A Spoonful of Sugar Helps the Medicine Go Down: The Relationship between Food Prices and Medical Expenditures on Diabetes

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Abstract

We investigate the impact of changes in the relative price of low- and high-carbohydrate foods on medical expenditures for diabetes care using Nielsen Homescan price data merged to the 2000-2005 Medical Expenditure Panel Survey. We find that an increase in low- (high-) carbohydrate food price increases (decreases) both the likelihood of a diabetes diagnosis and the level of medical expenditures among those with diabetes. We also find relatively small impacts of food prices on BMI that differ by gender. Policy simulations suggest subsidizing the low-carbohydrate food purchases of people with diabetes could result in significant reductions in health care costs.

Keywords: Medical expenditures, diabetes, food prices, food policy

Introduction

Diabetes exerts a significant toll on many Americans and the U.S. healthcare system. There were 23.6 million people, or 7.8 percent of the U.S. population, thought to suffer from diabetes in 2007. These individuals are at risk of a number of serious health complications, including heart disease, stroke, kidney failure, blindness, high blood pressure and nervous system disorders (Centers for Disease Control and Prevention (CDC), 2007). It is therefore no surprise that three in five people with diabetes experience at least one high-cost medical complication (Kaiser Family Foundation, 2007), and are put at significantly greater risk of premature death as of a result of their illness. In fact, diabetes is the seventh leading reported cause of death in the U.S. and was a contributor to 233,619 deaths in 2005 (CDC, 2007).

Diabetes is also expensive to treat, and people with diabetes were found to have medical costs 2.4 to 2.6 times higher than those without diabetes after adjusting for differences in demographic characteristics (Zhang et al., 2004). The American Diabetes Association (ADA) estimated in 2007 that the direct medical costs of treating diabetes were $116 billion, and the total costs associated with diabetes including disability and lost productivity were $174 billion (ADA, 2008a). This represents a 14 percent increase in inflation adjusted total costs from the ADA's last comprehensive report in 2002 and a 37 percent increase since 1997 (ADA, 2003; ADA, 1998). While a large proportion of these costs are paid by public and private health insurance, some individuals with diabetes face high out-of-pocket medical costs. For example, 20 percent of people with diabetes with public coverage and 23 percent of those without insurance spend more than half their disposable income on health care (Bernard, Banthin and Encinosa, 2006).

Diabetes and Dietary Recommendations

While the precise cause of diabetes is unknown, it is widely believed that genetics and environmental factors, such as poor diet and lack of physical activity, predispose many to developing diabetes and influence its severity. This is in part because high levels of adiposity can lead to insulin resistance (Kahn, Hull and Utzschneider, 2006). In fact, reductions in body weight by those with pre-diabetes can delay full onset of the disease and cause blood glucose levels to return to normal (CDC, 2007; ADA, 2009). Among those with diabetes, proper diet is necessary for both short- and long-term health. In particular, monitoring carbohydrate intake is required to prevent hyperglycemia (elevated blood glucose levels that may cause infection, dehydration, or ketoacidosis) and hypoglycemia (dangerously low blood glucose levels), both of which can lead to diabetic coma (ADA, 2008b). However, despite universal recognition of the importance of proper nutrition and body weight to the health of those with diabetes, there has been debate over how best to achieve these objectives. This debate has intensified recently and lead to changes in prevailing dietary recommendations by researchers and clinicians.

In many ways dietary recommendations for individuals with diabetes over the past 30 years have been consistent with the USDA's food pyramid in that they encourage balanced nutrition, and place specific emphasis on lowering intake of saturated fat and increasing dietary fiber.[1] Nonetheless, critics argue that past emphasis on lowering fat intake and promoting carbohydrate-rich foods, such as breads, grains, fruits and vegetables, as the basis of a healthy diet resulted in relatively high carbohydrate intakes leading to a rise in total calories consumed (Marantz, Bird, and Alderman, 2008; Wright et al., 2004). They point out that rising rates of obesity in the U.S. are coincident with the steady increase in the share of calories from carbohydrates (Arora and McFarlane, 2005). In addition, the promotion of low-fat, high-carbohydrate diets seems incongruent to some given that carbohydrate-restriction was the primary treatment modality for diabetes prior to the discovery of effective medications (Westman and Vernon, 2008).

In their 2007 *Nutritional Recommendations and Interventions for Diabetes*, the ADA specifically discouraged the adoption of low-carbohydrate diets (< 130g/day; ADA, 2007). However, in the face of mounting scientific evidence that low-carbohydrate, high-fat diets are no worse than, and possibly superior to, traditionally advocated low-fat, high-carbohydrate diets for weight loss and multiple aspects of diabetes management (Brehm et al., 2009; Kodama et al., 2009; Volek et al. 2009; Accurso et al. 2008; Shai et al., 2008), the ADA revised these recommendations one year later to drop this prohibition. Now the ADA includes low-carbohydrate diets among their recommended short-term weight loss strategies (ADA, 2008b). While some have remained critical of the ADA's failure to fully embrace low-carbohydrate diets ("ADA Finally Acknowledges Low-Carb Diets -- Kind Of ", 2009), it is clear that they have grown in popularity among the general public as well as among clinicians as a method of glycemic control for those with diabetes.

Economic Literature

Given the importance of carbohydrate intake and dietary composition in general to the prevalence and severity of diabetes, an important question for policymakers and public health officials is whether those with diabetes face economic incentives to perpetuate consumption patterns that are inconsistent with proper nutritional management of their disease. Such incentives may manifest in the form of relatively low prices for foods high in carbohydrates or saturated fat. Understanding these price effects is particularly important for the analysis of food policies, such as "fat taxes" that seek to alter consumption patterns by directly manipulating relative prices.

We are only aware of one study that is suggestive of the role relative prices play in the prevalence of diabetes. Specifically, Rashad (2006) found that the prices of two foods with low glycemic index (GI) values (orange juice and bananas) were positively associated with glycosylated hemoglobin (HbA1c, a measure of blood glucose), while two high-GI foods (bread and ice cream) were negatively associated with HbA1c among those without diabetes.[2] In contrast, there is a sizable and growing literature on the relationship between food prices and obesity, a condition closely related to diabetes. Both Lakdawalla and Philipson (2002) and Cutler, Glaeser and Shapiro (2003) cited advances in agricultural technology that led to declines in the relative price of food as one primary explanation for the observed growth of body weight over the past quarter century. In fact, the former attributed 40 percent of the growth in BMI between 1976 and 1994 to declining food prices.

Other researchers have attempted to attribute the growth in obesity to the consumption of foods that are widely considered to be less healthy. For example, Chou, Grossman, and Shafer (2004) found a positive correlation between the prevalence of fast food restaurants in certain areas and adult BMI, and a negative correlation between the relative price of fast food and BMI. Although Sturm and Datar (2005) failed to detect a similar relationship between fast food outlet density and the weight status of children, they did find that lower real prices for vegetables were associated with a lower gain in

BMI for children between kindergarten and third grade. Drewnowski (2007) has investigated the relationship between nutrient and calorie density and contemporaneous food cost for a broad range of commodities and determined that foods having greater energy density (in megajoules/kilogram) cost less per megajoule than nutrient dense foods. He interprets this as evidence that the prevalence of obesity is higher among the poor in part because the lower-cost (and better tasting) food they are likely to purchase is higher in calories than more expensive nutrient-rich food.

