Soda versus Cereal and Sugar versus Fat:
Drivers of Healthful Food Intake and the Impact of Diabetes Diagnosis

by

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Abstract

The authors examine how several consumer characteristics and marketing factors affect the healthfulness of households’ food-for-home intake, how the intake changes when there is a diagnosis of Type 2 diabetes, and whether the effects of the consumer and marketing factors change after diagnosis. They use a combination of households’ longitudinal grocery purchase information, survey data on their health status, and nutrition content of thirteen of the largest U.S. packaged food categories. They find that households with higher education and nutrition interest take in fewer calories, sugar, and total carbohydrates than others but those with higher self-control take in more because they offset lower intake of “unhealthy” categories like soft drinks with higher intake of “healthy” categories like cereal. Intake of sugar and carbohydrates decreases significantly in response to diagnosis but intake of fat and sodium increases. Education, nutrition interest, and self-control are not associated with healthier changes in response to diagnosis, but younger and higher income households, and those where the patient is female do make healthier changes. Implications of these and other findings for marketers, consumer researchers, and public health professionals are discussed.

Keywords: Health status, drivers of food choice, health halo bias, diabetes, self-control, household grocery shopping
We face a serious public health problem in the U.S. and around the world -- growing obesity and the consequent increase in incidence of diabetes, hypertension, and heart disease. According to the Centers for Disease Control and Prevention, about a third of U.S. adults are obese (Flegal et al. 2010). The incidence of diabetes has reached one in ten people and may be as high as one in three by 2050 (CDC 2010). It is also increasing at alarming rates in countries like India and China as those consumers adopt a more western diet. The burden of this shows up not only in economic costs of healthcare but also in reduced quality of life. The public health and food decision making literatures point to several reasons for the obesity epidemic. A widely noted factor is the easy availability and heavy marketing of calorie dense processed foods and sugar beverages. This has placed packaged food marketers in the cross-hairs. Indeed, public health is perceived as one of the most important issues facing these companies over the next several years (Promotion Optimization Institute Conference, Chicago, March 2011).

Consumer researchers, public health professionals, and marketers alike need to understand the drivers of food choice, the extent to which those with health problems make necessary changes in their diet, and how best to stimulate these changes. Our research addresses these issues in the context of Type 2 diabetes. Specifically, we answer three research questions. First, how do various factors identified in the literature as barriers or enablers of healthy choices affect households’ regular “food for home” intake? Second, how do households alter their intake in response to a household member’s change in health status with a diagnosis of diabetes? Third, how, if at all, does the effect of different barriers/enablers change after diagnosis? We compile a unique dataset to answer these questions, combining four years of monthly grocery purchases of a national panel of U.S. households with survey data on the health status of the panelists and information on the nutrient content of thousands of food items purchased by the panelists. For
each of our three research questions, we highlight below how our work contributes to the
literature and the kinds of insights it delivers.

*What is the role of various consumer and marketing factors in driving the healthfulness of food intake at home?* Research in the public health, food decision making, and health-protective behavior domains has examined several barriers and enablers that consumers face in making good dietary choices, controlling consumption, and pursuing health goals. Apart from aggregate comparisons of prices and availability of healthy foods in different demographic areas (French 2003; Horowitz et al. 2004; Jetter and Cassady 2006), however, most of this work is conducted in a lab setting manipulating single variables. While this has the important benefit of tight control, it is important to validate the findings with actual purchase behavior in the marketplace where consumers have to manage multiple goals, stimuli, and constraints.

We contribute to the literature by integrating the barriers/enablers that drive food choices into a model and quantifying their relative impact on the healthfulness of actual food intake at home. Further, we assess how these factors affect the quantity versus quality of intake by examining not only the amount but also sugar, total carbohydrate, fat, sodium, and calorie intake from the largest food categories that vary in perceived (and actual) healthfulness. We find, for example, that households whose heads are highly educated and interested in nutrition have lower intakes of all unhealthy nutrients but the impact of these and other consumer characteristics is much smaller than that of price. Further, households whose heads exert self-control, e.g., by not eating fast foods or late at night, actually take in more sugar, total carbohydrates, and calories. This is because they more than offset lower intake of unhealthy categories like carbonated soft drinks with higher intake of categories like cereal that have a positive health perception.
How does diabetes diagnosis change the healthfulness of food intake at home? The nutrition and medical literature examines diet changes of patients diagnosed with diabetes using food-frequency questionnaires or short-term diary records/dietary recalls, often in small samples. However, not only is recall inaccurate, there is also evidence that desirable dietary intake is over-reported (Salvini et al. 1989) and overall food consumption is under-reported, especially by obese patients (Salle, Ryan and Ritz 2006). Further, these studies only examine intake after diagnosis or the change from before to after diagnosis. Without accounting for trends and other market factors with a control group, the effect of diagnosis cannot be isolated. One consequence of these limitations is that there is substantial variation in findings across studies. They consistently report lower sugar intake among diabetics, but some studies find lower fat intake (Niewind et al. 1990; van de Laar et al. 2004), some find higher fat intake (Shimakawa et al. 1993; Virtanen et al. 2000), while others find no significant change in fat intake (Helmer et al. 2008). Similarly, some find lower sodium intake (Niewind et al. 1990) while others find the opposite (Munoz-Pareja et al. 2012; Vitolins et al. 2009).

We contribute to this literature by capturing the impact of diagnosis on actual food intake of a large national sample, doing so in a way that is unobtrusive and relatively long-term, and combining the internal validity of a before-and-after-with-control group design with the external validity of real marketplace behavior. We also provide insight not just on average change in nutrient intake but on the types of categories the change is sourced from and how it varies with patient characteristics. We find, for example, that households reduce sugar intake but increase fat intake. The sugar reduction is sourced from beverages where low-sugar alternatives are available but not from hedonic categories like cookies and ice cream. The increase in fat comes from categories like processed meat and salty snacks that are known to be unhealthy for diabetics.
but are low in sugar. Households where the patient is female make healthier changes across a broader set of categories than households where the patient is male. Also, households where the patient is not taking prescription (hereafter Rx) medication for diabetes make smaller changes across a wider set of food categories though their changes in total nutrient intake are similar to households where the patient is Rx treated.

*Does the impact of various barriers and enablers change after disease diagnosis?* The impact of consumer characteristics and marketing factors on health behaviors and food choices has been studied in the context of risk prevention not disease management. Further, this research has focused mainly on behavior initiation in one-shot choices, not sustained behavior change. However, findings from the one-shot risk prevention context may not apply to the sustained disease management context. For instance, the extent to which consumers engage in automatic versus deliberative or implemental processing (Gollwitzer and Bayer 1999), are motivated to act on health-related knowledge (Moorman and Matulich 1993), or deplete their self-control (Lord et al. 2010) may be quite different when a health threat has become a reality.

We contribute to this literature by comparing the impact of various barriers/enablers before and after diagnosis, i.e., in normal circumstances versus in the context of disease management. Only if a factor’s impact changes after diagnosis does it have the potential to explain why some households manage the disease better than others. Also, because we use several months of data before and after the year of diagnosis, our analysis speaks to sustained behavior change instead of immediate behavior initiation (Rothman et al. 2011). We find that those with high self-control or greater education and nutrition interest do not respond any better to diagnosis than others. Thus, these variables matter less in actual disease management than in risk prevention. However, households with higher incomes and younger patients make healthier
changes, cutting sugar and carbohydrates more. Fortunately, those whose intake of sugar was higher to begin with make bigger reductions. Family influence also matters. The size of the household doesn’t affect sugar reduction, which seems to be the primary goal of diabetics, but bigger families increase fat intake even more and don’t reduce carbohydrates as much as others.

The rest of the paper is organized as follows. We begin with our conceptual framework, identifying the key factors that influence the healthfulness of food intake and developing hypotheses about their impact. Next, we describe our data and measures and present the methodology by which we examine our three research questions. This is followed by our empirical findings, and we conclude the paper with the implications of our findings for marketers, consumer behavior researchers, and public health professionals.

**Conceptual Framework and Hypotheses**

Figure 1 depicts the conceptual framework that guides our analysis of the research questions identified previously. It has four key elements. The first is the outcome of interest in our work, i.e., the healthfulness of food-for-home intake. The second element consists of factors that are potential barriers or enablers for healthy choices. Their impact on the healthfulness of households’ intake is the focus of our first research question (RQ1 in the figure). The third element is the extent to which a change in health status brought about by diagnosis motivates households to make changes in intake (RQ2). The final element is the possibility that diagnosis may moderate the impact of the barriers/enablers (RQ3). In addition to these main elements, the framework shows that variation in food intake across households and over time may be driven by factors such as household requirements, seasonal effects, and regional differences, which need to be controlled for. Finally, it recognizes that diagnosis may change the level of some consumer
factors, as depicted by the dotted arrow from diagnosis to factors. Next, we develop the main elements of our framework in more detail.

< Insert Figure 1 About Here >

**Healthfulness of Food Intake**

Dietary guidelines for general health (USDA 2010) recommend that Americans should (a) reduce their total calorie intake in line with desirable body weight; (b) reduce intake of fat (especially saturated and trans fats), added sugar, sodium, and refined grains; and (c) eat more fat-free or low-fat dairy, fresh vegetables and fruit, whole grains, beans/legumes, and fish. Dietary guidelines for managing Type 2 diabetes (American Diabetes Association 2008, 2012; Mayo Clinic 2012) are very similar to these general guidelines except that there is a stronger emphasis on controlling carbohydrate intake. Patients are advised to eat fiber rich foods that are low in fat and calories and control their carbohydrate intake to manage blood glucose levels and reduce weight. In addition, they are asked to reduce sodium and fat intake because they are at higher risk for hypertension and heart disease. In terms of specific types of foods, they are advised to (a) reduce high calorie snacks and desserts; (b) avoid sugary drinks including regular soda and fruit drinks; (c) replace high fat dairy with low and fat-free dairy, processed grains with whole grains, processed meats with lean meats and skinless poultry; (d) eat fresh non-starchy vegetables and fruit, beans/legumes, and fish. In general, they are asked to replace processed food intake with unprocessed and fresh foods, and limit portion sizes even of healthful foods to control body weight.

