United States
Department
of Agriculture

USDA

Economic
Research
Service

Economic
Research
Report
Number 62

August 2008

Is Dietary Knowledge Enough?

Hunger, Stress, and Other Roadblocks To Healthy Eating

Lisa Mancino and Jean Kinsey

www.ers.usda.gov

Visit Our Website To Learn More!

You can find additional information about ERS publications, databases, and other products at our website.

www.ers.usda.gov

National Agricultural Library Cataloging Record:

Mancino, Lisa

Is dietary knowledge enough?: hunger, stress, and other roadblocks to healthy eating.

Economic research report (United States. Dept. of Agriculture. Economic Research Service); no. 62)

1. Diet—United States.
2. Consumer behavior—United States.
3. Food consumption—United States.
4. Obesity—United States.
5. Food—Caloric content.
6 Food—Fat content.
I. Kinsey, Jean.
II. United States. Dept. of Agriculture. Economic Research Service.
III. Title.

TX360.U6

Photo credit: Shutterstock and PhotoDisc.

United States Department of Agriculture

Economic Research Report Number 62

August 2008

A Report from the Economic Research Service

www.ers.usda.gov

Is Dietary Knowledge Enough?

Hunger, Stress, and Other Roadblocks to Healthy Eating

Lisa Mancino and Jean Kinsey

Abstract

Poor diets and rising obesity rates among Americans have persisted despite increased awareness and publicity regarding the benefits of a healthy lifestyle. This analysis of consumer food choice developed a consumer demand model to illustrate how both long-term health objectives and immediate visceral influences—long intervals between meals and away-from-home eating—can affect individuals' food choices. The model predicts that dietary knowledge will have less influence on food choices in the face of immediate visceral factors. The model predictions were tested using data from the 1994-96 Continuing Survey of Food Intake by Individuals and the companion Diet Health and Knowledge Survey. Longer intervals between meals and consumption of more food away from home both contribute to one's consuming more calories and more calories from solid fats, alcohol, and added sugars. Longer intervals between meals are also associated with lower diet quality.

Keywords: behavioral economics, food consumption, obesity, fixed effects, instrumental variables.

Acknowledgments

The authors greatly appreciate the thoughtful review suggestions from Joanne Guthrie, Economic Research Service (ERS); Dianne Whitmore Shazenbach, University of Chicago; Wen You, Virginia Tech; and Carol Olander, Food and Nutrition Service (FNS). We also thank Dale Simms for editorial expertise and Wynnice Pointer-Napper for layout and design.

Contents

Recommended citation format for this publication:

Mancino, Lisa, and Jean Kinsey. *Is Dietary Knowledge Enough? Hunger, Stress, and Other Roadblocks to Healthy Eating*, ERR-62, U.S. Department of Agriculture, Economic Research Service, August 2008

Summary

Poor diets and rising obesity rates among Americans have occurred concurrently with increased awareness and publicity regarding the benefits of a healthy lifestyle. This seeming contradiction provides an opportunity to incorporate elements of behavioral economics into consumer food choice analysis. This report presents a consumer demand model to illustrate how both long-term health objectives and immediate visceral influences—long intervals between meals, eating away from home, or time pressures—can drive individuals' food choices.

What Is the Issue?

A better understanding of how situational factors affect food choices will strengthen public programs aimed at improving diet, health, and nutrition. Knowing when individuals are more likely to forgo health concerns may suggest ways to combat the effect of such situations or to identify commitment mechanisms more in keeping with long-term health goals. And the likely relationship between visceral factors and food choices implies that analysis over shorter time periods, such as per eating occasion, may uncover important information that is hidden when food choices are aggregated over an entire day or more.

What Did the Project Find?

When individuals extend the interval between meals or consume more of their food away from home, they are significantly more likely to consume more calories and more calories from solid fats, alcohol, and added sugars (discretionary calories) at each eating occasion. For example, going 5 hours between meals instead of 4 adds about 52 calories for someone on a diet of 2,000 calories per day; extending that interval from 4 to 6 hours would add about 91 calories to the meal.

Going longer stretches between meals is also estimated to lower diet quality at each meal. The location at which someone makes his or her food choices and when these choices are made significantly affect what and how much is consumed. Not surprisingly, people are estimated to cosume more calories when eating foods from a restaurant compared with foods prepared at home—about 107 more calories per meal.

The model suggests that people who work more hours in a week—a proxy for time pressures—are also more influenced by the interval between meals than those who work fewer hours. As an individual who works more hours in a week goes longer between meals, he or she will choose a meal that is significantly higher in calories, higher in discretionary calories, and lower in diet quality. At 4 hours between meals, an individual who works 40 hours a week is estimated to eat about 20 percent more calories than someone who is not employed. At 8 hours between meals, the calorie discrepancy jumps to nearly 40 percent.

Our model shows that a situational change in caloric intake and diet quality is more pronounced among individuals who are less informed about diet and

nutrition. A person with a knowledge score of 50 (from USDA's Diet and Health Knowledge Survey) is estimated to increase per-meal caloric intake by about 28 percent when eating away from home, while a person whose score is 100 points is estimated to eat about only 12 percent more calories.

As people change their dietary goals based on prevailing nutritional beliefs, situational factors like hunger and time pressures will continue to interfere with long-term health objectives. Making specific reference to such situations and suggesting ways to mitigate their effects should enhance the usefulness of educational campaigns designed to improve diet quality. For example, encouraging consumers to take more active control in limiting the interval between meals and choosing nutrient-dense snacks, such as fruits and vegetables, may help them better align their intentions to eat well with their actual behavior. Limiting intake of foods prepared away from home is also estimated to significantly decrease caloric consumption. Thus, another possibility would be to encourage individuals to plan ahead or seek out information about nutrient and caloric content of foods prepared away from home.

How Was the Project Conducted?

A theoretical model of both long-term health objectives and short-term situational factors affecting food choices predicts that when individuals face intense visceral influences, such as hunger or stress, their information about health and nutrition will have a smaller impact. It also predicts that individuals who are less informed about health and nutrition, or face higher levels of stress, will be more likely to eschew their long-term goals when faced with visceral factors such as hunger. These hypotheses are tested using data from the 1994-96 Continuing Survey of Food Intake by Individuals and the companion Diet Health and Knowledge Survey, both administered by USDA. The analysis of choices made at each eating occasion enables the use of a fixed-effects estimator. This then controls for the endogeneity between dietary information and food choices. Instrumental variable estimators further account for endogeneity that may exist between food choices and meal timing.

Introduction

The public policy approach to improving the nutritional quality of Americans' diets has relied heavily on disseminating information, such as MyPyramid, about why and how to make food choices that promote health and prevent disease (USDA, 2006). Educational efforts like this may be paying dividends. For example, a 2001 study found that nearly 60 percent of sampled shoppers indicated that their grocery purchases were strongly affected by some health concern and 76 percent felt that healthy eating was a better way to manage their health than medication. These statistics had increased to 80 percent and 86 percent by 2002 (FMI, 2001, 2002). Sales of organic foods increased 17-21 percent per year between 1997 and 2004. Sales of functional/ fortified foods increased 34 percent between 2003 and 2004, whereas total food sales increased 2.4 percent over the same period (Food Institute Reports, 2004, 2005). In addition, the large volume of diet books and products sold to American consumers suggests we are aware of diet and health issues, curious about slimming down, and mindful of good health (Ackman, 2005).

