Diabetes and Diet: Behavioral Response and the Value of Health*

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Abstract

Individuals with complications of obesity are often reluctant to undertake dietary changes. Evaluating the reasons for this reluctance, as well as appropriate policy responses, is hampered by a lack of detailed data on behavioral response. I use household scanner data to estimate food purchase response to a diagnosis of diabetes. I infer diabetes diagnosis within the scanner data from new purchases of glucose testing products. I find that households engage in significant but small calorie reductions following diagnosis. The changes are sufficient to lose up to 10 pounds in the first year, but are approximately 20% of what would be suggested by a doctor. In the first month after diagnosis changes by food line up strongly with doctor advice: increases in fruits and vegetables and decreases in unhealthy foods. The decrease in unhealthy foods continues in the longer term but increases in healthy foods do not persist. I consider two applications. First, I compare these changes to what would be achieved by taxes or subsidies. A 10% tax on unhealthy foods would produce smaller changes than what is observed after diagnosis, but a 10% subsidy on healthy foods would have a much larger impact. Second, I evaluate the implied value of marginal calories under the assumption that the behavior change observed represents full-information optimization. I find that individuals value the marginal 100 calories per day at between 0.2 and 1.0 life years.

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1 Introduction

In many health contexts, individuals appear resistant to undertaking costly behaviors with health benefits. Examples include resistance to sexual behavior change in the face of HIV (Caldwell et al, 1999; Oster, 2012) and lack of regular cancer screening (DeSantis et al, 2011; Cummings and Cooper, 2011). Among the most common examples of this phenomenon is resistance to dietary improvement among obese individuals, or those with conditions associated with obesity (Ogden et al, 2007). Encouraging behavior change in this context is of significant policy importance: estimates suggest that the morbidity and mortality costs of obesity were $75 billion per year in the US in 2003 and rising (Wang et al, 2011). Dietary changes are a significant component of prevention and treatment.

Education and information campaigns – either through doctors or public health organizations – have been a common approach to this problem.[1] Evidence on whether better information can effect real change, however, is mixed (Hornik, 2002; Randolph and Viswanath, 2004; Elbel et al, 2009). One explanation for the limited success of these campaigns is that they do not successfully inform individuals; another possibility is that individuals are informed but put low value on their health. From a policy standpoint such campaigns may be considered against other approaches - for example, taxes or subsidies for particular foods. A key issue in evaluating these explanations and policy options is we have relatively little precise information on how individual or aggregate food purchases change with dietary advice.

In this paper I approach this question by using household scanner data to estimate individual response to a diagnosis of diabetes, both in the aggregate and by individual foods. Diabetes diagnosis comes with a focused set of dietary advice and information that highlights the benefits of improvement in health behaviors. Diabetes "Self Management Education" is a standard part of the medical reaction to diagnosis (Franz et al, 2002). The diagnosis event is therefore a strong information treatment; however, the added health benefit to dietary change before versus after diagnosis is minimal, or possibly negative (Wilding, 2014). Diabetics are a group of particular interest to policy makers since disease prognosis is generally thought to be improved with weight loss (Wilding, 2014) and the mortality and morbidity costs from diabetes are considerable (Yang et al, 2013).

The data used in this paper are from the Nielson HomeScan panel, a household scanner dataset which is commonly used in economics and marketing applications. Household participants in the panel are asked to scan the UPC codes of all grocery and drug store item purchases; households record quantity and prices of items. Panelists participate in the panel for varying periods, but typically for at least a year, and are incentivized for their participation. Other validation exercises have supported the quality of these data (Einav et al, 2010).

[1] See, for example, http://ndep.nih.gov/partners-community-organization/campaigns/ for diabetics in particular, and Michelle Obama's "Let's Move!" campaign (http://www.letsmove.gov/).

The dataset is naturally oriented to allow researchers to observe the evolution of food purchases within a household over time. I merge these data with a second dataset which provides calorie and nutrient information for foods, so I am able to observe an estimate of calories purchased as well as quantities and prices. Participants are not asked directly about their health. However, they are asked to scan over-the-counter drug store purchases. From these data I infer a diabetes diagnosis event in the household using information on purchases of glucose monitoring products. Specifically, I identify households who purchase glucose testing supplies at some point in the sample following at least 9 months of no purchases of this type (this exclusion period is intended to ensure this is a new diagnosis). I code this timing as the diagnosis event. A small survey of diabetics confirms that nearly all newly diagnosed diabetics acquire these products within a month of diagnosis, and most of them do so through direct purchase. Glucose monitoring is not a recommended treatment for conditions other than diabetes, so it is unlikely this procedure identifies non-diabetics.

Given this diagnosis event, the methodology in the paper is straightforward. Using a household fixed effects framework, I estimate the evolution of calories, quantities, nutrient and total expenditures after the event. The detailed nature of the HomeScan grocery data allows me to look at the overall purchase basket, and also at purchases for individual food groups. The estimation here is at the household level, not at the individual person level, since this is the level at which the data are provided. I limit to two person households for comparability and will also show results for single-person households (a much smaller sample) as a robustness check. When I discuss the magnitude of the changes I will address the issue of attributing changes across household members. In the end, this methodology identifies approximately 2600 two-person households with a diagnosis event.[2]

The first set of results estimates changes in overall calories, quantity of food and expenditures after diagnosis. A visual sense of the results appear in Figure 2. In the very first month of diagnosis there are limited changes, but following this we observe significant reductions in calories, quantities and expenditures. By each metric, the changes represent a reduction of 4% to 5% of grocery purchases. There is limited evidence of a change in nutrient mix – for example, away from fat and towards protein – following diagnosis. The results are very consistent across a number of robustness checks, including varying sets of time controls, estimating and adjusting for household-specific pre-trends and limiting to households with seemingly more reliable reporting patterns. Single-person households reduce their purchases at a similar rate. I explore demographic heterogeneity in these changes and find limited evidence of any differences across education, race, age or food access.

In the second set of results I turn to estimating changes by food group. I focus on whether the changes I observe are consistent with individuals accurately following doctors dietary advice. To precisely measure dietary advice, I fielded a small survey of doctors who treat diabetics and asked them to rank food modules as

[2]This is roughly consistent with what we would predict based on sample size. Diabetes incidence in this age group is about 1.4% per year. There are 25,481 two-person households in the data; over the 7 years considered, we would expect 2,394 diagnosis events.

a “good source of calories,” a “bad source of calories” or “neither good nor bad.” I group foods as “All Good” (indicating that all doctors surveyed felt this was a good source of calories), “All Bad” (all doctors felt it was bad), “Majority Good” and “Majority Bad”.

In the initial month after diagnosis individuals appear to make dietary changes which line up closely with doctor advice. One test of this can be seen in Figure 3, which shows the ratio of “All Good” to “All Bad” foods. This ratio spikes up in the initial month of diagnosis. This pattern of consistency with doctor advice also shows up if we look across all four groupings. However, this fades very quickly. By three months after diagnosis the ratio graph shows no significant change, and it is effectively zero by six months later. This is not to say that behavior change overall evaporates - it is clear from the aggregate results that it does not. Changes in intake of “Bad” foods if anything decrease more in the long-run than the short-run. But the increases in good foods do not persist. In the end, by six months after diagnosis, households are consuming a similar mix of food products, but just a bit less of all of them.

Evaluating the magnitude of these results in terms of their impact on weight loss is not straightforward for two reasons. First, we observe only household-level purchases, not allocations to individuals. Second, we do not observe all foods individuals eat. Many household may not remember to scan all grocery purchases and, even if they do, the data are not designed to capture food consumed away from home. I discuss these two issues and attempt to provide some bounding estimates on what they imply about the magnitudes. My favored estimate suggests a decrease of 4% to 5% in all calories after the first month. Scaled up to a typical individual, this would suggest a weight loss of approximately 10 pounds a year. I compare the prediction from this analysis to what is seen in data following newly diagnosed diabetics and find it lines up closely. This magnitude of change is approximately 20% as large as what the American Diabetic Association would recommend for the typical diabetic.

In the second part of the paper, I use these results in two applications, both related to the initial motivation. First, I use external data on the price elasticity of demand by food to estimate the tax (or subsidy) equivalent which would be predicted to produce a response similar to what is seen after diagnosis. If we think of this treatment as approximating a very strong and salient information campaign, this may provide some insight into the comparative value of information versus taxation. I find that for unhealthy foods (soda, dessert foods) the long-run changes among diabetics are equivalent to a 10% to 20% tax. For healthy foods, however, the subsidy equivalent is very small, even negative. Put differently: a 10% tax on soda would produce a much smaller change than I observe after diagnosis, but a 10% subsidy on vegetables would produce a much larger change. This suggests some potentially significant value of healthy food subsidies, which are much less discussed in policy circles than taxes on unhealthy foods.

In the second application, I interpret these results under a simple model in which individuals choose an optimal weight loss given the known health benefits of losing weight. I use external data on the link between weight loss among diabetics and health benefits; I consider mortality, disease remission and some quality of life benefits (urinary incontinence, erectile function). The estimates suggest individuals put relatively little value on health relative to diet. For example: a further reduction of 100 calories per day over the first year, the equivalent of a small soda, would increase expected survival by 0.2 to 1.0 life year. Under the assumption of optimization, this suggests individuals value calories at a high rate. Clearly there are significant assumptions which go into constructing this application, so it should be taken with much caution. However, if correct it may provide some clue as to why it is difficult to induce dietary improvements.

The primary contribution of this paper is to better understand this important health behavior and to speak to policy questions on how health behaviors may be improved. A secondary contribution, however, is to illustrate a new way that the HomeScan data might be used by health researchers. Although these data are commonly used in industrial organization and marketing applications, they have been less used to evaluate questions in health.

The rest of the paper is organized a follows. Section 2 gives some background on diabetes. Section 3 discusses the data and empirical strategy. Sections 4 and 5 describe the main results and discuss magnitude. Section 6 discusses the two applications and Section 7 concludes.

2 Background on Diabetes and Diabetes Management

Diabetes is a medical condition in which the pancreas cannot create enough insulin. There are two types. In Type 1 diabetes, the pancreas cannot make any insulin; this disease typically manifests in childhood and individuals with the illness must manage it with insulin injections to replace pancreatic function. In Type 2 diabetes the pancreas produces some insulin, but not enough to process all glucose consumed. This illness more commonly manifests in adulthood and is very often a complication of obesity. Medical treatment of Type 2 diabetes includes oral medication and, if the disease progresses, injected insulin. This paper will focus on Type 2 diabetes, which is more common and more responsive to behavior modification.

