Does information on health status lead to changes in exercise behavior? The effect of a diabetes diagnosis on exercise frequency and intensity

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Abstract

The purpose of this study is to empirically test whether receiving private health information leads to a change in health behavior. Specifically, we examined whether receiving a diabetes diagnosis leads to a change in physical exercise and, if so, whether responses differ by education and income. Using the Health and Retirement Study (HRS), we employed a regression discontinuity approach to estimate a causal effect of a diabetes diagnosis on changes in exercise frequency and intensity. Results show that subsequent to a diagnosis, individuals increased exercise frequency by engaging in physical activities one more time per week and increased intensity by 2 metabolic equivalents. The increase in frequency was greatest for individuals with a college degree and individuals not in the labor force, 2 and 1.6 more times per week, respectively. By contrast, there were no differences in the response to a diagnosis across subgroups on the exercise intensity margin. This shows that education and time costs have a large impact on exercise behavior in the management of chronic disease which in turn leads to disparities in the prevention of complications from type 2 diabetes. Understanding the role of education and how it interacts with private health information can inform policy regarding the allocation of resources in the treatment and management chronic diseases.

Keywords: Health information, Diabetes, Exercise, Regression discontinuity

1. Introduction

Prior studies suggest that education affects health through improving cognitive ability, and ultimately cognitive ability leads to healthier behaviors (Auld and Sidhu, 2005; Cutler and Lleras-Muney, 2010). Specifically, cognitive ability alters the way health information is processed. More educated individuals adopt healthier behaviors because they are more likely to understand the reasons to do so. Cutler et al. (2011) argued that even if less educated individuals had the same behavioral risk factors as more educated individuals, they would still have higher mortality. This implies that education is not only important in disease prevention but also important in preventing complications after disease

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onset. Indeed, Cutler et al. (2011) posits that the "the management of chronic health problems may have become more sophisticated in ways that favor those with more schooling."

The purpose of this study is empirically test this theory and contribute to the scant empirical evidence on the role of education in behavioral responses to receiving private health information regarding the presence of a chronic condition. Specifically, we examined whether receiving information on presence of diabetes leads to a change in physical exercise and, if so, whether responses differed by education and income. Lifestyle adjustments involve modifying a range of health behaviors. This study focuses on exercise behavior which has not been examined in this context. In doing so, we fill a gap in our understanding of exercise responses to private health information.

This study is closely related to Zhao et al. (2013) who investigated the roles of education and income in dietary responses to a hypertension diagnosis. Using a longitudinal dataset of individuals in China in a regression discontinuity design, they found that upon receiving a hypertension diagnosis, individuals reduced fat consumption, with higher income reducing more, but surprisingly no difference in reduction by education. Also related is a recent study that examined the impact of HRS biomarker notifications on a range of health behaviors (Edwards, 2013) assuming that biomarker readings are exogenous. By contrast, this study assumes that individuals, through their health behaviors, impact biomarker readings to a certain extent.

Two studies in the medical literature have also examined the effect of a new diabetes diagnosis on changes in health behaviors (Manschot et al., 2014; Keenan, 2009). Manschot et al. (2014) using a longitudinal dataset of individuals in the Netherlands, found that having a diabetes or heart disease diagnosis was associated with a higher likelihood of quitting smoking, a small reduction of fat consumption, but no change in exercise participation. Keenan (2009) found that individuals recently diagnosed with stroke, cancer, lung disease, heart disease, or diabetes were more likely to quit smoking. However, the identification strategies used in these studies preclude a causal interpretation due to the possibility of unobserved omitted factors. In addition, these two studies did not attempt to examine differential responses by income or education.