While shopper surveys and sales figures imply a national interest in improving diet, aggregate health statistics do not reflect these concerns. As of 2003-04, 66 percent of American adults were overweight and over one-third were also obese. Between 1976 and 2000, the number of individuals classified as obese more than doubled (Centers for Disease Control and Prevention (CDC), 2003).[1] During the same time span, there was a parallel rise in the incidence of diseases highly correlated with poor nutrition and overconsumption: cancer, strokes, heart disease, and diabetes (Surgeon General, 2001). In 2000, obesity accounted for an estimated $117 billion a year in direct and indirect economic costs; diabetes is estimated to account for another $132 billion (CDC, 2005).

[1]An individual is classified as obese if his or her body mass index (BMI), or ratio of one's weight in kilograms to one's squared height in meters, exceeds 30. An individual with a BMI between 25 and 30 is classified as overweight.

These conflicting trends highlight a disturbing inconsistency. While Americans demonstrate a concern about eating well and using diet to manage their health, they are getting heavier and increasing their risk of suffering from diet-related illnesses. A rift between long-term objectives and short-term desires can lead to time-inconsistent choices, where people switch their preference for a smaller, yet more immediate, reward over a larger but delayed reward when the time delay between receiving either reward is changed equally. A common example describes an individual who prefers 1 apple right now to 2 apples tomorrow, yet also prefers 2 apples in 51 days to 1 apple in 50 days (Thaler, 1981). Understanding which situations are more conducive to making these seemingly inconsistent choices can improve our understanding of the sometimes tenuous relationship between diet/health knowledge and food choices.

The burgeoning literature on behavioral economics suggests that insights gleaned from economic analysis can be improved by incorporating the presence and level of confounding factors, such as drive states (e.g., hunger, pain, fear), environmental factors, and other short-term circumstances (Loewenstein, 1996, 2000; Laibson, 2001; Read and van Leeuwen, 1998; Herman and Polivy, 2003). In turn, this may clarify how and when intentions are more likely to translate to actual behavior. The model developed by

Loewenstein (1996) shows that in the presence of intense visceral factors, such as hunger, thirst, or addiction, an individual will be compelled to make choices that undermine long-term health objectives. Using experimental results in conjunction with Loewenstein's model of visceral factors, Read and van Leeuwen (1998) found subjects' levels of hunger to be significantly correlated with observed inconsistencies. The snacks chosen for immediate consumption were significantly less healthful than those chosen for future consumption, while for both future and immediate consumption, the choices made by hungry individuals were less healthful. Herman and Polivy (2003) also examined whether behavioral economics models might be appropriate for the study of dieting and food choice. They find that when presented with tempting foods, dieters are more likely to display uninhibited eating in the presence of some motivational disruptions, such as emotional arousal, intoxication, or distress.

These findings indicate that there are situations where individuals behave in ways contrary to their own long-term self-interests. As O'Donoghue and Rabin (1999) point out, evidence of present-biased preferences brings up complex questions for public policy. In terms of obesity and poor nutrition, time-consistent preferences assume that an overweight or unhealthful individual may be making an optimal choice if he or she derives more pleasure from unhealthy behaviors than good health. As such, a heavy-handed nutrition policy, like taxing unhealthy foods to raise diet quality, would unambiguously make that person worse off. On the other hand, present-biased preferences assume that, while a person may respond rationally to current situations and make unhealthful choices, finding incentives that would make one less responsive to these situations will improve long-term well-being.

Such findings have important implications for econometric analysis of consumers' food choices. For one, empirical estimation that does not include relevant visceral factors, such as an individual's level of hunger, will yield biased estimates of the relationship between dietary information and food choices. Also, a better understanding of how situational factors affect food choices will strengthen programs aimed at improving diet, nutrition, and health outcomes. Knowing when individuals may be more likely to forgo health concerns might suggest ways to reduce the deleterious impact of such situations, or to identify commitment mechanisms that help individuals make choices that are more in keeping with their own long-term health goals.

Another important implication of the likely relationship between visceral factors and food choices is that analysis over shorter time periods, such as per eating occasion, may uncover important information that is hidden when food choices are aggregated over an entire day or more. Using the Continuing Survey of Food Intakes by Individuals (CSFII) and Diet and Health Knowledge Survey (DHKS) data to analyze food choices on this level transforms what is traditionally a cross-sectional data set into one more akin to a panel data set. This provides an opportunity to employ fixed-effects estimators, and this circumvents some of the endogeneity issues that can plague cross-sectional analysis of food demand. Instrumental variable estimators further reduce problems of endogeneity.

Theoretical Background

In economics, food can be viewed as both a consumption good and an investment. Through flavor, texture, and relief from hunger, food provides immediate gratification. Through nutrients and calories, it also confers costs and benefits for future health and well-being. Thus, economic models often employ a dynamic framework to model demand for health (Grossman, 1972), nutrient intake (Behrman and Deolalikar, 1990; Barrett, 2002), food choices as they relate to health and labor market activities (Pitt et al., 1990), and food choices as they relate to health and body weight (Cawley, 2004; Cutler et al., 2003). Typically, such models assume that individuals maximize utility over some timeframe using a discounted utility model:

$$U_t(c_t, \ldots, c_T) = U(c_t) + \sum_{\tau=1}^{T} \delta^{\tau} U(c_{t+\tau}) .$$

In this model, U($c_{t+\tau}$) is considered to be the individual's well-being at time t + τ, and δ^{τ} is the individual's discount function, or the relative weight attached at time τ to one's well-being in period t + τ. As such, the value we place on future well-being is less than the value of today's well-being, and the value of each subsequent period decreases at a constant rate. Although this assumption—referred to as *exponential discounting*—has become the norm in economic analysis, empirical findings often violate its theoretical predictions or underlying assumptions (Frederick et al., 2003). One frequently observed anomaly is that individuals tend to behave more patiently (by making choices that are consistent with their future savings or health goals) when evaluating tradeoffs that will occur at some point in the future than they would if these same tradeoffs were to occur more immediately. For example, most individuals will prefer $110 in 31 days over $100 in 30 days. Yet many of these same individuals will also prefer $100 right now over $110 tomorrow. In contrast, an exponential discounting model would predict that an individual who chooses $110 in 31 days over $100 in 30 would also choose $110 tomorrow over $100 today.

Repeated observance of time-inconsistent preferences has led some researchers to develop models in which individuals have preferences that are biased to prefer immediate rewards and delayed costs. These *present-biased preferences* allow individuals to have a declining discount rate between now and the next period, and a constant discount rate from then on. The result is that individuals will prefer an alternative that is usually less desirable or valuable over some time period simply because it is available sooner. These models have been extended to model individual consumption and savings behavior (Thaler and Shefrin, 1981; Akerlof 1991; Ainslie and Haslam, 1992; Laibson, 1997; Mullainathan and Thaler, 2000; O'Donoghue and Rabin, 1999, 2001).[2] They have also been used to explain why individuals have problems related to self-control, why they demonstrate reversals in preference, and how they can improve their longrun well-being through some commitment, such as 401(k) plans, that limit current consumption levels and thereby preclude procrastination.

[2]See Frederick et al. (2003) for a full review.

For food choice analysis, these models may not be entirely applicable because time-inconsistent behavior is attributed entirely to a reward's temporal proximity (Frederick et al., 2003; Loewenstein, 1996, 2000). In terms of food consumption, this means an individual will always be expected to choose the more immediately available food, regardless of his or her level of hunger. In reviewing the literature on weight loss, Herman and Polivy (2003) emphasize that making food immediately available is not sufficient to induce uninhibited eating bouts. Loewenstein (1996) develops a model that includes visceral influences—such as hunger, thirst, pain, and stress—in an individual's instantaneous utility function. An advantage of this model over the present-biased model described above (also referred to as hyperbolic or quasi-hyperbolic discounting models) is that it allows a broader range of situations to trigger present-biased behavior. At sufficient levels, visceral factors can create discrepancies between intended and actual behavior because an individual becomes unwilling to give up a good that alleviates the effects of a visceral influence in exchange for other goods that do not. For example, a man dying of thirst is unlikely to trade a glass of water for anything. This causes a collapsing of one's time perspective toward the present. Also, the discrepancy between the actual and desired value placed on a particular good or activity is assumed to increase with the intensity of the immediate good-relevant visceral factors.