Underlying many of these studies is the simple result from neoclassical price theory that consumers will substitute away from an unhealthy food if its relative price increases. In the context of a system of demand equations for multiple goods one can therefore determine whether commodity taxes levied on relatively less healthy foods will decrease BMI. Chouinard et al. (2007) do just this in the context of dairy products and find that while a "fat tax" would reduce fat consumption, consumer demand for high fat dairy products is inelastic so that the overall impact on BMI is small. This result is confirmed by Gelbach, Klick and Stratman (2007) who determine that a 100 percent tax on unhealthy foods (broadly defined) would only reduce BMI by 1 percent. More recent work by Goldman, Lakdawalla and Zheng (2009) confirms the small short-term effect of a fat tax on BMI, but suggests the long-term effect is somewhat larger. In particular, a 10 percent permanent increase in price per calorie would lead to a decrease in BMI of 3.6 percent over 30 years. It is interesting to note that the small short-term effects of price changes on body weight found by economists are consistent with findings by physiologists (using animal models) that individuals adjust the quantity of food they consume to maintain body weight despite changes to the caloric and nutrient composition of the food available (Jen et al., 1985; McHugh and Moran, 1978).

Finally, Schroeter, Lusk and Tyner (2008) develop a theoretical model that incorporates consumption decisions over a broad range of commodities in addition to physical activity decisions to investigate price and income effects on BMI. They find that a tax on food away from home (FAFH), which is often considered to be relatively less healthy, could *increase* BMI. This is because the home-prepared foods consumers would substitute towards as a result of the tax are actually higher in calories than are restaurant-prepared foods. In the two good case (high and low calorie food), consumer theory implies a tax on the high calorie food does indeed lead to a weight decrease if the two foods are compliments, but could either increase or decrease weight if the foods are substitutes.

If changes in relative prices give consumers incentives to purchase foods that lead to weight gain, it is equally likely that such food purchases have an impact on diseases that are closely linked to diet. Given the strong medical connection between carbohydrate intake and diabetes, it is conceivable that price effects could be an important factor in both the prevalence and severity of diabetes. To investigate this possibility, we build on an economic framework of the demand for food and medical care to derive empirical estimates of the impact of food prices on medical expenditures for diabetes.

Economic Framework and Empirical Approach

Following the standard neoclassical approach to consumer utility maximization, suppose that an individual $i = 1,...,N$ in time period $t = 1,...,T$ has preferences over her health, H_{it}, weight status, W_{it}, and composite commodities for low carbohydrates foods, C_{it}^{L}, high carbohydrate foods, C_{it}^{H}, and all other consumption goods (including leisure), C_{it}^{O}, defined by the following utility function:

(1) $$U_{it} = U(H_{it}, C_{it}^{L}, C_{it}^{H}, C_{it}^{O}, W_{it}(C_{it}^{L}, C_{it}^{H}, C_{it}^{O})).$$

In accordance with Grossman (1972), further assume that health is a stock variable defined by an initial level of health carried over from the previous period, weight status, investments in health made through expenditures on medical care, M_{it}, consumption goods, and random shocks, ε_{it}, such that

(2) $$H_{it} = h(H_{it-1}, W_{it}(C_{it}^{L}, C_{it}^{H}, C_{it}^{O}), M_{it}, C_{it}^{L}, C_{it}^{H}, C_{it}^{O}, \varepsilon_{it}).$$

To determine the optimal investment in health and goods consumption, the individual maximizes (1) subject to a budget constraint,

(3) $$p_t^M M_{it} + p_t^L C_{it}^L + p_t^H C_{it}^H + C_{it}^O \leq Y_{it},$$

where Y_{it} represents total disposable income, p_t^L, p_t^H, and p_t^M are the prices of low carbohydrate foods, high carbohydrate foods, and medical care, respectively, and the price of other goods has been normalized to 1. This results in a system of demand equations, which includes the demand for medical care. We write this below in expenditure form, and note that it can be easily modified to include socio-demographic determinants, $\mathbf{X_{it}}$:

(4) $$p_t^M M_{it} = ME_{it} = q(p_t^L, p_t^H, Y_{it}, \varepsilon_{it}; \mathbf{X_{it}}).$$

In addition, one can derive the following reduced form equation for weight status after substituting through optimal levels of food and goods consumption:

(5) $$W_{it} = w(p_t^L, p_t^H, Y_{it}, \varepsilon_{it}; \mathbf{X_{it}}).$$

Of particular interest is whether the demand for low- and high-carbohydrate food substitutes for, or is complementary to medical expenditures. Intuitively, we would expect that low-carbohydrate foods are substitutes for medical care $\left(\partial ME / \partial p^L > 0 \right)$ and high-carbohydrate food are complements with medical care $\left(\partial ME / \partial p^H < 0 \right)$ among people with diabetes. This is based on the underlying medical relationship between the consumption of carbohydrate-rich foods and the production of health for people with diabetes, and the substitute of one broadly grouped food commodity for the other when relative prices change.

Therefore, an increase in the relative price of low-carbohydrate foods would cause an individual with diabetes to substitute towards high-carbohydrate foods, leading to a deterioration in the biological markers that define diabetes and, more broadly, metabolic syndrome (such as blood glucose level, insulin concentrations, and insulin sensitivity; Volek et al., 2009). This increase in the severity of the individual's diabetes and associated co-morbidities ultimately results in a greater need for medical care to maintain their health status. We also seek to determine the relationship between relative prices and BMI, as recent research suggests that low-carbohydrate diets are conducive to the reduction of body weight, particularly when pursued in conjunction with a comprehensive weight loss strategy.

In order to empirically investigate the relationship between food prices and medical expenditures we adopt a specification that is linear in the log of medical expenditures, prices and income. Applying the log transformation is necessary to account for the fact that all of these variables (particularly medical expenditures and income) are skewed to the right.[3] It is also convenient in the sense that the estimated coefficients on prices are the elasticities of medical expenditures with respect to a one percent change in price. Our empirical specification is then

$$\log ME_{it} = \alpha_m + \delta_t + \sum_h \eta_h x_{it} + \sum_k \gamma_k \log p_{mt}^k + \beta \cdot \log Y_{it} + \varepsilon_{it} , \tag{6}$$

in which k indexes prices for foods with various carbohydrate levels and m indexes market areas. Our empirical specification for equation (5) is similar, except that we replace the log of medical expenditures with the log of BMI. We can also use the model in equation (6) to investigate whether changes in food prices impact the prevalence of diabetes in the general population as opposed to the severity of diabetes among those already diagnosed. To do this we simply replace the log of medical expenditures with an indicator of whether or not the individual had positive medical expenditures on diabetes treatment and estimate the regression using the full sample.

If local markets for food are reasonably efficient then we would not expect there to be significant price variation across commodities in a local area. However, there will be variation in prices across markets that are segmented by geography and economic factors as well as variation in prices over time. The model contains market area and time period specific intercepts (or fixed effects) to control for time-invariant market-level heterogeneity and aggregate time trends that might confound the relationship between prices and medical expenditures. Therefore, the identifying price variation in the model is within market areas over time. Also, since our price variables are computed at the market level we cluster-correct the standard errors in all our empirical models at the market level and use survey weights to make our estimates nationally representative.

Data

The primary data source for our empirical application is the 2000-2005 Medical Expenditure Panel Survey (MEPS). The MEPS is a comprehensive, nationally representative survey of the U.S. civilian non-institutionalized population, conducted annually since 1996, using an overlapping panel design. Respondents are interviewed about their medical care use and expenditures over the course of two years through five interview rounds. In addition, information from the household is supplemented by expenditure data collected directly from participants' medical service providers and pharmacies through a Medical Provider Component. We excluded those less than 35 years old and pregnant women to ensure that most of the individuals in our sample suffer from the more common adult-onset type 2 diabetes, rather than juvenile-onset type 1 diabetes or gestational diabetes, which differ from the former in biological basis and treatment.