These guidelines show that the healthfulness (or lack thereof) of food intake refers to the intake of calories, and nutrients like sugar, total carbohydrates, fat, sodium, and fiber. Much of the emphasis is on limiting calories and unhealthy nutrients. The only nutrient (other than
vitamins and minerals from fresh produce) that consumers are asked to increase is fiber. In line with this emphasis, our discussion focuses on the reduction of unhealthy intake.

Since the dietary guidelines underscore that the source of calories and nutrients also matters, it is important to study not just the total intake but the food categories from which it is sourced. Intake from specific categories is also important to study because prior research has shown that consumers categorize food categories as unhealthy or healthy, and their search, choices, and consumption are driven by whether a category has a healthy perception. For instance, Moorman et al. (2004) find that consumers who believe they are knowledgeable about nutrition are more selective about healthy versus unhealthy food categories than they are about less or more healthy options within a category. Wansink and Chandon (2006), Chandon and Wansink (2007), and Provencher, Polivy, and Herman (2009) find that consumers under-estimate calories and over-eat when a food has a positive health halo. Chernev and Gal (2010) and Chernev (2011) find that consumers lower their estimate of the total calories in a meal when a healthy option is added to an unhealthy meal, especially when they are exerting dietary restraint. Thus, these lab based studies show that consumers focus more on quality (healthy versus unhealthy categories) and less on the quantity they consume, especially of categories they perceive as being healthy.

Separating intake from categories that are perceived as more versus less healthy will permit us to see if these lab findings extend to food-for-home purchases in the marketplace, and provide insights about how adherence to dietary guidelines is helped or hindered by the health perceptions of different foods.

**Barriers/Enablers for Healthy Food Intake (RQ1)**

If all foods were equal in appeal to the human palate, availability, and affordability, and if consumers were knowledgeable about their healthfulness, they would choose healthy foods. But
that is not the case – sweet and fatty foods taste much better and are harder to resist; highly processed energy-dense foods are cheaper and more widely available; consumers don’t have sufficient knowledge to choose healthy foods; nor are they good at monitoring how much they eat. We reviewed the nutrition and public health literature as well as the consumer behavior literature on food decision making and health protective behavior to identify the key factors that enable healthy food choices or act as barriers. These factors are listed in Figure 1 and we discuss each one below. The effects of these factors can be stated in terms of either healthy or unhealthy intake. Since our substantive interest is in reduction of unhealthy intake, we state our hypotheses with respect to unhealthy intake.

**Health Knowledge:** This is the extent to which consumers have enduring health-related cognitive structures (Moorman and Matulich 1993). In order to make good choices, they need information about which foods are healthy and the cognitive ability and interest to utilize it (Bublitz, Peracchio and Block 2010). We expect health knowledge to have a negative effect on unhealthy intake, especially from categories that are perceived as unhealthy (Moorman et al. 2004).

**Self-control:** This is a person’s ability to over-ride natural and automatic desires and behaviors and pursue long-term goals at the expense of short-term temptations (Bauer and Baumeister 2011, p65). Perceived self-control has a positive effect on intent to engage in healthy behaviors (Bandura 1977; Rogers 1983). However, it is actual self-control that directly drives healthy choices (Ajzen 2002). Self-control is especially needed to avoid sweet, fatty and salty foods (Chandon and Wansink 2011; Drewnowski 1995), and a positive health halo bias may weaken the effect of self control for categories that are perceived as healthy. Therefore, we
expect self control to have a negative effect on unhealthy intake, mainly from categories that are perceived as unhealthy.

**Financial constraints:** This is the degree to which financial considerations prevent people from engaging in healthy behaviors. The constraints may be through high costs or through inability to pay, both of which are barriers to healthy eating (Bihan et al. 2010; Horowitz et al. 2004; Jetter and Cassady 2006). Clearly, those with discretionary money to spend on healthier foods are not constrained to buy less expensive unhealthy foods but recent research shows that such people just consume more of everything – both good and bad (French, Wall, and Mitchell 2010). Therefore we expect cost of unhealthy foods to have a negative effect on their intake and ability to pay to have a positive effect on unhealthy (as well as healthy) intake.

**Health status:** This refers to consumers’ wellness of body and mind and reflects their physical and mental ability to engage in healthy behaviors (Moorman and Matulich 1993). It includes not just actual health but also consumers’ perceptions of their health, which have been shown to drive various health-related behaviors (Martin 1997; Millunpalo et al. 1997). Health status may be associated with better choices if consumers work to preserve this state, but, it could also be that healthy consumers become complacent and/or unhealthy consumers feel pressure to improve their health. Therefore, we cannot predict the effect of health status.

**Social influence:** This refers to the influence of others in encouraging or interrupting healthy choices (see review by Bublitz, Peracchio, and Block 2010). It can result in overeating due to social facilitation of others or in restrained eating due to impression management (Hermann, Ruth and Polivy 2003). Social influence can play a role through family members at home, and those around whom food is consumed in public. In the context of eating at home with one’s family, the social facilitation effects are likely to overwhelm impression management
effects. Also, the existence of others in the family increases total food requirement. Thus, we expect family influence to have a positive effect on unhealthy (as well as healthy) intake.

*Prior Food Habits:* Much of a household’s grocery purchase behavior is automatic and habit driven (Ji and Wood 2007; Khare and Inman 2006). We expect the effect of prior food habits to be positive since consumers should purchase more of what they are habituated to.

*Availability of Healthy Food:* This refers to how accessible different foods are to consumers. Consumers in low income and inner city areas have limited access to healthy foods (Horowitz et al. 2004; Jetter and Cassady 2006) while easy availability of calorie-dense processed foods increases their consumption (Chandon and Wansink 2011; Kessler 2009). The greater the availability of healthy food categories and healthy options within categories, the less we expect unhealthy intake to be.

*Changes in Intake Due to Disease Diagnosis (RQ2)*

As discussed previously, the dietary guidelines for managing Type 2 diabetes recommend control of sugar, total carbohydrates, fat, and sodium. Thus, we expect to see a decrease in

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Table 1 summarizes the above discussion by listing conceptual definitions and hypotheses for each factor. We note that food choice and consumption is also influenced by sensory and other characteristics of the food itself, package characteristics, and mood (see reviews by Bublitz, Peracchio, and Block 2010 and Chandon and Wansink 2011). Since we conduct our analysis for each of several food categories, we will draw on category characteristics to explain differences in results across categories. Finally, since our focus is on total intake over a sustained period of time, individual package characteristics and consumers’ situational frame of mind is not relevant.
intake of these nutrients after diagnosis, especially from categories that are perceived as being unhealthy for diabetics. Since sugar most directly increases blood glucose level, we expect the largest decrease in sugar intake. Further, since diabetics control carbohydrates intake and some low carbohydrate foods like cheese and processed meat are high in fat, we expect the smallest reduction in fat intake. Also, we expect to see smaller reductions in intake from hedonic foods which are harder to resist (Chandon and Wansink 2011) and may be sought out to offset the emotional distress and mortality salience caused by diagnosis (Ferraro, Shiv, and Bettman 2005).

Gender of the diagnosed person may influence response. Men exhibit more risky and fewer healthy behaviors than women (Liang et al. 1999; Wardle et al. 2004) and they give lower priority to health in choosing foods (Fagerli and Wandel 1990). Further, women tend to scrutinize and process detailed information while men rely on schema and heuristic cues (Meyers-Levy 1989; Meyers-Levy and Sternthal 1991). Thus, we expect more reduction in unhealthy intake across more categories when the diagnosed household member is female.¹

Finally, although diabetes is a serious and chronic disease, there is variation in the severity of the symptoms and consequences. According to protection motivation theory (Rogers 1983; Ajzen 1988), the severity of negative outcomes increases motivation for behavior change. Thus, we expect more reduction in unhealthy intake when the disease is severe.

Interaction of diagnosis with barriers/enablers (RQ3)

For any of the barriers/enablers in our framework to explain why some households make better changes than others, their effects must be moderated by diagnosis. But, why should their impact change as a result of diagnosis? A serious disease like diabetes should motivate people to

¹ Since the gender and disease severity of the patient are only known after diagnosis, main effects of these factors on food intake are not applicable.
take better care of their health and motivation promotes information processing, attitudinal, and behavioral change (MacInnis, Moorman, and Jaworski 1991; Moorman and Matulich 1993).

The logic of diagnosis=higher motivation suggests that diagnosis will motivate consumers to better use their health knowledge and health status to reduce unhealthy intake. Indeed, Moorman and Matulich (1993) argue that such abilities have an impact on health-related behaviors only under conditions of high motivation. Thus, we expect the interactions of diagnosis with health knowledge and health status to be negative. Similarly, when consumers are motivated, they should make better use of the healthy foods available to them, so we expect the interaction with healthy food availability to be negative.

However, research on self-control shows that success bolsters confidence and further action while failure undermines both (Rothman et al. 2011). The “failure” of having got the disease despite high self-control may interrupt continued efforts. Also, managing multiple goals related to diabetes (e.g., eat better, lose weight, exercise) taxes cognitive resources and resource depletion interrupts self-control (Bauer and Baumeister 2011; Bublitz, Peracchio, and Block 2010; Vohs and Heatherton 2000). Given this tension between increased motivation and negative feedback/ resource depletion, the interaction of diagnosis with self-control is an empirical question.

Diagnosis should also moderate the effect of financial constraints. On the cost side, realizing that they must improve their diet to manage the disease should make households less likely to buy unhealthy products simply because they are cheap but additional medical costs may make them more price-sensitive. Therefore, the interaction of diagnosis with the cost side of financial constraints cannot be predicted. However, ability to pay should help households to substitute healthier (and more expensive) products for unhealthy ones once they realize the
importance of diet. Hence, we expect the interaction of diagnosis with the ability to pay side of financial constraints to be negative.

