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

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Abstract

Individuals with obesity appear to be reluctant to undertake dietary changes. Evaluating the reasons for this reluctance, as well as appropriate policy responses, is hampered by a lack of data on behavioral response to dietary advice. I use household scanner data to estimate food purchase response to a diagnosis of diabetes, a common complication of obesity. I infer diabetes diagnosis within the scanner data from purchases of glucose testing products.Households engage in statistically significant but small calorie reductions following diagnosis. The changes are sufficient to lose 6 to 11 pounds per year, but are only 10% to 20% of what would be suggested by a doctor. In the short term (1 month) changes by food type line up with doctor advice, but in the longer term only decreases in unhealthy food persist.I evaluate these changes in the context of a simple model of optimization under full information and find that individuals value the marginal 100 calories per day at between 0.2 and 1.0 life years. Analysis of heterogeneity suggests limited demographic heterogeneity but does identify some successful dieters. Those with large caloric reductions typically focus on a small number of food items. I compare the results to a policy of 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.

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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). There are many possible explanations for these failures. The campaigns may not successfully inform individuals. They may also fail to provide useful information on how to improve health. It is also possible that individuals are informed, but place a 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 focusing on a subset of individuals with a particular complication of obesity: Type 2diabetics. A diagnosis of type 2 diabetes 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). Individuals are given particular dietary advice (the most important component of which is caloric restriction) and regular doctor visits and required self-monitoring through glucose testing provides reminders and feedback. A 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). Observing behavior change among this group may, therefore, provide a sense of the magnitude of response to a strong information campaign.

This analysis requires observing panel data on dietary behaviors among a sample of individuals with a diabetes diagnosis. Standard data sources do not allow for this, particularly to the extent that we would like to see detailed information about dietary choices. In this paper I approach this question with a new methodology which utilizes household scanner data on grocery purchases. Specifically, I use data from the

[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/).

Nielsen HomeScan panel, a dataset which is commonly used in industrial organization and marketing applications. Household participants in the panel are asked to scan the UPC codes of purchases, including all grocery and drug store item purchases.[2] I use purchases of glucose testing products, following a period of exclusion, as a maker for new diabetes diagnosis.[3] I observe detailed evidence on food purchasing behavior before and after this event. Because the Nielsen data is at the UPC level I can look in great detail at types of food purchased. 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.

Given the data, the methodology in the paper is straightforward. Using a household fixed effects framework, and limiting to two-person households, I estimate the evolution of food purchase behavior after diagnosis. I argue this provides a causal effect of a diagnosis in the household on diet.[4]

The paper proceeds in two parts. In the first part of the paper I focus on the response of the average household in the sample. I estimate dietary responses in aggregate, and for individual foods. I describe a simple model of a fully informed agent and use it, along with these results, to comment on the implied "health value of diet" on average in the sample. The results in this part of the paper suggest that households do respond to diagnosis in a way that suggests they are well informed, but the responses are small and imply people place a very large value on their preferred diet. In the second part of the paper I explore heterogeneity across individuals in the hopes of identifying either particular groups who are more successful at behavior change, or particular dietary patterns which correlate with success at calorie reduction. In the conclusion of the paper I return to the motivating policy questions, focusing on the issue of taxes or subsidies as an alternative to information.

I begin with the average individual, looking at changes in overall calories after diagnosis; a visual sense of these results appears in Figure 2a. In the very first month of diagnosis there are limited changes, but following this there are significant reductions in calories. The change reflects approximately a 2.5% decrease in calories purchased. I look at nutrient mix and find a small increase in the share of calories from protein following diagnosis, although this is short-lived and represents only about a 1.5% change from baseline.

I subject these results to a number of robustness checks. These including varying time controls, excluding the diagnosis month and estimating household-specific pre-trends. I also consider limiting the sample to a balanced panel of individuals and excluding very low spenders (who Einav et al (2010) suggest are less reliable reporters). All of these show very similar results to the baseline. I estimate the impacts for the much smaller sample of single person households and show their changes are similar in terms of share. I also

[2] 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). Throughout the paper I will discuss various issues with the data which will need to be addressed in the empirical work.

[3] 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.

[4] The diagnosis is likely to be of only one household member; a limitation of the data is that we cannot allocation consumption to each person. This issue is discussed in more detail later.

estimate the effects limiting the sample of products to those which are almost always purchased at a store, since the HomeScan panel does not measure food away from home. This tests whether the impacts are likely to scale to the entire diet; I find the share changes are virtually identical. Finally, I identify a set of non-diabetic households which match to the treatment household on pre-period purchasing behavior and look at their changes in a "false" post-period. I find they do not show similar patterns. All of these results support the causal interpretation of the primary results.

I evaluate the magnitude of these results in terms of their impact on weight loss. This is complicated by observing only household level purchases and by the fact that we may not observe all foods consumed. I discuss bounding assumptions in light of these issues. My favored estimate suggests a decrease of 2.5% to 5% in calories. Scaled to a typical individual, this suggests a weight loss of 6 to 11 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.

Following the analysis of changes in behavior in the aggregate, 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 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 with doctor advice. They purchase more calories (and quantities) of the foods doctors say are good and fewer of those doctors say are bad. Over time, the decline in the bad food group persists, but the increase in good foods fade quickly (within 2 months). The initial consistency with doctor advice suggests information about good behaviors is being accurately conveyed; the long term decay in the purchase of good foods may suggest these changes are hard to sustain.

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 a variety of health benefits. The estimates suggest individuals put relatively little value on health relative to diet. For example: a further reduction of 100 calories per day over a year 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. This analysis should be taken with caution but, if correct, it may provide some clue as to why it is difficult to induce dietary improvements.

In the second part of the paper, I turn to heterogeneity. On average, behavior change in this sample is small. A natural following question is whether there are some individuals who engage in more substantial behavior change and, if so, what their characteristics are. This may help target policy. I first look for heterogeneity on some standard demographics - education, income, age, living in a food desert, etc. I find little evidence of differences in behavioral response across any of these groups. However, there is substantial heterogeneity across the sample. Some individuals appear to diet successfully - showing large reductions in calories per ounce of food purchased (a metric of diet quality) and in total calories. Others show no decrease or even an increase.

I use the data to identify a set of successful dieters - defined as those who decrease their calories per ounce by at least 10% - and a set of matched "unsuccessful" controls. The controls are matched on pre-period total calories, and pre-period calories from several commonly purchased food groups. I compare the details of behavior change across the two groups. The successful dieters reduce their calories enough to lose about 35 pounds in the first year. I find that their excess reductions are heavily concentrated in a few food groups - candy, cooking oil, sugar, shortening. The changes in these groups for the successful dieters are very large, typically a 40% to 50% reduction in calories compared the pre-diagnosis mean. One possible conclusion is that dietary success is facilitated by focusing on a few food groups which account for a bulk of "bad" calories.

The conclusion of the paper returns to policy questions and, in particular, seeks to evaluate how the magnitude of the results here compare to what would be expected from a policy of taxes or subsidies. 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. I find that for unhealthy foods (soda, dessert foods) the long-run changes among diabetics are equivalent to a 10 to 15% tax. For healthy foods, however, the subsidy equivalent is very small, even negative. Put differently: a 10% tax on soda would produce a change comparable to what I observe here, 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.

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 household scanner 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.

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 significant 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 upon 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. I argue it is therefore 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 Nielsen 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 Nielsen HomeScan

The primary dataset used in this paper is the Nielsen 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 Nielsen 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 Nielsen store-level data, where available. Einav, Leibtag and Nevo (2010) have a recent validation of the reliability of the HomeScan panel. I use Nielsen data available through the Kilts Center at the University of Chicago Booth School of Business. This data covers purchases from 2004 through 2012.