MEPS respondents are asked to report their medical conditions at several points during the survey. For "priority conditions" such as diabetes they are asked whether they have ever been told by a health care professional that they have diabetes. In addition, MEPS respondents are asked whether their medical visits or other events are related to any specific medical conditions. These responses are then professionally coded using the *International Classification of Diseases*, Ninth Revision (ICD-9), and subsequently collapsed to into 259 clinically relevant medical conditions using the Clinical Classification System developed by the Agency for Healthcare Research and Quality (2007). We identify medical events with CCS codes of 49 and 50 as being related to diabetes mellitus, and computed medical expenditures specifically for diabetes as well as for all medical conditions. This includes expenditures for inpatient events, ambulatory visits, prescription drugs, and home health care services. Less than 2 percent of the individuals who report being diagnosed with diabetes have no reported medical expenditures during the year. We dropped these individuals from the analysis based on the assumption that most of them were "pre-diabetic". Our final sample consists of 4,206 adult men and 5,352 adult women with diabetes. Because some individuals did not report their BMI, models that focus on BMI contain 3,990 men and 4,985 women.

Since the MEPS does not contain food prices, we used geographic information on household location to merge annual market-level average food prices from the 2000-2005 Nielsen Homescan scanner panel dataset. Homescan data consist of detailed demographic and purchase information for a representative sample of U.S. households that report the quantity and price of all foods purchased for at-home consumption.[4] Each household is equipped with an electronic home-scanning unit, and household members record every food purchase they make by scanning in the appropriate codes of the food products. The panel is geographically dispersed and is demographically balanced to match the U.S. population as closely as possible and household-level projection factors (weights) are available to make aggregate statistics representative at the market, regional, and national level.[5]

Homescan data are unique in that panelists record food purchases across all outlet channels, including grocery, drug, mass-merchandise, club, supercenter, and convenience stores. However, they do not include information on food bought away from home (primarily restaurant meals), so one needs to assume that such purchases do not bias the average prices paid by a household for its food-at-home purchases to conduct analyses of this type using Homescan data. Under this assumption, we calculate the average price paid per ounce for each of 630 broad food categories for every household. We then average these prices across households in each of the 50 Nielsen-defined market areas in the U.S., weighting each household by its projection factor. Our use of the Homescan data represents an improvement over previous studies on the effects of food prices that have used C2ER data (formerly ACCRA), which only contain information on a limited subset of food items from a targeted set of retail food outlets in a given geographic area[6].

In order to categorize the 630 food categories in the Homescan data by their carbohydrate content we merged in detailed nutritional information from the website www.nutritiondata.com. This web resource compiles nutrition information from the USDA and food industry sources, allowing us to map carbohydrate content in grams per ounce to each food. We stratified price per ounce of food by carbohydrate level and calculated the average price in each of the four quartiles of the carbohydrate distribution (0% - 25%, 26% - 50%, 51% - 75%, and 76% -100%) using market-level expenditure weights. Therefore, our analysis is based on the following four food group prices: low-carbohydrate; medium/low-carbohydrate; medium/high-carbohydrate; and high-carbohydrate.[7]

Because the Homescan data are representative of purchases by U.S. households, the specific foods that factor heavily into each price are those purchased most frequently. Broadly characterized, foods in the lowest carbohydrate quartile are meats, vegetables, and diet soft drinks, while foods in the two middle quartiles are fruits, dairy products, certain breads and bakery products, and fruit juices. In the highest carbohydrate quartile are sweets, cookies and baked goods, pasta, ready-to-eat cereals, pre-prepared meals, and regular soft drinks. The dominance of complex carbohydrates (rather than high-fiber foods) at the upper end of the carbohydrate distribution is reflected in the average calories of the foods in each group. From the lowest to the highest carbohydrate quartile these are 45.4, 29.2, 78.8, and 110.0 calories per ounce. Even though the lowest carbohydrate group has the highest percentage fat (41 percent), it still has lower average calories than the two highest carbohydrate food groups.[8] Research using the National Health and Nutrition Examination Surveys (NHANES) likewise suggests that carbohydrate-rich foods contribute significantly to total calorie intake. In particular, regular soft drinks contributed more than any other commodity to total energy, at 7.1 percent, followed by cakes and pastries at 3.6 percent (Block, 2004).

Other than prices our regression models control for the following factors: Net income per adult equivalent (total household income minus health insurance premiums divided by the square root of household size), race/ethnicity (white, black, hispanic, other race), respondent age (indicators for whether age was between 35-54, 55-64, or 65 or older), education level (no high school diploma, high school graduate, some college, bachelor's degree or higher), census region (northeast, midwest, south, or west), whether the respondent lives in an MSA, household composition (number of household members age 0-5, 6-17, 18-64, and 65 or older), and fixed effects for year and 50 market areas.[9] In addition, all price, income, and medical expenditure variables were inflated to 2005 USD and entered into the model in logarithmic form, and all models were estimated separately by gender.

Descriptive statistics for all variables used in our empirical analysis are contained in Table 1. At $10,478 per year, the average total medical expenditures for people with diabetes are high relative to the general population. In 2005, average medical expenditures for all adults 35 or older were approximately half this amount ($5,185). While respondents only reported $2,044 of these expenditures as being related to diabetes, it is likely that some individuals had difficulty determining the extent to which various co-morbidities were attributable to their diabetes. This is one reason why we estimate models using both total medical expenditures and medical expenditures for diabetes as dependent variables. The average BMI in our sample is 30.9, which is just above the cutoff of 30 for the clinical classification of obese. Another notable finding from Table 1 is that food prices are increasing in carbohydrate content.

Estimation Results

First, we investigate whether changes in food prices impact the prevalence of type 2 diabetes in the adult population using a linear probability model.[10] The elasticity estimates for women presented in Figure 1 conform to our expectations in that a 1 percent increase in the price of low-carbohydrate foods is associated with an increase in the prevalence of diabetes, while an analogous increase in the price of high carbohydrate foods is associated with a decrease in prevalence. These elasticities are relatively small in magnitude and only the one corresponding to medium/high carbohydrate foods is statistically significant. In contrast, the estimated price effects for men are larger, particularly the low-carbohydrate elasticity, which suggests a 10 percent increase in the price of low-carbohydrate foods is associated with a 3.8 percent increase in the prevalence of diabetes. However, the elasticities for men do not become negative at the upper end of the carbohydrate distribution as they do for women, though the highest quartile estimate is not statistically different from zero.

The elasticities of total and diabetes-specific medical spending with respect to a 1 percent change in each of the four carbohydrate prices for the sample of men with diabetes are shown in Figure 2. In this case we observe the systematic pattern consistent with our expectations of consumer substitution effects. Increases in the price of low-carbohydrate foods lead to higher medical expenditures, presumably due to consumer substitution towards high-carbohydrate foods that increase both blood glucose levels and the severity of diabetes. Symmetrically, increases in the price of high carbohydrate food are associated with lower medical expenditures. These effects are slightly larger and more precisely estimated in the model with medical expenditures on diabetes as the dependent variable. For example, a 10 percent decrease in the price of low carbohydrate foods reduces total expenditures by 4.2 percent, but diabetes-specific expenditures by 4.9 percent.

MEPS respondents that report suffering from diabetes are given a supplemental questionnaire that asks whether or not they treat their diabetes with diet (though not exclusively so). We subset to men who answered this question affirmatively and re-estimated the models to determine whether there was a different relationship between prices and medical spending among this group. Individuals attempting to control their disease with diet may be less price sensitive, and therefore, less likely to substitute towards high-carbohydrate foods when the price of low-carbohydrate foods increases. However, those relying on diet to control their blood glucose level may rely less on medication, such that the impact of any price driven change on consumption patterns would have a larger effect on expenditures. In the case of total expenditures, it appears that the latter effect dominates as the point estimates among those treating with diet are almost universally higher, and significantly so in the case of low-carbohydrate foods. Interestingly, no clear pattern emerges in this regards for medical expenditures on diabetes, although there is a loss of statistical precision in the smaller sample.