The health consequences of Type 2 diabetes relate to the possible buildup of glucose in the blood. This buildup can damage blood vessels, leading to a variety of problems. Complications from poorly managed diabetes include blindness, kidney failure, amputation of extremities (feet in particular), heart attack and stroke. Even with treatment Type 2 diabetics have significantly elevated mortality risk compared to non-diabetics (Taylor et al, 2013). Similar to other complications of obesity, Type 2 diabetes is on the rise in the US. An estimated 29 million Americans live with the disease, and 1.7 million new cases are diagnosed each year (CDC, 2014). The vast majority of these are Type 2 diabetes. Estimates from 2012 put the annual cost of diabetes to the US health care system at $176 billion, with $69 billion in further costs from reduced productivity (American Diabetes Association, 2013).

A central component of diabetes treatment is changes in diet and exercise behavior. Diet recommendations are made by the American Diabetic Association (Franz et al, 2002) and have several components. First and foremost is weight loss. A very large majority of Type 2 diabetics are overweight or obese, and the ADA recommends weight loss through a deficit of 500 to 1000 calories per day relative to what would be required for weight maintenance. The ADA also makes recommendations on the makeup of these calories: roughly 60-70% should be from carbohydrates, 15-20% from protein and less than 10% from saturated fat. Although in general a diet rich in whole grains and vegetables is recommended, the ADA has in recent periods noted that the amount of carbohydrate intake is more important than the source. Sucrose, for example, is okay to consume but should be consumed holding constant the caloric and nutrient mix. Put differently: concerns with excess soda consumption are not because soda is *per se* bad but because it generally leads to an increase in total calories.

The observation that weight loss is an important component of diabetes treatment is reasonably well accepted (Wilding, 2014). Williamson et al (2000), for example, shows individuals who lose weight after diagnosis have approximately a 25% decreased mortality rate compared to those who do not lose or who gain weight. Intensive lifestyle intervention has been shown to produce disease remission in a limited share of individuals (Gregg et al, 2012). The evidence is not uniform: a recent large-scale randomized trial has demonstrated limited benefits of a weight loss intervention on overall mortality, although intermediate outcomes were affected (Wing et al, 2013).

It is quite important to note that the benefits to weight loss are also very large *prior* to diagnosis. At least two randomized controlled trials (Lindstrom et al, 2006; Diabetes Prevention Program et al, 2002) have shown that weight loss programs for individuals at risk for (but not yet diagnosed with) diabetes can reduce the chance of diabetes onset. Given the large impact of diabetes on mortality, these changes have large mortality impacts. Progression to diabetes entails changes in pancreatic function that are difficult or impossible to reverse; avoiding those in the first place is naturally of value.

Given this, the change in the medical benefit to weight loss on diagnosis is likely quite small (it could even be negative). A major change at diagnosis, however, is the frequency of interaction with the medical system and the severity of the advice given. It may therefore be appropriate to think of diagnosis as largely an information treatment. Before and after the individual feels physically similar, and has a similar objective benefit to weight loss. The difference is they are provided with a much more specific and directed set of dietary advice and more frequent feedback on progress.

3 Data and Empirical Strategy

The primary data used in this paper cover consumer purchases and are collected by Nielson through its HomeScan panel. In addition, I make use of data from a small survey of doctors on dietary advice. These sources are described in the first subsection below. The second subsection discusses data limitations. The third subsection describes the empirical strategy used.

3.1 Consumer Purchase Data

3.1.1 Nielson HomeScan

The primary dataset used in this paper is the Nielson HomeScan panel. This dataset tracks consumers purchases using at-home scanner technology. Individuals who are part of the HomeScan panel are asked to scan their purchases after all shopping trips; this includes grocery and pharmacy purchases, large retailer and super-center purchases, as well as purchases made online and at smaller retailers. The Nielson data records the UPC of items purchased and panelists provide information on the quantities, as well as information on the store. Prices are recorded by the panelists or drawn from Nielson store-level data, where available. Einav, Leibtag and Nevo (2010) have a recent validation of the reliability of the HomeScan panel. I use Nielson data available through the Kilts Center at the University of Chicago Booth School of Business. This data covers purchases from 2004 through 2011.

I construct measures of quantity of food purchased in ounces and total expenditures. Where necessary, I convert non-ounce measurements (i.e. pounds) into ounces. In the case of products which are recorded in counts (i.e. eggs) I use external evidence on the weight of the item to convert to ounces.

All Nielson household are asked to scan all items with UPC codes; this will exclude items like loose coffee, loose vegetables or butcher-counter meats, among others. A subset of households, called Magnet Households, are asked to record these items as well. These records are typically limited to prices. Throughout the paper I will show results on expenditures for the whole sample as well as for Magnet households alone, which will give a sense of the importance of the exclusion of these items.

In addition to purchase data, Nielson records demographic information on individuals. This includes household size, structure, income, education of the household heads and age of household heads and children. The data also include information on individual zip codes. I merge in data from the USDA on "food deserts" by zip code; these are defined as low income census tracts more than 1 (10) miles away from a supermarket in urban (rural) areas.

The analysis will rely on the subset of two-person households for whom we infer a diabetes diagnosis during the panel (this inference is described in detail in Section 3.3). This includes 2,592 households; summary statistics for these individuals appear in Table 1. Panel A summarizes the demographics of these households, and Panel B summarizes characteristics of their trips and purchases. The average household records 9.2 shopping trips per month.

3.1.2 Gladson Product Information Data

I merge the Nielson data with nutrient information purchased from Gladson.[3] Gladson maintains a database of information on consumer products, including virtually all information available in the packaging. The primary information of interest is total calories and the nutrient breakdown. I use a single pull of the Gladson data as of 2010.

The Gladson data does not contain a UPC match for every code in HomeScan. I undertake a sequential match procedure similar to what is used in Dubois, Griffith and Nevo (2014). For 61% of purchases there is a direct UPC match to Gladson. For products which do not have a match in the Gladson data, I impute nutrition values based on product module, brand, description and size. I calculate average nutrition per size from the matched products and multiply it with the product sizes of the unmatched products to obtain the imputed values.[4]

Calorie and nutrient summary statistics appear in the final rows of Panel B of Table 1. The average household records purchases of 820 calories per person per day, with 12% of calories from protein, 13% from saturated fat and 52% from carbohydrates.

3.1.3 Doctor Survey Data

The discussion in Section 2 provides a sense of the general dietary advice for diabetics. To get more specific information, I fielded a small survey of doctors. Seventeen primary care doctors who treat individuals with diabetes were surveyed about food choices for diabetic patients. They were provided with a list of 62 food items designed to correspond to categories in the Nielson HomeScan data (examples: applesauce, shrimp, frozen vegetables). For each one, the doctors were asked to indicate if the item is a "Good Source of Calories", a "Bad Source of Calories" or "Neither Good nor Bad". In the analysis below we will classify foods into four groups: "All Good" (all 17 of the doctors reported this as a good source of calories), "Majority Good" (the majority of doctors report this as a good source of calories), "Majority Bad" (majority of doctors report this as a bad source of calories; this category includes foods with an equal number of good and bad rankings) and "All Bad" (all 17 of the doctors report this food as a bad source of calories). Appendix A lists the full set of items and their rankings.

[3] More information is available at http://www.gladson.com/.

[4] I mark products whose nutrition per size is more than 3 standard deviations away from the mean as outliers. I calculate averages ignoring these outliers. In addition, I can impute values for an unmatched product using matched products with identical product description or, more broadly, identical product module. I choose the criterion with the lower variance in nutrient values within matched products.

3.2 Data Limitations

This data has some significant advantages in addressing the questions here. The monitoring is passive, so we worry less about Hawthorne effects. Further, I observe food choices before and after diagnosis for the same individual, which has not been possible in large-scale data before. However, there are a number of limitations in the data which deserve discussion.

The central issue is that I observe only a subset of what households buy and consume. This is true for two reasons. First, Nielson panelists do not scan food consumed away from home. Second, even within the subset of food at home, it is very likely that individuals do not record all purchases. Einav et al (2010) validate the HomeScan data using a match with records from a retailer and suggest slightly less than half of trips are not recorded at all; among trips which are recorded, they find a high level of accuracy.

To get a sense of the magnitude of this issue, I compare with food diary data from the National Health and Nutrition Examination Survey (NHANES). Although the food diaries recorded in the NHANES are likely also be subject to under-reporting, the issue is likely to be less significant. Using the 2007-2008 NHANES (the date is chosen as the midpoint of the Nielson sample) I find adults report approximately 1862 daily calories in total, and 70% of these are eaten at home. This means that, in total, the calorie levels in HomeScan represent about 65% of calories at home (taking the NHANES as the baseline) and 44% of total calories.

A second issue is that for sample size reasons it is infeasible to limit to single-person households and I will use two-person households. It seems likely that in nearly all cases it is only one household member who is diagnosed, but what I observe is the overall household change. When I come to magnitudes I will again suggest bounding arguments based on assuming that the diabetic individual is responsible for as little as half of the change or as much as all of it. I will also show robustness analysis with single-person households.

Finally, as discussed, non-UPC coded items are recorded only by a subset of households. I will show results for these households separately.

For all of these reasons, the level of calories, quantities and expenditures is somewhat difficult to interpret. I will also report the changes in percentages, which may have an easier interpretation. In addition, when I move to discussing magnitudes in Section 5, I will discuss assumptions which will allow me to scale up to comment on overall dietary changes.

3.3 Empirical Strategy

The key empirical challenge here is identifying the timing of diabetes diagnosis. I do this using information on purchases of glucose testing products. Individuals with diagnosed diabetes need to monitor their blood sugar; doing so requires a glucose monitor and accompanying test strips. Individuals put a drop of blood on the test strip and it is read by the monitor, which reports blood sugar levels. This information is required for individuals to know if they are managing their disease effectively. Test strips are discarded after a single use; the monitor is a durable good.

The identifying assumption is that observing the purchase of any glucose testing product after a period of at least nine months of observing no such purchase is a marker of a new diagnosis. This assumption is consistent with medical guidance. I validate it using a small online survey of diabetics. Among a sample of 43 individuals with Type 2 diabetes who engage in glucose monitoring, 90% reported acquiring either a glucose monitor or test strips within the first month of diagnosis.

Having identified the timing of diagnosis using this procedure, the empirical strategy is straightforward. I run regressions of the form:

$$Y_{it} = \beta \mathbf{D_{it}} + \gamma_i + \mu_t + \psi_t \tag{1}$$

where Y_{it} is the outcome (calories purchased, etc) for household i in month t, $\mathbf{D_{it}}$ is a vector of indicators for diabetes status for household i in month t, γ_i is a household fixed effect, μ_t is a calendar month fixed effect (i.e. January, February) and ψ_t is a year fixed effect. In the primary analyses, $\mathbf{D_{it}}$ includes indicators for 1 to 6 months before diagnosis (as measured by test strip purchases), first month after diagnosis, 2 to 4 months after diagnosis and 5 to 7 months after diagnosis. Including a much longer follow-up is limited by the typical length of time households are in the sample. Standard errors are clustered at the household level.