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 Nielsen 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, Nielsen 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 3,591 households; summary statistics for these individuals appear in Table 1.[5] Panel A summarizes the demographics of these households, and Panel B summarizes characteristics of their trips and purchases. The average household records 11.1 shopping trips per month.

3.1.2 Gladson Product Information Data

I merge the Nielsen data with nutrient information purchased from Gladson.[6] 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.[7]

Calorie and nutrient summary statistics appear in the final rows of Panel B of Table 1. The average household records purchases of 1491 calories per person per day, with 11% of calories from protein, 13% from saturated fat and 53% from carbohydrates.

[5] Income, age and education are given in categories. For the purposes of summary statistics, I recode at the median of the categories. I will use the categories directly in any demographic analyses later.

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

[7] 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.

3.1.3 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 Nielsen 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.

3.2 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, Nielsen panelists do not scan food purchased 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 Nielsen sample) I find adults report approximately 1862 daily calories in total. The calorie levels in HomeScan therefore represent approximately 80% of calories (taking the NHANES as a baseline). An alternative baseline is to evaluate this relative to the calorie level which an average diabetic would require to maintain weight. I do a calculation in this spirit later and conclude this figure is approximately 2194. With this baseline, HomeScan records about 68% of 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 4.1.2, 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.

It is worth noting that I do not directly observe health information and it is possible that the purchasing behavior observed represents news about diabetes rather than a new diagnosis. In the most general sense, we can think of this as marking some diabetes-related event. Given the exclusion period, however, this event seems most likely to be a diagnosis. I will refer to this event as “diagnosis” for linguistic simplicity, but with this caveat in mind.

Having identified the timing of diagnosis using this procedure, the empirical strategy is fairly straightforward. Broadly, I use an “event study” method within the household to estimate the response to diagnosis timing. It is possibly important to adjust for other non-diagnosis time effects - in particular, time in the Nielsen sample (which could increase or decrease recorded purchases) and month-year effects. Doing this within the household fixed effects framework generates within household colinearity and makes the results difficult to interpret. It also constrains our estimation of these time effects to the small set of timing around diagnosis events.

Given this, I first use the entire sample - including individuals who are not diagnosed ever during this period - to residualize the outcomes with respect to month-year fixed effects and a linear control for time in the sample.[8] I use these residualized variables in the estimation.

Defining Y_{it} as the individualized outcome for household i in year t, I run regressions of the form:

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

where $\mathbf{D_{it}}$ is a vector of indicators for diabetes status for household i in month t and γ_i is a household fixed effect. In the primary analyses, $\mathbf{D_{it}}$ includes indicators for 1 to 3 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. 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), results where I lengthen the pre- or post-period and results in which I adjust for household-specific pre-trends.

Figure 1 shows the change in spending on testing supplies 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.

Table 2 shows a regression of the form described in Equation (1) with testing product spending as the Y_{it} variable. The regression results are consistent with the evidence in Figure 1.

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.

[8] Controlling more flexibly (i.e. quadratic, cubic) for this makes no difference.

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. In this section I also discuss the magnitude of the results in terms of potential weight loss. 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. The key summary metric for evaluating weight loss is calories. 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 calendar time-adjusted calories purchased on month-from-diagnosis dummies and household fixed effects.

In the very first month after diagnosis, calories purchased are roughly stable; if anything, increasing a bit.[9] In the months following diagnosis they decline by about 2000 calories per household per month; this represents a decline of about 2.5% from the pre-period mean. This decline is fairly stable over the period considered, although the decline is not significant in all individual months. There is no visual evidence of a pre-trend in the series prior to the inferred diagnosis.

I also consider food quantities and expenditures. It is worth noting that an improved diet links less directly to these variables; quantities could stay constant while diet improves. Figures 2b and c show these results. The patterns are similar to calories although in both cases the most striking feature is a large increase in quantities and expenditures in the first month after diagnosis. This is followed in future months by a decline.

In Table 3, I show the results of estimating Equation (1). Columns 1 shows the impact on calories. The evidence in this column echoes Figure 2a: an increase in calories in the first month, and a persistent decrease after. The decrease is around 2.5%. Columns 2-3 show impacts on quantities and expenditures for the whole sample; Column 4 shows the expenditure effects for the Magnet households, who also report non-UPC coded items. Again, the evidence in these columns is consistent with Figure 2: slight increases in the first month, followed by decreases in the following period. 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 5-8 look at the breakdown of calories and nutrient mix. In Column (5) I look at calories per ounce of food purchased, a summary measure of the caloric density of foods. This declines in the first month

[9] 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.

after diagnosis, indicating an improved diet on this dimension, although returns to baseline after. Columns 6-8 look at nutrients. Given their baseline average consumption, dietary advice would suggest an increase in protein and a decrease in saturated fat. Both of these changes appear in the short term (although are very minor in terms of magnitude) but seem to evaporate in the slightly longer term.

Before turning to a discussion of magnitudes, I pause to consider a number of robustness checks. I focus on the primary results on calories in Column 1 of Table 3. The regressions appear in Table 4.

The first three columns estimate impacts with varying approaches to time. Recall the primary results residualize everything with respect to month-year fixed effects and a control for time in HomeScan. Column (1) estimate the impacts with no time controls at all. Column (2) estimates the impact with the same controls but dropping the month of diagnosis. Column (3) uses a longer pre-period to estimates a household-specific pre-trend and adjust for that in the analysis. The results are extremely similar to the baseline in all cases.

Columns (4) through (6) vary the household set. Column (4) limits to households observed in all months. The results are similar. Column (5) looks at single person households. The sample size is smaller and the data is noisier, but the basic patterns remain. The changes are similar, slightly smaller, when we consider them as shares. Finally, in Column (6) I drop the bottom 25% of households based on pre-period expenditures.[10] 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 results are similar.

Columns (7) and (8) include either an earlier pre-period (Column 7) or another post-period (Column 8). The pre-periods are relatively flat in Column (7) and there is no evidence of a drop off in the effect in the longer post-period in Column (8).

Column (9) attempts to address the concern raised in the data discussion that we do not observe food away from home. I use the NHANES dietary data to identify a subset of foods for which at least 85% of consumption reports indicate are purchased at a store - that is, 85% of the time when I observe the food in the NHANES, it is reported as purchased at a store. The foods included in this sample are not surprising - milk, cereal, frozen dinners, etc. I then limit the analysis to only these foods, to see if behavior change differs. As Column (9) demonstrates, the changes in shares are almost exactly the same as the changes in the full sample of products.

Finally, Column (10) estimates a matching analysis. I use households without test strip purchases as controls. For each "treatment" household I select a control household which matches in household head age group and education level *and* is the closest match on calories for the five months leading up to diagnosis. The goal is to find a household with similar purchasing behavior in the "pre-period" and then estimate whether they change their purchasing behavior after "diagnosis." The results in Column (10) show they do not; the

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

changes for the matched controls are small and insignificant.

In general, the results in Table 4 suggest that the changes in calories observed in Table 3 are robust across a variety of specifications.

4.1.2 Magnitudes of Weight Loss

The evidence above suggests a 2.5% reduction in calories in response to diagnosis, but is not sufficient to comment on the magnitude of these changes for overall weight loss. Although the conversion between calories and weight loss is fairly straightforward, it is complicated here because we observe only household-level changes and do not observe all foods individuals purchase. 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 2.5% reduction in the overall calories purchased by the household (i.e. as in Table 3 Column 1, averaging the post-periods) the bounds on change for the diagnosed individual are 2.5% to 5%.