Analogous price elasticity estimates of the demand for medical care by women are shown in Figure 3. The results for total medical expenditures are very similar to those found for men, and the same pattern emerges of increases in the price of low (high) carbohydrate foods being associated with higher (lower) medical expenditures. Sub-setting to those who treat their diabetes with diet, we again observe a slightly larger price effect at the lower end of the carbohydrate distribution, but the same effect at the upper end (the total expenditure elasticity for all women with diabetes is statistically significant at $\alpha = .12$). The elasticity of medical expenditures on diabetes with respect to low-carbohydrate price is large and statistically significant for women who treat their disease with diet, but the analogous elasticity with respect to high-carbohydrate price is statistically indistinguishable from zero, rather than negative. Overall, it appears that women who treat their diabetes with diet are more vulnerable to price-induced changes in the consumption of low-carbohydrate foods.

The percentage changes in BMI associated with a 1 percent change in each of the food prices are displayed in Figure 4. The relative insensitivity of BMI to food price changes is consistent with the economic and physiology studies mentioned above. Nonetheless, some of the effects are precisely estimated and could be associated with more significant changes in weight over an extended period, as suggested by Goldman, Lakdawalla and Zheng (2009). In particular, an increase of 10 percent in the price of low-carbohydrate foods is associated with a 1.1 percent increase in BMI among men with diabetes. Furthermore, the health status of individuals with diabetes is more sensitive to changes in body weight than that of the general population.

Probably the most interesting finding from Figure 5 is that food price changes have an opposite effect on the BMI of women with diabetes compared to men. Again, the point estimates are small, but the elasticity with respect to high-carbohydrate price is precisely estimated. It suggests that a 10 percent increase in price is associated with a .8 percent *increase* in BMI. The reason for different underlying substitution effects between men and women is unclear, but it is possible that the calorie and fat content of the foods women substitute in the advent of a price change is different than men. For example, this result may reflect differential substitution towards or away from food-away-from-home, which is not explicitly captured in our model.

Our empirical approach imposes the restriction that price elasticities are constant across the population of adults with diabetes. In order to test whether this is consistent with the underlying data generating process, we estimated each BMI and medical expenditure model separately at the 20th, 40th, 60th, and 80th percentiles of the empirical distribution of the dependent variable using quantile regression. As expected, the statistical precision of the estimated elasticities dropped, but the point estimates suggest the price elasticities are constant across the BMI distribution. The same was true of medical expenditures by women, although we did find evidence that the elasticities might be larger for men at the lower end of the distribution of medical expenditures for diabetes. If validated by subsequent research, this would suggest that medical spending by men with low-severity diabetes is more responsive to relative price changes.

Conclusions and Policy Implications

Our elasticity estimates suggest that changes in the prices of low- and high-carbohydrate foods are associated with changes in the prevalence and severity of diabetes as well as with changes in the BMI of those suffering from diabetes. The observed relationship is broadly consistent with price-driven substitution away from low-carbohydrate foods towards high-carbohydrate foods leading to a deterioration of health status and resulting increase in medical spending. A causal interpretation of the estimated price effects requires the assumption that conditional on the model regressors (including market-area and year fixed-effects), there are no omitted factors correlated with market prices. In addition, several limitations of the study must be kept in mind: The estimates correspond to reduced form models and we are not able to explicitly account for food-away-from-home purchases; our categorization of foods is based on current consumption patterns, which could change in the future; and we must aggregate prices to relatively large market areas.

Despite these limitations, our results have potentially important implications for food and health care policy. In particular, they suggest policies that alter the relative price of high- and low-carbohydrate foods could be used to improve the health of people with diabetes and reduce their medical expenditures. While broad-based policies along these lines may not achieve the cost-savings to justify the distortion of relative prices, there is scope for policy interventions that specifically target people with diabetes to be welfare enhancing. From a practical standpoint, increasing the relative price of high-carbohydrate foods for this selected group seems impractical at best. However, it is feasible to provide vouchers or coupons that could be used to reduce the cost of low-carbohydrate foods. Some public and private insurers already enroll individuals with diabetes in disease management programs that could serve as a conduit for such interventions. Furthermore, our empirical results are most supportive of an intervention based on changes in the price of low-carbohydrate foods.

We conducted simulations of the net savings in medical costs of subsidizing the low- carbohydrate purchases and report them in Table 2. These savings equal the associated reduction in health care costs from a price-induced change in consumption less the cost of the subsidy in terms of food expenditures and administrative overhead. To calculate the latter we applied the subsidy level and a 5 percent overhead charge to expenditures on food-at-home purchases by adult men and women with diabetes 35 years and older, derived from multiple databases. An adjustment for the proportion of expenditures on low-carbohydrate foods was computed from Homescan, while the population proportions of adult men and women with diabetes was derived from the MEPS. These factors were applied to household food-at-home expenditure from the Consumer Expenditure Survey jointly with an adjustment to account for relative difference in calorie consumption between adults over and under the age of 35 that was computed using the NHANES.

The first row of Table 2 provides the baseline total medical expenditures per year for people with diabetes during our 2000-2005 sample period. This was $66 billion for men and $76 billion for women for a total of $142 billion per year. We then apply a 10 percent, 20 percent, or 30 percent subsidy to low-carbohydrate foods for adults with diabetes, which leads to significant reductions in medical costs. From this we subtract the food costs associated with each subsidy and find that annual savings are on the order of $6 billion, $12 billion, and $17 billion, respectively. To provide an indication of the statistical variability associated with these estimates, we report simulations that are based on the upper and lower bounds of the 90 percent confidence interval associated with our elasticity estimates. While the lower bound is 515 million or less, net savings at the upper bound are quite large. In this case the savings are achieved because the substitution towards low-carbohydrate foods reduces the severity of diabetes, but there is a further potential savings if the subsidies are applied more broadly.

In the bottom portion of Table 2 we report the net savings associated with a subsidy on low-carbohydrate foods for all adults over the age of 34. In this case the reduction in medical costs are greater because the subsidy reduces both the prevalence and the severity of diabetes, but the cost of the subsidy is likewise greater as the proportion of the 35 and older population with subsidized food purchases goes from 9 to 100 percent. On average, broader application of the subsidy results in lower, but still significant savings equal to $3 billion, $6 billion, and $8 billion for a 10 percent, 20 percent, and 30 percent subsidy. However, there are substantial negative net savings (reductions in medical costs do not out-weight food and administrative costs) at the lower bound estimates. In addition, while we may assume the welfare loss associated with the distortion in relative prices that is not captured by these simulations is relatively minor when the subsidy is given to adults with diabetes, it could be quite large when the subsidy is applied to the broader population.

Overall, the policy simulations suggest that targeted approaches to diet modification among people with diabetes through the subsidy of low-carbohydrate foods could significantly reduce medical costs. While further research is needed to identify the structural pathways through which food prices impact medical expenditures, we believe the potential savings make this a fruitful area for research efforts.

[1] The USDA food pyramid was initially released in 1992, but revised in 2005 to integrate physical activity and move away from presenting food groups in a hierarchy. An ADA consensus statement issued in 1979 steered individuals away from the high-fat, low-carbohydrate diet that had been recommended for many years towards a low-fat, high-carbohydrate diet, which the initial food pyramid likewise advocated (Nuttall and Brunzell, 1979; Arky, 1983) .