To represent the influence of visceral factors on behavior, Loewenstein develops a representation of preferences that includes a set of variables, α_{ti}, which represent how changing levels of the visceral factors affect intertemporal utility:

$$U=\Sigma_t u(x_{t1},\ldots,x_{tn}, \alpha_{t1},\ldots\alpha_{tn}, t),$$

where U represents total utility experienced at time t, $(x_{t1},\ldots,x_{tn})$ is a vector of consumption goods, and $(\alpha_{t1},\ldots\alpha_{tn})$ is a vector of visceral factors, such as hours of food deprivation, experienced at time t. This model assumes preferences are separable temporally so that visceral factors experienced at time t only influence the value of goods consumed at that same time. It is also assumed that visceral factors can be partitioned into subsets that influence only a single consumption variable. In the simplest case, each consumption variable x_i is influenced by at most one α_I, and can be represented as follows:

$$U=\Sigma_t u(v_1 (x_{t1}, \alpha_{t1}, t),\ldots v_n (x_{tn}, \alpha_{tn}, t)),$$

where $v_1()$ is the value of consuming x_{t1} at time t in the presence of some visceral factor α_{t1}. Each v_i function is assumed to be increasing in the good offered, decreasing in time delay, and either increasing or decreasing in α_{ti}. Also, x_{ti} and α_{ti} are assumed to be complements. For example, hunger can be argued to improve the enjoyment of eating food, but can make you feel worse when there is none available. In short, this model explicitly assumes that consumer choices will be significantly affected by strong visceral factors.

This model can illuminate how and why certain situations give rise to seemingly inconsistent food choices. Under a more neutral state, an individual may choose to consume the types and quantities of foods that are consistent with his or her long-term health objectives. As visceral factors intensify, however, the value of current utility increases relative to the value of future utility and the consumption of goods that provide immediate gratification will be consumed in greater amounts than when visceral factors are less intense.

Theoretical Model

For this study, we use a relatively simple, two-period utility maximization problem that incorporates Loewenstein's visceral factors approach. Although a dynamic model may be more realistic, the general insights derived from a two-period model are the same. We assume that consumers make consumption decisions on a per meal basis and discount future well-being by some factor, δ, that is strictly less than one. In both the current and future periods, utility is derived from food (F), a composite nonfood item (N), and the individual's health status (H). For simplicity, we assume strong separability between food and nonfood, such that the utility received from food is not influenced by the amount of nonfood at that time. An individual's level of health, however, is assumed to complement both food and nonfood consumption. We also assume the utility function to be continuous, twice continuously differentiable, strictly increasing, and strictly concave in health, food, and nonfood items.

A vector of relevant visceral factors (α) experienced at the time an individual makes his or her consumption decision influences the level of utility received at that time. To isolate the effects of visceral factors on food consumption decisions, it is assumed that α influences only the utility derived from food consumed at that time. Holding all else constant, we assume that increasing visceral factors, such as the level of hunger experienced at the current time, will increase the marginal utility from food consumption so that an individual will require more food to provide the same level of utility compared to some neutral level of hunger. Thus, food and hunger are assumed to be complements. Individuals are assumed to be naive and treat these visceral factors as exogenous[3] so that utility in both periods is derived from consumption of nonfood items, food (which is influenced by visceral impacts), and one's current level of health.

$$U = U_1(F(F_1; \alpha_1), N_1, H_1 + \delta U_2\,(F(F_2; \alpha_2), N_2, H_2). \qquad (1)$$

To isolate how individuals choose to balance immediate gratification from food against possible future health implications of these decisions, we assume that one's current health is a function of his or her past dietary choices. For simplicity, we also assume that only less healthful foods have a positive impact on current utility from food and that these same foods have a negative impact on future health. How much an individual knows about health and nutrition (η) is assumed to affect how well he or she translates poor dietary choices into future health effects. Individuals who know more about the links between diet, nutrition, and health perceive a greater health impact from an unhealthy diet than individuals who know little about diet and health. This then leads to the following health production function:

$$H_t = H_t\,(F_{t\text{-}1}; \eta_{t\text{-}1}) \qquad t = 1,2. \qquad (2)$$

Finally, in both the current and future periods, an individual faces the following budget constraint:

$$P_{Nt}\,N_t + P_{Ft}\,F_t = \mathrm{Y}_t \qquad t = 1,2, \qquad (3)$$

[3]Treating visceral influences as endogenous would complicate the model without providing additional insights. Fully sophisticated individuals would control visceral influences such that their optimal choice of food would be the same as that under a state of neutral visceral influences. Loewenstein (1996, 2000) argues that while individuals do control their situations, they underestimate the effect that visceral influences will have in the future. Thus, although our theoretical model could accommodate this by allowing individuals to have an underestimated idea of their future visceral levels, the ultimate findings of our model would be the same: As visceral factors increase, individuals would consume more food and the strength of dietary information on guiding food choices would decline.

where P_{Nt} is the price of nonfood items, P_{Ft} is the price of food, and Y_t is the individual's income. Substituting the health production function (2) into (1), the Lagrangian for this two-period optimization problem can be written as:

$$L = U_1(F(F_1;\alpha_1), N_1, H_1(F_0; h_0)) + \delta U_2(F(F_2; \alpha_2), N_2, H_2(F_1; h_1)) + \lambda_1(Y_1 - P_{F1}F_1 - P_{N1}N_1) + \lambda_2(Y_2 - P_{F2}F_2 - P_{N2}N_2). \quad (4)$$

The first-order conditions for optimal consumption of unhealthful foods and nonfood items (F_1, N_1) at time 1 are:

$$L_{F1} = U_{1F1} + \delta U_{2H2} H_{2F1} - \lambda_1 P_{F1} = 0 \quad (5a)$$

$$L_{N1} = U_{1N1} - \lambda_1 P_{N1} = 0 \quad (5b)$$

$$L_{\lambda 1} = Y_1 - P_{F1} F_1 - P_{N1} N_1 = 0, \quad (5c)$$

where U_{1F1} and U_{1N1} are the current marginal utilities from food and nonfood consumed in the first period, U_{2H2} is the marginal utility from health experienced in period 2, H_{2F1} is the marginal impact of the current period's poor food choices on next period's health, and λ_1 is the current marginal utility of wealth. For simplicity, we normalize prices and set P_{N1} equal to one. To be certain that these values of F_1, N_1 yield optimal values, we require the following condition to hold:

$$|\delta U_{2H2H2} H_{2F1}| < |(P_F)^2 U_{1N1N1} + U_{1F1F1} + \delta U_{2H2} H_{2F1F1}|. \quad (6)$$

Condition (6), along with Cramer's rule, can be used to determine how F_1 will change with specific parameters, such as current visceral influences and dietary awareness, and how the effect of dietary awareness on unhealthful food choices will change with the intensity of visceral influences.[4]

[4]A detailed account of the propositions and their proofs is available upon request.

Proposition 1: $\partial F_1 / \partial \alpha_1 > 0$

Increasing visceral factors in the current period will cause an individual to choose more unhealthful foods at that time.

Differentiating equations 5a-c with respect to α_1, rewriting the system of equations in matrix form, and solving this system of three equations using Cramer's rule, we find that the optimal choice of unhealthful foods will increase in the presence of relevant visceral factors as long as food and visceral factors (hunger, stress) are complements. Since $U_{1F1\alpha 1} > 0$ is true by construction, proposition 1 holds.