Unlike other health behaviors, improvements in exercise requires a greater investment of time. Time costs is a well established barrier to exercise (Meltzer and Jena, 2010). In this study, time is measured as exercise frequency, the number of times in a given period an individual engages in the activity[3]. Choosing to exercise not only involves deciding the frequency, but also deciding which form(s) of physical activity. The choice of activity determines the intensity of the exercise. This is often measured using the Metabolic Equivalency of Task (MET). For example, a person may report walking at a moderate pace twice a week. In this example, the exercise intensity is moderate and the frequency is 2 times per week. Since a health information shock may affect exercise through changes in intensity and frequency, we use both measures in our analysis.

We use Grossman's (1972) health capital model in which an individual's health is a stock variable, H_t, that depre-

[3]An individual also chooses the duration each time they engage in the activity. We are unable to explore duration in this study due to data limitations.

ciates at rate, δ_t where $\delta_t \in [0, 1]$, but can be augmented through investing in health by engaging in physical exercise to derive a testable hypothesis. In our framework, we allow individuals to misperceive their health because they misperceive their rate of depreciation. A diabetes diagnosis can be modeled as a type of private health information which informs individuals of their true rate of depreciation. Assuming individuals properly process private health information, we hypothesized that individuals will adjust to a diabetes diagnosis by increasing exercise frequency and intensity. We test this hypothesis using data from the Health and Retirement Survey (HRS). We also derive and test hypotheses for individuals with more education and higher wage income.

A key challenge to estimating the causal effect of a diabetes diagnosis on exercise is the presence of endogeneity. There may be unobserved omitted factors that increase the likelihood of being diagnosed with diabetes and is correlated with exercise behavior. To identify a causal effect if a diagnosis on changes in exercise behavior, we use the threshold for diabetes diagnosis in a clinical setting in a regression discontinuity (RD) approach. Since individuals cannot precisely control their HbA1c around the cut-point, readings above and below this level are plausibly exogenous.

Our results show that individuals responded to a diabetes diagnosis by adjusting both exercise frequency, increased by about once per week, and intensity, increased by about 2 METs. College educated and those out of the labor force increased exercise frequency more while the increase in intensity was about the same for all groups by education, income, and labor force status. Our results have important implications for health care policy. Preventing complications from type 2 diabetes can substantially reduce health care spending. Understanding the role of education and how it interacts with private health information can inform policy regarding the allocation of resources in the treatment and management diabetes.

2. Background

2.1. Type 2 Diabetes Mellitus

Type 2 diabetes mellitus is a chronic disease in which blood glucose levels are above normal. Insulin, a hormone produced in the pancreas, helps cells use glucose. Type 2 diabetes begins with insulin resistance, where cells fail to use insulin properly. Over time, as more insulin is needed, the pancreas gradually loses its ability to produce insulin. Type 2 diabetes is the seventh leading cause of death in the United States, affecting an estimated 25.8 million people (Centers for Disease Control and Prevention, 2011). If left untreated, complications result including cardiovascular disease, kidney disease, infection, ulcers of the foot leading to amputation, and blindness. Due to the combination of prevalence and complications, the direct and indirect costs of diabetes are substantial. In 2007, a total of $218 billion was attributed to the disease, $153 billion in direct medical costs and $65 billion in reduced productivity of the labor force (Dall et al., 2010).

Individuals may have diabetes without exhibiting any symptoms. It is recommended that individuals who suspect they have diabetes see their physician since only a physician can make a diabetes diagnosis. The most common measure for blood glucose levels is hemoglobin A1c (HbA1c) where higher HbA1c corresponds to higher risk of diabetes. The National Diabetes Data Group (NDDG) first standardized the criteria for a diabetes diagnosis in 1979, but in doing so acknowledged that "an arbitrary decision has been made as to what level justifies the diagnosis of diabetes" (National Diabetes Data Group, 1979). In the period when the hemoglobin A1c data used in this study was gathered, the criteria for a diabetes diagnosis was a hemoglobin A1c level 7% or greater (The International Expert Committee, 2009). The treatment for type 2 diabetes involves lifestyle changes to diet and exercise and only if individuals are unable to control blood glucose levels through lifestyle changes are oral medications then prescribed (Nathan, 2002; Ripsin et al., 2009; Short, 2012).

