1 for the 249 survey recipients who reported eating

[11] Because we sampled only residents of one state at a single point in time, all respondents are assumed to have faced the same prices. This same approach is taken by other analyses of the demand for away-from-home foods cited in this study.

out either almost every day or every 2–3 days; for the remaining 451 recipients, *FREQUENT* equals 0. We are primarily interested in whether *FREQUENT* depends on the level of importance placed by a consumer on nutrition. To capture the potential competition among a consumer's many preferences, we utilized the z-scores corresponding to a respondent's answers on the importance he or she places on various attributes of food. The variable *NUTRITION* represents the z-score corresponding to a respondent's evaluation of the importance of nutrition.[12]

To control for differences in dietary knowledge across consumers, the set of independent variables includes a count of the number of diet-related health problems correctly identified by a respondent as being possibly related to diet. This variable is denoted as *KWLDG*. Kim, Nayga, and Capps (2001), for example, used a similar variable in their analysis of consumer behavior, and found it to be endogenous. To address the potential for endogeneity bias, we take the same approach as Kim, Nayga, and Capps (2001), and follow the method of Rivers and Vuong (1988). By this method, one first estimates an equation explaining *KWLDG* as a function of selected exogenous variables. The regressors in that equation include an instrument correlated with *KWLDG*, but uncorrelated with the error terms in our demand equations.[13] Both the error term from this first-stage regression (v) and *KWLDG* itself then appear as independent variables in the demand models. A discussion of how we applied this method is provided in the appendix.

We also created 11 independent variables to control for various aspects of a consumer's lifestyle, as well as income and demographic characteristics. This vector of variables is labeled as **D**. One variable in **D** is a binary indicator, *XRCISE*, equal to 1 for the 365 respondents who reported exercising more than once a week, and 0 for the other 335 respondents. Another binary indicator is *BUSINESS*, which equals 1 for the 60 respondents who reported eating out primarily with business associates, and 0 for the remaining 640 respondents. The other variables in **D** include the per capita annual income of a respondent's household (*INCOME*), the square of this income (*SQINCOME*), a binary indicator of whether the respondent is female (*FEMALE*), the respondent's age (*AGE*), a binary indicator of whether the respondent had completed college (*COLLEGE*), a binary indicator of whether the respondent was employed for wages (*JOB*), and three binary indicator variables for the respondent's race/ethnicity (*ASIAN*, *HISPANIC*, and *BLACK*).

We follow existing studies and treat *INCOME* and the demographic variables in **D** as exogenous. It is also assumed *XRCISE* and *BUSINESS* can be modeled as exogenous, though we are unable to credibly test this assumption. As such, our estimated coefficients on *XRCISE* and *BUSINESS* would be biased if this assumption is wrong. For example, one might speculate that, because a consumer often eats large meals away from home, he or she is driven to exercise by the resulting need to work off extra calories.

Appending a normally distributed, stochastic error to the hypothesized relationship among *FREQUENT* and the independent variables yields the following equation for testing the first hypothesis under study:

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[12] Similar results were obtained using each respondent's raw answer on the semantic differential scales. This method may better approximate what a researcher would use, when including a consumer's concern for health in his or her model, but ignoring that same consumer's other needs and wants.

[13] The identifying instrument is a binary variable indicating an awareness of genetically modified foods.

$$(1)\qquad P(FREQUENT = 1) = F(\alpha_0 + \alpha_{\mathbf{D}}\mathbf{D} + \alpha_{12}KWLDG + \alpha_{13}v + \alpha_{14}NUTRITION),$$

where $F(\cdot)$ indicates the cumulative standard normal density, and $\alpha_{\mathbf{D}}$ contains 11 unknown parameters corresponding to each of the 11 variables in **D**. Similarly, α_{12} is the unknown parameter on *KWLDG*, α_{13} is the unknown parameter on v, and α_{14} is the unknown parameter on *NUTRITION*, the variable of primary interest.