Note that I include the month before purchase of monitoring products in the "pre-period" even though individuals are likely to have been diagnosed sometime during this month. In a robustness check I will exclude this month from the analysis. In other robustness checks I will show results in which I vary the way I control for calendar time (excluding time controls or including more detailed time controls) and results in which I adjust for household-specific pre-trends.

Figure 1 shows the change in purchase of monitoring equipment based on the definition of diagnosis timing used. By construction, the period before the first month of purchases is at zero. The very large spike in the first month is reflective of the fact that by definition individuals purchase some product in this month. In the following months, we see continued purchase of testing products, although with less frequency. These purchases are largely of test strips.

Table 2 shows regressions of the form described in Equation (1) with testing product purchases as the Y_{it} variable. Column 1 shows the impact on any purchase, and Column 2 shows the impact on total spending. The regression results are consistent with the evidence in Figure 1. Total spending drops off in later months, perhaps due to the storeable nature of test strips, but the purchase of any products continues to be highly significant.

One concern here is that we may not identify all diagnosed individuals. In fact, this is likely given that a share of individuals (about 40% in the online survey) get their monitoring or testing equipment through their doctor or insurer. This will mean we estimate our results from a sub-sample of diabetics, although it does not invalidate the interpretation of the results within this sample. A second concern is that this purchase behavior occurs for reasons other than diabetes diagnosis; this seems unlikely given that there is no other use for these products. A final issue is that this identifies a diagnosis *in the household*, but does not pinpoint an individual. I limit to two person households, but in the end can say concretely only what happens to household behavior after one member is diagnosed. This relates to the data limitations above.

4 Dietary Response to Diabetes Diagnosis

This section presents the baseline results in the paper. The first subsection below shows baseline estimates of response and discusses a number of robustness checks. The second subsection discusses the evidence on response by food group.

4.1 Aggregate Response

4.1.1 Baseline Estimates

I begin by giving a visual sense of the response patterns in the data. Figure 2a shows the change in total calories per month around the inferred diabetes diagnosis; this figure replicates the form of Figure 1. The numbers reported are coefficients in a regression of calories purchased on month-from-diagnosis dummies, household fixed effects and time controls.

In the very first month after diagnosis, calories purchased are stable.[5] In the months following diagnosis they decline by around 2000 calories per household per month; this represents a decline of about 4% from the pre-period mean. Although the monthly estimates are somewhat noisy, they are all of similar magnitudes. There is no visual evidence of a pre-trend in the series prior to the inferred diagnosis.

Figures 2b and c show similar graphs for quantities and expenditures. They show similar patterns. The quantity data are the most precise. This is not surprising since others (Einav et al, 2010) have argued that the price data are subject to more error, and the calorie data are inherently noisier given the construction. In the case of expenditures, we see a significant *increase* in expenditures in the first month, followed by a decline.

In Table 3, I show the results of estimating Equation (1). Columns 1-3 show impacts on calories, quantities and expenditures for the whole sample; Column 4 shows the expenditure effects for the Magnet households, who also report non-UPC coded items. The evidence in these columns is consistent with Figure 2: slight increases in the first month, followed by decreases in the following period. Depending on the exact

[5] Going forward, I will refer to the first test strip month as the time of diagnosis, with the understanding that this is only an inferred timing based on the strategy described in Section 3.3.

timing and outcome, the decrease is in the range of 3% to 5%. The changes for Magnet households, in Column 4, are larger in magnitude due to the overall higher expenditures in this group (as would be expected since they scan a larger share of purchases). However, the percent changes are extremely close to the overall sample.

Columns 5-7 look at the nutrient mix of calories. In this case, there is little evidence of any significant alteration. Dietary advice would suggest an increase in protein and a decrease in saturated fat from baseline, neither of which appears robustly in the data.

Before turning to heterogeneity across individuals or response by food groups, I pause to consider several robustness checks on these results. I will focus on the robustness of the results in Columns 1-3 of Table 3.

First, Panel A of Appendix Table C.1 shows the results excluding the month before the first purchase of monitoring equipment; diagnosis is likely to have happened sometime during this month, so it is unclear how it should be treated. The results are unchanged.

Panels B and C of Appendix Table C.1 show the results with varying time controls. Panel B uses a longer pre-period (extended to 12 months) to estimate a household-specific pre-trend and adjusts for that trend in the analysis.[6] Panel C includes month-cross-year fixed effects (rather than month *and* year fixed effects). The results remain significant and of similar magnitude in each of the specifications; adding the household-specific pre-trends increases the magnitudes slightly, but the confidence intervals overlap.

Appendix Table C.2 considers varying sets of households. In Panel A I limit the data to single-person households. Although this sample is smaller and there is inherently more noise, the patterns of change are similar. The levels are not comparable given that single-person households purchase less food, but the shares are in the same range as the two-person households. In Panel B I drop the bottom 25% of households based on pre-period expenditures.[7] Einav et al (2010) suggest a bimodal distribution of reporting quality across households, so dropping the bottom households in terms of expenditures may eliminate some households with poor reporting behavior. The level changes are increased, reflecting the overall larger purchase baskets for this group, but the changes in shares are unaltered.

In general, the results in these Appendix tables support the conclusions from Table 3. It also appears that the magnitude of change is similar over the whole period from 2 to 7 months after diagnosis; given this, going forward I will combine these into one group where it is not instructive to separate.

A natural following question is whether there is heterogeneity across individuals in these changes. I look at variation across standard demographic groups (education, income, race, age). To do this, I estimate regressions similar to the above, but interact the diabetes timing indicators with the demographic variables. I focus on calories, quantities and expenditures. The results (I report only the interaction terms for simplicity) are show in Appendix Table C.3. The estimates are noisy, but there is little consistent variation. Although a

[6]Formally I estimate the pre-trend and then generate residuals for the later period, which are then regressed on the same diagnosis timing variables.

[7]I use the 12 month pre-period to get a fuller picture of purchases.

few of the coefficients are marginally significant, they are not large and there is little consistency across measures.

The fact that we do not see more behavioral response among, for example, richer or better educated individuals is somewhat puzzling given that, in general, individuals in these groups engage in better health behaviors. One explanation is that because these groups are generally healthier, the individuals within the groups who end up with a diabetes diagnosis are negatively selected.

In addition to demographic interactions, I also look into interactions with food availability. A common argument is that the lack of availability of good food options in poor neighborhoods drives an inability to change behavior. I use the USDA definitions of food desert, and interact timing with whether the household is in a food desert. These results are shown in the final rows of Appendix Table C.3. There is again no evidence of an interaction.

The results in this section, particularly Table 3 suggest there are sustained, but moderate, changes in dietary behavior after diagnosis. I will discuss magnitudes later, but in general this change is large enough to lose some weight, but not nearly as large as would be suggested by a doctor for a typical Type 2 diabetes patient. I turn now to looking at how these changes vary by food group.

4.2 Response by Food Group

A significant advantage of the HomeScan panel is the ability to look at changes by particular foods, rather than just changes overall. I begin by looking at how changes vary across groups of foods which are considered better or worse health-wise. This allows us to ask whether behavior change lines up with doctor advice, as would be expected if these changes reflected an attempt to consume a better diet in response to diagnosis.

As discussed in the data section, I define a group of "All Good" foods which all doctors in the survey report as a good source of calories and a group of "All Bad" foods which all doctors report as a bad source of calories. Figure 3 shows the evolution of purchase ratio between the two in terms of calories, quantities and expenditures. In the very short term – the first two months after diagnosis – the ratio of good to bad food increase by 2% to 3%. This change is, however, very short-lived: by three months after diagnosis, the ratio is insignificantly different from baseline.

In Table 4, I show regression evidence on the level changes for good foods (Panel A) and bad foods (Panel B). I look at calories, quantities and expenditures, and also separate out expenditures for Magnet households. The latter is especially important because loose vegetables are in the set of items that only Magnet households record. For good foods, calories, quantities and expenditures all increase in the first month and then return to baseline (or even lower in the case of quantities) following this. This is true for the entire sample and for the Magnet households alone. For bad foods, there is a decrease in the short-run and an even larger decease in the longer run.

This evidence gives a clue as to why we see a delayed effect in the aggregate data. In the short term households seem to increase good foods and decrease bad foods in a way that roughly equalizes calories, and actually increases expenditures (since good foods are more expensive). In the slightly longer run the increases in good foods are not sustained and the decreases in bad foods are sustained and amplified, leading to an overall decrease.

I can look in more detail across all food groups ranked by the surveyed doctors. As specified in the data section, I define four groups: "All Good", "Majority Good", "Majority Bad" and "All Bad" based on the doctor rankings. For each food group I estimate changes in calories, quantities and expenditures. I then calculate the changes as a share of the baseline by group. The results are shown in Figures 4a, b and c. In the short-run across all three outcome measures there is a strong gradient in doctor advice, with increases in expenditures in many categories. In the longer run these increases decrease or turn to decreases, and the decreases sustain. By the 5 to 7 month period, there is little or no relationship between doctor advice and changes in purchases.

The overall picture is consistent with what we see in Table 4. In the short-run, individuals change their behavior in ways very consistent with what would be recommended by a doctor. In the longer run they sustain the reductions in unhealthy foods, but the increases in good foods do not persist. One explanation is that individuals make a strong effort initially to align with the guidelines, and they then learn which guidelines are more or less difficult to follow. Regardless of the explanation, the short-run evidence here does suggest that - at least qualitatively - individuals seem to be fairly sophisticated about appropriate dietary choices.

It is also possible to describe changes by food group without reference to doctor evaluations; these category-level changes will come into play again when below when I discuss applications. For each food category I separately regress calories, quantities or expenditures on indicators for the first month after diagnosis or 2 to 7 months after diagnosis. I extract the "short-run" and "long-run" effect coefficients. Table 5 reports the evidence for the five largest decreases and five largest increases; Appendix Table C.4 summarizes the results for all modules.

The largest short-run decreases come from soda, desserts and juice; the long-run is similar, although prepared foods become more important. Notable in the increases is that the short-run has both much larger increases and also those which are more consistent with medical advice. This is, again, consistent with the doctor evidence above.

4.3 Summary of Response

The evidence in the two subsections above paints a fairly consistent picture. Households change their purchasing behavior following a diabetes diagnosis. In the very short-run they change the mix of foods to favor "good" foods at the expense of "bad" ones. In the slightly longer run there are significant overall changes in calories purchased, but very little change in the mix of foods or nutrients.

The next section will discuss the magnitude of this response, and I will then turn to two applications which use the results on behavior change to analyze a particular set of policies and comment on preferences.