While adjustments to diet and exercise are both recommended, only exercise can delay the onset of diabetes (Pan et al., 1997; Eriksson et al., 1999; Tuomilehto et al., 2001). Upon onset, exercise has been shown to be very effective in controlling the disease (Boul et al., 2001; Castaneda et al., 2002; Dunstan et al., 2002) and a small number of individuals may even achieve remission (Gregg EW et al., 2012). In addition, medication in conjunction with exercise improves glycemic control beyond that achieved by medication alone (Boul et al., 2001; Castaneda et al., 2002; Dunstan et al., 2002). Even without weight loss, exercise has been shown to effectively lower blood glucose, cholesterol, and blood pressure (Marwick et al., 2009; Sigal et al., 2004, 2006).

2.2. Data

The data for this study is from the Health and Retirement Study (HRS), a nationally representative sample of more than 30,000 individuals born between 1931 and 1941 and their spouses who could be of any age. Information on demographics, physical health, health behaviors, insurance coverage, financial status, and labor market status is collected in survey waves every two years since 1992. In 2006, the HRS added an Enhanced Face-to-Face Interview (EFTF) to the core interview (Crimmins et al., 2013). The EFTF interview includes a set of blood and saliva samples. Roughly half of the households were randomly selected for the EFTF interview in 2006 while the remainder were interviewed in 2008. Individuals who participated in an EFTF were notified of their biomarker readings and later informed of their test results by mail. For this study, we merged the 2006 and 2008 HRS Biomarkers files with the RAND HRS Data file[4]. Since the 2006 and 2008 Biomarker files sampled different individuals, the biomarkers dataset is a cross-section whereas the RAND dataset is a panel.

2.3. Variables

The survey question for presence of diabetes was worded as:

> Has a doctor has ever told you that you have ... diabetes or high blood sugar?

[4]The RAND HRS Data file is an easy to use longitudinal data set based on the HRS data. It was developed at RAND with funding from the National Institute on Aging and the Social Security Administration.

We constructed a dichotomized variable for presence of diabetes equal to one if the response was "yes" and zero if the response was "no". Note that the study sample only contains individuals who never reported presence of diabetes at baseline. Therefore, first difference transformation of the variable for presence of diabetes yields a dichotomous variable equal to one if there is a new diabetes diagnosis and zero if the person was not diagnosed.

The percentage amount of glycosylated hemoglobin (HbA1c) in the blood is a common measure for blood glucose levels. In general, individuals who have not been diagnosed with diabetes do not directly observe their HbA1c levels. However, individuals who participated in the EFTF were informed of their HbA1c reading by mail and directed to see a physician or health care professional to be retested if their HbA1c reading was 7 or above [5]. The HRS Biomarkers file contains HbA1c readings for individuals in the HRS as a continuous variable. This variable, normalized to zero at the cut-point, was used as the running variable. A dichotomous variable to mark the cut-point for a diabetes diagnosis, referred to as the assignment variable, was constructed as equal to one if the respondent's HbA1c is 7 or greater and zero otherwise.

In years 2004–2010, respondents were asked how frequently they participated in vigorous, moderate, and light physical activities. The questions were phrased as:

> How often do you take part in sports or activities that are vigorous, such as running or jogging, swimming, cycling, aerobics or gym workout, tennis, or digging with a spade or shovel?
>
> And how often do you take part in sports or activities that are moderately energetic such as, gardening, cleaning the car, walking at a moderate pace, dancing, floor or stretching exercises?
>
> And how often do you take part in sports or activities that are mildly energetic, such as vacuuming, laundry, home repairs?