Outlet Choice

This study also seeks to determine whether a consumer limits his or her choice of outlet type to secure healthful foods away from home. To create demand models for this test, we defined two dependent variables. Each of these variables is a binary indicator of whether a survey respondent reported dining at a type of foodservice outlet. The first of these variables is denoted as *FAST*. It equals 1 for the 415 consumers who reported consuming fast food, and 0 for all other households. The other dependent variable is *FINE*. It is coded similarly, but equals 1 for the 443 consumers who reported patronizing fine-dining establishments, and 0 for all other households.

Further, to gauge whether consumers who claimed to choose outlets based on the healthfulness of foods were more or less likely to report patronizing either type of establishment, we created the dummy variable *HLTH*. This variable equals 1 for the 128 respondents who reported choosing an outlet based on the healthfulness of its foods, and 0 for the other 572 respondents.

As before, we control for *KWLDG* and the variables in **D**. Thus, again applying the method of Rivers and Vuong (1988), and appending a normally distributed, stochastic error to the hypothesized relationship among each of the dependent and independent variables yields the following two equations:

$$(2)\qquad P(FAST = 1) = F(\beta_0 + \beta_{\mathbf{D}}\mathbf{D} + \beta_{12}KWLDG + \beta_{13}v + \beta_{14}HLTH),$$

$$(3)\qquad P(FINE = 1) = F(\theta_0 + \theta_{\mathbf{D}}\mathbf{D} + \theta_{12}KWLDG + \theta_{13}v + \theta_{14}HLTH).$$

Equations (1)–(3) were estimated using a weighted probit model.

Results for Models with Preferences for a Healthful Diet

Estimation results are presented in table 2. To test the fit of these models, the value of the dependent variable was predicted to be 1 if the estimated probability for that observation equals or exceeds 0.5. By this method, estimates of (1), (2), and (3) correctly predict 66%, 67.6%, and 65.4% of the observations on *FREQUENT*, *FAST*, and *FINE*, respectively.[14]

Among the results from the first phase of the analysis, the coefficient on *NUTRITION* is negative and statistically significant at the 5% level in (1).[15] Consistent with our

[14] This compares favorably with the naive guess of either all ones or all zeros for the value of each dependent variable, which would correctly predict 64.4%, 59.3%, and 63.3% of the observations.

[15] The level of significance is based on a one-tailed test. Theory dictates that the direction of *NUTRITION* can only be zero or negative.

Table 2. First Phase, Parameter Estimates

	Model		
Variable	(1) *FREQUENT*	(2) *FAST*	(3) *FINE*
Constant	-0.940**	3.177***	0.975**
	(0.410)	(0.432)	(0.388)
INCOME	0.027***	-0.018***	0.009*
	(0.006)	(0.006)	(0.006)
SQINCOME	-0.0001**	-0.00009**	-0.000001
	(0.00005)	(0.00004)	(0.00004)
COLLEGE	0.479***	-0.172	-0.024
	(0.118)	(0.117)	(0.112)
AGE	-0.040***	-0.021**	0.022**
	(0.011)	(0.010)	(0.009)
FEMALE	-0.949***	-0.047	0.635***
	(0.216)	(0.200)	(0.192)
JOB	-0.792***	0.039	0.545**
	(0.239)	(0.225)	(0.214)
ASIAN	-0.434	0.829**	0.216
	(0.332)	(0.361)	(0.315)
BLACK	-0.909***	0.627**	-0.031
	(0.328)	(0.291)	(0.268)
HISPANIC	-0.487*	-0.124	0.738**
	(0.258)	(0.237)	(0.232)
BUSINESS	0.414**	-0.725***	-0.053
	(0.203)	(0.207)	(0.211)
XRCISE	-0.509***	-0.323**	0.337**
	(0.149)	(0.142)	(0.137)
KWLDG	1.233***	-0.488	-1.383***
	(0.458)	(0.435)	(0.420)
v	-1.205***	0.510	1.401***
	(0.460)	(0.436)	(0.423)
NUTRITION [a]	-0.125**		
	(0.075)		
HLTH		-0.158	0.693***
		(0.137)	(0.144)
Auxiliary Statistics at Convergence:			
Log-Likelihood Statistic	-352.969	-392.354	-434.969
% Correctly Predicted	66%	67.6%	65.4%

Notes: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are standard errors.