5 Magnitudes

The evidence above shows changes in diet in response to diagnosis but is not sufficient to comment on the magnitude of these changes since, as discussed, we observe only household-level changes and do not observe all foods individuals purchase. Observing that behavior does change after diagnosis and on which foods is of some interest on its own, but an estimate of the magnitude of this change would allow us to comment on the implications for overall weight loss, and on how these changes compare to official recommendations. In this section I describe and implement a scaling procedure to comment on magnitudes.

The first issue in scaling is the use of household-level data. It seems reasonable to assume that at least half of the changes in food intake should be assigned to the diagnosed individual. For scaling, I adopt bounds and assume the affected individual accounts for between half and all of the calorie reduction. This means that when we observe a 4% reduction in the overall calories purchased by the household (i.e. as in Table 3 Column 1) the bounds on change for the diagnosed individual are 4% to 8%. The evidence on single-person households (Appendix Table C.2) would suggest the lower bound is the best fit.

The second issue in scaling is that we do not observe all foods people consume. Even if individuals accurately scan all foods that they purchase at the grocery store, we do not see foods consumed outside the home. Further, if households fail to scan some of their purchased foods, those will not be observed. On average, individuals record 824 calories purchased per household member per day. I will adopt the simple scaling assumption that the percent change on the items we observe is the same as on the items we do not observe.

There is some empirical support for this assumption at least as it applies to total grocery purchases. Magnet households, which are asked to record a larger share of purchases, have share changes similar to the overall sample. In Appendix Table C.2, when we drop households with very limited reporting, we again see very similar changes in shares. Both of these facts suggest that the share assumption may reasonably describe overall changes in grocery purchases. More difficult to test is the assumption that this share also applies to foods away from home. This may be indirectly tested in some sense by asking whether the inferred calorie change implies weight loss consistent with what we observe in other data on diabetics, but it is not possible to test this directly in these data.

These assumptions together imply a range of percent change in calories. I apply these to an estimate of the total caloric intake of the average person in this sample. I generate this based on medical estimates of caloric intake required to maintain weight[8], and use weight estimates for diabetics in a matched age range from

[8]Source: https://www.bcm.edu/research/centers/childrens-nutrition-research-center/caloriesneed.cfm

the NHANES. This procedure suggests a baseline of 2194 calories on average (2513 for men, 1875 for women).

Using the results in Column 1 of Table 3 and applying the scaling described above, I estimate the overall caloric reduction in the range of 4.3% to 8.6%, or between 94 and 188 calories per day. This would translate to between 0.80 and 1.6 pounds per month, or 10 to 20 pounds per year assuming these changes occur in all months of the year. My preferred figure – based on the observation that single-person households decrease calories about half as much as two-person households – is 0.8 pounds per month, or 10 pounds per year.

It is useful to compare this figure to data on measured weight loss among diabetics after diagnosis. In general, individuals diagnosed with diabetes do seem to lose some weight after diagnosis. The most directly comparable study is Feldstein et al (2008). These authors use electronic medical records from Kaiser Permanente to analyze weight change among 4135 individuals aged 21 to 75 newly diagnosed with diabetes. The authors report weight changes by month. To generate comparable figures, I use the weight changes at eight months from Feldstein et al (2008) and compare to predicted weight change at eight months as calculated from the calorie changes observed in Nielson. I assume, consistent with the data, no change in calories in the first month and then calorie changes in the months following.

The average weight change in Feldstein et al (2008) is a weight loss of 5.1 pounds. The predicted weight change range from the Nielson is 5.7 to 11.3, with 5.7 as the preferred figure. This match suggests these changes are roughly the right order of magnitude.

These changes are much smaller than what would be medically recommended for most diabetes patients. The American Diabetes Association (Franz et al, 2002) recommends a caloric deficit of at least 500 calories per day, roughly five times what we see here. This reduction would lead to a weight loss of approximately 50 pounds per year. This is of course far above what most individuals achieve.

Overall, the magnitude analysis suggests the changes observed are sufficient to produce some small weight loss, although short of sufficient to produce very large changes in BMI. It is, of course, crucial to keep in mind the assumptions that go into this calculation. However, it is comforting that what they imply about weight loss lines up with what we observe in other data.

6 Applications

I turn now to two applications which use the evidence above. Understanding how individuals with diabetes change their dietary behavior is of some *per se* interest. It may give clues as to how dietary advice might be best structured and which food purchases are likely to be most responsive. In this section I look to push the data a bit further to comment on policy and preferences.

In the first subsection below I use estimates of the price elasticity of demand by food types to analyze the tax equivalents of the changes we observe in behavior. Effectively, I ask – for a large set of the food groups

– how large a tax or subsidy would be required to produce an equivalent change. This is a question with some policy relevance since taxing unhealthy foods (or subsidizing healthy ones) is an increasingly discussed policy option (see, for example, Leonhardt (2010)). It is often seen as an alternative to programs which attempt to educate individuals about the risks of unhealthy food. A diagnosis of diabetes brings significant, and likely salient, dietary advice, although little actual change in the benefit to a better diet (as discussed in Section 2). I argue it is possible to think of this as a proxy for a very intensive educational intervention, and it is therefore of some interest to compare these changes to what we would expect from a policy of taxes and subsidies.

In the second subsection, I assume that the choices I observe in Nielson reflect optimizing dietary behavior under full information and use a simple model to estimate what this implies about the value individuals put on dietary enjoyment relative to their health.

6.1 Tax Equivalents

Evaluating the tax or subsidy equivalent of the diagnosis-produced changes in demand requires estimates of the price elasticity by food group. I use estimates from a review article (Andreyeva, Long and Brownell, 2010). These authors aggregate evidence from 160 studies on price elasticity to produce mean elasticity estimates for 16 groups, including soda, sugar and sweets, vegetables, eggs, etc. A full list and the elasticity estimates are reported in Appendix Table C.5. I match these groups to product modules in Nielson, using the same product module groups I estimate effects for in Section 4.2. Not all products can be matched to an elasticity estimate; for example, there is no elasticity estimate reported for nuts, reflecting the fact that no studies have estimated price elasticity for nuts. In these cases, I exclude the module. The second column of Appendix Table C.5 lists the product groups which are matched to each elasticity category.

Given these estimates, it is straightforward to generate a tax or subsidy equivalent. Consider the formula for price elasticity:

$$\frac{\%\Delta Q}{\%\Delta P} = \epsilon$$

From the Andreyeva et al (2010) data I have an estimate of ϵ for each food group. From the evidence in Section 4.2 I have an estimate of the $\%\Delta Q$. Together, I use these to calculate the $\%\Delta P$ which would produce this change, which is the tax or subsidy equivalent.

I estimate the tax equivalent of both the short-run (first month) and long-run (two to seven months) changes. In both cases I focus on the changes in quantities (not calories or prices) since this is the closest parallel to what is used in calculating the price elasticity estimates.

Figures 5a and b show the tax equivalents by group for the short-run (Sub-Figure a) and longer run (Sub-Figure b). In the short-term, the changes in many good items - fruit, vegetables, yogurt - are equivalent to reasonable subsidies, on the order of 10% to 20%. The changes in soda and dessert consumption are also equivalent to a 10% to 20% tax. In the long-term, likely the more interesting case, consumption of most groups decreases so few have subsidy equivalents. An exception is diet desserts, which people increase their consumption of as if they are virtually 100% subsidized. The soda changes are the most striking, equivalent to a 20% tax on soda.

A perhaps more focused way to address this question is to identify several "healthy" and "unhealthy" foods which would be likely targets for taxes or subsidies and ask how a plausible tax or subsidy level would impact behavior relative to the impact of diagnosis. This is done in Table 6, which uses long-term changes in quantities. The first rows look at unhealthy foods which are plausible tax targets: soda, desserts, sugar and sweet baked goods (donuts, etc). I show the percentage change in quantity after diagnosis and the predicted percentage change with a 10% tax. With the exception of sugar, the diagnosis-based changes are comparable or larger than the effect of a 10% tax.

The last rows consider healthy foods – fruits, vegetables, fish and yogurt – which are plausible subsidy targets. The columns are equivalent, except I show the predicted impact of a 10% subsidy. Here, the subsidy performs much better at increasing purchases than diagnosis.

The conclusions here suggest that moderate taxes would be required to produce behavioral response similar to what we observe from this "intervention." This is certainly in the range of what policy has discussed and implemented (Mytton, Clarke and Rayner, 2012). Whether this suggests taxes are better than intensive educational campaigns depends on how distortionary we think taxation is, as well as how close a broad education campaign could get to the treatment effects observed here.

A perhaps more striking point is that this suggests that subsidies may be much better than information at producing increases in healthy food purchases. This is perhaps not very surprising given the evidence in Section 4.2, although adding the price elasticity estimates allows us to rule out the possibility that the minimal changes in healthy foods are due to generally low demand elasticity.

6.2 Preference for Diet

In this section I consider what the evidence on behavior change implies about individual valuation of health compared to the value they place on their ideal diet. The key question is whether we can quantify how much individuals must value their diet in terms of health. What does the data indicate about how many years of life an individual would be willing to trade for an extra soda every day?

In principle, this question could be addressed with cross-sectional data on diet and health: the link between weight and health is known, and observing that someone is overweight must imply that they value their diet more than the health tradeoffs. Conceptually, I will use a similar logic with these data. However, this setting has several empirical advantages.

First, we know individuals who have been recently diagnosed with diabetes will have significant medical contact and be receiving advice about diet choices. It is therefore more reasonable to imagine that individuals in this sample – relative to a general population of overweight individuals – are aware of the health benefits of weight loss, and are aware of the medical recommendations on diet.

Second, I am able to observe the magnitude of behavior change and evaluate the benefit of further changes relative to this magnitude. Effectively, the average individual in this sample is making choices sufficient to lose some weight (perhaps 10 pounds a year) but not more. We can therefore evaluate the benefit of further reductions relative to this level. This is especially useful since the impacts of weight loss on health are non-linear: if the data suggested caloric reductions sufficient to lose 50 pounds in a year, the conclusions about implied health valuation would be very different.

Below, I first discuss an extremely simple framework for addressing the question of how individuals trade off health and diet, and then discuss the empirical conclusions. It is crucial to keep in mind that the assumptions here are quite strong, and the results should be taken with caution.

6.2.1 Framework

Consider an individual who has utility over two things: their health, and the taste value of their diet. Both of these are a function of calories, with health initially increasing in caloric intake and then decreasing. Taste utility is also increasing and then decreasing, although I assume the inflection point is above the inflection point for health (i.e. taste utility continues to increase with caloric intake over a range where health is declining). Assume taste and health are additively separable. Health utility over calories will depend on some fixed demographic characteristics of the individual which I denote X. Denote calories consumed as C, taste utility U_T and health utility $U_{H,X}$ where the double subscript on health utility captures the function's reliance on baseline.