Diagnosis can moderate the effect of social influence in multiple ways. For at home eating, if family influence makes it harder for the patient to change, the interaction should be positive. However, if family members also make healthy changes, the interaction should be negative (greater reduction in unhealthy intake). Thus, the direction of the interaction is an empirical question. Finally, there is more room for improvement if unhealthy intake is habitually high to begin with. Thus, we expect the interaction of diagnosis with prior food habits to be negative. Our hypotheses for these interactions are also summarized in Table 1.

**Data and Methodology**

We combine four sources of data to conduct our analysis. The first is a nationwide home-scan panel dataset from IRI which contains weekly grocery purchases from January 2006 to December 2009. These purchases, which we aggregate to the monthly level, cover the complete set of IRI packaged goods categories and encompass not just grocery and drug stores but also mass stores and warehouse clubs. The second is a health survey administered by IRI in November of each year from 2005 to 2008 that includes information on each household member’s health status and health related perceptions and behaviors. The third is a database of nutrient content of individual items within the food categories we analyze. The fourth is a consumer survey we conducted to determine how healthful each of the food categories in our study is perceived to be.

< Insert Table 2 About Here >

**Selection of Food Categories**
Our analysis is based on thirteen of the largest packaged food and beverage categories in the US. Although fresh vegetables and fruit are recommended in all dietary guidelines, scanner data only track packaged foods with UPC codes. Therefore, we are unable to study intake of fresh foods. Since packaged foods are generally processed, and dietary guidelines emphasize control of calories and unhealthy nutrients from processed foods, we focus on intake of calories, sugar, total carbohydrates, fat, and sodium. Table 2 provides information on average nutrient content and calories per serving of the thirteen categories. Serving size is obtained from the eCFR (2011) database of reference amounts of foods customarily consumed per eating occasion. We do not use the serving size on product labels because manufacturers can manipulate those to make the nutrients per serving appear reasonable (Mohr, Lichtenstein, and Janiszewski 2012).

As the table shows, these categories vary significantly, especially in sugar and fat content. Further, it is interesting to note differences in the standard deviation of nutrient content for various categories. For instance, CSD, juice and yogurt have high standard deviations of sugar content in line with the availability of less versus more unhealthy SKUs, while ice cream and cookies have relatively low standard deviations showing the lack of healthier alternatives in these categories. Interestingly, processed meats and frozen dinners have relatively large standard deviations of fat and calories showing that these categories do offer less versus more unhealthy

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2 We did examine unprepared frozen and canned vegetables. Main effects of our model variables on number of servings were largely as expected but there was no significant change in intake due to diagnosis. Since they are a very small source of sugar, fat, calories etc., we have not included them in our analysis. Among the 20 largest IRI categories, we deleted bread because our nutrient database does not provide adequate coverage of that category, and beverages like bottled water, tea, and coffee because they are small sources of the nutrients we study.

3 The guidelines recommend higher fiber intake, but we do not study it as a separate nutrient because the categories in our study don’t contain much fiber. The American Diabetes Association states that half the grams of fiber can be subtracted from total grams of carbohydrates if an item contains more than 5 grams of fiber per serving. We did our analysis with this modified measure of carbohydrate intake and found our results were unchanged. We also did our analysis with saturated fat instead of total fat and found similar results. Finally, we do not study protein because the guidelines do not recommend a change in protein intake.
SKUs. These differences highlight the importance of examining not only the amount of a category but also the calorie and nutrient intake from it. They will also be helpful subsequently in understanding why there is greater reduction of unhealthy intake after diagnosis in some categories than in others.

In order to determine which categories have a less versus more positive health perception in the minds of consumers, we conducted a survey of US adults using an online panel. In our sample of 190 adults, 55% were male, 49% had a college degree, 37% were 45 years or older, 35% had a household income of $65,000 or more, and 34% knew someone in their immediate circle of relatives and friends with Type 2 diabetes. We asked these consumers to rate each of the categories in our study on how healthy they think it is. Following Moorman and Slotegraaf (1999), we used a scale from 1 (Not at all healthy) to 7 (Very healthy). We first asked them to rate the healthfulness of all the categories in general, and then their healthfulness for persons with Type 2 diabetes. Average ratings from this consumer survey are also included in Table 2.4

We note that (a) there is reasonable but not perfect consistency between the objective nutrient content of the categories and consumers’ perceptions of their healthfulness; and (b) there are a few differences in perceived healthfulness of categories in general versus for diabetes patients. In particular, high sugar and high fat categories like CSD, ice cream, cookies, salty snacks, and frozen dinners are perceived as being unhealthy, with average ratings not greater than 3, both in general and for diabetes. Juice, cereal, and crackers are not considered unhealthy in general but their perceived healthfulness is significantly lower for diabetes, which makes sense given their carbohydrate content. In our empirical analysis, we will distinguish between

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4 These averages are fairly consistent with those obtained from nutritionists by Moorman and Slotegraaf (1999), although some categories like cereal and frozen dinners are rated lower in our survey, presumably since dietary guidelines now recommend greater control of carbohydrates.
categories that are perceived as more versus less unhealthy, using the general healthfulness perceptions for examining main effects and the diabetes specific healthfulness perceptions for examining response to diagnosis. In the remainder of this paper, we use “unhealthy” and “healthy” categories with reference to these consumer perceptions of healthfulness.

Selection of Sample

Beginning with the 24,390 households in our panel with at least two years of survey and purchase data, we first create two groups – those with diabetes in the household (5980) and those without (18410). We draw our “diabetes households” from the former and our “control households” from the latter. The health survey provides information on whether a household member has diabetes at the time of the survey, i.e., in November of a given year. Thus, if no member reported having diabetes in November 2006 but one or more reported having the disease in November 2007, we know they were diagnosed sometime during Nov ‘06 –‘07. To ensure long enough pre- and post-diagnosis periods, we include in our “diabetes group” households with a diagnosis during Nov ‘06-‘07 or during Nov ‘07-‘08. Since we do not have the exact date of diagnosis and to make sure we have a clean pre- and post-period, we do not include in our analysis the year during which diagnosis occurred. Finally, to ensure that the diagnosed patient’s characteristics will be represented in our model (which uses the average values for the household heads), we only include those households where the patient is a household head. This procedure provides a sample of 578 diabetes households, 48.8% of which have male diagnosed member.

We then use propensity scores (Rosenbaum and Donald 1983) to match the diabetes households to control households. Matching each of the diabetes households to their two nearest neighbors using a minimum caliper criterion of 1% without replacement provides a control group of 1155 households. The matching is done on average values of all demographics and other
characteristics for the household heads. Also, we select, as far as possible, the same pre- and post-periods for a control household as for the diabetes household to which it is matched. T-tests confirm that there is no significant difference between the two groups on means of the matching variables. Details of the matching procedure are available upon request.

< Insert Table 3 About Here >

**Measures**

Our measures of the dependent variables and the barriers/enablers in the conceptual framework of Figure 1 are summarized in Table 3, along with representative studies from the literature that use similar measures. A few points regarding our measures deserve note. First, the dependent variables are measured as monthly purchases of the household. Second, measures of all the consumer characteristics are averaged for the household head(s), who are defined as (up to two) persons responsible for most household decisions. All the patients in our sample are household heads, so the patient’s own characteristics are always captured.\(^5\) Third, Figure 1 allows for a potential impact of diagnosis on consumer characteristics (e.g., health status, self control). In our data, these changes are too small to model. Still, we use pre-diagnosis values of all measures to ensure that our results are not confounded by these changes.

Fourth, all the large IRI food categories are available throughout the period to all panelists in the stores where they shop, so availability of healthy categories is not included in our model. However, as discussed previously, there is variation across categories in the availability of less versus more healthy SKUs and we use this to explain our results across categories. Fifth, we measure disease severity by whether the patient is being Rx treated since the likelihood of

\(^5\) We also repeated all our analysis using only the diagnosed member’s characteristics and found no substantive difference in results.
taking Rx drugs is higher if the disease is severe (63.8% are Rx treated in our sample). Although Bolton and colleagues (2006 and 2008) show that drugs may boomerang whereby those who use them reduce healthy behavior, we expect that the severity effect hypothesized previously (i.e., greater reduction in unhealthy intake) is more likely for a serious disease.

The hypothesized effects of the measures in Table 3 naturally follow those of the underlying constructs discussed previously and summarized in Table 1. However, a few deserve elaboration. First, non-price promotions act as a proxy for a price cut under automatic and low cognition decision making, which is typical of normal grocery shopping (Inman, McAlister, and Hoyer 1990), so their main effect is expected to be positive. However, we expect a negative interaction of diagnosis with non-price promotions since such promotions should become less effective as diagnosis makes consumers more deliberative in their shopping. Second, we expect a positive interaction of diagnosis with age in line with the arguments regarding health status in the previous section (older people are lower in health status and the interaction with health status was hypothesized to be negative). Additionally, the disease is clearly more aggressive if a person becomes diabetic at a younger age and he/she is likely to be exposed to its ravaging consequences over a longer period. Therefore, younger people should be more motivated to reduce unhealthy intake after diagnosis.

Model

We estimate equations for total monthly intake of calories and four nutrients across the thirteen categories (five equations) as well as monthly amount (number of servings), calorie, and nutrient intake for each individual category (six equations per category). This allows us to examine how households change (a) their total intake of calories and nutrients from the largest food categories, (b) the amount of each category, and (c) the extent to which they choose
healthier options (e.g., lower sugar, lower fat) within the category. The basic model to quantify the "difference-in-difference" response to diagnosis for each dependent variable is as follows:

$$Y_{hncm} = \beta_0 + \beta_1 \text{Diab}_h + \beta_2 \text{Post}_{hm} + \beta_3 \text{Diab}_h \times \text{Post}_{hm} + e_{hncm} \tag{1}$$

where $Y$ is the dependent variable of interest (e.g., monthly grams of sugar from a category) the subscripts refer to household $h$, variable (e.g., servings, calories, sugar, etc.) $n$, food category $c$, and month $m$. “Diab” is a dummy variable that equals 1 for diabetes households. “Post” is a dummy variable that equals 1 if the month is in the post-diagnosis period. $\beta_3$ is the difference-in-difference response to diagnosis, i.e., the amount by which the pre- to post-period change in average $Y$ differ for the diabetes versus control group.\(^6\)

To examine whether response differs depending on the gender and prescription treatment status of the diagnosed member, we include interactions of Female and NotRx (not treated by Rx drugs) dummy variables with Diab*Post. Further, since we want to quantify the effects of the variables in Table 3 on household intake and determine whether these effects change after diagnosis, we include main effects of those variables and their interactions with Diab*Post. For completeness, we also include lower order interactions with Diab and Post. Also, to improve statistical power, we control for other variables due to which purchases may vary temporally or across households. These control variables are market and month dummies, weighted average price and promotion of all the categories except the focal one to account for budget constraint effects, and average monthly expenditure on all IRI food categories in the initialization period to account for unobserved differences in households’ total needs. This results in our final model (where the variables are as defined in Table 3):

\(^6\)There is a subscript $h$ for the Post variable because the pre- and post-periods vary for different diabetes households and therefore their matched control households.