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 1491 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 Table 4, when I drop households with very limited reporting, we again see very similar changes in shares. Further, when I limit to foods which are consumed largely at home, the share changes remain the same. All of these facts suggest that the share assumption may reasonably describe overall changes in grocery purchases.

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[11], and use weight estimates for diabetics in a matched age range from 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

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

overall caloric reduction in the range of 2.5% to 5%, or between 54 and 109 calories per day. This would translate to between 0.5 and 0.95 pounds per month, or 6 to 11.3 pounds per year assuming these changes occur in all months of the 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 Nielsen. I assume, consistent with the data, an increase 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 Nielsen is 2.9 to 6.3 pounds. The 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, five to ten 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 far 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 is observed in other data.

4.2 Response by Food Group

The results above show aggregate changes in calories. A significant advantage of the HomeScan data is the granularity, which allows me to estimate changes by individual food group. I can observe whether changes across foods are consistent with doctor advice, as would be expected if the changes are driven by the information provided in response to diagnosis.

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 3a shows the evolution of calories from the two groups over time; Figure 3b shows the evolution of quantities. The latter may be more useful for looking at consumption of good foods, many of which are very low calorie. In either graph we observe an uptick in good food purchases in the first month, but this change disappears by the second month after diagnosis. In contrast, declines in calories and quantities from bad foods begin in the first month and persist.

In Table 5, I show regression evidence on these changes for good foods (Panel A) and bad foods (Panel B). I look at calories, quantities and expenditures. For good foods, calories, quantities and expenditures all increase in the first month and then return to baseline following this. For bad foods, there is a decrease in the short-run and an even larger decease in the longer run. Overall, the ratio of good to bad foods increases in the early months, although by the end of the period considered it is back to baseline.

This analysis uses only a subset of foods. I can also look in more detail across all food groups ranked by 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 and quantities. I then calculate the changes as a share of the baseline by group. The results are shown in Figures 4a and b. In all time periods there is a gradient in doctor advice: good foods are increased relative to bad foods. This relationship is more consistent and pronounced in the initial month after diagnosis. By the five to seven month period there is no clear difference among the bad and majority good foods, and the "All Good" foods have reverted to baseline.

The overall picture is consistent with what we see in Table 5. 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 evidence does support a view of informed behavior change in this population.

As a final note, it is also possible to describe changes by food group without reference to doctor evaluations. For each food category I separately regress calories and quantities 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. Appendix Table C.1 reports the evidence for the five largest decreases and five largest increases. The largest short-run decreases come from soda, shortening and juice; the long-run is similar, although desserts become more important. Increases, in either the short or long run, are fairly small but do seem to be concentrated in lower caloric density foods, consistent with the doctor evidence.

In general, the evidence across food demonstrates two things. First, individuals appear to be fairly sophisticated in their behavior change in the sense that the changes they make line up with the changes that doctors would recommend. This is notably not limited to the comparison of foods which all doctors consider "good" and those which all doctors consider "bad" but extends to comparisons within sets of items where doctors disagree. Second, increases in "good" foods seem to be much more difficult to sustain than decreases in "bad" foods. In the long run, all the changes we observe are a result of sustained reductions in unhealthy foods, not substitution towards healthy foods.

5 Implied Value of Diet

Together, the evidence in Section 4 suggests the individuals observed here have an understanding of the appropriate behavioral response to this health news. This is evidenced most strongly by the changes by food group, which line up closely with doctor advice. On the other hand, in terms of magnitude the changes are small.

In this section I use these results to consider, under a fully rational model, what the evidence on behavior change implies about individual valuation of health compared to the value they place on their ideal diet. Put simply: 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. The fact that the changes by food type line up with doctor advice is supportive of this assumption.

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 5 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.

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. I assume that taste depends only on calories, although that assumption would be trivial to relax. 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:

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

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.

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 estimates in Section 4.1.2 I work from the assumption that individuals lose 6 to 11 pounds in the first year. I then ask what the health benefit would be of losing an additional ten pounds over this first year, an action 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 6 I report, for the set of outcomes and citations with appropriate data, some information on the study methodology and the implied 100-calorie-pre-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[12] 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 6 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.[13]

The second row of Table 6 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).[14] The estimates suggest an additional 100 calorie reduction per day would lead to a 4.0 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

[12] 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.

[13] 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.

[14] 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.

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).

Discussion

Together, the data suggest that there would be significant and valuable health benefits from small additional dietary changes. The conclusion, in the context of this fully rational model, is that individuals must value their dietary choices very highly. One hundred calories is equivalent to one small soda per day, or one small cookie. The data suggest individuals would prefer to lose a significant life-year period, and accept lower quality of life while alive rather than giving up these items. One thing to note is that the individuals in this sample may be less amenable to behavior change than the average individual in the population; on the way to a diabetes diagnosis individuals are typically warned about the consequences of obesity and this set of individuals obviously ignored that. However, it seems more plausible that this group is representative of the large share of Americans who are obese, which is arguably the group which would be targeted in any anti-obesity programming.

It is important to note, of course, that this analysis requires significant assumptions, both 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 valuations here are quite stark and even if we thought the truth was the value of diet is half or a quarter of what is estimated here, it would still be striking.

To the extent that preferred diet does have a very high value, this may shed light on why it is so difficult to effect behavior change among overweight individuals with information about health costs of diet. If we take the results here as the impact of full, salient, information on the value of diet, it may seem hopeless to try to effect significant changes with a standard educational campaign.

6 Response Heterogeneity: Demographics and Successful Diets

The evidence in Sections 4 and 5 focuses on behavior change on average. The apparent conclusion of Section 5 is that individuals place, on average, low value on their health. From a policy standpoint, this may suggest information provision is of limited value in effecting behavior change.

In this section I turn to heterogeneity across individuals in behavioral response. It is possible that small changes on average mask large changes in some sub-groups. If so, it may suggest that *targeted* information campaigns are of more value. Further, the HomeScan data provides an unusual opportunity to observe the specifics of dietary changes among successful dieters, which may provide additional insight into what behaviors characterize dietary success.

I undertake three analyses. First, I undertake some standard heterogeneity analyses, estimating interactions between behavior change and pre-diagnosis characteristics, including demographics and pre-diagnosis dietary qualities. Second, I explore the basic heterogeneity across households in behavior change by estimating the range of behavior change after diagnosis. Third, drawing from this second analysis, I use the data to identify "successful" dieters and compare them to a matched set of "unsuccessful" ones on both demographics and characteristics of dietary change.

Throughout this section I focus on two outcomes: calories, the primary outcome considered, and calories per ounce. Reductions in both of these are considered positive dietary change.

6.1 Heterogeneity on Pre-Diagnosis Characteristics

In this section I consider heterogeneity in response by demographics and pre-period diet.

I consider a set of standard demographics : education, income and age. In addition, I use individual zip code to match each individual to whether or not they live in a "food desert" as defined by the USDA. For each demographic breakdown, I estimate behavior change in calories and calories per ounce and compare results across group. The results are shown in Table 7 which reports level effect coefficients and percent changes from baseline. The bottom line is there is relatively little variation by demographic group. In the long term, high education and younger individuals, and those who do not live in a food desert, reduce their calories more. But these differences are small and not strongly echoed in the calorie per ounce results. The largest differences are across age groups, where individuals under 50 reduce their calories by 4%, versus only 2.5% for those over 65, but these differences are still not enormous and the confidence intervals certainly overlap.

It may seem puzzling that we do not see more demographic heterogeneity. In many settings higher education and higher income individuals undertake more positive health behaviors. Although that is marginally true here in the case of education the effect is quite limited. One possibility is that the selection into the sample in the first place differs. If those individuals with high education are generally healthier, then those who develop diabetes despite this may be worse in some unobservable way.