Total utility from calories is given by:

$$U(C) = U_T(C) + U_{H,X}(C)$$

where U_T is taste utility and U_H is health utility. Health utility over calories will naturally be a function of current weight and other demographics, which I denote $\mathbf{X}$. I assume that taste depends only on calories, although that assumption would be trivial to relax.

This function will be maximized subject to a budget constraint. Define P_C as the price per calorie of the lowest price basket of calories. Given some food budget I_F we have:

$$I_F \geq P_C \times C$$

Given this setup, there are two types of individuals. For individuals whose food budget allows them to purchase calories only up to a range where both taste *and* health are increasing in the number of calories, there will be a corner solution. This group will simply purchase as many calories as they can afford.

Most individuals in the US are unlikely to be in this situation; the majority of households in the US are able to afford sufficient calories for subsistence. For this group, the budget constraint does not bind and the condition for maximization is given:

$$\frac{dU_T}{dC} = -\frac{dU_{H,X}}{dC}$$

In the region above subsistence/weight maintenance and below the point at which taste begins to diminish, we have $\frac{dU_T}{dC} > 0$ and $\frac{dU_{H,X}}{dC} < 0$. The equality therefore implies an interior solution.

What this implies is quite straightforward. On the margin, for an individual who is optimizing their caloric intake, they must value the last calorie in terms of taste as much as it cost them in terms of health. If we know the health consequences of the marginal calorie, it is straightforward to observe this must also be the taste value of that calorie, denominated in terms of health. I implement this calculation empirically using external evidence on the link between weight loss and health among diabetics.

6.2.2 Empirical Evidence

There is substantial empirical evidence that weight loss has health benefits for diabetic individuals. To implement the above calculations, I reviewed the literature on this and extracted studies which showed health benefits to weight loss and which quantified these benefits in terms of pounds lost.

Based on the preferred point estimate in Section 5 I work from the assumption that individuals reduce 100 calories per day, and therefore would lose 10 pounds in the first year. I then ask what the health benefit would be of losing ten additional pounds over this first year, which would require a further caloric reduction of approximately 100 calories per day. Under the assumption of optimization, individual must value the 100 calories at least this much in terms of taste.

Much of the data on the link between health and weight comes from a trial called the "Look AHEAD" trial, which randomized individuals into an intensive lifestyle intervention and which produced more weight loss in the intervention than the control group. On average, the intervention group lost more wight than the control group. However, I am not exclusively using the randomized variation here, since doing this calculation requires extracting some continuous estimate of the weight loss impact. Many studies of outcomes in this trial report not only the treatment-control difference but also an estimate of the impact per kilogram of weight lost.

In Table 7 I report, for the set of outcomes and citations with appropriate data, some information on the study methodology and the implied 100-calorie-per-day health valuation; details of all calculations here are in Appendix B. The first row looks at all-cause mortality; this data does not come from Look AHEAD but, instead, from a separate study which followed a cohort of overweight diabetics and recorded weight loss variation across individuals (Williamson et al, 2000). This study found significant impacts of weight loss on survival. The calibration suggests that for someone aged 50, a further reduction of 100 calories per day would produce between 0.2 and 1 additional year of life. This effect is quite large. Using a value of $115,000 per life year[9] and discounting at 3%, this suggests individuals value the marginal 100 calories per day at between $37 and $132.

It is important to note that although the weight loss is generally a key component of diabetes treatment, not all studies find an impact on mortality. In particular, the Look AHEAD trial, referenced above, notably did not see difference across treatment and control groups in cardiovascular mortality (Wing et al, 2013). This result is not included in Table 7 because the study did not estimate effects per weight loss for this outcome, but should certainly be noted. Using these data, one would conclude no cardiovascular mortality benefit from calorie reduction.[10]

The second row of Table 7 focuses on partial or complete diabetes remission - that is, achieving glucose levels in the normal range without medication. These data come from the Look AHEAD trial (Gregg et al, 2012).[11] The estimates suggest an additional 100 calorie reduction per day would lead to a 3.3 percentage point increase in the chance of partial or complete remission over the first year. Since diabetics have significantly elevated mortality compared to non-diabetics, remission is a key outcome.

The bottom rows of the table focus on quality of life outcomes considered in this study. The marginal 100 calories are valued in terms of sleep apnea (0.27 events per hour), erectile function (0.6 change in erectile function score), and male and female urinary incontinence (1.4 to 1.6 percentage point change in incidence). Monetary values for these are somewhat difficult to state precisely, but estimates suggests that the economic burden of these conditions, particularly urinary incontinence, may be large (Milsom et al, 2014).

I focus in this table on final outcomes but evidence from Look AHEAD and other data also show impacts of weight loss on intermediate outcomes, including glucose control, blood pressure and triglycerides (Espeland, 2007).

The analysis here requires significant assumptions - in translating the HomeScan evidence into weight loss, in estimating the impact of weight on health and in connecting the two. It should therefore be taken with appropriate caution. However, the results as stated suggest that individuals value their dietary choices very highly relative to health. One hundred calories is equivalent to one small soda per day. The data suggest

[9] This is based on the US DOT standard $9.1 million VSL (http://www.dot.gov/sites/dot.gov/files/docs/VSL_Guidance_2014.pdf) and a life expectancy of 78 years.

[10] The results from this study are fairy controversial, with critics arguing the differences in weight loss by the end of the trial were too small to detect differences in mortality events. The study did find impacts on markers of cardiovascular health and disease remission. A more subtle issue with using these data in drawing conclusions here is that this study was not released until 2013. If the goal is to approximate the information individuals in the sample would have had at the time of making these choices, the older data may be more relevant.

[11] All of the rows following mortality use data from Look AHEAD. Although in all cases I rely on the non-experimental variation in the calibration, in each of these outcomes the treatment-control difference in the study is statistically significant.

individuals would prefer to lose a significant life-year period, and accept lower quality of life while alive rather than giving up this soda. To the extent that valuations like this may also hold for the general population of overweight individuals, this sheds light on why it is so difficult to effect behavior change with information about health costs of diet.

7 Conclusion

The primary results presented here suggest that households respond to health information by changing their dietary choices. These changes are significant, although they are small relative to what a doctor would recommend. The pattern of changes in the period immediately following diagnosis suggest good information about what foods are recommended, and which are not. In the longer run, households do not seem to persist with increases in healthy foods, although decreases in unhealthy foods persist.

The larger question underlying this work is what solutions - policy or otherwise - might prompt greater behavioral response. The baseline behavioral response suggests that the message about what to eat is getting through to newly diagnosed individuals. Despite this, at least some of these changes - particularly the increases in healthy food - do not seem to be sustained. This may suggest that more than information is required to generate behavior change on this dimension. Simple policy experiments suggest that, especially for increasing purchases of healthy foods, subsidies may be a more productive way to change behavior. The results suggest that overall valuation of health is relatively low compared to the value placed on particular dietary choices.

In addition to the contribution to understanding of dietary behavior change, this paper also suggests a new application of household scanner data to look at questions in health.

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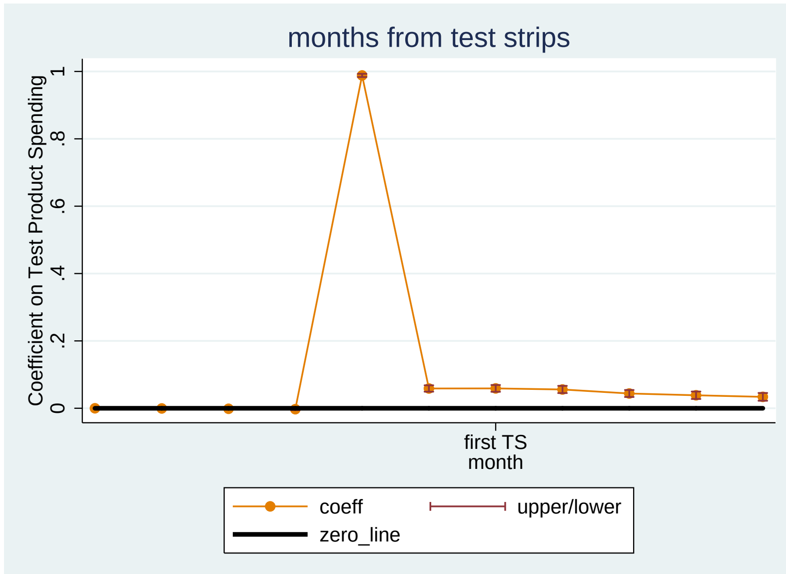
Figure 1: **Test Strip Purchases**

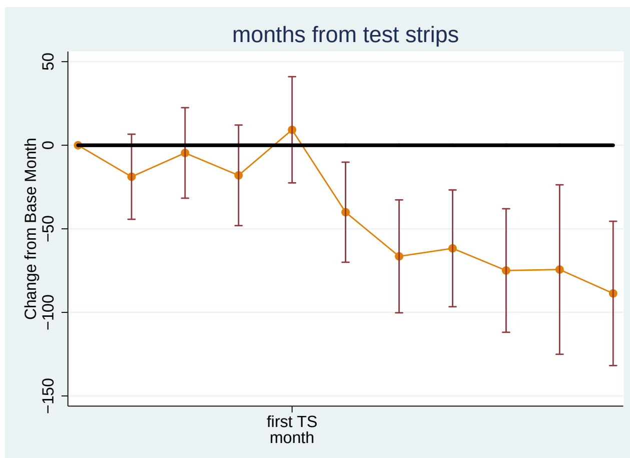


Notes: This figure shows data on purchasing any test strip products around the inferred diagnosis timing. Coefficients are from a regression which controls for month, year and household fixed effects.

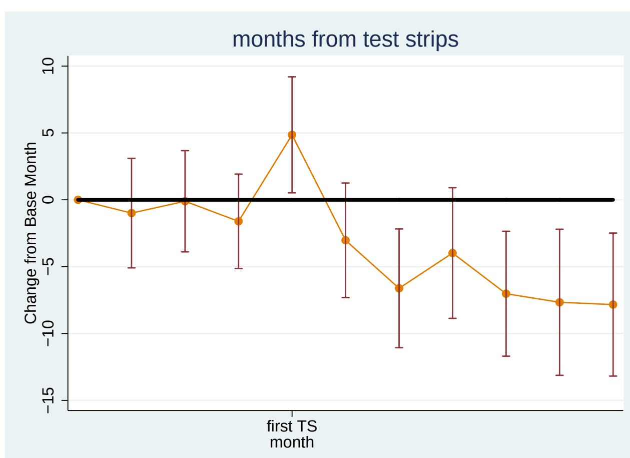
Figure 2: **Behavior Change: Calories, Quantities and Spending**

(a) Calories

(b) Quantity in Ounces

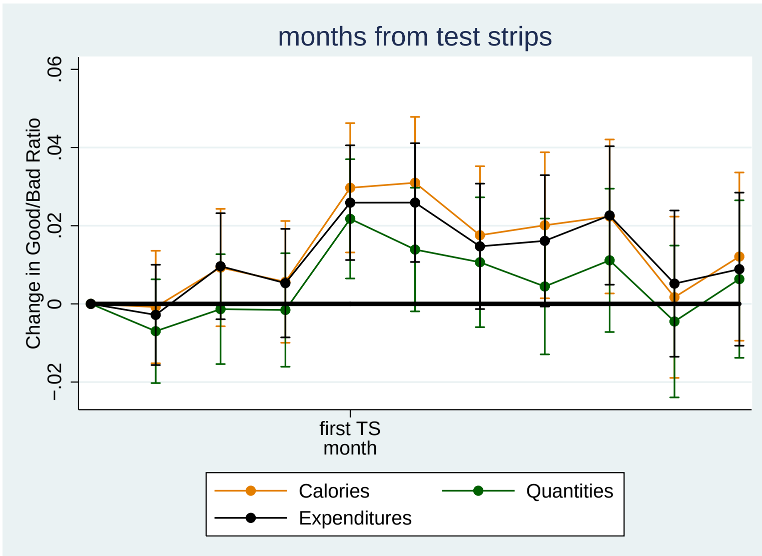


(c) Expenditures



Notes: These figures show coefficients from regressions of the various outcome variables on months from inferred diagnosis. Error bars show 90% confidence intervals.