Respondents were allowed a choice of five responses for each question recorded as ordinal values from 1 to 5 where 1="every day", 2="more than once per week", 3="once per week", 4="one to three times per month", or 5="never". The ordinal values from the responses were translated to cardinal values in order to meaningfully interpret changes in exercise frequency and intensity.

The five responses were normalized to a time span of one month. If the response represented a range, the midpoint was used. "Every day" was assigned a frequency of 30 times per month. "More than once per week" was assigned a frequency of 16 times per month since it refers to 2-6 times per week with a midpoint of 4 times per week. "Once per week" was assigned a frequency of 4 times per month. "One to three times per month" was assigned a frequency of 2 times per month. "Never" was assigned a frequency of zero.

A continuous variable for exercise frequency was constructed equal to the average frequency for vigorous, moderate, and light exercise. This measure captures variation in the average frequency of exercise. If an individual increases

[5] See Edwards (2013) for details.

the frequency of moderate exercise but decreases the frequency of vigorous exercise, there is no change in the exercise frequency and no change in the exercise intensity, so long as the frequency of moderate or vigorous exercise is non-zero.

We translated the examples of physical activities provided in the survey questions into Metabolic Equivalent of Task (MET) values using the Compendium of Physical Activities. Each activity listed in the survey questions for vigorous, moderate, and light exercise was assigned a single MET value[6]. We then averaged the MET associated with each activity by the three levels of exercise intensity. In the end, we obtain a single MET value for vigorous, 7.1, moderate 4.1, and light exercise, 2.9.

A continuous variable for exercise intensity was constructed equal to the MET value associated with the highest intensity of physical activity the respondent reported participating in. For example, suppose a respondent reported no vigorous exercise, moderate exercise 3 times a week, and light exercise every day, then the exercise intensity is 4.1. If a respondent reported never participating in any of the three intensities of activities, then the exercise intensity is assigned a value of 1.

2.4. Study sample

The RAND panel dataset contains 30,671 unique individuals and 10 waves. Since the survey questions on exercise were only asked in waves 7-10, waves 1-6 were excluded from the sample. After constructing variables for exercise frequency, exercise intensity, and diabetes status, we first-differenced the panel dataset to obtain changes in these variables. Note that changes in the diabetes status variable yields a dichotomous variable equal to one for a new diabetes diagnosis and zero otherwise. This is because diabetes is a chronic condition and once an individual indicates presence of diabetes, this status persists for the remainder of the panel. Also, changes in the diabetes status variable for individuals who already have diabetes yields a zero values since it is not a new diagnosis. For this reason, we exclude individuals who had diabetes in the previous period. This yields a dataset with 44,660 person-wave observations for waves 8-10 comprised of individuals who were newly diagnosed with diabetes and those who were never diagnosed.

We then merge the HbA1c variable from the HRS Biomarker files to this dataset matching on the individual identifier and next wave resulting in 10,073 person-wave matched observations. Since the HbA1c variable is a cross-section, this represents 10,073 unique persons in either wave 9 or 10. Also, since the HbA1c variable is matched to the next wave, wave 9 has the wave 8 HbA1c values while wave 10 has the wave 9 HbA1c values. Thus, the HbA1c values in the previous wave are used in the analysis. Excluding missing data in the exercise, diabetes diagnosis, and HbA1c variables, the final dataset contains 9,253 observations.

[6]Metabolic equivalent, or MET, is defined as the rate of energy consumption during a specific physical activity. A MET of 1 represents the energy cost of sitting quietly. In cases where the activity involves more than one form, we used the averaged MET across all forms of the same activity. For example, swimming could involve for freestyle, backstroke, or breaststroke and the average MET value across all forms of swimming is 7.86. See Ainsworth et al. (2011) for details.

Table 2 shows the sample means for the final dataset. The average exercise frequency is 9 times per month or a little over two days per week. The average exercise intensity is 5 METs equivalent to a moderate intensity. While there is an overall decline in exercise frequency, the decline is smaller among those with a new diabetes diagnosis. Similarly, there is an overall decline in exercise intensity but among those newly diagnosed with diabetes, there is an increase in exercise intensity. Consistent with previous findings in the literature, more educated and higher income individuals exercise more often and at a higher intensity.