In addition to demographics, I also consider variation in behavioral response by characteristics of diet prior to diagnosis. I focus two measures of diet "quality": the share of saturated fat in the diet (less is better) and the share of protein (more is better, at least in the range considered here). I divide individuals into high and low groups based on their pre-period consumption, and consider the calorie and calorie per ounce changes after diagnosis. These results are shown in Panel B of Table 7.

The one striking result in this Panel is that individuals who enter the sample with a relatively low protein intake (hence, a worse diet) evidence larger reductions in calories and calories per ounce of food than those who enter with a better diet on this dimension. It is possible that these individuals have such a poor diet that there are small changes they can make which make a huge difference, while those with a better diet would have to make more difficult changes. In the case of the saturated fat breakdown there is little in the way of a consistent message.

Overall, these results do not suggest that much would be gained on behavior change by targeting particular groups. There are effectively no demographic groups which show really extreme changes. Even if (motivated by Panel A of Table 7) we isolate high education, young people who do not live in a food desert, the estimated calorie reduction is still only 4%.

6.2 Variation in Behavioral Response

A second approach to heterogeneity is to simply ask how much variation there is across the households in the sample in their dietary success rates. This is akin in some ways to a quantile regression, but in this case the panel nature of the data makes it simpler to just describe the changes across households in summary statistics. I focus in this analysis on calories per ounce of food purchased as the measure of dietary change. I use this rather than basic calories to avoid simply identifying people who change their scanning behavior in the post-period. A reduction in calories per ounce of food is strongly indicative of an improvement in diet and, as we will see, correlates strongly with overall caloric changes.

Using the data I calculate, for each household, the percent change in calories per ounce from the pre-diagnosis period to the later post-diagnosis period (2 to 7 months). Figure 5a shows a histogram of changes in this variable across the sample.[15] The figure demonstrates substantial heterogeneity across individuals. The median household in the sample does not change their calories per ounce at all. Ten percent of the sample reduces by more than 20% of their calories, whereas another ten percent increases by at least 30% of their calories. If we take a reduction of 10% as a measure of a successful diet (I will use this benchmark below), roughly 25% of households in the sample achieve this.

Changes in calories per ounce strongly correlate with changes in calories, as can be seen in Figure 5b. To generate this figure I define groups based on 20 quantiles of the change in calories per ounce variable and summarize the percent change in total calories by bin. The largest changers are reducing calories by around 20%. Approximately 20% of the sample reduces by more than ten percent of total calories.

Overall, this suggests that the lack of identifiable heterogeneity in Section 6.1 does not reflect a total lack of heterogeneity across the sample. There is a wide range of dietary success and failure, it simply does not

[15] I truncate the data at -100% change at 100% change, which drop 0.7% of households.

seem to correlate with demographics. A final illustration of this point appears in Figure 5c, which replicates Figure 5b but with average income rather than calorie changes. There is little or no systematic relationship here; a similar result holds for education.

6.3 Characteristics of Successful Diets and Dieters

The evidence above suggests that there are successful and less successful dieters. It seems possible that by identifying those individuals who are more or less successful at dieting may allow us to identify some dietary patterns which are more successful than others. This approach requires the detail inherent in the HomeScan data, which allows me to isolate changes by food types.

In this section I use the data, as above, to locate "successful" dieters. I then match these households to households who look similar in the pre-diagnosis period but do not appear to diet successfully. I compare the pre- and post- dietary patterns across the groups.

Matching Procedure

I identify successful dieters based on data on calories per ounce of food purchased. I define a household as dieting successfully if they decrease their calories per ounce of food purchased by at least 10% from the pre-diagnosis period to the late post-diagnosis period (2 to 7 months). This definition yields 820 households who are successful dieters. The remainder of the households are defined as "unsuccessful". For each successful dieter household I identify a matched unsuccessful household. I match in the following way: I limit the data to households in which the average total calories purchased in the pre-period are within 15,000 calories per month. Within this set, I choose the household with the most similar purchase level for the food modules with at least 2000 calories purchased on average per household per month (this is 8 module groups). This matched household is designed to be similar in the pre-period on both their total consumption and their mix of consumption. Similar results are found if I match only on total consumption of calories.

Results

Consistent with the evidence in Section 6.2, successful dieters decrease calories dramatically compared to the matched controls. The result is shown in Appendix Figure C.1. In the pre-period the successful dieters closely match the controls and in the post-period they show dramatically larger declines in calories purchased. This successful group has a 16% reduction in calories purchased from baseline. Applying the magnitude procedure suggested in Section 4, this reduction would amount to about a 37 pound weight loss per year if sustained.

Turning now to the details of dietary changes, I consider first the nutrient changes for successful dieters and unsuccessful controls. Changes in share of calories from saturated fat are similar across the two groups, as are changes in the share of calories from carbohydrates. The one notable difference is the successful dieters increase their share of calories from protein more significantly - an average of about a 1 percentage point increase, or about 10% of the baseline - in the post-period. The matched controls do not show any changes.[16]

Looking in more detail, figure 6 shows evidence on behavior change by food module group (as used in Section 4.2). The blue bars show the change in calories from the pre-period to the late post-period (2 to 7 months after) for the successful households, and the red bars for the matched unsuccessful households. A small number of high-calorie categories account for the bulk of the differences. In particular, five categories (desserts, shortening and oil, prepared foods, sugar and flour) account for about 78% of the difference in caloric changes between groups. These groups are also a large share of pre-period calories, but not nearly as large (37%). The successful dieters show some increases on "good" foods - vegetables, milk - although these are fairly small. The only category in which the matched households show sizable declines is soda (although the changes for the successful dieters are still larger). The caloric reductions come from a combination of lower quantities purchased in each category as well as substitution towards fewer calories per ounce of food. For the more staple groups (flour, sugar) nearly all of the changes come from quantities; in the others, most changes come from reductions in calories per ounce.

I dis-aggregate the data further, focusing on the five categories which account for the vast majority of the differences. Even within these categories, a small number of product types account for nearly all of the differences in caloric reductions: seven (of the 168) product module groups account of 75% of the difference in calorie changes (these categories account for 40% of total calories). Table 8 lists these product groups as well as the excess calorie reduction for each, and the share change for the successful dieters and unsuccessful matches. The categories are unsurprising: candy, cooking oil, shortening, flour and sugar. The successful dieters show substantial reductions on these categories - at least 40% and in many cases more. This is especially striking since, as noted, these are two person households. A 50% reduction in candy purchases may, in fact, mean an elimination of this product for the affected individual. The matched households show either no change or, in a few cases, some increase in purchases of these products.

These data suggest that dieters are successful by undertaking large changes on a small number of high-calorie categories rather than by reducing a small amount on all foods. One possible interpretation of this result is that dietary advice should focus on emphasizing large changes on a few items - perhaps individually tailored to existing dietary habits - rather than pushing on a total diet overhaul. Showing that this is the case is, however, beyond the scope of this paper.

[16]Table with these results are available from the author.

7 Discussion and Conclusion

The results presented here suggest that households respond to a negative obesity-related health shock by changing their dietary choices. These changes are statistically significant, but they are quite 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. In the context of a fully rational model, the small behavior changes here suggest that on average individuals place only very limited value on their health relative to their preferred diet.

There is significant heterogeneity across the sample in dietary success, although it does not seem to correlate with either demographics or food availability. When I use the detail in the HomeScan data to isolate the dietary patterns of successful households, I find that households with significant caloric reductions achieve them largely by reducing a lot on a small number of food categories.

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.