\(^7\)We tested for a difference in response during the first six months of the post-diagnosis period versus subsequently. Since the difference was not significant in most cases, we report results with one post-period effect.
\[
Y_{\text{hncm}} = \beta_0 + \beta_1 \text{Post}_{\text{hm}} + \beta_2 \text{Diab}_h + \beta_3 \text{Diab}_h \times \text{Post}_{\text{hm}} + \beta_4 \text{Female}_h \times \text{Diab}_h \times \text{Post}_{\text{hm}} + \\
\beta_5 \text{NotRx}_h \times \text{Diab}_h \times \text{Post}_{\text{hm}} + \beta_6 \text{Education}_h + \beta_7 \text{Nut}_{\text{Int}}_h + \beta_8 \text{Beh}_\text{ctrl}_h + \beta_9 \text{Income}_h + \\
\beta_{10} \text{Net}_{\text{price}}_{\text{hcm}} + \beta_{11} \text{Nonprice}_{\text{promo}}_{\text{hcm}} + \beta_{12} \text{Percv}_{\text{hlth}}_h + \beta_{13} \text{Age}_h + \beta_{14} \text{Famsize}_h + \\
\beta_{15} \text{Init}_{\text{intake}}_{\text{hnc}} + \text{interactions with Diab}_h + \text{interactions with Post}_{\text{hm}} + \text{interactions with Diab}_h \times \text{Post}_{\text{hm}} + \text{control variables} + \epsilon_{\text{hncm}}
\] (2)

All continuous variables are mean-centered before estimation. The five equations for total intake of calories and nutrients are jointly estimated using Seemingly Unrelated Regression (SUR). The largest VIF in any equation is 5.23, showing that multi-collinearity is not a problem. The category level equations are estimated using Tobit because the categories are not purchased every month by every household, leading to zero values of the dependent variables.\(^8\)

**Results**

It is impractical to report estimates for all equations, so we organize our results according to the three research questions drawing from the relevant model estimates as needed.

< Insert Table 4 About Here >

**RQ1: Effects of Barriers/Enablers on Unhealthy Intake**

*Effects on total intake:* Table 4 provides SUR estimates of the main effects of our model variables on total intake of calories and the four nutrients. Given the presence of interactions, these main effects represent the impact on pre-period intake of the control group. Adding in the interactions with Diab gives the impact on pre-period intake of the diabetes group. We did not hypothesize interactions with Diab and most of these are indeed not significant. Even when they are significant, the sign and significance of the pre-period impact is the same for the control and diabetes groups. Therefore, we discuss the former (main effects) below.

\(^8\) Using multivariate tobit is econometrically intractable for such a large number of equations. However, we estimated multivariate models across nutrients within a category as well as for a given nutrient across categories. Although the error correlations were significant, there were no substantive differences in the key model coefficients compared to the univariate tobit results we report in the paper.
The table shows that most of the effects are consistent with our hypotheses. Education, nutrition interest, net price, family size, and initial intake all have the expected effects on intake of calories, sugar, carbohydrates, fat, and sodium. The effects of age and income are largely insignificant, reflecting the opposing mechanisms we discussed previously. The effect of perceived health is largely negative, suggesting that those in good health are motivated to maintain their status by reducing unhealthy intake. The only two counter-intuitive effects are those of behavioral control and non-price promotion -- the former are mostly positive although we expected the opposite and the latter are mostly insignificant. However, the category level effects that we discuss next help explain these results.

To assess the relative importance of the different variables, we compute, for each nutrient, the change in intake for a one standard deviation increase in each variable and include it in parentheses in Table 4. The table shows that initial intake has the largest effect, which is not surprising since it captures heterogeneity in habits/preferences. This is followed by price and family size, both of which have very substantial and approximately equal effects. The relative importance of the other variables is substantially smaller.

< Insert Table 5 About Here >

Effects on intake from unhealthy and healthy categories: Table 5 summarizes the main effects of the model variables on intake from unhealthy and healthy categories. The tobit models are estimated for each of the thirteen categories but we use the meta-analytic procedure of adding Zs (Rosenthal 1991, p93) to summarize the effect of each independent variable on each dependent variable in the two groups. The statistic shows whether the effect is statistically

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9 As noted in Table 3, categories whose average rating of general healthfulness is not significantly greater than 3 are placed in the “unhealthy” group. Our results are substantively unchanged if we use a cut-off of 4.
significant across categories in each group (see Ailawadi et al. 2010 and Geyskens, Gielens, and Gijsbrecht 2010 for similar meta-analytic analyses). Of course, one can only change intake of a nutrient from categories that contain it. Thus, categories with “ns” for a nutrient in Table 2 are excluded for that nutrient.

Table 5 reveals some important insights. First, all the variables in our model have the expected effects on all intake from the unhealthy group. Education, nutrition interest, behavioral control, and net price have negative effects while non price promotion, family size, and initial intake have positive effects. And perceived health has negative effects consistent with motivation to preserve good health. Second, we find the hypothesized positive effects of promotion in these category level models despite an insignificant effect on total intake. This difference is because households do respond to promotions in individual categories, but budget constraints do not allow them to respond simultaneously to promotions across several categories (as in the total intake model). The effects of cross-price and cross-promotion (weighted average in other categories), which are not shown in the table but are control variables in the category models, are negative, consistent with the existence of a budget constraint.

Third, education and nutrition interest do not affect intake from foods in the healthy group. Thus, households with health knowledge pay attention to unhealthy versus healthy categories but not to less versus more healthy options in the healthy categories, consistent with Moorman et al. (2004) who document such patterns especially for subjective knowledge.

Fourth, high behavioral control people take in significantly more sugar, carbohydrates, etc. from healthy categories, which more than offsets lower intake from the unhealthy group. This is consistent with the lab findings we reviewed earlier that suggest health-conscious consumers
may be most susceptible to health halo biases. It also explains our previous finding of a positive effect of behavioral control on total intake.

< Insert Figure 2 About Here >

RQ2: Changes in Unhealthy Intake Due to Diagnosis

*Change in total intake:* Figure 2 summarizes the changes in total intake of nutrients and calories across the thirteen categories made by diabetes households in response to diagnosis. It depicts with black bars the estimates of the Diab*Post (or difference-in-difference) coefficient from the SUR model of total intake. Since all the continuous variables in the model are mean-centered, these estimates represent the change in monthly intake by the average diabetes household in which the diagnosed patient is a male whose disease is being treated with Rx medication. The black bars show that on average such households reduce sugar and total carbohydrate intake by 155.3 and 103.7 grams respectively but increase fat and sodium intake by 70.9 grams and 2041 mg respectively, without making any significant change in calorie intake. It is interesting to compare this magnitude of the impact of disease diagnosis with the impact of internal motivators like nutrition interest and self-control on one hand and marketing variables like price on the other (Table 4). For sugar intake, for example, the impact of net price is as strong as the impact of diagnosis, whereas the impact of internal motivators is much smaller.

We find no significant difference between Rx treated and not Rx treated households with respect to change in total intake. However, there is a difference for households where the patient is female instead of male. The figure depicts the differential changes made by “female patient” households with grey bars and confirms our hypothesis that they would make better changes. They reduce total carbohydrates and calories by 147.3 grams and 1086 kcals over and above
“male patient” households and they increase fat and sodium by 38.5 grams and 2232 mg less than male patient households.

Change in intake from unhealthy and healthy categories: In order to examine which categories the total changes are sourced from, we utilize the Diab*Post response coefficients in the category-level tobit models. Since tobit coefficients do not directly reflect the effect size, we compute the magnitude of response as follows for all statistically significant coefficients. We set all continuous variables at their means and dummy variables (Female and NotRx) at 0, and compute the expected value (Wooldridge 2002, Chapter 16) of the dependent variable for four groups: pre- and post-period for the diabetes and control groups. The magnitude of response is the difference in difference (“post minus pre” for diabetes group minus “post minus pre” for control group) of the expected value. We report these magnitudes in Table 6. We also report the differential magnitudes for female and not Rx treated patient households.

< Insert Table 6 About Here >

We begin with response from the average diabetes household with a male Rx treated patient. They reduce sugar, and therefore carbohydrates, from CSD and juice, both of which are perceived as unhealthy for diabetes. Interestingly, however, the reduction comes not from consuming less but from choosing low-sugar alternatives within the categories. This can be seen from the fact that there is no significant change in amount of juice and an increase in amount of CSD. Second, the increase in fat intake comes mainly from salty snacks and processed meats. The corresponding increase in calories from these categories offsets the reduction from the two sugary beverage categories. Essentially, these households focus on cutting sugar and they do so where it is easiest, i.e., in categories where low sugar alternatives are available, not in more hedonic categories like cookies and ice-cream which are harder to resist and which offer fewer
low sugar alternatives.\textsuperscript{10} The increase in salty snacks and processed meats, despite their unhealthy perception, may be because their glycemic load is not as high as other foods and they are convenient to consume. There is a small increase in intake from healthy categories like yogurt and soup, but, for the most part, changes, both desirable (sugar and carbohydrate reduction) and undesirable (fat and sodium increase) are sourced from unhealthy categories.