Proposition 2: $\partial F_1 / \partial \eta_1 < 0$

Increasing an individual's awareness about the negative impact of poor dietary choices on future health will cause him or her to eat fewer unhealthful foods.

Using the same technique and differentiating the first-order conditions with respect to h_1 and again solving this system of equations via Cramer's rule, individuals with higher levels of health information will choose fewer unhealthful foods as long as $U_{2H2}H_{2F1h1} < 0$. We assume that an individual who is more informed about the links between diet and health will be better able to assess the negative health effects of his or her poor food choices, thus

$H_{2F1\eta 1} < 0$.[5] This then ensures that an individual will respond to an increase in health information by choosing fewer unhealthful foods for current consumption.

Proposition 3: $\partial^2 F_1 / \partial\eta_1 \partial\alpha_1 = \partial^2 F_1 / \partial\alpha_1 \partial\eta_1 < 0$

As visceral factors increase at a given time or eating occasion, an individual's health information will have less impact on his or her food choice. Alternatively, individuals with higher levels of health and dietary information will be less affected by visceral factors than individuals with lower levels of dietary information.

Again, differentiating the first-order conditions with respect to η_1 and then differentiating each with respect to α_1, we find that $\partial^2 F_1 / \partial\eta_1 \partial\alpha_1$ is less than zero as long as

$$\left|\delta U_{2H2} H_{2F1F1\eta 1} \partial F_1 / \partial\alpha_1\right| < \left|U_{1F1F\alpha 1} \partial F_1 / \partial\eta_1 + \delta U_{2H2H2} H_{2F1\eta 1} \partial F_1 / \partial\alpha_1\right|. \quad (7)$$

Our goal is to sign comparative statics for a typical individual, not all mathematically possible utility and health production functions. We therefore make additional, but reasonable, assumptions. The first is that the health production function is convex—the negative effect of poor food choices on health increases as an individual's health status decreases. Another is that better dietary information is assumed to simply shift the health production function inward while leaving the rate at which poor food choices affect overall health unchanged. Thus, $H_{2F1F1\eta 1} = 0$. Similarly, we can assume that increasing visceral factors simply causes an outward shift in the utility one receives from food. We can also assume that increasing visceral factors causes the marginal utility received from food to increase, but at a decreasing rate. Simply put, as visceral factors like hunger or stress intensify, additional amounts of food increase overall utility at lower rates. This conforms with the idea that many people tend to make poorer food choices when hungry or under stress. As long as we assume that $U_{1F1F\alpha 1} \leq 0$, condition (7) will hold. This in turn implies that $\partial^2 F_1 / \partial\eta_1 \partial\alpha_1 < 0$.

[5]By assumption, information affects only how accurately one relates dietary choices to health outcomes. It does not have an impact on the level of enjoyment derived from health.

Empirical Implications and Economic Model

The theoretical model implies that demand for unhealthful foods at time t will be a function of income, prices, visceral factors, and health at time t. To test whether visceral influences weaken the impact of health information on food choices, we also include the interaction of visceral factors and nutrition information. Empirically, demand for unhealthful food in the current period can be specified as follows:

$$F_{it} = \beta' X_{it} + u_i + e_{it}, \qquad (8)$$

where F_{it} is the amount of unhealthful food individual i consumes at each eating occasion t, X_{it} is a vector of the aforementioned parameters—income, prices, current health status, visceral factors—and the interaction of dietary information and visceral influences, u_i is the individual effect, and e_{it} is the individual, time-specific error term. If there is more than one observation for an individual, as there is in this study, ordinary least squares (OLS) estimates will yield inefficient parameter estimates if the error terms are correlated across observations for a given individual.

A random-effects (RE) model will yield efficient and consistent estimates as long as the individual specific disturbance (u_i) is uncorrelated with the other regressors, X_{it}. However, given the interdependence of current health, dietary awareness, and food choices, this condition will likely not be met. For example, an individual recently diagnosed with diabetes may be more aware of diet and nutrition. This same person would also have greater incentives to improve his or her diet quality and manage the timing of his or her meals. Not accounting for this health condition in the RE estimator would then bias estimates on both the impact of dietary awareness and the interval between meals.

As such, a fixed-effects (FE) model, as specified below, will yield consistent estimates as long as the remaining individual-specific, time-specific disturbance (e_{it}) is also uncorrelated with the regressors (Green, 1990):

$$(F_{it} - \overline{F}_i) = \beta' (X_{it} - \overline{X}_i) + (e_{it} - \overline{e}_{it}), \qquad (9)$$

where $\overline{F}_i$, $\overline{X}_i$, and $\overline{e}_i$ represent individual averages. Continuing with the previous example, a fixed-effects estimator allows one to tease out the impact of time-varying variables, such as the interval between meals. In this case, the FE estimates would measure the impact of meal timing on diet quality for a given individual with specific health conditions and dietary awareness. If, however, the time-specific disturbances are also correlated with the regressors, a fixed-effects model with instrumental variables (FE-IV) can be used to obtain unbiased estimates (Evans et al., 1993). Theoretically, there is reason to suspect that the error terms will be correlated with the explanatory variables because some visceral factors, such as how long one goes between meals, are arguably endogenous and/or possibly measured with error. Thus, we attempt to circumvent this issue through the use of instrumental variables.

We use Stata 9.0 for our empirical analysis. Specifically, we use xtset to identify the nature of our panel data. We specify each individual as the panel variable and each meal as the time variable. We then use xtivreg, a fixed-effects instrumental variable (FE-IV) estimator that uses a two-stage, least-squares within estimator. We also employed random-effects (RE) and fixed-effects (FE) estimators, using generalized least squares. However, the Hausman test statistics indicate that these results were biased.[6] We therefore only describe variables used in the FE-IV estimation and limit our discussion and presentation of these FE-IV results.

[6]We do not reject the null-hypothesis that the difference between the FE and FE-IV coefficients are not systematic for one model. However, even if the null hypothesis is rejected, FE-IV estimates are consistent.

Data

The data for this study come from the USDA's 1994-96 Continuing Survey of Food Intakes by Individuals (CSFII) and the companion Diet and Health Knowledge Survey (DHKS). Through dietary recalls, the CSFII contains information on the foods and nutrients consumed over 2 nonconsecutive days. The DHKS provides information on peoples' attitudes and knowledge about diet, health, and nutrition. In each CSFII household, the DHKS was administered to only one adult over 20 years old who reported at least 1 day of food intake. To maintain a clear link among food consumption, visceral influences, and dietary awareness, this analysis includes only individuals who were also given the DHKS. In total, we have information on 5,645 individuals who reported an average of 6.4 eating occasions, for a total sample of 36,312 observations. Descriptions of variables used in the empirical analysis and their summary statistics are in table 1.

Dependent Variables

Calories. For the empirical analysis, the first step is to provide a suitable and measurable definition of unhealthful food choices made at each eating occasion. As energy imbalance and large portion sizes are often linked to weight gain and ultimately poor health, one measure used in this study is the number of calories consumed at an eating occasion. As such, one dependent variable is the share of recommended calories consumed at a specific eating occasion.[7] It is the number of calories an individual consumes divided by an individual's daily estimated energy requirement (EER), multiplied by 100. An individual's EER is calculated using the equations from the Institute of Medicine (2002), which is a function of an individual's age, gender, height, weight, and physical activity.[8] As an example, if an individual's daily EER is 2,000 calories and he or she consumes 500 calories at breakfast, then the dependent variable at that eating occasion is 25.