One alternative approach that has been suggested in policy circles is taxation of unhealthy food or subsidies of healthy foods (for a discussion of this in policy circles, see Leonhardt (2010)). Such a policy could come in a general form (e.g. a broad "soda tax") or in a more targeted way (e.g. subsidized fruits and vegetables for WIC or SNAP recipients). If we take the "experiment" in this paper as a proxy for an intensive educational intervention, it may be of some interest to compare these changes to what we would expect from a policy of taxes or subsidies.

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.2. I match these groups to product modules in Nielsen, 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.2 lists the product groups which are matched to each elasticity category.

Given these estimates, it is straightforward to generate a tax or subsidy equivalent. Price elasticity is known and, from the data here, I have an estimate of the percentage change in quantity. I use these together to calculate the percentage change in price which would produce the equivalent change, which is the tax (or subsidy) equivalent. I estimate the tax equivalent of the long-run (two-to-seven months) changes. The results, by module are show in Figure 7. The consumption of most groups decreases, at least a bit, in the long term so most groups have tax rather than subsidy equivalents. An exception is diet desserts and diet shortening, where household increase their consumption as if these are hugely subsidized. The category with the largest tax equivalent change is sugar: the changes observed here are equivalent to about a 30% sugar tax.

The primary policy target for taxes on unhealthy foods is soda. The results here suggest a soda tax of 11% would be produce an overall change similar to what is seen in response to diagnosis. Similarly, fruits and vegetables are the most common subsidy targets. Given the changes in these categories, virtually *any* subsidy would preform better at increasing purchases.

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. On the flip side, the evidence suggests that increasing consumption of healthy food may be better accomplished with a subsidy-type approach.

As noted, the primary contribution of this paper is to better understanding dietary behavior change and to comment on policy. However, the paper also suggests a new application of household scanner data to look at questions in health.

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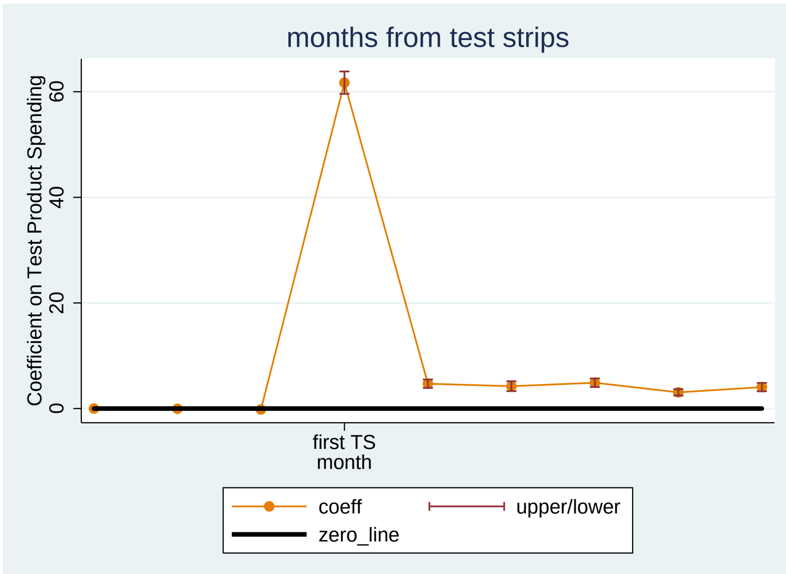
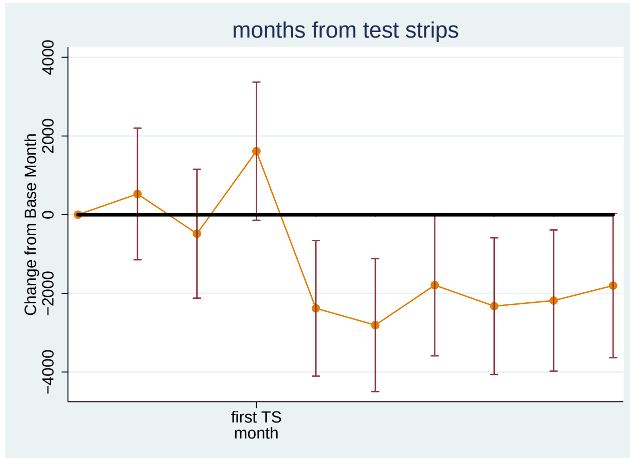
Figure 1: **Testing Supply Purchases**



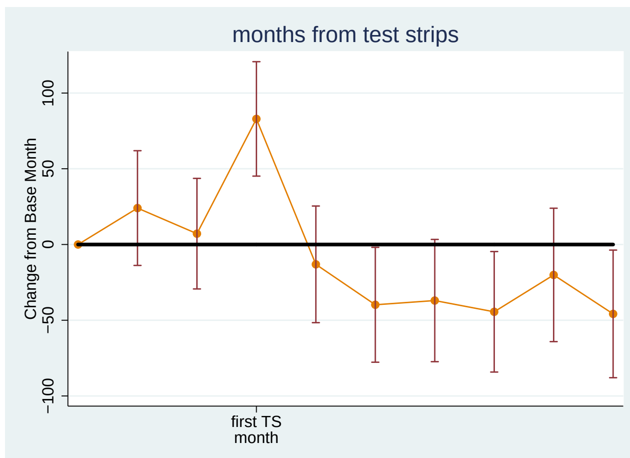
Notes: This figure shows data on purchasing any test strip products around the inferred diagnosis timing. Coefficients are from a regression which uses time-adjusted data and controls for household fixed effects.

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

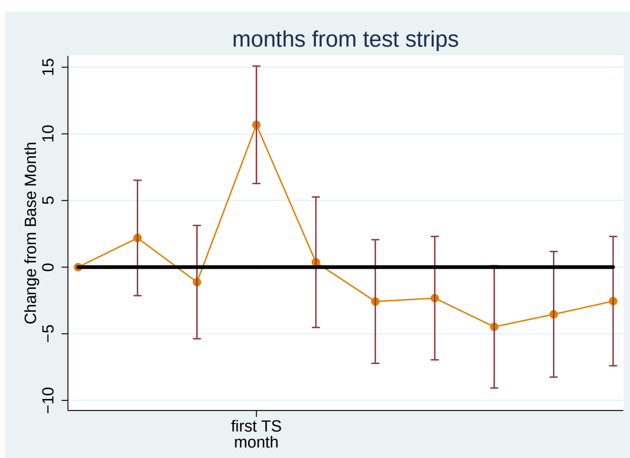
(a) Calories



(b) Quantity in Ounces



(c) Expenditures



Notes: These figures show coefficients from regressions of the various outcome variables on months from inferred diagnosis. All outcomes are residualized with respect to month-year fixed effects and a linear control for time in sample and all regressions include household fixed effects. Error bars show 90% confidence intervals.