The second column of Table 6, which shows the difference in response when the diagnosed patient is a female versus a male, reveals two major patterns, both of which are consistent with our expectations. First, we see changes across a wider range of categories, and second, the changes are generally healthier than for households with male patients. These households do not increase processed meats as much, which means they do not increase fat and sodium intake as much. And they make significant reductions in intake of hedonic categories like ice cream and cookies as well as convenient categories like frozen dinners, which means they reduce carbohydrates and calories more. One result that seems counter-intuitive at first is the smaller reduction in sugar from CSD compared to male patient households, especially given the reduction in number of servings. However, women consume more diet drinks than men (Storey, Forshee, and Anderson 2006), so there is less room to further reduce CSD sugar intake.

The third column of the table, which shows the difference in response when the diagnosed patient is not Rx treated, reveals a different, though not necessarily better or worse pattern of changes. These households make smaller changes in amounts of high sugar and high fat categories like CSD, processed meats, and salty snacks, which is consistent with our expectation of an overall weaker response. Interestingly, however, they also make small

\textsuperscript{10} We do not see a significant reduction in fat intake from milk and yogurt which offer low fat options because consumers are already using primarily the low fat options. The share of full fat milk in our data is only 20\%.
reductions in other categories like soup and milk, the exception being cheese. Overall, the changes are smaller and spread over more categories.

< Insert Table 7 About Here >

RQ 3: Moderation of the Effects of Barriers/Enablers by Diagnosis

Table 7 provides estimates of the interaction between diagnosis (Diab*Post) and our model variables from the SUR model of total intake. The table shows that many of the interactions, notably those related to education, nutrition interest, price, and promotion, are not significant. Importantly, therefore, these variables do not explain why some households make better changes after diagnosis than others. The effects of behavioral control, age, income, family size, and initial intake are significantly moderated by diagnosis, at least for some nutrients. Since a similar pattern repeats in the category level tobit models, we do not report those results. We simply highlight which categories the significant effects come from.

The interactions that are significant are largely consistent with our hypotheses. First, the effect of age becomes more positive after diagnosis for sugar and carbohydrate intake. In other words, younger diabetes households cut sugar and carbohydrates more than older ones. The category level models show that these effects come mainly from unhealthy cookies and ice-cream but also from yogurt. However, the effect is not significant for fat and total calories because younger households offset this decrease with an increase in intake of cheese which is perceived as healthy. Second, the income interaction is negative for sugar, carbohydrates, sodium, and calories. High income does enable bigger reductions after diagnosis. These are sourced from a mix of categories like frozen dinners, crackers, cheese, and milk.

Third, the effect of family size is positively moderated by diagnosis for all except sugar. The change in sugar intake due to diagnosis is not significantly different for small versus large
families, but the influence of family members makes it harder to reduce intake of other nutrients. The category level results show that the effect comes mainly from ice cream, processed meat, and salty snacks. Thus diabetes patients seem to be able to overcome family influence in cutting the unhealthy nutrient that is most salient, sugar. But, they are more susceptible to family influence for hedonic categories.

Fourth, the interaction effect of initial intake is negative as we expected for sugar and carbohydrates. The category level results show that this effect comes mainly from CSD, cookies, and cereal. However, there are two categories, processed meat and crackers, where the interaction is actually positive, i.e., households whose intake was higher to begin with increase it even more after diagnosis. Finally, the interaction effect of behavioral control is positive, though only marginally significant, for fat and sodium. Those with high behavioral control increase intake of these nutrients more than others and the increase is sourced from processed meats.

**Discussion**

In this paper, we have studied how various factors that have been identified in lab research as barriers or enablers for healthy food choice affect the healthfulness of households’ normal grocery food purchases, how the healthfulness of food intake changes when there is a diagnosis of Type 2 diabetes in the household, and whether the impact of various factors changes after the diagnosis. We have accomplished this using a unique combination of households’ longitudinal grocery purchase information, rich survey data on their health status, and nutrition content of various foods. By identifying households with a new diagnosis and matching them to a control group, we have conducted a before-and-after-with-control-group analysis of response to diagnosis. Thus, our work combines the internal validity of an experiment with the external
validity of actual purchase behavior in the marketplace. Our findings have important implications for researchers, marketers, and public health professionals, which we discuss below.

**Implications for researchers**

Our integrated model confirms that consumer characteristics like education, nutrition interest, and self control as well as marketing variables like price and promotion affect healthfulness of food choice. Prior research has demonstrated their effect on purchase intent and choices in the lab. We show that the effects hold up with actual marketplace behavior. In addition, however, we are able to assess the relative impact of these factors and find that habit is by far the most important, followed by price, while the impact of consumer characteristics is substantially smaller. These results show that the impact of phenomena like nutrition labeling or ego depletion needs to be established not just in the lab or through surveys but in the marketplace where other factors like price have large effects.

Our results regarding the effect of self control on food choice corroborate the health halo bias demonstrated in the lab research we reviewed previously. We find that high self control people have lower intake of calories, sugar, total carbohydrates, fat, and sodium from categories like CSD and salty snacks that are generally perceived to be unhealthy but they offset this with higher intake from categories like cereal, milk, and yogurt that are perceived to be healthy. It is notable that the health halo bias is pervasive and strong enough to show up in total nutrient intake across a wide range of categories consumed at home, and that it is exhibited with respect to self-control but not with respect to education or nutrition interest. It is also notable that normal grocery shopping behavior is consistent with simple heuristics of healthy versus unhealthy categorization and more selection across the two types than within (Moorman et al. 2004), but diagnosis makes people more deliberative and interrupts such heuristics. Diabetes
households make changes in both healthy and unhealthy categories and they select healthier options within categories like CSD.

Our analysis of whether diagnosis moderates the effects of these consumer and marketing variables has several implications for researchers. For the most part, the impact of knowledge and self-control does not change after diagnosis -- those with high self-control or knowledge do not respond better to diagnosis. Thus, previous findings regarding the positive role of these variables in risk prevention do not extend to disease management. This underscores the importance of studying response to actual health problems in addition to potential risk and of examining actions in the marketplace over time in addition to intentions in laboratory experiments. Also, we know that motivation increases healthy behaviors, but our findings suggest that the impact of intrinsic motivation is different from the motivation that comes from disease diagnosis. Perhaps disease diagnosis is an “equalizer” in that even those with low self-control and knowledge realize they must make changes when they get a disease like diabetes.

Our finding that diagnosis makes the impact of family size on unhealthy intake bigger underscores the challenge that patients face in not only controlling their own temptations but in having to do so in the face of family needs and preferences. They seem to be able to overcome family influence in curtailing sugar intake, which they likely view as most important, but not in curtailing other intake. More research is needed on understanding how family influence plays a role and therefore how it can be managed. Our finding that diabetes households cut sugar but increase fat also suggests an avenue for further research on how consumers balance their food intake. Khare and Inman (2006, 2009) demonstrate that consumers bracket their intake of calories and individual nutrients across meals within a day and across days. Our results suggest that such bracketing may occur not just within but also across nutrients.
Finally, our finding that response is not better or worse among those who take Rx medication compared to those who do not suggests that more research is needed on this issue. Consumers may lean on drugs as a substitute for healthy behavior when they are dealing with problems like smoking cessation or weight reduction that are not immediately debilitating, but when the problem is a serious disease they do change behavior. Interestingly, those who are not Rx treated make broader albeit smaller changes while those who are make more focused changes. This may be because those whose disease is more severe (and therefore need Rx drugs) are more focused on immediate and concrete goals (keep blood glucose level under control) and therefore make narrow changes while those whose disease is less severe are focused on longer term and more abstract goals (eat healthy to prevent disease from worsening) and therefore make broader changes (e.g., Liberman, Sagristano, and Trope 2002).

Implications for marketers

Our research highlights the conundrum faced by packaged food companies. Clearly, they have to continue to increase their sales and profits. But, they must develop and market their products responsibly in order to address the growing obesity and public health crisis. If marketers do not proactively develop healthier food options and price them competitively, they will face significant sales drops and increased legislative scrutiny as has been seen in the alcohol and tobacco industries. Indeed, the CSD industry is already feeling the heat (New York Times 2010). It is in the interest of stakeholders in companies like Coca Cola and PepsiCo to encourage the broadening of product portfolios beyond sugary beverages rather than resist it as they currently seem to be doing (Wall Street Journal 2011).

The fact that diabetes households make large switches from high to low sugar CSD and juice drinks reveals an opportunity for food companies to develop direct substitutes for unhealthy
foods without compromising taste and convenience. Part of the reason that we do not see reduction in sugar and fat intake from products like ice-cream is because these hedonic categories are harder to resist but part of it is also because these categories don’t offer healthier options (as seen in the high mean and relatively low standard deviation of sugar and fat content per serving). Our results also show that convenient foods that are low in both sugar/glycemic load and fat have a real market opportunity.

Finally, marketers need to break from the current norm of charging a premium price for healthier alternatives in the category. A comparison of SKU prices in our data reveals that the least unhealthy SKUs in categories like processed meat and cookies are priced at a premium of as much as 50% over the most unhealthy ones. Price is a big factor in food choice. Indeed, we find that its impact is as large as that of disease diagnosis. Thus, it is in the interest of marketers to make their healthier options affordable so that consumers can shift to those options instead of reducing their total purchases of the category. That this will work is evidenced by our finding with respect to the substantial switch from regular to diet CSD where there is no price premium for the latter. The need for smart pricing is also underscored by the fact that affordability, as reflected in income, becomes more important after diagnosis.

Implications for public policy

The increase in fat intake by diabetes households reveals the need for better communication, irrespective of why the increase occurs. It is important to examine not only the guidelines provided to patients but also how they are processed. Past research has highlighted the importance of goal salience (Cheema and Bagchi 2011). Even if information on the negative effect of fat is provided, patients may focus selectively on lowering “sugar” because that goal is made more salient by the need to regularly check blood glucose levels. One solution is to include
counts of fat and calories, not just carbohydrates, in diabetes meal plans. Another is to simply and clearly identify options that are low in both sugar/glycemic load and fat. Our work shows that consumers do recognize that processed meats and salty snacks are unhealthy in general as well as for diabetics. However they may feel licensed to indulge in salty snacks as they limit their intake of other unhealthy foods (Dhar and Simonson 1999), and they may see processed meats as the lesser of the evils in managing their blood glucose levels.