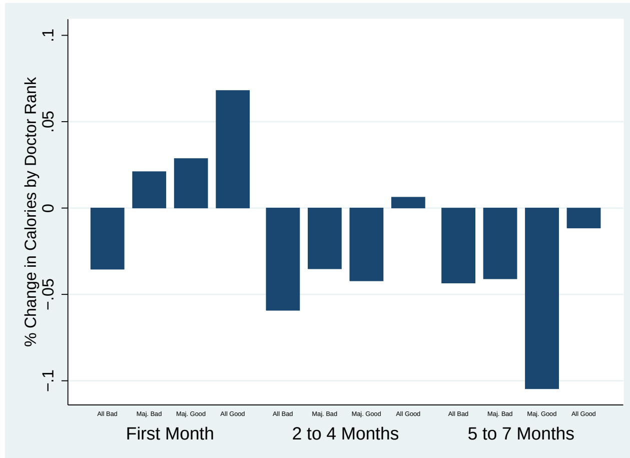
Figure 3: **Changes in Ratio of "Good" to "Bad" Foods**



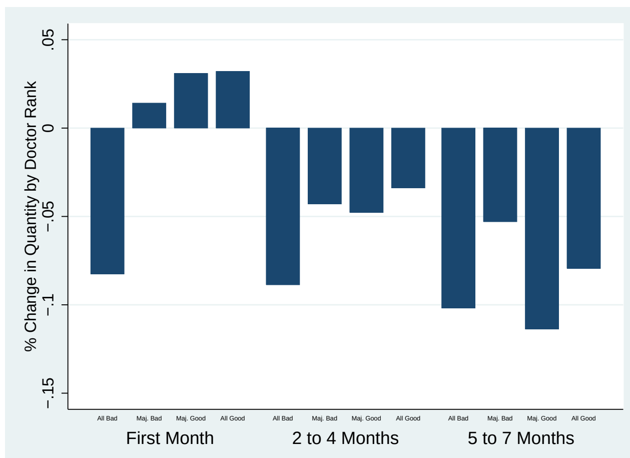
Notes: This figure shows coefficients from a regression of the ratio of good to bad foods (in terms of calories, expenditures and prices) on time from inferred diagnosis. Good foods are defined as those which all doctors surveyed say are a good source of calories; bad foods are defined as those which all doctors surveed say are a bad source of calories. Error bars show 90% confidence intervals.

Figure 4: **Behavior Change by Doctor Advice**

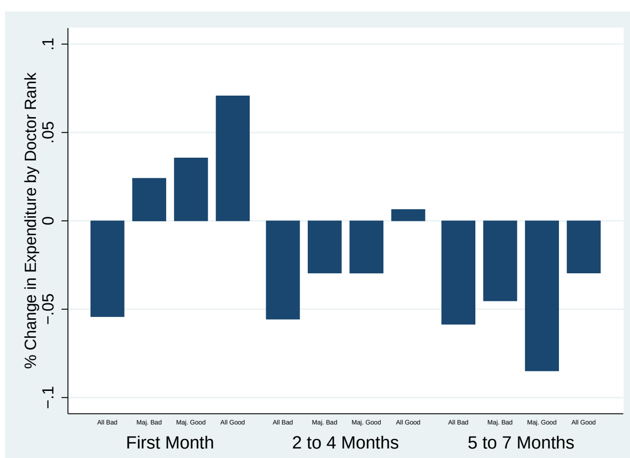
(a) Calories



(b) Quantity in Ounces



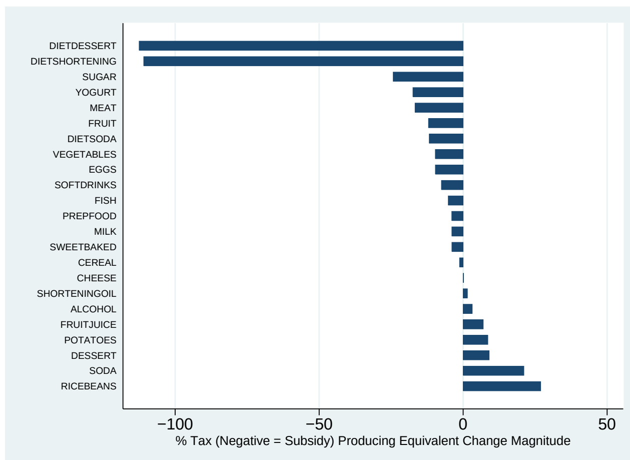
(c) Expenditures



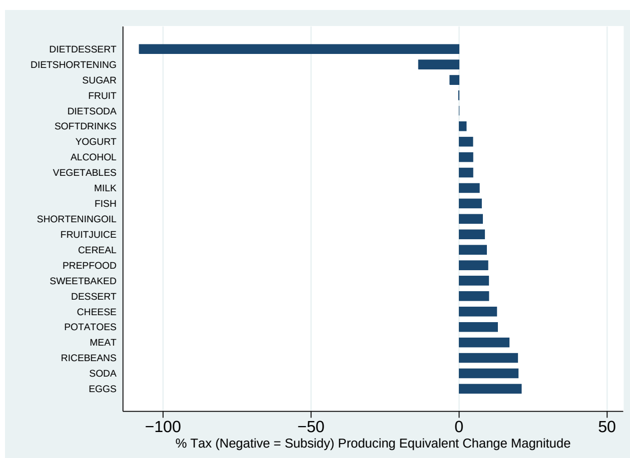
Notes: These graphs show changes in calories, quantities and expenditures on foods with varying doctor rankings. Changes are reported as a share of the mean. "All Good" are foods which all doctors in the sample reported as good sources of calories; "Maj. Good" are those items which more doctors report as a good source of calories than a bad source. The corresponding "Bad" labels are defined in the same way. The data is constructed by regressing each item on diagnosis timing measures separately and then summing the coefficients and mean expenditures by group.

Figure 5: **Tax Equivalents**

(a) First Month



(b) Two to Seven Months



Notes: These graphs shows tax rates which would produce the same magnitude change as produced by the diagnosis event. Sub-Figure a uses the short term (first month) quantity changes. Sub-Figure b uses the longer term (2 to 7 month) quantity changes. Elasticity estimates come from Andreyeva, Long and Brownell, 2010.

Table 1: **Summary Statistics**

Panel A: Panelist Demographics			
	Mean	*Standard Deviation*	*Sample Size*
HH Head Age Group (range 1-9)	7.8	1.4	2592
HH Head Education Group (range 1-6)	4.0	1.1	2337
HH Income Group (range 3 to 30)	19.8	5.6	2592
White (0/1)	0.84	0.37	2578
In Food Desert (0/1)	0.35	0.48	2592
Panel B: Panelist Shopping Behavior			
Avg. Number of Trips/Month	9.2	5.6	29,988
Shopping Behavior (Per Household/Month):			
Quantity in Ounces	1109.8	840.8	29,988
Expenditures	$140.73	$126.48	29,988
Calories (Gladson Data)	49,485	33,038	29,988
Share Carbohydrates (Gladson Data)	0.52	0.13	29,892
Share Protein (Gladson Data)	0.12	0.04	29,935
Share Saturated Fat (Gladson Data)	0.13	0.06	29,902

Notes: This table reports summary statistics on demographics (Panel A) and panelist shopping behavior (Panel B). Age groups range from 1 (under 25) to 9 (over 65); education groups range from 1 (grade school only) to 6 (post-graduate education). Income groups range from 3 (under $5000) to 30 ($200,000 +). Quantity and expenditure data come from Nielson data directly. Quantities are in ounces and items which are not reported in ounces are converted to ounces. Calories and nutrients are generated by merging the Nielson panel with Gladson data. The details of this merge are in Section 3.1.2.

Table 2: **Test Supply Purchases By Inferred Diagnosis Time**

Outcome:	*Any Testing Purchase*	*Testing Supply Spending*
First Month After	0.990***	58.49***
	(.002)	(1.42)
Two-Four Months After	0.060***	2.67***
	(.004)	(0.64)
Five-Seven Months After	0.042***	0.50
	(.005)	(0.85)
Household Fixed Effects	YES	YES
Year/Month FE	YES	YES
R-squared	0.78	0.39
Number of Obs.	25,355	25,355

Notes: This table reports evidence from regression of testing supply purchase on timing from diagnosis. Diagnosis is defined as the first month in which any testing supplies are purchased.