[a] By theory, the appropriate test of significance is $H_0: \alpha_{14} \geq 0$, i.e., a one-tailed test.

hypothesis, a consumer is less likely to dine out very frequently if he or she places a higher level of importance on the nutritional attributes of foods, controlling for all other demand determinants.

We also find preliminary evidence that preferences for health can drive a consumer to restrict his or her choice of restaurant. The coefficient on *HLTH* is positive and significant at the 1% level in (3). Consumers selecting an outlet for the healthfulness of its foods are more likely to patronize a fine-dining establishment.

Other interesting findings are observed with respect to *XRCISE*. The coefficient on this variable is significant at the 5% level in all equations and shares the same signs as the coefficients on the *HLTH* and *NUTRITION* variables. For example, those consumers who claimed to exercise at least once a week also reported eating out less frequently, were more likely to patronize fine-dining restaurants, and were less likely to buy fast food. Although further research is needed to understand the link between exercise and diet, these preliminary results support the possibility that exercising and placing a greater priority on diet might be complementary.

Notably, the coefficient on *KWLDG* is significant in (1) and (3) at the 1% level. The estimated coefficient on this variable is positive in the equation for frequency of eating out, which is consistent with past literature and the theoretical expectation, as discussed earlier. By contrast, the estimated coefficient on *KWLDG* is negative in (3). While consumers seeking out a restaurant for the healthfulness of its foods are more likely to patronize a fine-dining establishment, this effect can be negated by a greater knowledge of health and nutrition. In fact, research shows that foods traditionally consumed at full-service restaurants are not nutritionally superior to fast food, although the two types of foods have different nutrient characteristics (Lin, Frazao, and Guthrie, 1999).

Results When Other Preferences Compete with Nutrition and Health

The second phase of this analysis involves augmenting (1), (2), and (3) with variables capturing the other preferences of consumers. We wish to test whether these other variables are significant, and whether estimates of the unknown parameters from the first phase of the analysis are unbiased. It has been shown in our discussion of the data that a correlation exists among some of a consumer's preferences. If a preference other than *NUTRITION* is included in the true model of (1), Yatchew and Griliches (1985, p. 135) demonstrate that the estimated coefficient on an included variable will converge in probability to

$$\frac{\alpha + \delta\gamma}{\sqrt{\delta 2\sigma_v^2 + 1}},$$

where α is the true coefficient on the included variable, δ is the true coefficient on the omitted variable, γ is the coefficient on the included variable in an auxiliary regression of the omitted variable on all included variables, and σ_v^2 is the conditional variance of the omitted variable given all included variables. Thus, if convenience is an omitted variable in (1), then $\hat{\alpha}_{14}$, the estimated coefficient on *NUTRITION*, also may be capturing the impact of a consumer's preferences for convenience.[16]

To test whether a consumer's preferences for convenience complement or compete with a concern for health, we augmented (1). In addition to *NUTRITION*, included among the independent variables is the z-score associated with the level of importance placed on ease of preparation by the respondent, *EASE*.[17] We similarly supplemented

[16] The form of the omitted-variable bias reflects our use of a probit model. However, in general, if there is a correlation between omitted and included variables, then coefficients estimated by linear and logistic regression will be biased as well (e.g., Greene, 1997).

[17] We also tried including level of importance placed on taste. However, this attribute was not significant, nor did its inclusion significantly affect other results.

(2) and (3) with variables capturing the consumer's preferences for convenience and an enjoyable dining experience. The first of these variables is *CNVNT*, equal to 1 for the 433 respondents who reported choosing a restaurant for the convenience of its location, and 0 for the remaining 267 respondents. The other variable, *AMBIENCE*, equals 1 for the 468 survey respondents who reported choosing a restaurant for the quality of the dining experience, and 0 for the other 232 consumers.

Table 3 provides estimation results for the augmented models, including the marginal effects of variables. Compared with the results shown in table 2, the augmented equations correctly predict 67.3%, 68.1%, and 68.9% of the observations on *FREQUENT*, *FAST*, and *FINE*, respectively. The coefficient on *EASE* is positive and significant at the 1% level in the augmented equation for whether a consumer frequently dines out. People who more strongly prefer foods requiring little further preparation are more likely to frequently eat out. The probability of eating out frequently increases by 8.2% for a unit increase in the relative importance placed by the individual on ease of preparation, regardless of a person's concern for a healthful diet.