Healthy Meal Index. Low nutrient intake is also correlated with poor health and weight outcomes. Ideally, we would like a measure of nutrient intake per unit of energy consumed, such as nutrient density relative to energy density. At this time, however, there is no standard definition for this measure. To deal with this issue, we try three separate measures of nutrient quality. The first makes use of calculations from an individual's Healthy Eating Index for 1994-96. We refer to this measure as the HEI score. This index, which ranges from 0 to 100, summarizes how well an individual's daily food intake conforms to the 1995 *Dietary Guidelines for Americans*. The components of this index are an individual's intake of fruits, vegetables, grains, dairy products, meat, fat, saturated fat, sodium, and cholesterol (Bowman et al., 1998). To make this measure usable on a per-meal basis, we use a SAS program (available upon request from the USDA) to calculate an individual's daily HEI score.[9] We then augment the program to calculate what each person's daily score would have been in the absence of each eating occasion on a specific day.

The dependent variable at each eating occasion is the difference between what that individual's HEI score actually was on that day of intake and what it would have been in the absence of that specific eating occasion. For example,

[7] A potential weakness of looking at the relationship between meal timing and calories consumed on a per meal basis is that calories consumed at each meal may not adequately reflect total calories consumed over a day. Someone who frequently eats small meals could ultimately consume more total calories over the day. Using the same CSFII data and looking at calories consumed throughout the day, however, Mancino and Kinsey (2004) also found a positive and significant correlation between time between meals and total calories consumed.

[8] In our calculations, we assume that all individuals are inactive because the activity data available in the CSFII are not precise enough to include as part of the EER calculation.

[9] The official HEI score also includes a variety component. However, it is very difficult to calculate the change in daily HEI score while including this component. For that reason, the HEI scores in this study only include 9 components. Thus, the range of scores is from 0 to 90. We feel this does not alter results dramatically, especially since the HEI-2005 score does not include a variety component.

Table 1
Variables, definitions and summary statistics

Variable	Definition	Mean (standard deviation)
Calories	Percent of daily energy requirements consumed at eating occasion	22.26 (19.68)
Healthy Meal Index (HMI)	How much higher HEI score (0-100 points) would have been without eating occasion	3.44 (6.21)
HMI2005	HEI 2005 density score at eating occasion (0-100 points)	37.70 (13.22)
SOFAAS per meal	Calories from solid fats, alcohol, and added sugar (0-20 points)	10.29 (9.30)
Interval	Hours elapsed between current and previous eating occasion	3.66 (2.22)
Share restaurant food	Share of food from restaurant (calories)	13.39 (33.51)
Brunch	1 if classified as brunch; 0 otherwise	0.01
Lunch	1 if classified as lunch; 0 otherwise	0.22
Dinner	1 if classified as dinner; 0 otherwise	0.30
Snack	1 if classified as snack; 0 otherwise	0.42
Weekend	1 if dietary recall occurred on a weekend; 0 otherwise	0.26
Knowledge	Score on dietary knowledge assessment (0-100)	71.71 (13.35)
Work hours	Number of hours worked in previous week	23.46 (23.39)
Interaction: Interval* knowledge	Interval*score on dietary knowledge assessment (0-100)	260.51 (164.64)
Interaction: Interval*work hours	Interval*Number of hours worked in previous week	86.40 (117.23)
Interaction: Sharefafh*knowledge	Share of restaurant food*score on dietary knowledge assessment	954.42 (2,434.42)
Interaction: Sharefafh*work hours	Share of restaurant food*Number of hours worked in previous week	400.55 (1,314.51)

Each variable's standard deviation is listed below its mean for all continuous variables.
Sample size is 36,312, with 5,645 individuals who report an average of 6.43 eating occasions.

if an individual's HEI score on the first day of intake was 65 and that score would have been 60 had he or she not eaten breakfast that day, the dependent variable for that individual at that breakfast eating occasion would have a value of 5. Thus, higher values for this variable represent meal choices that are more nutritious. We refer to this variable as the Healthy Meal Index (HMI) to be clear that it is meant to gauge the nutritional quality of each eating occasion, whereas the HEI measures diet quality over an entire day.

Each of the 10 HEI components falls within the range of 1 to 10. Thus, someone who ate more than his or her recommended levels of fruit or vegetables could not score bonus points by doing so. Similarly, there are limits to "penalties" for overconsumption of salt, cholesterol, fat, and saturated fat. This top and bottom coding within components enables the HEI score to be more than a simple linear function of each meal's score. In the absence of such coding, however, the sum of HMI scores over an entire day would equal an individual's daily HEI score.

Healthy Meal Index, 2005. In 2005, the USDA and Department of Health and Human Services updated the *Dietary Guidelines for Americans*. More recently, the USDA has created the HEI-2005 (Guenther et al., 2007), which reflects the 2005 *Dietary Guidelines* and addresses some shortcomings of the HEI score. For example, it did not assess caloric intake or excesses of some components such as added sugars or alcohol. Also, the HEI score did not differentiate between types of vegetables, grains, or fats. As such, a serving of french fries and a serving of kale contributed equally to an individual's HEI score.

Intuitively, it seems better to gauge the links between dietary knowledge in 1994-96 and dietary intake in 1994-96 using the HEI score derived from the dietary guidelines promoted during this same time. However, we also run estimates using a Healthy Meal Index based on the HEI-2005 score to see how visceral influences, dietary knowledge, and meal location influence alternative measures of diet quality. The 12 components that make up the HEI-2005 score are total fruit, whole fruit, total vegetables, dark green and orange vegetables and legumes, total grains, whole grains, milk, meat and beans, oils, saturated fat, sodium, and calories from solid fats, alcohol, and added sugar (SoFAAS). Scoring for 10 of the 12 components is based on caloric density—either cups, grams, or ounce equivalents per 1,000 grams. Scoring for sodium and SoFAAS is calculated as a percent of energy. As such, it is easier to translate this daily measure into a per meal measure. We simply calculate each of the 12 components using the calories consumed at that meal instead of the total calories consumed over the entire day. We refer to this measure as the Healthy Meal Index 2005 (HMI-2005).

Calories from Solid Fats, Alcohol, and Added Sugar (SoFAAS). The twelfth component—SoFAAS—measures discretionary calories. Excess calories and energy imbalance are the cause of weight gain, and limiting discretionary calories is an effective way to reduce caloric intake without necessarily reducing nutrient intake. We run a final model that estimates how visceral influences and other explanatory variables influence intake of discretionary calories, or SoFAAS, at a meal.

Explanatory Variables

According to the theoretical model, per-meal food demand will be a function of food prices, income, current health, and meal-specific visceral factors such as hunger.[10] Although the CSFII does not explicitly ask individuals how hungry they were at each eating occasion, it does provide information on the time elapsed between eating occasions. We therefore use the interval between meals, measured in hours, as a proxy for an individual's level of hunger at a specific eating occasion. This effect may change after longer periods without food, so we also include a quadratic term for the interval between meals.

[10]Because we do not discuss the results of the random effects (RE) estimates in the body of the paper, we do not describe the time-invariant explanatory variables, such as proxies for health status, income, and prices, that were used in these models.

We include the type of eating occasion (breakfast, lunch, dinner, or snack) and whether or not the dietary recall occurred on a weekend or weekday, as these variables may also affect individuals' food choices. The data on dietary intake come from 2 nonconsecutive days, so there are two observations each day (the first eating occasion) where it is not possible to calculate the interval between meals. Rather than lose these observations, we assign the mean interval between meals for each individual and use that as the level of hunger for the first eating occasion (Cohen et al., 2003).