Table 3: **Behavior Change After Inferred Diabetes Diagnosis**

Outcome:	*Calories*	*Quantity in Oz.*	*Spending ($) All*	*Spending ($) Magnet HH*	*Share Cal: Carbohydrates*	*Share Cal: Protein*	*Share Cal: Saturated Fats*
First Month After	518.9	22.2	5.72***	6.59*	-0.002	0.002*	-0.002
	[0.010]	[0.020]	[0.041]	[0.037]	[-0.004]	[0.015]	[-0.013]
	(641.2)	(14.0)	(1.87)	(3.50)	(.003)	(.001)	(.001)
Two-Four Months After	-1989.1***	-41.0***	-3.52**	-5.32*	-0.001	-0.0005	0.001
	[-0.040]	[-0.036]	[-0.025]	[-0.030]	[-0.003]	[-0.004]	[0.005]
	(575.1)	(11.2)	(1.56)	(2.95)	(.002)	(.001)	(.001)
Five-Seven Months After	-2387.4***	-61.2***	-6.27***	-9.50***	0.0001	-0.003***	0.002
	[-0.047]	[-0.055]	[-0.050]	[-0.053]	[-0.0002]	[-0.030]	[0.012]
	(769.7)	(16.6)	(1.91)	(3.53)	(.003)	(.001)	(.001)
Household Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Year/Month FE	YES	YES	YES	YES	YES	YES	YES
R-squared	0.47	0.59	0.69	0.68	0.32	0.37	0.33
Number of Obs.	25,278	25,278	25,278	11,889	25,195	25,230	25,203

Notes: This table shows the primary results on aggregate changes. The omitted category is 1 to 4 months before diagnosis. All coefficients are reported in levels. Figures in square brackets represent the change as a share of baseline average. Standard errors are in parentheses. Magnet households are those who also scan and report prices for non-UPC coded goods. *significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table 4: **Effects for "Good" and "Bad" Foods**

Panel A: Good Foods				
Outcome:	*Calories*	*Quantity in Oz.*	*Spending ($)*	*Spending ($) Magnet HH*
First Month After	301.5***	8.40**	0.95***	1.06***
	(102.5)	(3.5)	(0.24)	(0.38)
Two-Seven Months After	10.1	-7.67**	-0.03	-0.15
	(91.8)	(3.48)	(0.21)	(0.35)
Baseline Level	4319	196.3	12.38	14.52
Panel B: Bad Foods				
Outcome:	*Calories*	*Quantity in Oz.*	*Spending ($)*	*Spending ($) Magnet HH*
First Month After	-203.8	-7.9**	-0.35	-0.62*
	(212.1)	(3.1)	(0.23)	(0.35)
Two-Seven Months After	-444.9***	-9.7***	-0.53***	-0.67**
	(165.1)	(2.5)	(0.20)	(0.31)
Baseline Level	7255	106.1	9.60	10.41

Notes: This table reports the impact of diagnosis timing on purchases of good and bad foods. The omitted category is 1 to 4 months before diagnosis. Good foods are defined as those which all doctors surveyed say are a good source of calories; bad foods are defined as those which all doctors surveyed say are a bad source of calories. Standard errors are in parentheses. Magnet households are those who also scan and report prices for non-UPC coded goods. *significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table 5: **Individual Food Group Changes**

Short Term: First Month						**Long Term: Two-Seven Months**					
Calories		*Quantity in Oz.*		*Spending ($)*		*Calories*		*Quantity in Oz.*		*Spending ($)*	
Food Group	*Effect Size*	*Food Group*	*Effect Size*	*Food Group*	*Effect Size*	*Food Group*	*Effect Size*	*Food Group*	*Effect Size*	*Food Group*	*Effect Size*
Soda	-191.5*	Soda	-4.65*	Soda	-0.26*	Prep. Food	-540.1*	Milk	-7.94*	Prep. Food	-1.32*
Dessert	-88.8	Fruit Juice	-3.17	Fruit Juice	-0.21*	Soda	-230.5*	Prep. Food	-6.85*	Meat	-0.35
Rice/Beans	-78.5*	Dessert	-2.21	Alcohol	-0.18	Dessert	-157.1	Soda	-5.35*	Cheese	-0.31*
Shortening	-62.1	Potatoes	-1.57	Pizza	-0.11	Pasta	-154.7*	Fruit Juice	-3.93*	Alcohol	-0.30
Prep. Food	-56.4	Pizza	-0.68	Prep. Food	-0.09	Milk	-131.8*	Dessert	-2.46	Fruit Juice	-0.29*
Flour	102.9	Bread	2.86*	Coffee/Tea	0.33*	Fruit	13.2	Peanut Butter	0.13	Breakfast Foods	0.06
Peanut Butter	131.2*	Vegetables	3.35*	Fruit	0.36*	Diet Desserts	37.6*	Sugar	0.16	Fruit	0.08
Milk	133.9*	Milk	4.55	Meat	0.44	Peanut Butter	44.1	Diet Desserts	0.34*	Coffee/Tea	0.14
Nuts	175.6*	Diet Soda	5.55*	Snacks	0.49*	Flour	91.6	Nuts	1.07*	Diet Dessert	0.18*
Bread	187.2*	Soft Drinks	5.62	Vegetables	0.54*	Nuts	147.4*	Flour	1.14	Nuts	0.33*

Notes: This table shows the food modules with the largest decreases (top five rows) and increases (bottom five rows) in calories, quantities and expenditures in the short term and longer term. A full list of changes and baseline levels appears in Appendix Table C.4. * significant at at least the 10% level.

Table 6: **Tax Equivalents, Long Term Changes**

Food Group	*% Change Quantity After Diabetes*	*% Change Quantity From 10% Tax*
Soda	-15.8%	-7.9%
Dessert	-3.4%	-3.4%
Sugar	1.1%	-3.4%
Sweet Baked Goods	-3.4%	-3.4%
Food Group	*% Change Quantity After Diabetes*	*% Change Quantity From 10% Subsidy*
Fruit	0.1%	7.0%
Vegetables	-2.7%	5.8%
Fish	-3.8%	5%
Yogurt	-3.0%	6.5%

Notes: This table shows the percentage change in quantity by food group after diagnosis and the predicted changes from a 10% tax (for the bad foods) or 10% subsidy (for the good foods). Price elasticity estimates by group come from Andreyeva, Long and Brownell, 2010.

Table 7: **Implied Calorie Valuations in Terms of Health**

Outcome [Citation]	*Description of Study*	*Effect of Daily 100 Calorie Reductoin (10 pounds to 20 Pounds)*
Morality [CITE]	Twelve year follow-up on mortality among overweight people diagnosed with diabetes. Those who lose more weight compared with those who lose less.	11.3% reduction in hazard rate of death. For someone aged 50: 0.8 percentage point reduction in chance of dying over 12 years; total of 0.21-1.0 life years gained.
Diabetes Remission	One-year follow-up of intensive lifestyle intervention which prompted greater weight loss than control.	3.3 percentage point increase in chance of partial or complete diabetes remission in first year.
Sleep Apnea	One-year follow-up of intensive lifestyle intervention which prompted greater weight loss than control.	Reduction of 2.7 apnea index events per hour.
Erectile Function (Men)	One-year follow-up of intensive lifestyle intervention which prompted greater weight loss than control.	0.60 (scale of 0-26) increase in erectile function score.
Urinary Incontinence (Men)	One-year follow-up of intensive lifestyle intervention which prompted greater weight loss than control.	1.4 percentage point reduction in weekly incontinence (base rate: 10.2%)
Urinary Incontinence (Women)	One-year follow-up of intensive lifestyle intervention which prompted greater weight loss than control.	1.6 percentage point reduction in development of weekly incontinence (base rate 12.2%)

Notes: Details of the studies and caclulations are in Appendix XX.

Appendix A: Doctor Survey Results

The table below lists each food group which was covered in the doctor survey, the number of doctors who voted it a "Good Source of Calories" and those who voted a "Bad Source of Calories". Although all 17 doctors were asked about each group not all rows add to 17 because doctors could also indicate the product was neutral.

Product	*Number Report "Good Source"*	*Number Report "Bad Source"*	*Product*	*Number Report "Good Source"*	*Number Report "Bad Source"*
Frozen Pizza	0	17	Lite Dressing	4	3
Cookies	0	17	Cold Cereal	7	4
Chocolate chips	0	17	Olives	7	4
Cookie mix	0	17	Canned Vegetables	8	3
Soda	0	17	Ground Beef	9	6
Flavored Syrup	0	17	Canned Beans	9	5
Frozen Biscuits	0	17	Soup	9	5
Ice Cream	0	17	Frozen Fruit	9	5
Cake mix	0	17	Natural Cheese	10	5
Slice-n-Bake Cookies	0	17	Breakfast Bars	10	4
Sugar	0	17	Salsa	10	3
Mayonnaise	0	16	Olive Oil	11	0
Spam	0	14	Peanut Butter	12	3
Butter	0	14	Dried Fruit	12	3
Creamer	0	12	Tuna	12	1
Potato Chips	1	16	Cottage cheese	13	2
Jam	1	16	Egges	13	1
Salad Dressing	1	15	Frozen Vegetables	14	1
Pasta Dinner	1	15	Yogurt	14	0
Snack Crackers	1	14	Shrimp	15	1
Bread	1	12	Hot Cereal	15	0
Margerine	1	12	Fresh Fruit	15	0
Juice	2	13	Chicken	16	0
Flour	2	8	Fish	17	0
Regular Milk	3	11	Low Fat Milk	17	0
Potatoes	3	9	Vegetables	17	0
Applesauce	3	8	Nuts	17	0
Pretzels	4	9	Dried Beans	17	0
Pasta	4	9			
Rice	4	9			
Pickles	4	3			

Appendix B: Health and Weight Calculations

This appendix describes, for each row in Table 7, how I generate the link between weight loss and health. In all cases these are then combined with the observation that reducing 100 calories per day would cause additional weight loss of about 10 pounds per year. I begin from a baseline of 10 pounds, so I ask about the effect of moving from a weight loss of 10 to a weight loss of 20 pounds.

Mortality The mortality data come from Williamson et al (2000). This is a twelve year studying following overweight individuals with diabetes. They estimate a linear impact of weight loss on mortality rate from 0 to 30 pounds. The estimate is a -0.33 reduction in death rate over this range. Due to linearity, this translates to a -0.11 reduction in death rate moving from 10 to 20 pounds. To estimate this in life years I use someone age 50 as an example and use life table data from the CDC to estimate the impact of this reduction in death rates in each year on total survival. The range of values provided in the paper represent either the assumption that the benefit only accrues for 12 years (the length of the study) or the assumption that it accrues for the rest of life.

Remission Remission data come from Gregg et al (2012). The authors report the impact of tercile of weight loss in he first year on diabetes remission. I use evidence from Espeland (2007) on weight loss in the first year to calculate the midpoints within each tercile. I then estimate the impact of a 1% weight loss on the 1 year remission chance (it is 0.8 percentage points). I translate this to the impact of moving from 10 to 20 pounds using initial weight.

Sleep.Apnea Sleep apnea data come from Foster et al (2009). The authors report a reduction in sleep apnea events of 0.6 events per hour per kilogram lost; the range of weight loss contains the 10 to 20 pound range. I multiply by 10 pounds in kilograms.

Erectile Function Erectile function data comes from Wing et al (2010). The authors report a -0.148 change in erectile function measure for each 1% weight loss. I use informatoin on the baselin weight of the sample to estimate the impact of moving from 10 to 20 pounds.

Urinary Incontinence (Men) Estimates come from Breyer et al (2014). The authors report 1kg of weight loss reduces the odds of having weekly incontinence by 3%; the base rate is 10.2% . This translates to a reduction of 0.30 percentage point per kilogram, which I scale up to the 10 to 20 pound weight loss.