A consumer's choice of outlet to patronize depends upon preferences for convenience and for an enjoyable dining experience. At the 5% level, the coefficient on *CNVNT* is positive in the equation predicting *FAST*, while the coefficient on *AMBIENCE* is positive in the equation predicting *FINE*, but negative in the equation for *FAST*. For example, a consumer is 16.8% more likely to buy fast food if he or she seeks out convenient restaurants, but 10.9% less likely to do so if he or she picks a restaurant for the quality of the dining experience.

The statistical significance of variables capturing other preferences suggests omitting these variables from demand models can bias estimates of the unknown parameters on some included variables. To illustrate, we regressed *EASE* on all the independent variables in (1). As shown in table 4, the coefficient on *NUTRITION* is negative and significant at the 1% level in this auxiliary regression. Using the formula of Yatchew and Griliches (1985), we further find that the coefficient on *NUTRITION* in the first column of table 2, when *EASE* is omitted from the model, is approximately equal to the sum of 0 and an estimate of the omitted-variable bias. This is specified as follows:

$$0 + \frac{\hat{\delta}\hat{\gamma}}{\sqrt{\hat{\delta}2\hat{\sigma}_v^2 + 1}} = \frac{(0.270)(-0.455)}{\sqrt{(0.270)(2)(0.601) + 1}} = -0.107 \approx -0.125,$$

where $\hat{\delta}$ is the coefficient on *EASE* from the first column of table 3, $\hat{\gamma}$ is the coefficient on *NUTRITION* from table 4, and $\hat{\sigma}_v^2$ is our estimate of the mean squared error in the auxiliary regression reported in table 4. By contrast, as also shown in table 4, the coefficient on *XRCISE* is statistically insignificant in the auxiliary regression of *EASE* on the independent variables in (1). It follows that the coefficient on *XRCISE* in (1) does not suffer much from omitted-variable bias and, in fact, our estimate of this coefficient changes relatively little when the augmented specification of (1) is estimated.[18]

[18] The probability limit of the coefficient on *XRCISE* in (1) is scaled by quantity in the denominator of the formula of Yatchew and Griliches (1985).

Table 3. Second Phase, Parameter Estimates and Marginal Effects

	Augmented Model					
	(1) *FREQUENT*		(2) *FAST*		(3) *FINE*	
Variable	Estimated Coefficient	Marginal Effect	Estimated Coefficient	Marginal Effect	Estimated Coefficient	Marginal Effect
Constant	-0.985** (0.412)		2.907*** (0.448)		0.670 (0.412)	
INCOME	0.028*** (0.006)	0.009	-0.017*** (0.006)	-0.006	0.007[a] (0.006)	0.003
SQINCOME	-0.0001** (0.00005)	-0.00004	0.00009* (0.00004)	0.00003	0.000003[a] (0.00005)	0.000001
COLLEGE	0.418*** (0.120)	0.132	-0.125 (0.119)	-0.047	-0.018 (0.115)	-0.007
AGE	-0.039*** (0.011)	-0.012	-0.019* (0.010)	-0.007	0.018* (0.010)	0.007
FEMALE	-0.969*** (0.217)	-0.306	-0.049 (0.204)	-0.019	0.646*** (0.196)	0.248
JOB	-0.764*** (0.240)	-0.249	0.051 (0.229)	0.019	0.558** (0.219)	0.216
ASIAN	-0.325 (0.334)	-0.089	0.833** (0.366)	0.248	0.145 (0.319)	0.055
BLACK	-0.818** (0.332)	-0.189	0.776*** (0.293)	0.240	-0.163 (0.275)	-0.064
HISPANIC	-0.433* (0.263)	-0.117	0.176 (0.247)	0.064	0.600** (0.246)	0.209
BUSINESS	0.471** (0.207)	0.154	-0.795*** (0.211)	-0.312	-0.042 (0.214)	-0.012
XRCISE	-0.503*** (0.150)	-0.152	-0.303** (0.145)	-0.114	0.291** (0.140)	0.111
KWLDG	1.243*** (0.460)	0.386	-0.483 (0.442)	-0.179	-1.353*** (0.431)	-0.522
v	-1.214*** (0.462)		0.519 (0.444)		1.343*** (0.434)	
NUTRITION	-0.004 (0.085)	-0.002				
EASE	0.270*** (0.090)	0.082				
HLTH			-0.062 (0.142)	-0.023	0.516*** (0.149)	0.187
CNVNT			0.450*** (0.112)	0.168	0.106 (0.111)	0.041
AMBIENCE			-0.296** (0.121)	-0.109	0.745*** (0.114)	0.288
Auxiliary Statistics at Convergence:						
Log-Likelihood Statistic	-348.424		-380.357		-412.862	
% Correctly Predicted	67.3%		68.1%		68.9%	