It is also important to account for the fact that consumers, especially those with high self-control, over-consume supposedly healthy foods. Nutrition programs for obesity and diabetes risk prevention must therefore be aimed at not just reducing consumption of obviously unhealthy foods but also monitoring intake of supposedly healthy ones. In addition, the fact that family influence makes it harder to reduce carbohydrate, fat, and sodium intake highlights the need to educate not only the patients but also other decision-makers at home. Family decisions often create conflict due to individual preferences and limited resources, and changing diet requires the cooperation of family members. Therefore, communications, suggested diets, and interventions must be designed from the perspective of the entire family. This is particularly important in households where the patient is a male since our results show that such households make less desirable changes than female patient households.

Our finding that diagnosis moderates the effect of age offers both good and bad news. The good news is that younger people, who will be exposed to the ravaging consequences of the disease over a longer period, are more careful about sugar intake. The bad news is that they are not more careful about fat and sodium intake which further increases their risk of hypertension and heart disease, problems that diabetics are already susceptible to. The cost of this, both in reduced quality of life and economic terms is substantial.
Finally, our findings regarding the impact of price and income reinforce a major challenge. Although sensitivity to price does not change after diagnosis, it is the strongest factor driving regular food choices. Income, on the other hand, gains importance after diagnosis. High income households make better changes after diagnosis, probably because they can afford to switch away from processed foods to healthier, fresh foods that are more expensive. Thus, financial considerations are key in normal shopping behavior and in facilitating desirable changes after diagnosis. They must be alleviated by identifying less expensive healthy options especially for economically disadvantaged groups. On the flip side, a vast body of research has shown that taxing vice products like tobacco reduces smoking (see the International Agency for Research on Cancer handbook for a summary). Some policy makers are considering the same idea to fight obesity, as evidenced by Denmark’s introduction of a food fat tax (BBC 2011).

We conclude with the hope that the limitations of our work spur additional and much needed field research on consumer response to major changes in health status. Clearly, one limitation of our data is that we cannot isolate the response of the patient from that of the household but it is notable that we see significant changes even at the household level. Second, we have studied the largest packaged food categories that constitute a substantial part of total food purchases, but we did not have the data to study intake of fresh foods or food consumption away from home. Third, we have documented changes made in the medium-term, spanning a period of several months before and after diagnosis. Future research should examine whether these changes are sustained over the longer-term horizon. Finally, we have not studied feedback effects. Ongoing effort is a function of the discrepancy between expected and achieved goals, so future research should examine how the progress, or lack thereof, toward blood glucose control and weight loss goals affects food purchase behavior.
References


Provencher, Véronique, Janet Polivy, and C. Peter Herman (2009), "Perceived Healthiness of Food. If it's Healthy, You Can Eat More!" Appetite, 52 (2), 340–344.


<table>
<thead>
<tr>
<th>Construct</th>
<th>Hypotheses for Effects on Unhealthy Intake (Research Questions 1 &amp; 3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Health Knowledge:</strong></td>
<td>RQ1: Health knowledge has a negative main effect on unhealthy intake.</td>
</tr>
<tr>
<td>Enduring health-related cognitive structures. Information about what is healthy and the cognitive ability and interest to utilize it.</td>
<td>RQ3: The interaction of diagnosis with health knowledge has a negative effect on unhealthy intake.</td>
</tr>
<tr>
<td><strong>Self Control:</strong></td>
<td>RQ1: Self control has a negative main effect on unhealthy intake.</td>
</tr>
<tr>
<td>Ability to over-ride natural and automatic desires and behaviors and pursue long-term goals at the expense of short-term temptations. Both perceived self-control and actual behavior reflecting self-control are relevant.</td>
<td>RQ3: We cannot predict the direction of the interaction effect of diagnosis and self-control.</td>
</tr>
<tr>
<td><strong>Financial Constraints:</strong></td>
<td>RQ1: Cost of unhealthy foods has a negative main effect on unhealthy intake.</td>
</tr>
<tr>
<td>Degree to which financial considerations constrain food choice. Both the cost and consumers’ ability to pay are relevant.</td>
<td>RQ3: We cannot predict the direction of the interaction effect of diagnosis and cost.</td>
</tr>
<tr>
<td><strong>Health Status:</strong></td>
<td>RQ1: We cannot predict the main effect of health status on unhealthy intake.</td>
</tr>
<tr>
<td>Consumers’ wellness of body and mind. Both perceived and actual health are relevant.</td>
<td>RQ3: The interaction effect of diagnosis and health status on unhealthy intake is negative.</td>
</tr>
<tr>
<td><strong>Social Influence:</strong></td>
<td>RQ1: Influence from other family members has a positive main effect on unhealthy intake.</td>
</tr>
<tr>
<td>Influence of others in one’s food choices. Presence and preferences of other family members are relevant for food-for-home choices.</td>
<td>RQ3: We cannot predict the direction of the interaction effect of diagnosis and family influence.</td>
</tr>
<tr>
<td><strong>Prior Food Habits:</strong></td>
<td>RQ1: Prior unhealthy food habits have a positive main effect on unhealthy intake.</td>
</tr>
<tr>
<td>Habitual behavior that reflects food preferences and can be automatic.</td>
<td>RQ3: The interaction effect of diagnosis and prior unhealthy habits on unhealthy intake is negative.</td>
</tr>
<tr>
<td><strong>Availability of Healthy Food:</strong></td>
<td>RQ1: Availability of healthy foods has a negative main effect on unhealthy intake.</td>
</tr>
<tr>
<td>Consumers’ access to healthy food categories and healthy options within categories</td>
<td>RQ3: The interaction effect of diagnosis and healthy food availability on unhealthy intake is negative.</td>
</tr>
</tbody>
</table>
### TABLE 2
LIST OF PRODUCT CATEGORIES AND NUTRIENT CONTENT

<table>
<thead>
<tr>
<th>Category</th>
<th>Sugar (g)</th>
<th>Total Carbohydrates (g)</th>
<th>Fat (g)</th>
<th>Sodium (mg)</th>
<th>Calories (kcal)</th>
<th>Perceived Healthiness (general)</th>
<th>Perceived Healthiness (diabetes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cereal</td>
<td>10.8 (3.2)</td>
<td>28.7 (5.4)</td>
<td>2.9 (2.3)</td>
<td>139 (88)</td>
<td>152.5 (12.7)</td>
<td>H 4.0 (1.4)</td>
<td>H 4.4 (1.3)</td>
</tr>
<tr>
<td>Cheese</td>
<td>ns</td>
<td>ns</td>
<td>7.7 (1.7)</td>
<td>248 (135)</td>
<td>99.6 (16.7)</td>
<td>H 4.4 (1.3)</td>
<td>H 4.1 (1.5)</td>
</tr>
<tr>
<td>Cookies</td>
<td>10.4 (1.5)</td>
<td>20.3 (1.4)</td>
<td>5.8 (1.2)</td>
<td>91 (41)</td>
<td>137.8 (10.0)</td>
<td>UH 1.9 (.9)</td>
<td>UH 1.4 (.9)</td>
</tr>
<tr>
<td>Crackers</td>
<td>1.9 (1.7)</td>
<td>20.5 (2.4)</td>
<td>4.2 (1.8)</td>
<td>226 (101)</td>
<td>130.4 (11.9)</td>
<td>H 3.4 (1.3)</td>
<td>UH 2.9 (1.5)</td>
</tr>
<tr>
<td>CSD</td>
<td>19.0 (12.2)</td>
<td>19.4 (12.3)</td>
<td>ns</td>
<td>ns</td>
<td>74.1 (46.9)</td>
<td>UH 1.6 (.9)</td>
<td>UH 1.3 (.8)</td>
</tr>
<tr>
<td>Frozen Dinners</td>
<td>4.7 (2.2)</td>
<td>30.5 (10.0)</td>
<td>9.7 (4.5)</td>
<td>536 (222)</td>
<td>256.3 (83.0)</td>
<td>UH 3.0 (1.2)</td>
<td>UH 2.8 (1.3)</td>
</tr>
<tr>
<td>Ice Cream</td>
<td>15.8 (2.6)</td>
<td>19.4 (2.8)</td>
<td>6.8 (2.5)</td>
<td>56 (25)</td>
<td>147.1 (18.4)</td>
<td>UH 2.3 (1.2)</td>
<td>UH 1.5 (.9)</td>
</tr>
<tr>
<td>Juices</td>
<td>26.4 (5.3)</td>
<td>28.4 (5.6)</td>
<td>ns</td>
<td>42 (101)</td>
<td>114.6 (22.1)</td>
<td>H 4.6 (1.4)</td>
<td>UH 3.0 (1.8)</td>
</tr>
<tr>
<td>Milk</td>
<td>12.0 (.4)</td>
<td>12.6 (.4)</td>
<td>4.1 (3.1)</td>
<td>157 (57)</td>
<td>122.2 (24.5)</td>
<td>H 5.5 (1.3)</td>
<td>H 4.8 (1.5)</td>
</tr>
<tr>
<td>Processed Meats</td>
<td>ns</td>
<td>ns</td>
<td>9.0 (4.8)</td>
<td>529 (223)</td>
<td>120.3 (40.9)</td>
<td>UH 2.9 (1.4)</td>
<td>UH 2.9 (1.4)</td>
</tr>
<tr>
<td>Salty Snacks</td>
<td>ns</td>
<td>16.9 (4.9)</td>
<td>8.1 (3.1)</td>
<td>245 (145)</td>
<td>151.8 (16.8)</td>
<td>UH 2.0 (.9)</td>
<td>UH 1.9 (1.1)</td>
</tr>
<tr>
<td>Soup</td>
<td>3.6 (3.0)</td>
<td>20.5 (5.8)</td>
<td>5.6 (3.1)</td>
<td>713 (211)</td>
<td>157.3 (40.6)</td>
<td>H 3.9 (1.4)</td>
<td>H 3.7 (1.7)</td>
</tr>
<tr>
<td>Yogurt</td>
<td>17.1 (4.5)</td>
<td>20.9 (4.8)</td>
<td>.9 (.7)</td>
<td>91 (29)</td>
<td>120.0 (22.0)</td>
<td>H 5.5 (1.1)</td>
<td>H 4.5 (1.6)</td>
</tr>
</tbody>
</table>

**Notes:** Calories and nutrients are average values per serving, with standard deviations in parentheses; Perceived healthiness ratings are average values on a scale of 1 (very unhealthy) to 7 (very healthy), with standard deviations in parentheses.