To test the proposition that dietary awareness will have less influence on food choice in the presence of strong visceral influences, we include an interactive term to estimate the effects of dietary knowledge as hunger increases. Responses from the DHKS are used to create an index to measure knowledge about health and nutrition for each individual. One-third of this knowledge index is created by summing the number of questions an individual answered correctly about the links between diet and health.[11] Specifically, individuals were asked if they knew how many servings of fruit, vegetables, meat, dairy, and grains they should consume each day. They scored one point for each correct answer. Another third of this index is created from scoring correct answers about the amounts of cholesterol, fat, and saturated fat in specific foods. The remaining third of the information index comes from the DHKS questions on the importance of certain dietary practices, such as eating enough fruits, vegetables, and fiber; limiting intake of fat, cholesterol, saturated fat, salt, and sugar; and maintaining a healthy body weight.

[11]Specific questions and answers used to create the dietary knowledge score are available from the authors upon request.

Where an individual makes his or her food choices may affect the types and amounts of foods consumed. To gauge this effect, we calculate the share of calories consumed at each meal that come from a restaurant (restaurants with table service, fast-food places, pizza places, and bars/taverns).[12] We also estimate if the effect of dietary knowledge wanes when consuming foods away from home because typically there is less health information about foods purchased at restaurants.

[12]We chose this technique over creating a similar dichotomous variable because some eating occasions contain foods from multiple sources.

Finally, stress of time pressures associated with work and family requirements may be a visceral influence that, like hunger, affects food choice. As a proxy for work requirements, we use the number of hours worked in the previous week. Although this specific variable is not in our empirical estimation, we do include an interactive term to determine whether hunger has a stronger effect on individuals who are more time constrained through work. We also interact *hours worked* with food away from home to estimate if time stresses increase an individual's vulnerability to certain pitfalls of eating away from home, such as an expanded array of unhealthy food choices or less information about diet/nutrition.

Instrumental Variables

Using a fixed-effects estimator should drastically reduce the correlation between the disturbance terms and the other explanatory variables. However, it is possible that the variable we use to proxy an individual's level of hunger may be correlated with some unobserved time-varying factor. Obtaining unbiased, efficient estimates requires that the additional variables be both relevant and independent. Because we assume a fixed-effects estimator, the instruments also need to vary across observations for a single individual. Therefore, some time-invariant variables, such as health conditions of other family members, are not viable options. In the fixed-effects model, there are four variables that are created using the interval between meals (hunger, hunger squared, the interaction of hunger with dietary knowledge, and the interaction of hunger with hours worked).[13] Thus, these variables may be correlated with the individual-specific, time-varying error term. One possible instrument is to use the time of day an eating occasion occurred. The time of day is exogenous—while people may choose how long they go between meals, they do not choose the actual time

[13]The share of calories consumed away from home may also be correlated with the time-specific error term. We had originally treated this variable as endogenous, but the resulting instrumental variable (IV) estimator was overidentified. We chose to focus on the endogeneity involved with the interval between meals because of our theoretical model.

of day. However, certain times, such as 4 p.m., may be more correlated with longer intervals between meals compared to 12:30 p.m. Following the technique developed by Arellano and Bond (1991), we also use lags of the endogenous variables as instruments.[14] How long one has gone between meals previously is likely to be correlated with how long one has gone between meals at present. However, feeling hungry at lunch should not influence how hungry one feels at dinner.[15]

In summary, we employ a fixed-effects estimator with instrumental variables (FE-IV) described as follows:

$$(F_{it} - \overline{F}_i) = \beta'(X_{it} - \overline{X}_i) + \gamma'(\alpha_{it} - \overline{\alpha}_i) + (e_{it} - \overline{e}_i) \qquad (10a)$$

$$(\alpha_{it} - \overline{\alpha}_i) = \xi' + (Z_{it} - \overline{Z}_i) + (\varepsilon_{it} - \overline{\varepsilon}_i). \qquad (10b)$$

We use four different dependent variables: the share of an individual's recommended daily caloric intake consumed at an eating occasion; the difference between what an individual's HEI score would have been in the absence of that specific eating occasion and what it was on that day of intake (HMI); the HEI-2005 density score per eating occasion (HMI-2005); and the share of discretionary calories consumed at each eating occasion (SoFAAS). In each model, we include proxies for visceral factors—stress and hunger—and the interaction of these visceral factors with nutrition information as explanatory variables.

[14]This requires us to drop the first eating occasion of each day.

[15]One alternative adopted by both Park and Davis (2001) and Abdulai and Aubert (2004) is to follow the method developed by Lewbel (1997), where the second and third moments of the endogenous variables are used as additional instruments in the IV estimation. We pursued this strategy as well, but found that in all cases, the models were overidentified.

Results

Estimation results, the Hausman test statistic comparing the FE-IV results to the FE results, and the Godfrey-Hutton test for overidentification are reported in table 2. In three out of the four models, the high values on the Hausman tests indicate that there are systematic differences between the instrumental (IV) and non-IV estimates. For estimation of the HMI-2005 scores, we cannot reject the hypothesis that the FE-IV estimates do not differ significantly from the FE estimates. However, the results of the FE-IV model are still consistent under the null hypothesis. Thus, we focus on the FE-IV estimates and discuss only those results that are statistically significant at the 5-percent level or above. However, we are more confident of our model's estimating changes in calories and changes in diet quality using the HMI score because the higher values of the Godfrey-Hutton test indicate that the models for SoFAAS and HMI-2005 may be overidentified, meaning that not all of the instruments are valid.

The interaction terms make it difficult to judge the impact of time between meals and eating food away from home by simply looking at the estimated coefficients. Thus, we ran simulations using the sample means and changing variables of interest to measure the impact of changing specific variables.[16]

[16]For all simulations, we assume the respondent scores 75 on the knowledge index, works 40 hours per week, has gone 4 hours between meals, and eats all of his or her foods at home. We use mean values for meal name and weekend. We then change each assumption to estimate the effect of changing values of interest.

Our results indicate that increasing the interval between meals will have a significant impact on consumption volume and diet quality. In general, as the time interval between eating occasions increases, the calories consumed at the latter meal increase, nutritional quality (HMI, HMI-2005) of that meal decreases, and consumption of discretionary calories (SoFAAS) rises. Our estimates suggest that going 5 hours between meals instead of 4 adds about 52 calories for someone on a diet of 2,000 calories per day; extending that interval from 4 to 6 hours would add about 91 calories. The impact on diet quality is also significant. Recall that a higher HMI or HMI-2005 implies a more nutritious meal or snack and a higher SoFAAS score indicates fewer discretionary calories consumed. Using the HMI score, going from 4 to 5 hours is estimated to reduce diet quality by 0.4 point, while going from 4 to 6 hours lowers this score by 0.6 point. Using the HMI-2005 score, these same changes in the timing between meals lead to a 0.75- and 1.25-point reduction in HMI-2005 score and a 1.7- and 2.7-point reduction in the per-meal SoFAAS score (out of a total score of 20).

The location at which someone makes his or her food choices (share restaurant food) and when these choices are made significantly affect what and how much is consumed. Not surprisingly, people are estimated to eat more caloric meals when eating foods from a restaurant compared with foods prepared at home—about 107 more calories per meal. They also consume more discretionary calories (solid fats, alcohol, and added sugars) when eating meals away from home—our estimates indicate an individual's SoFAAS score would fall by 2 points when eating away from home.