Notes: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are standard errors.

[a] *INCOME* and *SQINCOME* are jointly significant at the 5% level.

Table 4. Regression of Omitted Variable (*EASE*) on Included Variables in (1), Parameter Estimates

Variable	Estimated Coefficient	Variable	Estimated Coefficient
Constant	0.137	*ASIAN*	-0.429***
	(0.132)		(0.115)
INCOME	-0.002	*BLACK*	-0.435***
	(0.002)		(0.090)
SQINCOME	0.00002	*HISPANIC*	-0.371***
	(0.00002)		(0.081)
COLLEGE	0.270***	*BUSINESS*	-0.169*
	(0.051)		(0.092)
AGE	-0.005***	*XRCISE*	-0.023
	(0.002)		(0.050)
FEMALE	0.056	*KWLDG*	0.007
	(0.048)		(0.016)
JOB	-0.171***	*NUTRITION*	-0.455***
	(0.057)		(0.032)

Auxiliary Statistics:
$R^2 = 0.328$
F-Statistic = 25.73

Notes: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are standard errors.

Conclusions and Policy Implications

Controlling for nutritional knowledge and other consumer characteristics, this study finds evidence that preferences for a healthful diet, convenience, and an enjoyable dining experience all contribute to consumer behavior. Moreover, as these preferences can be correlated, research should not estimate the impact of preferences for nutrition on behavior without considering potentially competing preferences. Estimation results may suffer from omitted-variable bias.

For social marketers, the results of this study underscore the value of appealing to a variety of consumer preferences in campaign materials. A consumer with a limited budget and limited time must make choices among options like eating at a fancy restaurant, eating at a fast-food establishment, or cooking a meal in his or her own kitchen. Further, our findings suggest that a consumer's ultimate choice among these options depends not only on preferences for a healthful diet and nutrition, but on the consumer's desires for convenience and an enjoyable dining experience. From this result, we conclude that consumers can be more easily persuaded to choose the most nutritious option if that option is also convenient and enjoyable.

Thus, to better affect behavior, social marketers may want to reinforce their messages by promoting options which do not compromise convenience or the enjoyment of a dining occasion (see also Palmer and Leontos, 1995). A case in point is the 5-A-Day National Partnership whose members include the National Cancer Institute and the U.S. Department of Agriculture (USDA). While working with restaurants to increase offerings of fruits and vegetables, the 5-A-Day campaign is promoting an image of fruits and vegetables as convenient and tasty (e.g., Fried Humphreys, 2004). Another case in point is the Power of Choice, jointly administered by the USDA and the Department of Health and Human Services (DHHS). That campaign takes account of the many facets of an adolescent's lifestyle while coaching youth on making healthful decisions vis-à-vis fast-food restaurants (USDA/Food and Nutrition Service, 2003).

Our results also provide evidence suggesting that social marketers might encourage fast food restaurants to offer more healthful menu options. In particular, health-conscious consumers are more likely to patronize full-service eateries. Presumably, fast-food restaurants would like to draw more of these consumers into their stores. In fact, some large chains already appear to understand the need to serve such consumers. Subway, McDonald's, and Burger King all introduced low-carb menu items in 2004, alongside existing low-calorie products tailored toward health-conscious patrons, such as salads.