[2] The glycemic index is a ranking of carbohydrates according to their effect on blood glucose levels. Foods with a high (low) GI produce relatively larger (smaller) fluctuations in blood glucose.

[3] The two most popular functional forms in medical expenditure modeling are the log-OLS and General Linear Model (GLM) variants. Since we are interested in elasticities, we avoid difficulties in re-transforming our estimates to the raw-scale, which is the principal drawback of the log-OLS approach. Furthermore, the GLMs can be highly inefficient if the log scale residuals are leptokurtotic (coefficient of kurtosis > 3), which is the case here (Manning and Mullahy, 2001).

[4] For the years 2000-2003, USDA purchased the Fresh Foods subsample of Homescan that included households that reported both UPC and Non-UPC food products, so that the sample size was between 7,100 and 8,800 households per year, while in 2004 and 2005, USDA purchased the full Homescan sample containing over 39,000 households.

[5] Demographic information includes age, gender, race, ethnicity, education, occupation of head(s) of household and household income, size, composition, and location.

[6] For more detailed information about the C2ER (ACCRA) data and methodology, see the C2ER COLI report at http://www.coli.org/surveyforms/colimanual.pdf

[7] We chose to group foods by total carbohydrate content as opposed to glycemic index or glycemic load for several reasons. First, the latter were not available for all of the individual food items in our database. But more importantly, our discussions with dieticians and interpretation of ADA guidelines suggest that most individuals with diabetes are advised to monitor total carbohydrate intake, which is easily observed on nutrition labels.

[8] In general, the association between the percentage carbohydrates and percentage fat across the food groups is not inversely linear. For example, the second highest carbohydrate quartile also has the second highest percentage fat.

[9] Our estimates are invariant to whether indicators for insurance status are included in the models.

[10] Complete regression results for all of the models we estimate are reported in Tables A1 and A2 of the appendix.

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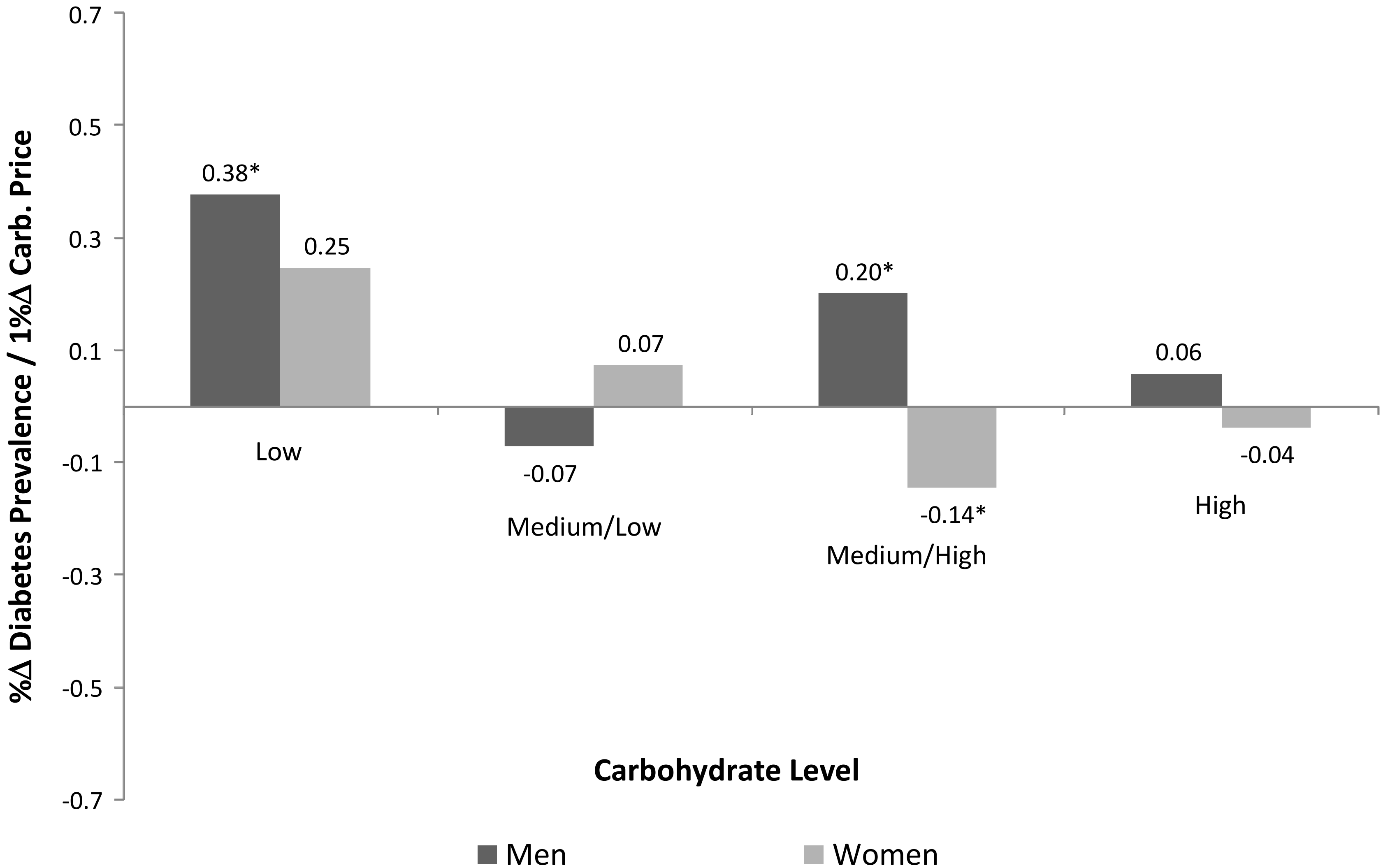
Tables and Figures

Table 1. Descriptive Statistics for Adults 35 and Older With Diabetes (N=9,558)

Variable	Mean†	Stan. Dev.	Min.	Max.
Total medical expenditures*	10,477.760	17,827.570	7.602	345,883.000
Medical expenditures on diabetes*	2,043.587	4,725.422	3.102	128,108.000
Price per oz – low carb.*	.206	.025	.105	.271
Price per oz – med/low carb.*	.210	.056	.090	.978
Price per oz – med/high carb.*	.229	.086	.103	1.467
Price per oz – high carb*	.260	.035	.145	.434
BMI	30.950	6.767	13.248	72.300
Net HH Income / square root of HH size	31,376.910	26,241.840	0.354	298,299.400
Treats diabetes w/ diet	.816	.388	0	1
Female	.519	.500	0	1
White	.676	.468	0	1
Hispanic	.116	.320	0	1
Black	.161	.367	0	1
Other race	.048	.213	0	1
Age 35 – 54	.295	.446	0	1
Age 55 – 64	.258	.437	0	1
Age 65+	.448	.497	0	1
No high school diploma	.307	.461	0	1
High school graduate	.338	.473	0	1
Some college	.184	.387	0	1
Bachelors degree or higher	.162	.369	0	1
Midwest	.213	.409	0	1
South	.397	.489	0	1
West	.207	.405	0	1
Northeast	.183	.387	0	1
Residence in MSA	.760	.427	0	1
No. HH members 0 - 5	.061	.304	0	4
No. HH members 6 – 17	.270	.688	0	9
No. HH members 18 – 64	1.278	1.154	0	9
No. HH members 65+	.713	.799	0	4
Self-reported information	.602	.489	0	1
Year 2000	.136	.343	0	1
Year 2001	.146	.354	0	1
Year 2002	.162	.368	0	1
Year 2003	.168	.374	0	1
Year 2004	.188	.391	0	1
Year 2005	.199	.400	0	1