Figure 3: **Changes in "Good" and "Bad" Foods**

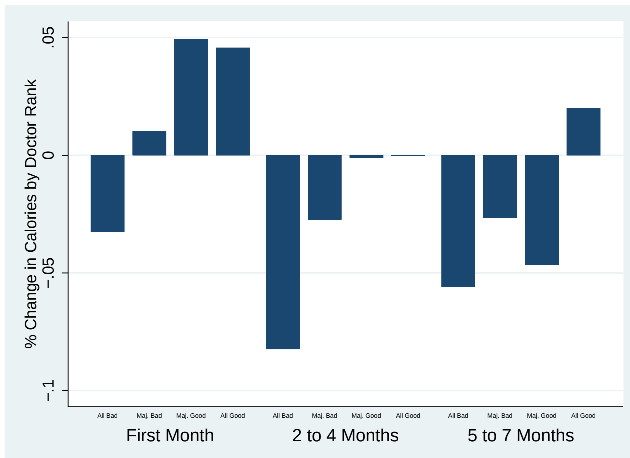
(a) Calories

(b) Quantity in Ounces

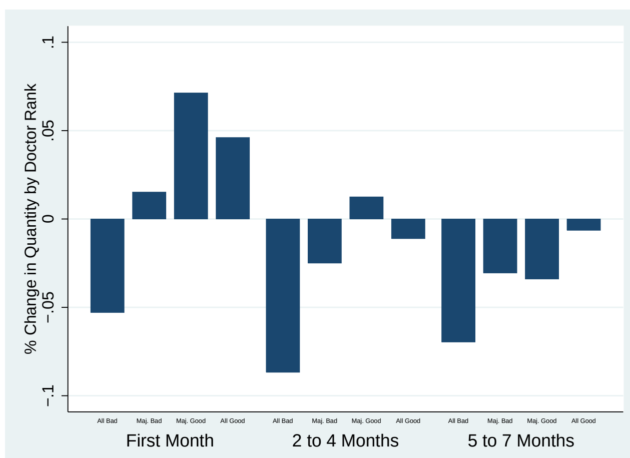
Notes: This figure shows coefficients from regressions of good and bad food calories and quantities on time from inferred diagnosis. Outcome measures are residualized with respect to month-year fixed effects and a linear control for time in Nielsen sample. Good foods are defined as those which all doctors 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. Error bars show 90% confidence intervals.

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

(a) Calories



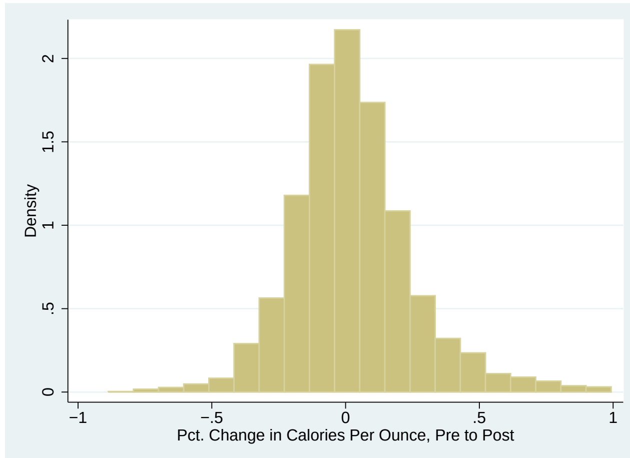
(b) Quantity in Ounces



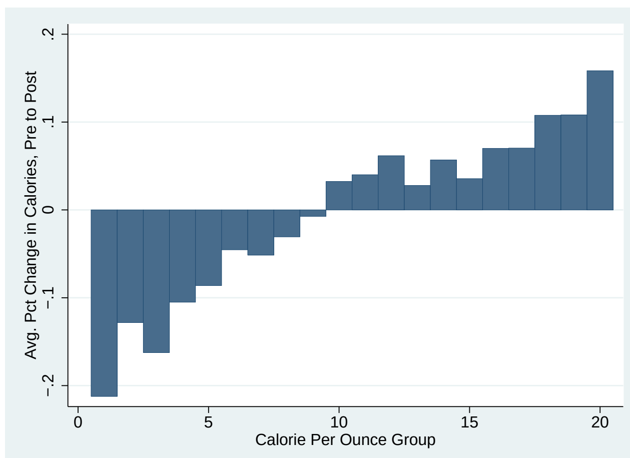
Notes: These graphs show changes in calories and quantities on foods with varying doctor rankings. Changes are reported as a share of the mean. Measures are all residualized with respect to month-year fixed effects and a linear control for time in Nielsen sample. "All Good" are foods which all doctors 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: **Range of Behavioral Response**

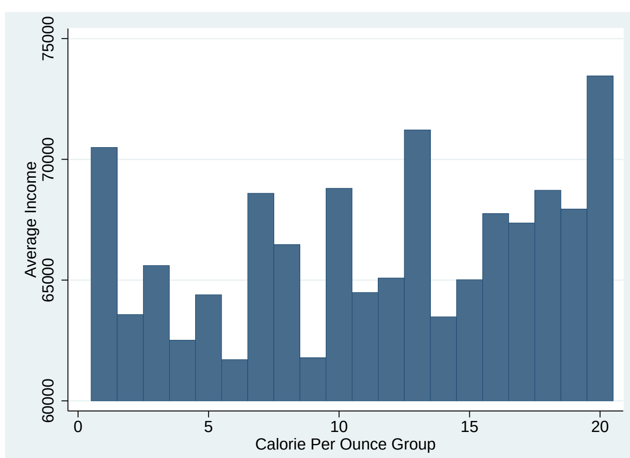
(a) Histogram of Percent Change in Calories Per Month



(b) Percent Change in Calories by Calories Per Ounce Group

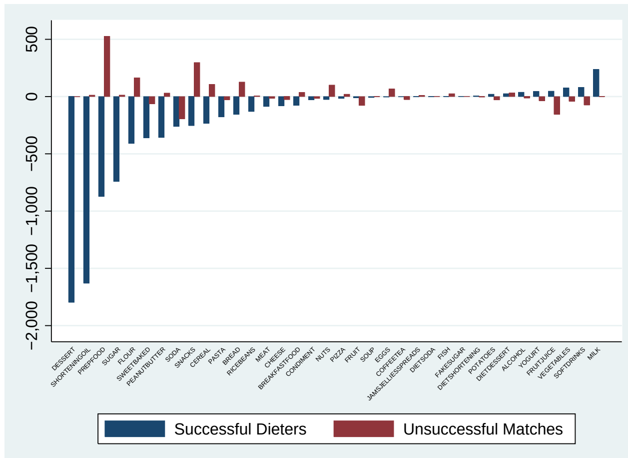


(c) Income by Calories Per Ounce Group



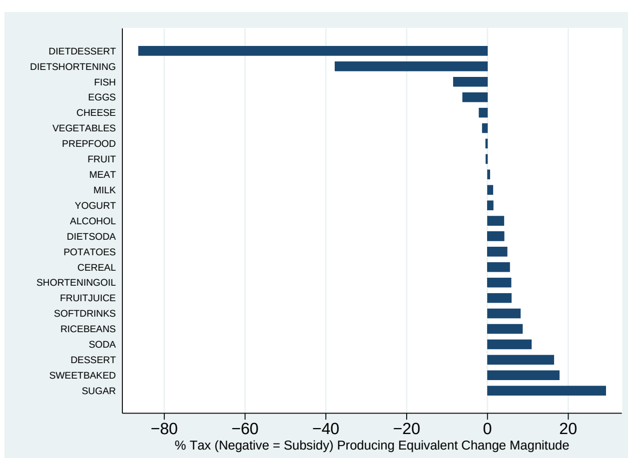
Notes: These graphs show heterogeneity across individuals on behavioral response. Sub-Figure a is a histogram of the percent change in calories per month from the per-period to the late post period (2 to 7 months after diagnosis). Sub-Figure b summarizes the percent change in total calories purchased by these calorie per ounce groups. Sub-Figure c summarizes the income per ounce group.

Figure 6: **Calorie Changes by Category for Successful Dieters and Unsuccessful Matched Controls**



Notes: This graph shows calorie changes by category for successful dieters (>=10% reduction in calories per ounce from pre to late post period) and unsuccessful matched controls. Matching is based on total calorie levels in the pre-period and calorie levels for any module categories with an average of at least 2000 calories purchased per month.