Until the situation regarding the healthfulness of away-from-home foods can be resolved, social marketers might also incorporate preferences for convenience and enjoyment into their broader marketing campaigns, including those promotions not specifically targeting away-from-home foods. For example, our results suggest that information on how to eat a balanced diet might encourage consumers to keep a stock of relatively easy-to-prepare and yet healthful foods at home. As shown by our findings, preferences for convenience can drive consumers to eat away from home often, even if such foods are typically not as nutritious as what consumers tend to eat at home. By keeping a stock of healthy but convenient at-home foods, people may not find themselves in need of away-from-home foods, such as fast food, as often.

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Appendix: Method Used to Address Potential Endogeneity of Dietary Knowledge

Past research suggests nutritional knowledge might be endogenous in our models of frequent dining out. Consumers who dine out frequently, cook at home less often. It could be argued that by cooking at home less often, these consumers may have less access to nutritional claims made by food manufacturers or nutrition information labels. Thus, similar to Kim, Nayga, and Capps (2001), we use the method of Rivers and Vuong (1988) to accommodate the potential endogeneity of dietary knowledge. For identification, the set of independent variables explaining *KWLDG* must contain at least one additional variable that is correlated with *KWLDG*, and uncorrelated with where consumers obtain the food they eat. Past analyses, mostly studying the demand for at-home foods, use a consumer's level of formal education as the instrument of choice. However, for the case of away-from-home foods, it has been argued

Table A1. Regression of Dietary Knowledge on Exogenous Variables, Parameter Estimates

Variable	Estimated Coefficient	Variable	Estimated Coefficient
Constant	0.563*	*ASIAN*	0.449*
	(0.310)		(0.271)
INCOME	-0.004	*BLACK*	0.426**
	(0.006)		(0.210)
SQINCOME	0.00002	*HISPANIC*	0.327*
	(0.00005)		(0.190)
COLLEGE	0.005	*BUSINESS*	-0.041
	(0.120)		(0.216)
AGE	0.020***	*XRCISE*	0.207*
	(0.004)		(0.116)
FEMALE	0.403***	*AWARE*	0.249**
	(0.112)		(0.111)
JOB	0.420***		
	(0.133)		

Auxiliary Statistics:
$R^2 = 0.071$
F-Statistic = 4.36

Notes: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are standard errors.

that formal education can be related to demand both through its association with dietary knowledge and through an effect on a household's ability to manage time (e.g., Stewart and Yen, 2004).

In this study, we employ a different instrument based on knowledge of genetically modified foods. One question in the survey asked consumers whether they would try genetically modified (GM) foods at a restaurant, if that food was healthful. Respondents could select "yes" or "no" as well as indicate being insufficiently aware of GM foods to provide any opinion. Using this survey question, we created the instrument *AWARE*, which equals 1 for respondents having an opinion on GM foods (good or bad), and equals 0 otherwise. About half of the sample claimed knowing enough about GM foods to provide an opinion. We believe this variable is a sound instrument. Being aware of broader food issues, such as genetic modification, is likely correlated with nutritional knowledge. However, this awareness is not expected to be correlated with the intricacies of how often and where one eats away-from-home foods.

While it might be argued that a person who felt GM food was "bad" would avoid dining out, we believe this is unlikely as GM foods are pervasive throughout the food marketing system. Because many conventional foods sold at both supermarkets and restaurants typically contain GM ingredients, individuals seeking to avoid GM foods would need to be selective about where they acquire their at-home foods too. As pointed out by Shoemaker, Johnson, and Golan (2003), large shares of common crops, such as corn and soybeans, are grown from GM seed. These crops are then used in manufacturing the processed foods bought at supermarkets every day, and no GM foods have required labeling thus far. Recently though, it has become somewhat easier to avoid GM foods, for those who desire to do so. The National Organic Program, implemented in October 2002, excludes any GM food from being labeled as "organic." As discussed earlier, however, our data collection efforts ended in June 2002. Estimates of our knowledge equation using *AWARE* are reported in table A1 above.