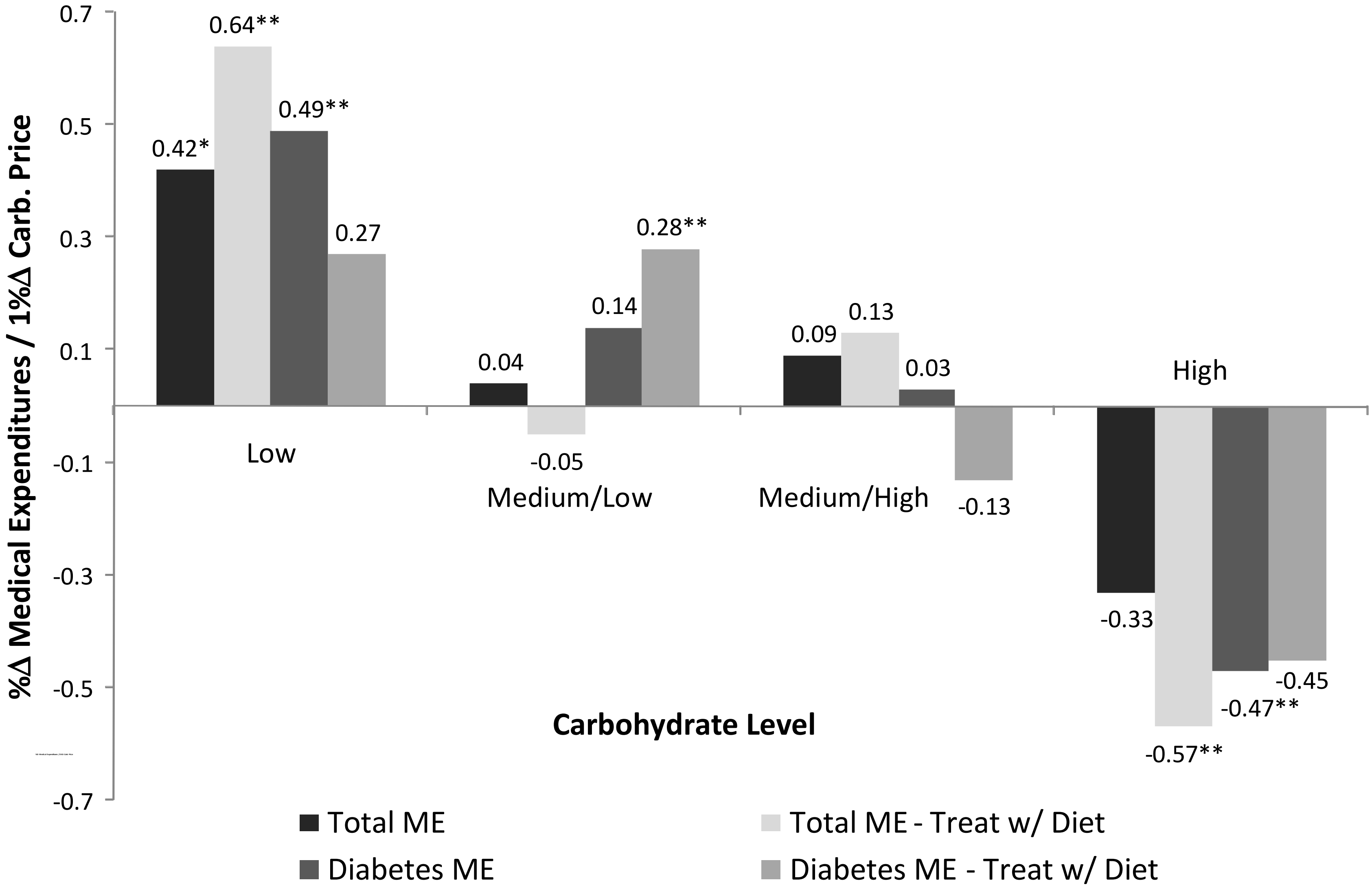
* In 2005 USD; †Means are weighted.

Figure 1. Elasticities of Diabetes Prevalence With Respect to Carbohydrate Price



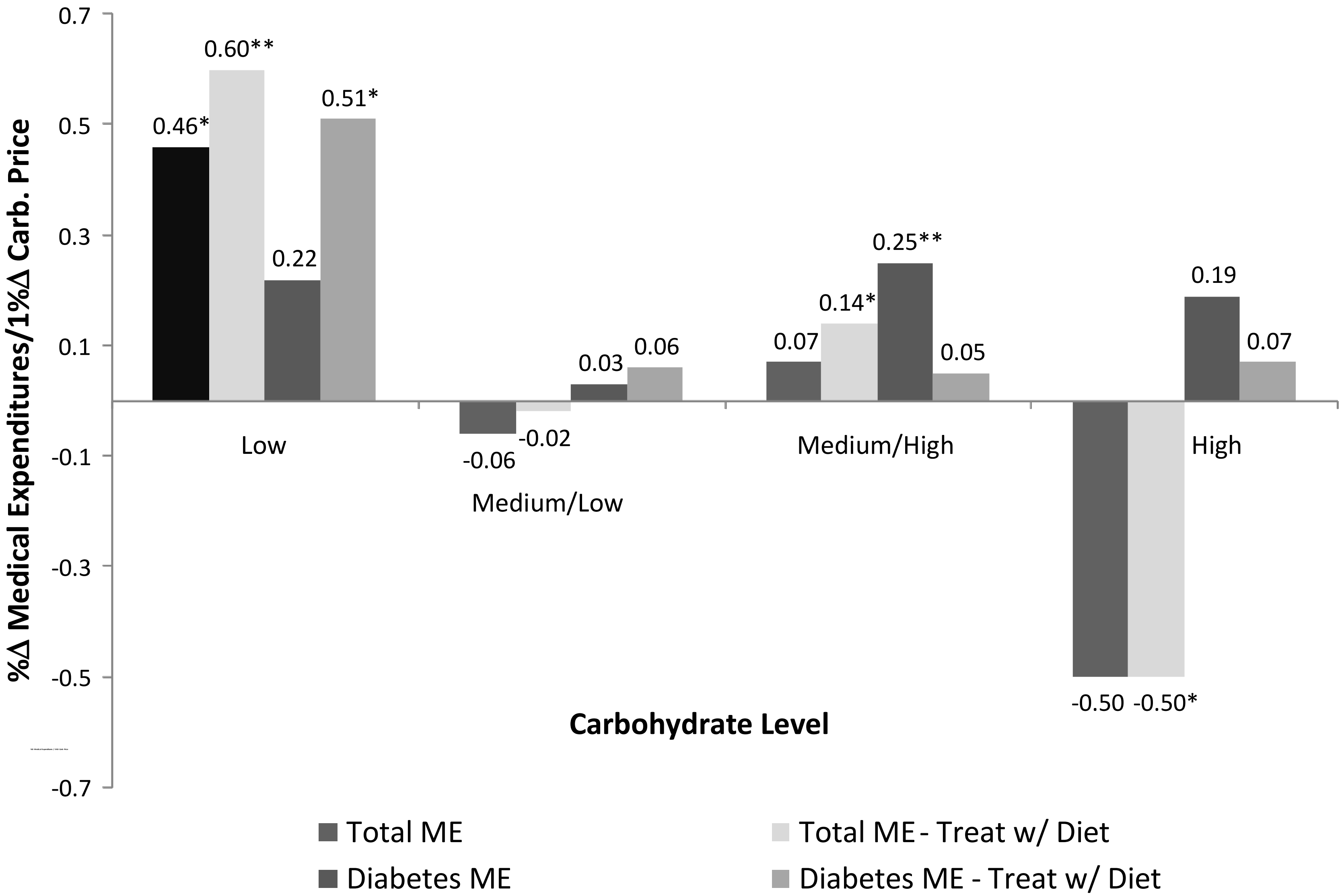
Note: Asterisks (*,**,***) denote statistical significance at the 10, 5, and 1 percent levels.