Urinary Incontinence (Women) Estimates come from Phelan et al (2012). The authors report 1kg of weight loss reduces the odds of developing weekly incontinence by 3%; the base rate is 12.2% . This translates to a reduction of 0.36 percentage point per kilogram, which I scale up to the 10 to 20 pound weight loss.

Appendix C: Table and Figures

Table C.1: **Main Result Robustness: Alternative Time Definitions, Controls**

Panel A: Exclude Diagnosis Month			
Outcome:	*Calories*	*Quantity in Oz.*	*Spending ($)*
First Month After	485.1	17.5	5.03**
	(677.3)	(15.7)	(1.97)
Two-Four Months After	-2047.8***	-48.1***	-4.49**
	(625.8)	(13.3)	(1.77)
Five-Seven Months After	-2481.9***	-71.4***	-7.8***
	(810.5)	(19.8)	(2.12)
Panel B: Household-Specific Pre-trends			
Outcome:	*Calories*	*Quantity in Oz.*	*Spending ($)*
First Month After	226.7	14.5	2.92***
	(689.3)	(15.1)	(1.96)
Two-Four Months After	-2659.8***	-57.1***	-8.46**
	(715.4)	(14.8)	(1.93)
Five-Seven Months After	-3618.4***	-87.0***	-14.5***
	(1012.6)	(21.8)	(2.50)
Panel C: Month-Year Fixed Effects			
Outcome:	*Calories*	*Quantity in Oz.*	*Spending ($)*
First Month After	505.3	21.9	6.04***
	(641.2)	(14.3)	(1.88)
Two-Four Months After	-2013.7***	-40.0***	-3.27**
	(582.1)	(11.4)	(1.57)
Five-Seven Months After	-2391.1***	-60.0***	-5.96***
	(777.9)	(17.3)	(1.94)

Notes: This table replicates the results in Columns (1) through (3) of Table 3, with varying time definitions and controls. Panel A excludes the month of diagnosis. Panel B uses a longer period of months prior to diagnosis to estimate and adjust for a household-specific trend. Panel C includes month-cross-year fixed effects rather than month and year fixed effects separately. Panel C contains no time controls. The omitted category in Panels B and C is 1 to 4 months before diagnosis. All coefficients are reported in levels. Standard errors are in parentheses. *significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table C.2: **Main Result Robustness: Alternative Groups**

Panel A: Single Person Households			
Outcome:	*Calories*	*Quantity in Oz.*	*Spending ($)*
First Month After	902.7	0.32	3.29
	[0.031]	[0.0004]	[0.037]
	(741.4)	(16.1)	(3.42)
Two-Four Months After	-899.5	-40.6**	-4.40**
	[-0.031]	[-0.060]	[-0.050]
	(630.6)	(16.3)	(2.19)
Five-Seven Months After	-875.7	-36.2*	-7.50**
	[-0.030]	[-0.053]	[-0.085]
	(833.4)	(21.0)	(3.08)
Number of Obs.	10,183	10,183	10,183
Panel B: Drop Bottom 25% in Expenditures			
Outcome:	*Calories*	*Quantity in Oz.*	*Spending ($)*
First Month After	-71.5	11.2	4.68**
	[-0.001]	[0.009]	[0.030]
	(813.3)	(17.7)	(2.27)
Two-Four Months After	-3053.7***	-56.1***	-4.34**
	[-0.052]	[-0.043]	[-0.027]
	(727.2)	(14.1)	(1.84)
Five-Seven Months After	-3248.8***	-70.0***	-6.12***
	[-0.055]	[-0.055]	[-0.039]
	(972.4)	(21.1)	(2.23)
Number of Obs.	18,885	18,885	18,885

Notes: This table replicates the results in Columns (1) through (3) of Table 3 with varying samples. Panel A uses single-person households. Panel B drops the 25% of households with the lowest average expenditures in the period before diagnosis. The omitted category is 1 to 4 months before diagnosis. All coefficients are reported in levels. Figures in square brackets represent the change as a share of the baseline average. Standard errors are in parentheses. *significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table C.3: **Changes by Demographic Group**

	First Month After	*Two to Seven Months After*
Education		
Calories	-911.9 (620.6)	95.4 (427.6)
Quantities	-8.1 (13.6)	-0.51 (9.29)
Price	-1.6 (1.7)	-0.71 (1.23)
Yearly Household Income		
Calories	-201.3*(109.9)	59.5 (68.9)
Quantities	-2.3 (2.4)	0.67 (1.65)
Price	0.06 (0.33)	0.30 (0.23)
Household Head Age		
Calories	1033.0**(455.0)	89.8 (355.3)
Quantities	8.63 (10.7)	-0.74 (8.3)
Price	-1.06 (1.40)	-0.51 (1.01)
White		
Calories	2205.4 (1668.7)	-697.0 (1230.1)
Quantities	63.8*(34.9)	37.7 (23.4)
Price	9.33**(4.6)	4.0 (3.2)
Food Desert		
Calories	-918.2 (1261.7)	40.2 (829.0)
Quantities	-30.4 (25.6)	15.9 (18.7)
Price	-0.49 (3.79)	3.55 (2.48)

Notes: Coefficients shown are interactions between the demographic measure and the timing variable. Each row represents a separate regression with the stated outcome variable. Level effects are included in the regression but not reported. Standard errors are in parentheses. *significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table C.4: **Effects by Food Module**

	Calories			*Quantities*			*Prices*		
	Initial Level	*First Month Effect*	*2-7 Month Effect*	*Initial Level*	*First Month Effect*	*2-7 Month Effect*	*Initial Level*	*First Month Effect*	*2-7 Month Effect*
alcohol	271.75	6.87	2.63	22.83	-0.43	-0.64	5.65	-0.18	-0.30
bread	3482.82	187.16	-67.69	46.37	2.87	-1.00	5.08	0.24	-0.11
breakfast food	714.95	19.14	-16.09	8.40	0.63	-0.02	1.69	0.25	0.07
cereal	1591.54	6.54	-99.01	15.61	0.12	-0.87	2.42	0.05	-0.09
cheese	2176.26	-34.74	-130.58	27.95	-0.02	-1.57	6.40	0.00	-0.31
coffee/tea	409.71	-4.28	-17.89	22.35	0.87	-1.16	3.35	0.33	0.14
condiment	749.87	4.94	-55.65	33.17	-0.40	-1.52	3.83	-0.02	-0.10
dessert	7139.60	-88.86	-157.14	72.10	-2.22	-2.46	10.52	0.26	0.02
diet dessert	124.09	43.37	37.55	0.95	0.36	0.35	0.99	0.25	0.18
diet shortening	52.26	20.07	4.70	1.16	0.62	0.08	0.17	0.06	0.01
diet soda	6.99	0.72	-0.78	59.57	5.55	-0.00	2.98	0.21	0.03
eggs	680.31	22.20	-43.21	1.36	0.04	-0.08	1.15	0.02	-0.08
fake sugar	5.14	1.80	1.47	1.40	0.42	0.08	0.75	0.23	0.01
fish	222.33	-0.61	-11.92	6.04	0.16	-0.23	1.64	0.01	-0.10
flour	973.31	102.93	91.59	10.52	0.92	1.15	0.50	0.04	0.01
fruit	975.03	78.35	13.18	29.16	2.46	0.04	2.99	0.36	0.08
fruit juice	876.51	-28.96	-89.50	59.90	-3.18	-3.93	3.02	-0.21	-0.29
jam	220.06	-8.07	-26.02	3.42	0.05	-0.23	0.50	0.07	0.00
meat	514.26	53.05	-70.35	11.41	1.37	-1.39	9.88	0.44	-0.35
milk	3419.05	133.95	-131.75	196.02	4.55	-7.95	5.79	0.11	-0.27
nuts	1327.79	175.59	147.40	8.17	1.33	1.08	1.98	0.30	0.33
pasta	900.28	-16.14	-154.69	8.73	-0.14	-1.53	0.68	-0.02	-0.09
peanut butter	815.70	131.19	44.15	4.39	0.44	0.13	0.54	0.09	0.04
pizza	553.55	-45.49	-64.67	8.18	-0.68	-0.97	1.59	-0.11	-0.16
potatoes	730.06	-18.22	-43.35	31.63	-1.57	-2.39	1.23	-0.02	-0.04
prep. food	4794.53	-56.37	-540.01	86.72	2.78	-6.86	23.54	-0.10	-1.32
rice/beans	367.08	-78.52	-45.20	4.08	-0.64	-0.47	0.25	-0.03	-0.01
shortening/oil	5597.85	-62.17	-115.57	34.80	-0.25	-1.33	3.93	-0.06	-0.15
snacks	3048.65	98.62	-112.00	25.28	0.81	-1.02	5.23	0.49	-0.00
soda	1430.76	-191.51	-230.51	33.94	-5.66	-5.36	2.39	-0.27	-0.18
soft drinks	193.35	-14.85	-3.54	94.26	5.63	-1.82	1.58	0.11	0.05
soup	397.14	-13.83	-20.11	24.31	0.02	-2.41	2.38	0.05	-0.19
sugar	1529.85	98.69	-0.13	14.97	1.24	0.16	0.70	0.05	0.00
sweet baked goods	2347.05	8.28	-88.76	21.80	0.29	-0.74	3.72	0.19	-0.01
vegetables	809.89	16.08	-31.85	59.82	3.36	-1.63	6.77	0.54	-0.18
yogurt	300.11	36.29	-8.58	9.73	1.10	-0.29	1.29	0.22	0.02

Notes: This table reports the changes in purchases by food module after inferred diagnosis.

Table C.5: **Elasticity Matches**

Food Group	*Matched Elasticity Category*	*Price Elasticity Estimate*
alcohol	alcohol	-0.60
bread	no match	
breakfast food	no match	
cereal	cereal	-0.60
cheese	cheese	-0.44
coffee/tea	no match	
condiment	no match	
dessert	sugar/sweets	-0.34
diet dessert	sugar/sweets	-0.34
diet shortening	fats	-0.48
diet soda	soft drinks	-0.79
eggs	eggs	-0.27
fake sugar	no match	
fish	fish	-0.50
flour	no match	
fruit	fruits	-0.70
fruit juice	juice	-0.76
jam	no match	
meat	beef/poultry/pork	-0.72
milk	milk	-0.59
nuts	no match	
pasta	no match	
peanut butter	no match	
pizza	no match	
potatoes	vegetables	-0.58
prep. food	food away from home	-0.81
rice/beans	vegetables	-0.58
shortening/oil	fats	-0.48
snacks	no match	
soda	soft drinks	-0.79
soft drinks	soft drinks	-0.79
soup	no match	
sugar	sugar/sweets	-0.34
sweet baked goods	sugar/sweets	-0.34
vegetables	vegetables	-0.58
yogurt	dairy	-0.65

Notes: This table reports the food groups and the elasticity groups they are matched to, along with the price elasticity. Elasticity groups and estimates come from Andreyava et al, 2010.