- **ns** = not a significant source of the nutrient (less than 1 gram for sugar, and less than 1% of USDA recommended daily allowance for others).

- **UH** = Placed in “unhealthy” group if mean perceived rating is not significantly greater than 3.

- **H** = Placed in “healthy” group if mean perceived rating is significantly greater than 3.
### TABLE 3
MEASURES OF CONSTRUCTS IN EMPIRICAL ANALYSIS

<table>
<thead>
<tr>
<th>Construct</th>
<th>Measures</th>
<th>Representative References</th>
<th>Effect on Unhealthy Intake</th>
</tr>
</thead>
</table>
| **Healthfulness of Food Intake** | **Total Intake:** Household’s total monthly intake of sugar, carbohydrates, fat, sodium, and calories across the 13 categories = Number of servings purchased of an item times the content per serving, summed across all products purchased in any of the 13 categories.  
**Category Intake:** Household’s monthly intake of servings, sugar, carbohydrates, fat, sodium, and calories from each of the 13 categories = Number of servings purchased of an item times the content per serving, summed across all products purchased in a given category. | Helmer et al. 2008; Niewind et al. 1990; Virtanen et al. 2000 | Main | Interaction |
| **Health Knowledge**             | **Education:** Highest level of education: 1 (grade school or less) to 8 (post graduate work)  
**Nutrition Interest (Nut_int):** a) I often read nutrition labels on food; 1 (disagree) to 3 (agree)  
b) How concerned are you about refined / processed food; 1 (not at all) to 3 (very)  
c) How concerned are you about trans fat in food; 1 (not at all) to 3 (very) | Moorman & Matulich 1993; Andrews, Netemeyer & Burton 2009 | - | - |
| **Self Control**                 | **Behavioral Control (Beh_ctrl):** a) On a weekly basis how often do you exercise  
b) On a weekly basis how often do you eat late at night  
c) On a weekly basis how often do you eat at fast-food restaurants  
d) On a weekly basis how often do you take multivitamins  
All from 1 (most days) to 3 (rarely/never), a and d are reverse-coded | Bagozzi, Moore & Leone 2004; Baumeister et al. 2006 | - | ? |
| **Financial Constraints**        | **Income:** Household income: 1 ($10K per year or less) to 12 (more than $100K)  
**Net Price:** Weighted average net price (after price promotions) per serving  
**Non-Price Promotion (Nonprice_promo):** Weighted average % of SKUs on feature or display without price cut | Bihan et al. 2010; Ailawadi & Neslin 1998; Wansink 1996  
Inman, McAlister & Hoyer 1990 | + | - |
| **Health Status**                | **Perceived Health (Percv_hlth):** a) My health is: 1 (poor) to 4 (excellent)  
b) I’m much healthier than most people my age: 1 (disagree) to 3 (agree)  
Age: 1 (18-29 years) to 6 (65 and over) | Cole & Gaeth 1990; Millunpalo et al. 1997; Moorman & Matulich 1993 | ? | - |
| **Social Influence**             | **Family Size (Famsize):** Number of members in household | | + | ? |
| **Prior Food Habits**            | **Initial Intake (Init_intake):** Household’s average monthly intake of category/nutrient in initialization period (first three months) | Ailawadi & Neslin 1998 | + | - |

Note: All Consumer characteristics are average for the household heads.  
* Gender of the household heads relates to self-control but at least one of the household heads is female in over 95% of our sample so there is little variation on this variable.  
* Interaction with Diagnosis.
<table>
<thead>
<tr>
<th></th>
<th>Sugar</th>
<th>Carbohydrates</th>
<th>Fat</th>
<th>Sodium</th>
<th>Calories</th>
</tr>
</thead>
<tbody>
<tr>
<td>Education#</td>
<td>-20.20**</td>
<td>-34.42*</td>
<td>-17.15***</td>
<td>-541.57**</td>
<td>-307.34**</td>
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<tr>
<td></td>
<td>(-25.91)</td>
<td>(-44.14)</td>
<td>(-21.99)</td>
<td>(-694.43)</td>
<td>(-394.09)</td>
</tr>
<tr>
<td>Nutrition Interest</td>
<td>-68.85**</td>
<td>-85.32**</td>
<td>-40.59***</td>
<td>-1084.57**</td>
<td>-764.65***</td>
</tr>
<tr>
<td></td>
<td>(-40.08)</td>
<td>(-49.66)</td>
<td>(-23.63)</td>
<td>(-631.29)</td>
<td>(-445.08)</td>
</tr>
<tr>
<td>Behavioral Control</td>
<td>98.22**</td>
<td>208.08***</td>
<td>6.26</td>
<td>1228.98</td>
<td>1062.40**</td>
</tr>
<tr>
<td></td>
<td>(38.71)</td>
<td>(82.00)</td>
<td>(2.47)</td>
<td>(484.29)</td>
<td>(418.65)</td>
</tr>
<tr>
<td>Income</td>
<td>-14.00**</td>
<td>-9.29</td>
<td>-0.95</td>
<td>-63.33</td>
<td>-46.47</td>
</tr>
<tr>
<td></td>
<td>(-39.53)</td>
<td>(-26.23)</td>
<td>(-2.68)</td>
<td>(-178.78)</td>
<td>(-131.19)</td>
</tr>
<tr>
<td>Net Price</td>
<td>-737.46***</td>
<td>-963.26***</td>
<td>-259.00***</td>
<td>-15631.20***</td>
<td>-7166.13***</td>
</tr>
<tr>
<td></td>
<td>(-224.93)</td>
<td>(-320.52)</td>
<td>(-93.56)</td>
<td>(-1819.08)</td>
<td>(-2507.27)</td>
</tr>
<tr>
<td>Non Price Promotion</td>
<td>420.71*</td>
<td>218.46</td>
<td>40.36</td>
<td>4158.98</td>
<td>1582.43</td>
</tr>
<tr>
<td></td>
<td>(47.63)</td>
<td>(24.46)</td>
<td>(4.27)</td>
<td>(210.67)</td>
<td>(170.73)</td>
</tr>
<tr>
<td>Perceived Health</td>
<td>-78.49***</td>
<td>-112.89***</td>
<td>-6.58</td>
<td>-959.52***</td>
<td>-565.52***</td>
</tr>
<tr>
<td></td>
<td>(-62.62)</td>
<td>(-90.06)</td>
<td>(-5.25)</td>
<td>(-765.50)</td>
<td>(-451.17)</td>
</tr>
<tr>
<td>Age</td>
<td>22.88</td>
<td>10.96</td>
<td>16.12</td>
<td>59.90</td>
<td>123.81</td>
</tr>
<tr>
<td></td>
<td>(20.99)</td>
<td>(10.05)</td>
<td>(-14.79)</td>
<td>(-54.96)</td>
<td>(-113.58)</td>
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<tr>
<td>Family Size</td>
<td>137.31***</td>
<td>255.71***</td>
<td>40.83***</td>
<td>2421.80***</td>
<td>1553.29***</td>
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<tr>
<td></td>
<td>(145.70)</td>
<td>(271.34)</td>
<td>(43.33)</td>
<td>(2569.77)</td>
<td>(1648.19)</td>
</tr>
<tr>
<td>Initial Intake</td>
<td>.39***</td>
<td>.37***</td>
<td>.36***</td>
<td>.33***</td>
<td>.36***</td>
</tr>
<tr>
<td></td>
<td>(1312.99)</td>
<td>(2260.38)</td>
<td>(590.15)</td>
<td>(12028.25)</td>
<td>(16028.98)</td>
</tr>
</tbody>
</table>

Note: The effect on intake of a standard deviation change in the independent variables is reported in parentheses.

* p < 0.10; ** p < 0.05; *** p < 0.01.

#For example, read as: For a one unit (one standard deviation) increase in education, a household’s monthly intake of sugar across the categories in our analysis decreases by 20.20 (25.91) grams.
<table>
<thead>
<tr>
<th>Table 5: Main Effects of Barriers/Enablers on Intake from Unhealthy and Healthy Categories</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Effect on Sugar Intake From</strong></td>
</tr>
<tr>
<td>UH</td>
</tr>
<tr>
<td>Education#</td>
</tr>
<tr>
<td>Nutrition Interest</td>
</tr>
<tr>
<td>Behavior Control</td>
</tr>
<tr>
<td>Income</td>
</tr>
<tr>
<td>Net Price</td>
</tr>
<tr>
<td>Non Price Promotion</td>
</tr>
<tr>
<td>Perceived Health</td>
</tr>
<tr>
<td>Age</td>
</tr>
<tr>
<td>Family Size</td>
</tr>
<tr>
<td>Initial Intake</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Effect on Sodium Intake From</strong></th>
<th><strong>Effect on Calorie Intake From</strong></th>
<th><strong>Effect on Servings Intake From</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>UH</td>
<td>H</td>
<td>UH</td>
</tr>
<tr>
<td>Education</td>
<td>-4.91***</td>
<td>-0.73</td>
</tr>
<tr>
<td>Nutrition Interest</td>
<td>-5.31***</td>
<td>1.05</td>
</tr>
<tr>
<td>Behavior Control</td>
<td>-1.75*</td>
<td>4.52***</td>
</tr>
<tr>
<td>Income</td>
<td>-1.61</td>
<td>1.85*</td>
</tr>
<tr>
<td>Net Price</td>
<td>-15.45***</td>
<td>-8.94***</td>
</tr>
<tr>
<td>Non Price Promotion</td>
<td>38.99***</td>
<td>20.90***</td>
</tr>
<tr>
<td>Perceived Health</td>
<td>-4.60***</td>
<td>2.69***</td>
</tr>
<tr>
<td>Age</td>
<td>0.08</td>
<td>1.64</td>
</tr>
<tr>
<td>Family Size</td>
<td>4.52***</td>
<td>11.43***</td>
</tr>
<tr>
<td>Initial Intake</td>
<td>64.84***</td>
<td>78.45***</td>
</tr>
</tbody>
</table>