Figure 2. Elasticities of Medical Expenditure With Respect to Carbohydrate Price for Men With Diabetes



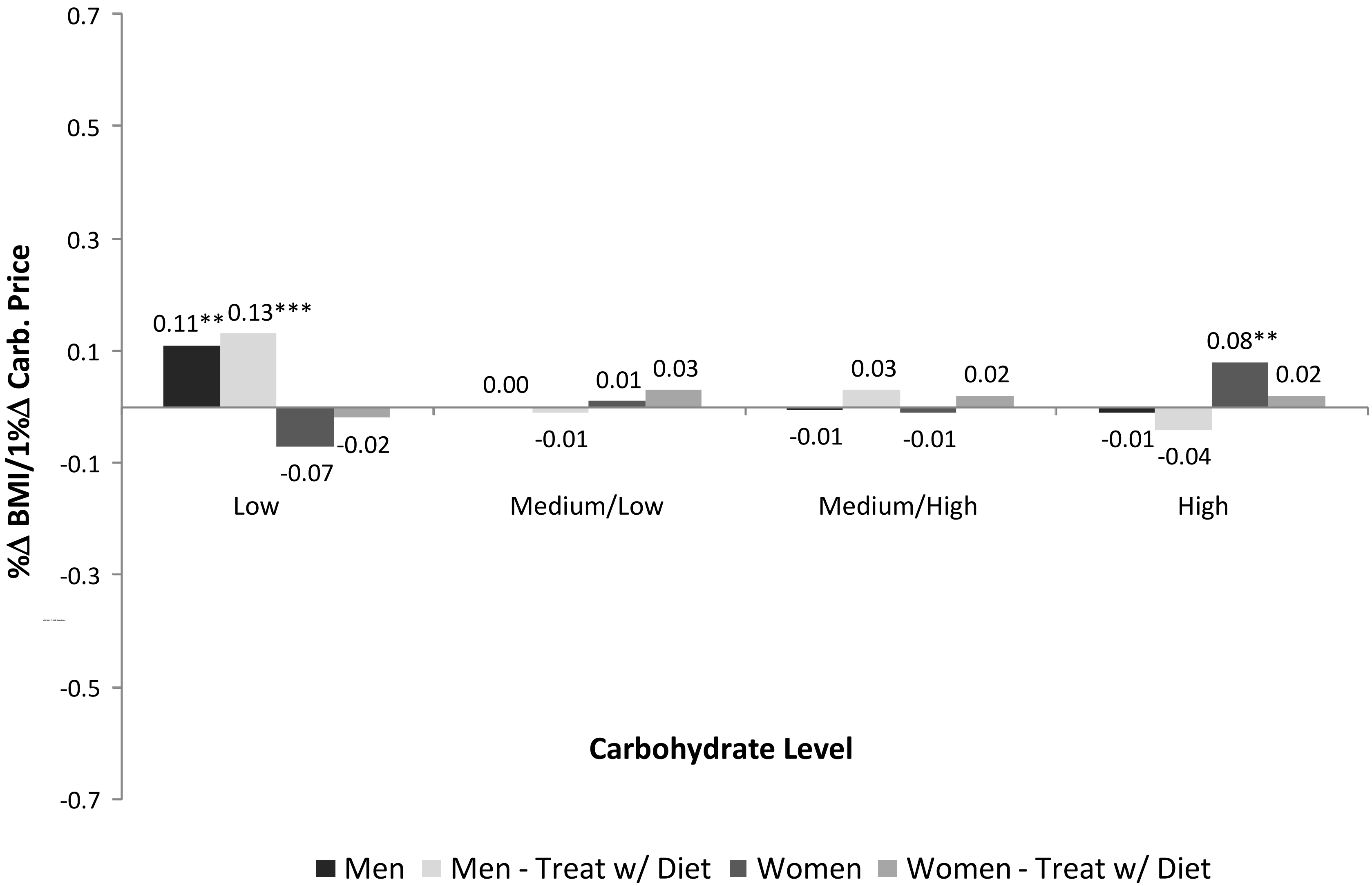
Note: Asterisks (*,**,***) denote statistical significance at the 10, 5, and 1 percent levels.

Figure 3. Elasticities of Medical Expenditure With Respect to Carbohydrate Price for Women With Diabetes



Note: Asterisks (*,**,***) denote statistical significance at the 10, 5, and 1 percent levels.

Figure 4. Elasticities of Body Mass Index With Respect to Carbohydrate Price for Men and Women With Diabetes



Note: Asterisks (*,**,***) denote statistical significance at the 10, 5, and 1 percent levels.

Table 2. Net Savings in Total Yearly Medical Expenditures from a Subsidy on Low Carbohydrate Foods (Millions of 2005 USD, 90% C.I. in Parenthesis).

Subsidy Level	Men	Women	Total
Baseline Medical Expenditures	66,459	75,733	142,192
Adults 35 or Older With Diabetes			
10 percent	2,469 (-289, 5,227)	3,111 (461, 5,762)	5,580 (172, 10,989)
20 percent	5,724 (-578, 10,454)	6,223 (921, 11,524)	11,947 (343, 21,978)
30 percent	7,407 (-868, 17,356)	9,334 (1,382, 17,286)	16,740 (515, 34,642)
All Adults 35 or Older			
10 percent	1,590 (-3,400, 6,575)	1,201 (-3,919, 6,320)	2,791 (-7,319, 12,895)
20 percent	3,181 (-6,801, 13,150)	2,401 (-7,838, 12,641)	5,582 (-14,639, 25,790)
30 percent	4,771 (-10,202, 20,202)	3,602 (-11,756, 18,960)	8,373 (-21,958, 39,163)

Appendix

Table A1. Regression Estimates for Men.

Regressor	N = 41,663	Full Sample w/ Diabetes (N = 4,206)			Treat Diabetes w/ Diet (N = 2,733)		
	Diabetes Diagnosis	Log(Total Med. Exp.)	Log(Diabetes Med. Exp.)	Log(BMI)	Log(Total Med. Exp.)	Log(Diabetes Med. Exp.)	Log(BMI)
Log(Price - low carb.)	.035 (.019)	.424 (.252)	.489 (.196)	.109 (.042)	.638 (.261)	.272 (.301)	.133 (.048)
Log(Price - med/low carb.)	-.007 (.009)	.036 (.157)	.141 (.108)	.001 (.019)	-.052 (.180)	.276 (.133)	-.008 (.020)
Log(Price - med/high carb.)	.019 (.010)	.091 (.115)	.026 (.098)	-.005 (.018)	.131 (.146)	-.131 (.221)	.033 (.026)
Log(Price high carb.)	.005 (.016)	-.333 (.248)	-.470 (.221)	-.015 (.041)	-.567 (.281)	-.455 (.324)	-.037 (.055)
Hispanic	.023 (.007)	-.417 (.094)	-.042 (.087)	-.049 (.012)	-.453 (.097)	.038 (.103)	-.033 (.015)
Black	.035 (.008)	-.152 (.064)	.056 (.076)	-.028 (.008)	-.183 (.075)	.000 (.074)	-.026 (.014)
Other race	.025 (.012)	-.445 (.156)	-.115 (.123)	-.078 (.017)	-.355 (.188)	-.108 (.151)	-.084 (.023)
Age 35 – 54	-.112 (.011)	-.341 (.155)	.191 (.110)	.057 (.021)	-.516 (.174)	.143 (.158)	.056 (.026)
Age 55 – 64	-.035 (.013)	-.033 (.143)	.256 (.122)	.043 (.020)	-.254 (.148)	.217 (.158)	.045 (.023)
High school graduate	-.023 (.006)	-.117 (.058)	-.102 (.064)	.003 (.013)	-.167 (.064)	-.047 (.085)	.006 (.016)
Some college	-.017 (.006)	-.025 (.095)	-.063 (.067)	.010 (.013)	.034 (.075)	.018 (.064)	.017 (.015)
Bachelors degree or higher	-.038 (.006)	.012 (.069)	-.031 (.088)	-.025 (.013)	-.015 (.076)	-.016 (.096)	-.006 (.014)
Midwest	-.043 (.006)	.284 (.077)	.205 (.106)	.008 (.015)	.187 (.085)	.137 (.116)	.045 (.020)