Figure 7: **Tax Equivalents to Changes in Quantities**



Notes: This graph shows tax rates which would produce the same magnitude change as produced by the diagnosis event. The change I consider is the change between the pre-period and the late post-period (2 to 7 months after diagnosis). 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	61.9	11.8	3573
HH Head Years of Education	13.9	2.33	3233
HH Income	$66,181	$52,751	3536
White (0/1)	0.85	0.36	3591
In Food Desert (0/1)	0.36	0.48	3568
Panel B: Panelist Shopping Behavior			
Avg. Number of Trips/Month	11.1	7.2	32,232
Shopping Behavior (Per Household/Month):			
Quantity in Ounces	2090.5	1354.8	32,232
Expenditures	$261.09	$187.10	32,232
Calories (Gladson Data)	89,490	54,708	32,232
Share Carbohydrates (Gladson Data)	0.53	0.11	32,144
Share Protein (Gladson Data)	0.11	0.03	32,176
Share Saturated Fat (Gladson Data)	0.13	0.06	32,132

Notes: This table reports summary statistics on demographics (Panel A) and panelist shopping behavior (Panel B). Household age, income and education are computing at the median of reported categories. Quantity and expenditure data come from Nielsen 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 Nielsen 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:	*Testing Supply Spending*
First Month After	61.78***
	(1.29)
Two-Four Months After	4.68***
	(0.37)
Five-Seven Months After	3.48***
	(0.28)
Household Fixed Effects	YES
R-squared	0.39
Number of Obs.	32,324

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. Purchases measure is residualized with respect to for month-year fixed effects and a linear trend for time in sample.

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

Outcome:	*Calories*	*Quantity in Oz.*	*Spending ($) All*	*Spending ($) Magnet HH*	*Calories per Ounce*	*Share Cal: Carbohydrates*	*Share Cal: Protein*	*Share Cal: Saturated Fats*
First Month After	1602.01*	72.5***	10.3***	10.1***	-0.92***	-0.0009	0.002***	-0.002**
	[0.017]	[0.035]	[0.039]	[0.032]	[-0.020]	[-0.002]	[0.019]	[-0.016]
	(884.4)	(18.6)	(2.29)	(3.81)	(.331)	(.002)	(.0005)	(.001)
Two-Four Months After	-2343.8***	-40.1***	-1.82	-1.64	0.087	-0.006***	0.002***	0.0005
	[-0.026]	[-0.019]	[-0.007]	[-0.005]	[0.002]	[-0.010]	[0.015]	[0.004]
	(623.6)	(14.8)	(1.71)	(2.90)	(.280)	(.001)	(.0004)	(.0008)
Five-Seven Months After	-2124.2***	-47.0***	-3.87**	-5.06*	0.448	-0.005***	0.000	0.001
	[-0.023]	[-0.022]	[-0.015]	[-0.016]	[0.009]	[-0.008]	[0.000]	[0.008]
		(16.2)	(1.81)	(3.05)	(.273)	(.001)	(.000)	(.001)
Household Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
R-squared	0.52	0.59	0.67	0.67	0.36	0.37	0.40	0.28
Number of Obs.	32,232	32,232	32,232	16,258	32,119	32,144	32,176	32,132

Notes: This table shows the primary results on aggregate changes. The omitted category is 1 to 3 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. All outcome measures are residualized with respect to month-year fixed effects and a trend in time since enollment. 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: **Robustness Checks: Calories**

	Time Robustness			**Household Type Robustness**			**Extend Period**		**Home Food**	**Matched Controls**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	No Time Controls	*Exclude Diag. Month*	*Add HH Pre-Trends*	*Balanced Panel*	*Single Person Households*	*Exclude Low Spenders*	*Add Months Before*	*Add Months After*		
1-3 Months Before							-830.8			
							(667.4)			
First Month After	1676.00*	1431.6	1367.2	1530.3	1475.23 [0.027]	-572.4 [-0.005]	881.2	1611.8*	425.9 [0.014]	244.3
	(890.6)	(933.2)	(928.7)	(998.3)	(925.6)	(1098.1)	(935.1)	(884.4)	(332.5)	(847.5)
2-4 Months After	-2960.7***	-2591.6***	-2683.2***	-1621.3***	-1120.7* [-0.021]	-4457.5*** [-0.042]	-2932.1***	-2385.7***	-730.8*** [-0.024]	-71.5
	(632.8)	(697.2)	(814.1)	(689.5)	(685.1)	(773.6)	(714.8)	(610.7)	(253.9)	(611.5)
5-7 Months After	-3250.5***	-2442.8***	-2410.9***	-1451.8**	-567.1 [-0.010]	-3921.9*** [-0.037]	-2577.4***	-2307.2***	-751.0*** [-0.025]	-109.6
	(688.4)	(740.6)	(1038.0)	(717.4)	(752.6)	(823.3)	(728.5)	(651.3)	(280.1)	(749.4)
8-12 Months After								-3284.5***		
								(618.7)		
Household FE	YES	YES	YES	YES	YES	YES	YES	YES		YES
R-squared	0.53	0.54	0.51	0.52	0.54	0.44	0.51	0.50		0.52
Number of Obs.	32,232	28,868	30,637	25,500	12,950	24,058	38,831	48,819		28,845

Notes: This table replicates the results in Columns (1) Table 3, under varying robustness checks. Household pre-trends (Column (3)) are estimated from pre-diagnosis data. Low spenders (Column (6)) are those in the bottom 25% of the spending distribution. Omitted category in Column (7) is four to five months before. Column (9) limits to food categories where at least 85% of the NHANES consumption of the category is purchased at a store. Square brackets (Columns (5), (6) and (9) show percentage changes from baseline; these are provided because the baseline levels differ). Matched control analysis (Column 10) matches diabetic to non-diabetic households based on demographics and calorie purchases in the five months leading up to diagnosis. The omitted category is 1 to 3 months before diagnosis except in Column (7). All coefficients are reported in levels.Calorie outcome measure is residualized with respect to month-year fixed effects and a trend in time since enrollment. Standard errors are in parentheses. *significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table 5: **Effects for "Good" and "Bad" Foods**

Panel A: Good Foods			
Outcome:	*Calories*	*Quantity in Oz.*	*Spending ($)*
First Month After	170.0**	8.29***	0.87***
	(80.9)	(2.9)	(0.20)
Two-Four Months After	-17.0	-1.71	-0.10
	(65.2)	(2.56)	(0.16)
Five-Seven Months After	30.6	-1.17	-0.22
	(69.4)	(2.72)	(0.17)
Baseline Level	4065	174.0	$11.70

Panel B: Bad Foods			
Outcome:	*Calories*	*Quantity in Oz.*	*Spending ($)*
First Month After	-198.1	-5.7**	-0.06
	(162.7)	(2.74)	(0.18)
Two-Four Months After	-505.9***	-9.5***	-0.47***
	(118.4)	(2.44)	(0.14)
Five-Seven Months After	-328.5**	-7.7*	-0.37**
	(131.0)	(4.49)	(0.17)
Baseline Level	6823	112.1	$8.68

Notes: This table reports the impact of diagnosis timing on purchases of good and bad foods. The omitted category is 1 to 3 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. Outcomes are residualized with respect to month-year fixed effects and a linear control for time in Nielsen sample. Standard errors are in parentheses. *significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table 6: **Implied Calorie Valuations in Terms of Health**

Outcome [Citation]	*Description of Study*	*Effect of Daily 100 Calorie Reduction (10 pounds to 20 Pounds)*
Morality	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.	4.0 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.	0.67 (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.	1.35 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.	1.63 percentage point reduction in development of weekly incontinence (base rate 12.2%)

Notes: Details of the studies and calculations are in Appendix B.