3. Empirical framework

To derive a testable hypothesis, we begin with Grossman's (1972) model of health production in which an individual's health is a stock variable, H_t, that depreciates at rate, δ_t where $\delta_t \in [0, 1]$, but can be augmented through investing in health by engaging in physical exercise:

$$H_{t+1} = I(F_t, N_t) + (1 - \delta_t)H_t \tag{1}$$

where F_t is exercise frequency and N_t is exercise intensity, I is the health investment function, $I_F > 0$, and $I_N > 0$. Health capital, market goods, and intense exercise are factors in the utility function:

$$U_t = U(H_t, X_t, N_t). \tag{2}$$

While individuals derive utility from health and market goods, $U_H > 0$ and $U_X > 0$, they derive disutility from intense exercise, $U_N < 0$ (Meltzer and Jena, 2010).

We assume that individuals misperceive their health because they misperceive the rate of depreciation:

$$\tilde{H}_t - H_t = \left(\delta_t - \tilde{\delta}_t\right) H_t = \epsilon_t \tag{3}$$

where $\tilde{\delta}_t \in [0, 1]$ is the perceived rate of depreciation and ϵ_t is an i.i.d. error. For example, if $\delta_t - \tilde{\delta}_t > 0$, then perceived health is better than true health.

In the next period, individuals receive private health information, s_{t+1}, which allows them to observe their true depreciation rate. Individuals then adjust their perceived depreciation rate according to how well they process private health information:

$$\tilde{\delta}_{t+1} = f(s_{t+1}) = \begin{cases} \delta_{t+1} & \text{if information is processed} \\ \tilde{\delta}_t & \text{otherwise.} \end{cases} \tag{4}$$

In the case that true depreciation at time $t + 1$ is greater than perceived depreciation at time t, $\delta_{t+1} - \tilde{\delta}_t > 0$, or, equivalently, perceived health at time t is better than true health at time $t + 1$, $H_{t+1} - \tilde{H}_t^* < 0$, to return to the optimal perceived health capital at time t, $\tilde{H}_t^*$, health investment must increase at time $t + 1$. Specifically, individuals will choose $F_{t+1}^* > F_t^*$ and $N_{t+1}^* > N_t^*$ iff $\tilde{H}_t^* > H_{t+1}$.

Assuming individuals are able to process private health information, we hypothesize that individuals will adjust to a diabetes diagnosis by increasing exercise frequency and intensity. Furthermore, assuming that individuals with higher wage incomes have higher time costs, they will choose to adjust by increasing exercise intensity rather than frequency. Finally, if more educated individuals are more able to process the private information, they will adjust more than lower educated individuals[7].

4. Estimation

We begin with a basic model for the relationship between changes in exercise behavior and a new diabetes diagnosis

$$\Delta Y_i = \beta_0 + \beta_1 \Delta D_i + \Delta \eta_i \tag{5}$$

where ΔY_i is the change in either exercise frequency or intensity, ΔD_i is a dichotomous variable for a new diabetes diagnosis, $\Delta \eta_i$is an error term, and β_0 is a constant.

A key challenge to estimating the causal effect of a diabetes diagnosis on exercise is the presence of endogeneity. There may be unobserved omitted factors that are correlated with both diabetes and exercise. For example, individuals who are diagnosed with hypertension are more likely to be diagnosed with diabetes and hypertension diagnosis may be positively correlated with exercise. The estimated parameter on ΔD_{it} using ordinary least squares (OLS) would be biased away from zero if hypertension diagnosis is omitted from the model.