Regressor	N = 41,663	Full Sample w/ Diabetes (N = 4,206)			Treat Diabetes w/ Diet (N = 2,733)		
	Diabetes Diagnosis	Log(Total Med. Exp.)	Log(Diabetes Med. Exp.)	Log(BMI)	Log(Total Med. Exp.)	Log(Diabetes Med. Exp.)	Log(BMI)
South	-.012 (.004)	.176 (.078)	-.061 (.090)	.022 (.021)	.012 (.065)	-.131 (.064)	.043 (.031)
West	-.021 (.005)	.394 (.079)	.044 (.085)	.033 (.018)	.249 (.067)	-.029 (.061)	.055 (.025)
Residence in MSA	-.015 (.007)	.005 (.073)	.062 (.064)	.001 (.011)	.071 (.062)	.012 (.056)	-.011 (.013)
No. HH members 0 - 5	-.014 (.003)	-.185 (.073)	-.085 (.066)	.001 (.017)	-.183 (.077)	-.148 (.080)	-.006 (.019)
No. HH members 6 – 17	-.006 (.002)	-.171 (.037)	-.053 (.034)	-.001 (.006)	-.198 (.049)	-.056 (.042)	.000 (.006)
No. HH members 18 – 64	.014 (.003)	-.126 (.038)	-.059 (.030)	.018 (.006)	-.097 (.035)	-.076 (.034)	.016 (.006)
No. HH members 65+	.019 (.007)	-.093 (.063)	-.027 (.050)	-.009 (.013)	-.163 (.080)	-.047 (.078)	-.012 (.014)
Log(Net HH income per a.e.)	-.003 (.002)	-.055 (.014)	-.056 (.016)	-.001 (.003)	-.033 (.021)	-.064 (.018)	-.003 (.002)
Self-reported information	.010 (.004)	-.015 (.057)	-.024 (.044)	.017 (.012)	.012 (.074)	-.005 (.048)	.013 (.014)

Note: All models contain market area and year fixed effects. Standard errors are cluster-corrected at the market level.

Table A2. Regression Estimates for Women.

Regressor	N = 49,442	Full Sample w/ Diabetes (N = 5,352)			Treat Diabetes w/ Diet (N = 3,525)		
	Diabetes Diagnosis	Log(Total Med. Exp.)	Log(Diabetes Med. Exp.)	Log(BMI)	Log(Total Med. Exp.)	Log(Diabetes Med. Exp.)	Log(BMI)
Log(Price - low carb.)	.023 (.018)	.460 (.213)	.219 (.258)	-.070 (.042)	.599 (.249)	.511 (.266)	-.024 (.052)
Log(Price - med/low carb.)	.007 (.010)	-.063 (.108)	.033 (.128)	.007 (.020)	-.020 (.145)	.063 (.131)	.027 (.022)
Log(Price - med/high carb.)	-.013 (.007)	.068 (.060)	.247 (.100)	-.013 (.010)	.144 (.081)	.048 (.106)	.017 (.014)
Log(Price high carb.)	-.003 (.027)	-.500 (.318)	.195 (.261)	.077 (.033)	-.504 (.284)	.066 (.308)	.020 (.069)
Hispanic	.048 (.007)	-.400 (.096)	-.073 (.091)	-.010 (.011)	-.358 (.103)	.029 (.108)	-.023 (.014)
Black	.080 (.007)	-.141 (.061)	.012 (.070)	.028 (.013)	-.122 (.072)	.104 (.080)	.029 (.013)
Other race	.036 (.009)	-.493 (.121)	.093 (.099)	-.096 (.025)	-.465 (.106)	.210 (.100)	-.109 (.028)
Age 35 – 54	-.122 (.010)	-.534 (.082)	-.227 (.105)	.156 (.019)	-.512 (.120)	-.186 (.115)	.156 (.022)
Age 55 – 64	-.059 (.009)	-.314 (.095)	-.118 (.097)	.103 (.017)	-.301 (.123)	-.047 (.096)	.115 (.016)
High school graduate	-.035 (.005)	-.044 (.048)	-.020 (.059)	.001 (.008)	-.068 (.070)	.018 (.074)	.005 (.010)
Some college	-.043 (.006)	-.067 (.058)	-.001 (.069)	.000 (.019)	-.095 (.065)	.062 (.072)	.008 (.018)
Bachelors degree or higher	-.061 (.005)	-.045 (.079)	-.158 (.084)	-.035 (.014)	-.059 (.072)	-.090 (.110)	-.026 (.016)
Midwest	-.013 (.011)	.037 (.068)	.053 (.172)	-.001 (.012)	-.012 (.079)	.041 (.288)	.024 (.011)

Regressor	N = 49,442	Full Sample w/ Diabetes (N = 5,352)			Treat Diabetes w/ Diet (N = 3,525)		
	Diabetes Diagnosis	Log(Total Med. Exp.)	Log(Diabetes Med. Exp.)	Log(BMI)	Log(Total Med. Exp.)	Log(Diabetes Med. Exp.)	Log(BMI)
South	-.008 (.021)	-.062 (.063)	-.083 (.121)	-.021 (.014)	-.171 (.046)	-.103 (.199)	-.003 (.015)
West	-.023 (.011)	.008 (.121)	-.041 (.148)	.036 (.011)	-.054 (.051)	-.101 (.204)	.066 (.013)
Residence in MSA	.001 (.005)	-.042 (.070)	.007 (.069)	-.012 (.012)	.008 (.080)	-.034 (.083)	-.008 (.013)
No. HH members 0 - 5	-.006 (.003)	-.153 (.056)	.034 (.073)	.027 (.011)	-.227 (.085)	-.015 (.081)	.029 (.012)
No. HH members 6 – 17	-.011 (.001)	-.060 (.030)	-.002 (.034)	.009 (.006)	-.024 (.048)	.010 (.045)	.017 (.005)
No. HH members 18 – 64	.011 (.003)	-.114 (.040)	-.077 (.042)	-.007 (.006)	-.124 (.046)	-.104 (.047)	-.005 (.007)
No. HH members 65+	-.006 (.005)	-.231 (.059)	-.152 (.058)	.011 (.010)	-.171 (.081)	-.111 (.053)	.021 (.012)
Log(Net HH income per a.e.)	-.006 (.001)	-.019 (.012)	-.027 (.013)	-.002 (.002)	-.018 (.017)	-.033 (.014)	-.003 (.003)
Self-reported information	.011 (.004)	-.094 (.051)	.003 (.061)	.073 (.012)	-.071 (.063)	-.065 (.083)	.079 (.013)

Note: All models contain market area and year fixed effects. Standard errors are cluster-corrected at the market level.