Table 7: **Heterogeneity: Demographics and Starting Diet**

Panel A: Demographics				
Outcome:	***Calories***		*Calories Per Ounce*	
	First Month	*2-7 Months*	*First Month*	*2-7 Months*
Education				
High (>=College)	1734.7 [0.020]	-2332.9*** [-0.022]	-0.49 [-0.010]	0.95*** [0.021]
Low (<=HS)	2141.1 [0.021]	-1852.4 [-0.018]	-1.50** [-0.031]	-0.78 [-0.016]
Income				
High (>=$75K)	3235.6** [0.040]	-1192.8 [-0.014]	0.47 [0.010]	1.17*** [0.025]
Low (<=$35K)	1748.9 [0.018]	-2475.3** [-0.025]	-1.27** [-0.027]	0.25 [0.005]
Age				
Younger (<=50)	1680.5 [0.018]	-3483.6*** [-0.039]	-0.62 [-0.013]	0.57 [0.012]
Older (>=65)	1411.4 [0.015]	-2241.6** [-0.025]	-0.99** [-0.021]	-0.013 [-0.000]
Food Desert				
No	1908.8* [0.021]	-2546.6*** [-0.028]	-1.08*** [-0.023]	0.25 [0.005]
Yes	884.3 [0.010]	-1742.7* [-0.020]	-0.78 [-0.017]	0.14 [0.003]
Panel B: Pre-Period Diet				
Outcome:	***Calories***		*Calories Per Ounce*	
	First Month	*2-7 Months*	*First Month*	*2-7 Months*
Saturated Fat Share				
Low	2217.5* [0.025]	-3277.6*** [-0.037]	-0.31 [-0.007]	0.21 [0.004]
High	1419.3 [0.015]	-1274.5 [-0.013]	-1.56*** [-0.032]	0.31 [0.006]
Protein Share				
High	4483.6*** [0.053]	704.7 [0.008]	0.36 [0.008]	1.46*** [0.033]
Low	-842.3 [-0.008]	-5292.1*** [-0.054]	-2.23*** [-0.044]	-0.95*** [-0.018]

Notes: This table reports interactions between behavior change and demographics. Each row in the calorie columns represents a single regression; each row in the calories per ounce columns represents a separate regression. The omitted category is 1 to 4 months before diagnosis. Outcomes are residualized with respect to month-year fixed effects and a linear control for time in Nielsen sample. Figures in square brackets represent percent changes from baseline. Pre-period diet is defined based on the period 1 to 4 months prior to diagnosis. *significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table 8: **Individual Product Module Changes, Successful Dieters and Matched Controls**

Module Group	*Excess Reduction, Successful vs. Matches*	*% Change Successful*	*% Change Controls*
Chocolate Candy	-1114	-44%	12%
Sugar (granulated, brown, powdered)	-712	-43%	0.70%
Salad and Cooking Oil (i.e. canola, vegetable)	-710	-48%	-0.80%
Frozen Entrees (meat)	-559	-75%	1.5%
Flour (white, wheat, other)	-539	-36%	16%
Non-Chocolate Candy	-534	-50%	11%
Shortening (i.e. Crisco)	-401	-58%	34%

Notes: This table shows the changes for these food groups in calories for successful dieters and unsuccessful matched controls. Successful dieters reduce their calories per ounce by at least 10%. Controls are matched based on pre-period total calories and pre-period calories for all food groups with at least 2000 calories purchased on average per household-month. * significant at at least the 10% level.

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	Eggs	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 6, 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 6 to 11 pounds per year. I begin from this baseline and ask about the impacts of reducing a further 100 calories per day, translating to approximately 10 pounds per year.

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 by reducing a further 10 pounds from baseline. 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 the 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 increasing weight loss by 10 pounds from baseline pounds using an estimate of 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 range from 6 to 20 pounds pound range. I multiply by 10 pounds (4.53 kg).

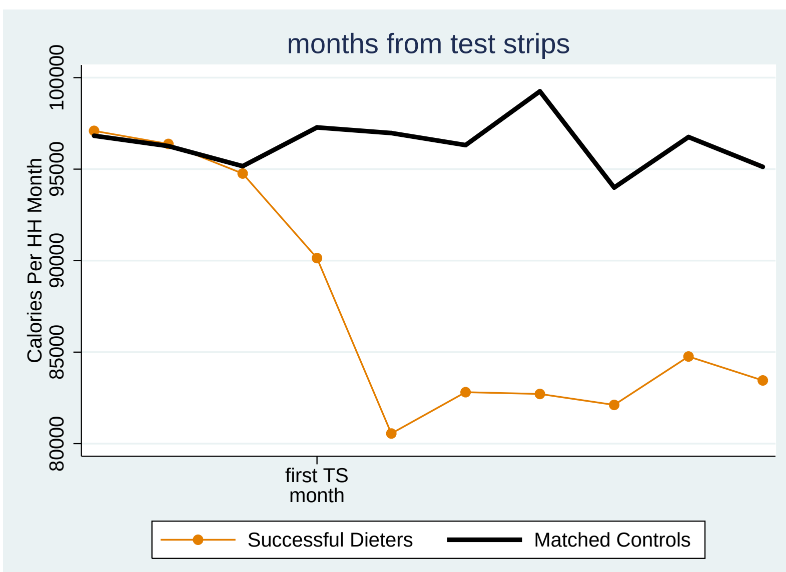
Erectile Function Erectile function data comes from Wing et al (2010). The authors report a -0.148 change in erectile function measure for each 1% weight loss. I use information on the baseline weight of the sample to estimate the impact of increasing weight loss by 10 pounds (4.53kg).

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 points per kilogram, which I scale up to 10 pounds (4.53kg).

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 10 pounds (4.53kg).

Appendix C: Figures and Tables

Figure C.1: **Calories for Successful and Unsuccessful Dieters**



Notes: This figure shows evidence on calories purchased for "successful dieters" (at least 10% reduction in calories per ounce) and matched controls. Households are matched based on calorie levels in the three months before diagnosis. Calories are residualized relative to month-year fixed effects and a linear control for time in Nielsen sample. For this raeson the levels are not interpretable, althoguh of cousre the trends are.

Table C.1: **Individual Food Group Changes**

Short Term: First Month				**Long Term: Two-Seven Months**			
Calories		*Quantity in Oz.*		*Calories*		*Quantity in Oz.*	
Food Group	*Effect Size*	*Food Group*	*Effect Size*	*Food Group*	*Effect Size*	*Food Group*	*Effect Size*
Soda	-77.4	Soda	-2.95	Dessert	-247.3*	Soft Drinks	-6.94
Shortening	-68.8	Alcohol	-1.43	Soda	-168.6*	Soda	-4.74*
Sugar	-56.4	Dessert	-1.17	Sugar	-162.8*	Fruit Juice	-3.45*
Dessert	-19.6	Fruit Juice	-0.32	Sweet Baked Goods	-136.2*	Diet Soda	-2.99
Fruit Juice	-39.1	Sugar	-0.25	Shortening	-121.2	Dessert	-2.96*
Cereal	70.4	Prep. Food	4.01*	Fish	9.4	Fish	0.25
Snacks	70.9	Vegetables	5.70*	Eggs	11.0	Prep. Food	0.26
Peanut Butter	88.5	Milk	7.38*	Diet Desserts	22.8*	Vegetables	0.39
Bread	105.9*	Soft Drinks	7.62	Bread	36.4	Bread	0.41
Milk	110.3*	Diet Soda	7.73*	Nuts	60.3	Nuts	0.45*

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. * significant at at least the 10% level.

Table C.2: **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.