A surprising finding, however, is that overall diet quality is estimated to significantly improve when eating foods prepared away from home. The HMI estimates suggest that meals away from home would add about 5 points

Table 2

Estimation results

FE-IV Estimates[a]	Calories	Healthy Meal Index	Healthy Meal Index 2005	SOFAAS per meal
	Parameter estimates (Standard errors)			
Interval	3.384**	-1.417**	-2.351*	-3.463***
	(1.637)	(0.599)	(1.227)	(0.945)
Interval^2	-0.305***	0.109***	0.137*	0.313***
	(0.0957)	(0.0353)	(0.0718)	(0.0553)
Share restaurant food	0.133***	0.0216***	0.0249*	-0.0296***
	(0.0185)	(0.00686)	(0.0140)	(0.0108)
Brunch	2.935**	0.668	-0.310	-0.0938
	(1.208)	(0.444)	(0.906)	(0.698)
Lunch	5.494***	2.866***	2.869***	0.330
	(0.931)	(0.342)	(0.703)	(0.542)
Dinner	12.46***	4.843***	4.658***	-0.412
	(0.947)	(0.348)	(0.713)	(0.549)
Snack	-8.103***	-0.0609	-4.961***	-0.957***
	(0.564)	(0.207)	(0.426)	(0.328)
Interval*knowledge	0.00784	0.00453	0.00715	-0.00613
	(0.0176)	(0.00639)	(0.0131)	(0.0101)
Interval*work hours	0.0289***	-0.00782**	-0.00402	-0.0141**
	(0.0102)	(0.00376)	(0.00767)	(0.00591)
Sharefafh*knowledge	-0.000730***	-0.000340***	-0.000670***	-0.0000397
	(0.000247)	(0.0000914)	(0.000187)	(0.000144)
Sharefafh*work hours	-0.000610***	0.00000157	0.000286***	0.000268***
	(0.000139)	(0.0000515)	(0.000105)	(0.0000811)
Weekend	1.431***	0.00916	-0.795***	-0.628***
	(0.246)	(0.0904)	(0.185)	(0.142)
Constant	8.153***	4.085***	42.85***	21.05***
	(1.846)	(0.678)	(1.384)	(1.066)
Overall R^2	.2911	0.0724	0.0704	0.0159
Sample size	35,151	35,835	35,452	35,452
Hausman Test Statistic[b]	32.32***	25.95***	14.60	66.36***
Godfrey-Hutton J-statistic[c]	7.03	0.00	10.64**	31.91***

Note: Instruments: Time of eating occasion, lagged values of each endogenous variable. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

[a] Endogenous variables: Interval, Interval^2, Interval*knowledge, and Interval*work hours.

[b] H0: Difference between FE and FE-IV estimates is not systematic.

[c] H0: All of the instruments are valid.

to one's total daily HEI score, whereas the HMI-2005 suggests a meal away from home would add 3 points compared with meals at home.

People eat more at brunch, lunch, and dinner than at breakfast. Lunch and dinner are also estimated to significantly add to daily diet quality—both the HMI and HMI-2005 scores indicate lunches were almost 3 points higher than breakfast, and dinners were over 4 points higher than breakfast. Food consumed as snacks is significantly smaller compared to other eating occasions, but may lower diet quality—both the HMI-2005 and the SoFAAS were significantly lower for snacks.

Examining the interaction of dietary information and visceral factors provides mixed support for our theoretical hypotheses. In all cases, the coefficient on the interval*knowledge variable is not significant. One way to interpret this would be that dietary knowledge has no impact on one's reaction to longer intervals between meals. Or, the length of the interval between meals may have no effect on the relationship between dietary knowledge and food choices.

In support of our hypothesis, however, we find that our proxy for time pressures interacts significantly with the interval between meals (interval*work hours). Our estimates suggest that people who work more hours in a week are also more influenced by the interval between meals than those who work fewer hours. As an individual who works more hours in a week goes longer between meals, he or she will choose a meal that is significantly higher in calories, higher in discretionary calories, and lower in diet quality, as measured by the HMI-2005. At 4 hours between meals, an individual who works 40 hours a week is estimated to eat about 20 percent more calories than someone who is not employed. At 8 hours between meals, the fully employed individual is estimated to eat nearly 40 percent more calories than someone who is not employed.

We also find that a situational change in caloric intake and diet quality is more pronounced among individuals who are less informed about diet and nutrition. A person with a knowledge score of 50 is estimated to increase per-meal caloric intake by about 28 percent when eating away from home, while a person whose score is 100 points is estimated to eat about only 12 percent more calories when eating away from home. Using the 1994-96 measure of diet quality, we find that increasing health information is associated with making healthier choices, both at home and away from home. When eating at home, a person with a knowledge score of 100 scores about 1 point higher on the HMI than someone with a score of 50. However, this difference falls to 0.8 point when eating away from home. This may be because information about nutrient content is more difficult to obtain on foods prepared away from home.

However, when using the HMI-2005 to measure diet quality, we find that diet quality responds differently to knowledge depending on whether a person is eating at home or away from home. At home, a person who scored 100 on the knowledge index scored about 1.43 points higher than someone who scored 50 on the knowledge index. Away from home, however, the person with a perfect knowledge score was estimated to score nearly 2 points lower on the HMI-2005 than someone who scored 50 on the knowledge index. However, it should be noted that in all cases—calories, HMI, and HMI-2005—the estimated effect of this variable is relatively small and not statistically significant.

Contrary to our theoretical hypothesis, the interaction between hours worked and eating away from home was estimated to significantly improve diet choices (share restaurant food*work hours). While individuals who are fully employed are again estimated to eat more calories at each meal than individuals who are not, this difference shrinks as the share of food away from home increases. When eating at home, individuals who work 40 hours a week are estimated to eat about 92 calories more per meal than those who worked 0 hours. When eating away from home, this difference shrinks to 43 calories per meal. Thus, we find that people who report working more hours away from home are also better able to make healthful choices when eating out, perhaps because it is something they do more regularly.

Conclusion

The sharp increase in overweight and obesity among Americans has occurred concurrently with increased awareness and publicity regarding the benefits of a healthy lifestyle. Examining this phenomenon provides an opportunity to incorporate elements of behavioral economics into consumer food choice analysis. In such analysis, both long-term health objectives and short-term situational factors drive individuals' food choices.

The interaction among these long-term goals and short-term situations can then explain seemingly time-inconsistent choices. The resulting theoretical model predicts that when individuals are experiencing strong visceral influences, such as hunger or stress, their information about health and nutrition will have less impact on their actual food choices. It also predicts that individuals who are less informed about health and nutrition, or consume more food prepared away from home, will be more likely to eschew their longrun goals when faced with short-term situational factors such as hunger. The value of this model is that it explicitly identifies elements that increase demand for goods and services that offer more immediate gratification.

The empirical results confirm that incorporating findings from behavioral economics into the analysis of nutrient intake illuminates how situational factors and long-term health objectives affect our food choices. Specifically, when individuals extend the period between meals or consume more of their food away from home, they are significantly more likely to consume more calories at each eating occasion. Going longer intervals between meals, especially when working more hours in a week, also reduces the diet quality of specific meals.

This study also suggests that in the face of visceral influences, one's intentions may have little to no impact on actual food choices. As people change their dietary goals based on prevailing nutritional beliefs, situational factors like hunger and time pressures will continue to interfere with their long-term health objectives. Making specific reference to such situations and suggesting ways to mitigate their effects should enhance the usefulness of educational campaigns designed to improve diet quality. For example, encouraging consumers to take more active control in limiting the interval between meals and choosing nutrient-dense snacks, such as fruits and vegetables, may help them better align their intentions to eat well with their actual behavior. Limiting intake of foods prepared away from home is also estimated to significantly decrease caloric consumption. Thus, another possibility would be to encourage individuals to plan ahead or seek out information about nutrient and caloric content of foods prepared away from home.

References

Abdulai, A., and D. Aubert. 2004. "A Cross-Section Analysis of Household Demand for Food and Nutrients in Tanzania," *Agricultural Economics* 31: 67-79.

Ainslie, G., and N. Haslam. 1992. "Hyperbolic Discounting" and "Self-Control," in *Choice Over Time*, George Loewenstein and John Elster (eds.). New York: Russel Sage Foundation.