Note: H denotes Healthy Categories, UH denotes Unhealthy Categories.
Numbers are meta-analytic Z-statistics for the effect of each variable across the food categories in a given group; *p <0.10; **p<0.05; ***p<0.01
#Read as: The meta-analytic Z for the main effect of education on sugar intake from sugar-containing food categories perceived as healthy is insignificant at +1.40. The meta-analytic Z for the main effect of education on sugar intake from sugar-containing food categories perceived as unhealthy is significantly negative at -2.27.
## TABLE 6
CHANGE IN INTAKE FROM UNHEALTHY AND HEALTHY CATEGORIES DUE TO DIAGNOSIS

<table>
<thead>
<tr>
<th>Intake</th>
<th>Response in Households where Patient is Male &amp; Rx Treated</th>
<th>Differential Response if Patient is Female</th>
<th>Differential Response if Patient is not Rx Treated</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sugar</td>
<td>CSD: -90.0 g Juice: -31.0 g Ice-cream: -13.9 g</td>
<td>CSD: +51.8 g</td>
<td>^H Milk: -22.6 g</td>
</tr>
<tr>
<td>Total Carbs</td>
<td>CSD: -93.0 g Juice: -31.4 g Salty Snacks: +52.0 g ^H Soup: +5.8 g</td>
<td>Cookies: -26.3 g Crackers: +19.7 g CSD: +54.8 g Ice Cream: -17.8 g</td>
<td>Salty Snacks: -37.5 g ^H Milk: -23.9 g ^H Soup: -11.7 g</td>
</tr>
<tr>
<td>Fat</td>
<td>Cereal: -3.2 g Processed Meat: +19.4 g Salty Snacks: +41.1 g ^H Soup: +1.2 g</td>
<td>Cookies: -7.3 g Crackers: +7.3 g Frozen Dinners: -4.6 g Processed Meat: -10.5 g</td>
<td>Cookies: -6.7 g Processed Meat: -10.7 g Salty Snacks: -14.9 g ^H Cheese: +11.6 g ^H Milk: -9.4 g ^H Soup: -2.5 g</td>
</tr>
<tr>
<td>Sodium</td>
<td>Processed Meat: +913.1 mg Salty Snacks: +775.4 mg ^H Soup: +306.6 mg</td>
<td>Crackers: +279.3 mg Frozen Dinners: -277.9 mg Ice Cream: -56.0 mg Processed Meat: -714.7 mg</td>
<td>Crackers: -231.0 mg Processed Meat: -569.2 mg Salty Snacks: -609.1 mg ^H Cheese: +479.4 mg ^H Milk: -212.7 mg ^H Soup: -608.2 mg</td>
</tr>
<tr>
<td>Calories</td>
<td>CSD: -319.3 kcal Juice: -130.0 kcal Processed Meat: +261.3 kcal Salty Snacks: +444.7 kcal ^H Yogurt: +38.0 kcal</td>
<td>CSD: +198.3 kcal Cookies: -173.8 kcal Crackers: +146.0 kcal Frozen Dinners: -101.7 kcal Ice Cream: -149.0 kcal Processed Meat: -176.0 kcal</td>
<td>Cookies: -147.7 kcal Processed Meat: -139.8 kcal Salty Snacks: -290.1 kcal ^H Cheese: +163.9 kcal ^H Milk: -231.8 kcal ^H Soup: -82.9 kcal</td>
</tr>
<tr>
<td>Servings</td>
<td>CSD: +4.0 Processed Meat: +2.0 Salty Snacks: +1.6 ^H Yogurt: +0.4</td>
<td>Cookies: -1.3 Crackers: +0.9 CSD: -3.1 Frozen Dinners: -0.5 Ice Cream: -1.0 Processed Meat: -1.5</td>
<td>CSD: -3.2 Processed Meat: -1.1 Salty Snacks: -2.1 ^H Cheese: +1.9 ^H Milk: -1.5 ^H Soup: -0.6</td>
</tr>
</tbody>
</table>

Note: Only categories with significant effects are included in the table.

^H Category is perceived as healthy for diabetes. All others are perceived as unhealthy.

# For example, read as: Households where the patient is male and Rx treated reduce monthly sugar intake from CSD by 90.0 g on average. The reduction is 51.8 g less (i.e., 90.0-51.8 =38.2 g) if the patient is female and the reduction is not statistically different from 90.0 g if the patient is not Rx treated.
**TABLE 7**

INTERACTION EFFECTS OF DIAGNOSIS AND BARRIERS/ENABLERS ON TOTAL INTAKE

<table>
<thead>
<tr>
<th></th>
<th>Sugar</th>
<th>Carbohydrates</th>
<th>Fat</th>
<th>Sodium</th>
<th>Calories</th>
</tr>
</thead>
<tbody>
<tr>
<td>Education</td>
<td>23.13</td>
<td>26.37</td>
<td>-14.71</td>
<td>-444.70</td>
<td>-44.48</td>
</tr>
<tr>
<td>(29.66)</td>
<td>(33.81)</td>
<td>(-18.86)</td>
<td>(-570.22)</td>
<td>(-57.04)</td>
<td></td>
</tr>
<tr>
<td>Nutrition</td>
<td>79.47</td>
<td>93.91</td>
<td>9.79</td>
<td>-44.86</td>
<td>296.29</td>
</tr>
<tr>
<td>(46.26)</td>
<td>(54.66)</td>
<td>(5.70)</td>
<td>(-26.11)</td>
<td>(172.46)</td>
<td></td>
</tr>
<tr>
<td>Behavioral Control</td>
<td>-2.80</td>
<td>55.41</td>
<td>77.32*</td>
<td>2961.48*</td>
<td>1081.21</td>
</tr>
<tr>
<td>(-1.10)</td>
<td>(21.84)</td>
<td>(30.47)</td>
<td>(1166.99)</td>
<td>(426.06)</td>
<td></td>
</tr>
<tr>
<td>Income#</td>
<td>-32.20**</td>
<td>-46.93**</td>
<td>-9.32</td>
<td>-570.98**</td>
<td>-319.26**</td>
</tr>
<tr>
<td>(-90.91)</td>
<td>(-132.47)</td>
<td>(-26.31)</td>
<td>(-1611.76)</td>
<td>(-901.20)</td>
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<tr>
<td>Net Price</td>
<td>87.07</td>
<td>119.57</td>
<td>70.04</td>
<td>3390.64</td>
<td>1950.33</td>
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<tr>
<td>(26.56)</td>
<td>(39.79)</td>
<td>(25.30)</td>
<td>(394.59)</td>
<td>(682.38)</td>
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<tr>
<td>Non Price Promotion</td>
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<td>991.08</td>
<td>262.76</td>
<td>2731.35</td>
<td>6189.32</td>
</tr>
<tr>
<td>(71.08)</td>
<td>(110.95)</td>
<td>(27.77)</td>
<td>(138.36)</td>
<td>(667.76)</td>
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</tr>
<tr>
<td>Perceived Health</td>
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<td>-9.29</td>
<td>3.00</td>
<td>847.42</td>
<td>68.38</td>
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<td>(-9.58)</td>
<td>(-7.41)</td>
<td>(2.40)</td>
<td>(676.06)</td>
<td>(54.56)</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>76.95*</td>
<td>111.53*</td>
<td>-17.49</td>
<td>90.28</td>
<td>255.23</td>
</tr>
<tr>
<td>(70.60)</td>
<td>(102.32)</td>
<td>(-16.05)</td>
<td>(82.83)</td>
<td>(234.15)</td>
<td></td>
</tr>
<tr>
<td>Family Size</td>
<td>52.94</td>
<td>101.57*</td>
<td>48.31***</td>
<td>1605.30**</td>
<td>931.16**</td>
</tr>
<tr>
<td>(56.17)</td>
<td>(107.77)</td>
<td>(51.27)</td>
<td>(1703.38)</td>
<td>(988.06)</td>
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<tr>
<td>Initial Intake</td>
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<td>-.02**</td>
<td>.01</td>
<td>.01</td>
<td>-.01</td>
</tr>
<tr>
<td>(145.89)</td>
<td>(-124.01)</td>
<td>(13.68)</td>
<td>(335.87)</td>
<td>(-554.28)</td>
<td></td>
</tr>
</tbody>
</table>

Note: The effect on intake of a standard deviation change in the independent variable is reported in parentheses.

* p<0.10; ** p<0.05; *** p<0.01.

#For example, read as: For a one unit (one standard deviation) increase in education, a household’s monthly intake of sugar across the categories in our analysis decreases by 32.2 (90.91) grams more due to diagnosis.
FIGURE 1: CONCEPTUAL FRAMEWORK

Barriers/Enablers for Healthy Food Intake
- Health Knowledge
- Self Control
- Financial Constraints
- Health Status
- Social Influence
- Prior Food Habits
- Availability of Healthy Food

Disease Diagnosis
- Gender of patient
- Severity of disease

Control Variables
- Market and Time Effects
- Household Requirements
  … etc.

Healthfulness of Food Intake
- Total:
  Calories, unhealthy and healthy nutrient intake

  Sourced from:
  Unhealthy vs. healthy food categories
  Less vs. more healthy options within food categories

RQ1

RQ2

RQ3
FIGURE 2
AVERAGE CHANGES IN INTAKE DUE TO DIAGNOSIS

- Sugar: Male Patient -155.3, Female Diff. -147.3
- Carbohydrate: Male Patient -103.7
- Calories: Male Patient -1086

- Fat: Male Patient 70.9, Female Diff. -38.5
- Sodium: Male Patient 2041, Female Diff. -2232