Akerlof, G.A. 1991. "Procrastination and Obedience," *American Economic Review* 81(2): 1-19.

Ackman, D. 2005. "Big News on Fat Front," *Forbes Magazine*. January 12.

Arrelano, M., and S. Bond. 1991. "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *The Review of Economic Studies* 58(2): 277-297.

Barrett, C.B. 2002. "Food Security and Food Assistance Programs," in *Handbook of Agricultural Economics, Volume 2*, B. Gardner and G. Rausser (eds.). Elsevier Sciences.

Behrman, J.R., and A.B. Deolalikar. 1990. "The Intrahousehold Demand for Nutrients in Rural South India: Individual Estimates, Fixed Effects and Permanent Income," *The Journal of Human Resources* 25(4): 665-696.

Bellisle, F., and M-F. Rolland-Cachera. 2001. "How Sugar-Containing Drinks Might Increase Adiposity in Children," *The Lancet* 357: 490-491.

Bhargava, A., L. Franzini, and W. Narendranathan. 1982. "Serial Correlation and the Fixed Effects Model," *The Review of Economic Studies* 49(4): 533-549.

Bowman, S.A., M. Lino, S.A. Gerrior, and P. Bastiosis. 1998. *The Healthy Eating Index:1994-1996.* U.S. Department of Agriculture, Center for Nutrition Policy and Promotion. CNPP-5. http://www.cnpp.usda.gov/hei94-96.PDF

Cawley, J. 2004. "An Economic Framework for Understanding Physical Activity and Eating Behaviors," *American Journal of Preventive Medicine* 27(3S): 117-125.

Centers for Disease Control and Prevention. 2003."1991–2001 Prevalence of Obesity Among U.S. Adults, by Characteristics." http://www.cdc.gov/nccdphp/dnpa/obesity/trend/prev_char.htm

________. 2005. "Chronic Disease Overview." http://www.cdc.gov/nccdphp/overview.htm

Cohen, J., P. Cohen, S. West, and L. Aiken. 2003. *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences* (3rd ed.). Mahwah, NJ: Erlbaum.

Cutler, D.M., E.L. Glaeser, and J.M. Shapiro. 2003. "Why Have Americans Become More Obese?" NBER Working Paper 9446. http://www.nber.org/papers/w9446

Evans, W.N., L.M. Froeb, and G.J. Werden. 1993. "Endogeneity in the Concentration-Price Relationship: Causes, Consequences and Cures," *The Journal of Industrial Economics* 41(4): 431-438.

Food Institute Reports. 2004-2005. *Weekly Newsletter of The Food Institute*, Elmwood Park, NJ, March 10, 2004, and January 31, 2005, editions.

Food Marketing Institute. 2001a "Reaching Out to the Whole Health Consumer," *Prevention Magazine*. Rodale Incorporated.

___________. 2002. *Shopping for Health*, Washington, DC. http://www.fmi.org

Frederick, S., G. Loewenstein, and T. O'Donoghue. 2002. "Time Discounting and Time Preference: A Critical Review," *Journal of Economic Literature* 40: 351-401.

Green, W.H. 1990. *Econometric Analysis.* New York, Macmillan Publishing Company.

Grossman, M. 1972. "On the Concept of Health Capital and the Demand for Health," *The Journal of Political Economy* 80: 223-225.

Guenther, P.M., J. Reedy, S.M. Krebs-Smith, B.B. Reeve and P.P. Basiotis. 2007. *Development of the the Healthy Eating Index-2005: Technical Report.* Center for Nutrition Policy and Promotion, U.S. Department of Agriculture.

Herman, C.P., and J. Polivy. 2003. "Dieting as an Exercise in Behavioral Economics," *Time and Decision*. George Lowenstein, Daniel Reed and Roy Baumeister (eds.), New York: Russel Sage Foundation.

Hoch, S.J., and G.F. Loewestein. 1991. "Time-Inconsistent Preferences and Consumer Self Control," *The Journal of Consumer Research* 17(4): 492-507.

Institute of Medicine of the National Academies. 2002. "Energy," *Dietary Reference Intakes for Energy, Carbohydrate, Fiber, Fat, Fatty Acids, Cholesterol, Protein, and Amino Acids (Macronutrients).* Washington, DC: The National Academies Press.

Kuchler, F., and B-H Lin. 2002. "The Influence of Individual Choices and Attitudes on Adiposity," *International Journal of Obesity* 26:1017-1022.

Laibson, D. 2001. "A Cue-Theory of Consumption," *The Quarterly Journal of Economics* 116: 81-119.

_______. 1997. "Golden Eggs and Hyperbolic Discounting," *Quarterly Journal of Economics* 112: 443-477.

Lewbel, A. 1997. “Constructing Instruments for Regressions with Measurement Error when no Additional Data are Available, with an Application to Patents and R&D,” *Econometrica* 65: 1201-1213.

Loewenstein, G. 2000. “Emotions in Economic Theory and Economic Behavior,” *The American Economic Review* 90(2): 426-432.

___________. 1996. “Out of Control: Visceral Influences on Behavior,” *Organizational Behavior and Human Decision Processes* 65(3): 272-292.

Mancino, L., and J. Kinsey. 2004. *Diet Quality and Calories Consumed: The Impact of Being Hungrier, Busier, and Eating Out.* WP-04-02. The Food Industry Center, University of Minnesota.

Mullainathan, S., and R. Thaler. 2000. “Behavioral Economics.” NBER Working Paper #7984.

O’Donoghue, T., and M. Rabin. 2001. “Choice and Procrastination,” *Quarterly Journal of Economics* 116: 121-160.

____________________. 1999. “Doing it Now or Later,” *American Economic Review* 89: 103-124.

Park, J., and G.C. Davis. 2001. “The Theory and Econometrics of Health Information in Cross-Sectional Nutrient Demand Analysis,” *American Journal of Agricultural Economics* 83: 840-851.

Pitt, M.M., M.R. Rosenzweig, and N. Hassan. 1990. “Productivity, Health and Inequality in the Intrahousehold Distribution of Food in Low-Income Countries,” *The American Economic Review* 80(5): 1139-1156.

Read, D., and B. van Leeuwen. 1998. “Predicting Hunger: The Effects of Appetite and Delay on Choice,” *Organizational Behavior and Human Decision Processes* 76(2): 189-205.

The Surgeon General’s Call To Action To Prevent and Decrease Overweight and Obesity. 2001. http://www.surgeongeneral.gov/news/pressreleases/pr_obesity.PDF

Thaler, R.H. 1981. “Some Empirical Evidence on Dynamic Inconsistency,” *Economic Letters* (8): 201-207.

Thaler R.H., and H.M. Shefrin. 1981 “An Economic Theory of Self Control,” *Journal of Political Economy* 89(2): 392-410.

United States Department of Agriculture, Center for Nutrition Policy and Promotion (CNPP). 2006. “Development of MyPyramid,” http://www.cnpp.usda.gov/MyPyramidDevelopment.htm

United States Department of Agriculture. 2006. “USDA 2006 Budget Summary,” http://www.usda.gov/agency/obpa/Budget-Summary/2006/FYbudsum.pdf

Variyam, J.N. 2003. *Factors Affecting the Macronutrient Intake of U.S. Adults*. U.S. Department of Agriculture, Economic Research Service, Technical Bulletin No. 1901.

Variyam, J.N., J. Blaylock, and D. Smallwood. 1995. *Modeling Nutrient Intake: The Role of Dietary Information*. U.S. Department of Agriculture, Economic Research Service, Technical Bulletin No. 1842.

_______1996. "A Probit Latent Variable Model of Nutrition Information and Dietary Fiber Intake," *American Journal of Agricultural Economics* 78: 628-639.