Our identification strategy is to use the HbA1c cut-point for a clinical diabetes diagnosis as a source of random assignment. In general, individuals can control their HbA1c levels through health behaviors. Since individuals cannot precisely control their HbA1c around the cut-point, readings above and below this level are plausibly exogenous. Due to the small sample size, especially around the cut-point, our primary estimation method is a parametric estimation which makes use of all data points. We also present nonparametric estimates in Section 5.1.

Diabetes is diagnosed by a physician such that the private health information is delivered in a clinical setting. However, not everyone above the cut-point receives a diabetes diagnosis and persons below the cut-point may be diagnosed with diabetes. Because the cut-point does not coincide with a diagnosis, and only those diagnosed receives private health information in a clinical setting, our initial set-up is a fuzzy RD design.

The fuzzy RD design is equivalent to a two stage least squares (2SLS) estimation framework with a polynomial function of HbA1c as the included instrument and the HbA1c threshold variable as the excluded instrument. The predicted probability of a new diabetes diagnosis, determined by discontinuous jump in HbA1c above the threshold, are used in the second stage to estimate the effect of a new diagnosis on a change in exercise frequency and intensity.

[7]Zhao et al. (2013) suggested that more educated individuals may be more informed about their health such that private health information would be more informative for the less educated. Under this scenario, more educated individuals are less responsive since a diagnosis yields little new information for them.

In this framework, the structural and first stage equations are

$$\Delta Y_i = \beta_0 + \beta_1 \Delta D_i + f(r_i) + \Delta\eta_i \tag{6}$$

$$\Delta D_i = \alpha_0 + \alpha_1 Z_i + f(r_i) + \Delta\mu_i \tag{7}$$

where r_i is a continuous variable for HbA1c values in the previous wave, Z_i is a dichotomous variable for HbA1c greater than 7 in the previous wave, and $f(\cdot)$ is a polynomial function of HbA1c values in the previous wave.

An alternate set-up is a sharp design. This set-up is valid if we believe that individuals may directly respond to the information that their HbA1c is above normal and attempt to self-treat their condition by changing their exercise behavior. If true, then a physician need not deliver private health information for there to be adjustments to exercise behavior. A sharp design is implemented as

$$\Delta Y_i = \gamma_0 + \gamma_1 Z_i + f(r_i) + \Delta\nu_i \tag{8}$$

By comparing the results from the sharp and fuzzy designs, we can test the null hypothesis that private health information delivered by a physician induces a change in exercise behavior against the alternate hypothesis that private health information directly induces a change in exercise behavior. Assuming physicians adhere to clinical guidelines regarding the treatment of diabetes, a diabetes diagnosis is accompanied by specific recommendations to increase exercise. In contrast, private health information in the form of a high HbA1c reading does not convey any information regarding the risks of diabetes or the benefits of exercise as a treatment option.

4.1. Preliminary checks

RD design is only appropriate if individuals cannot manipulate the values of the assignment variable. This is true in the context of a diabetes diagnosis given that 1) HbA1c is not directly observable, especially among individuals who do not have diabetes and have not been directed to monitor their blood glucose levels 2) individuals with HbA1c around the cut-point may not exhibit any symptoms 3) individuals cannot precisely control their HbA1c around the cut-point. We follow Lee and Lemieux (2010) and perform checks based on parametric estimation of the observables and nonparametric estimation of unobservables to verify that there are no non-linearities around the cut-point.

Figure 1 shows the distribution of HbA1c values using kernel density estimation with a bandwidth of 0.2. The sample size around the cut-point is small indicating that few with HbA1c greater than 7 have not been diagnosed with diabetes in the study sample. The distribution resembles a normal distribution and there are no discontinuities around the cut-point. Figure 2 shows education, income, labor force participation, and whether the person has visited a doctor at baseline. The open circles denote unconditional averages of HbA1c value for a bin and corresponding unconditional average value for the observable both using a bandwidth of 0.2. The solid curve is a kernel-weighted local polynomial smoother with a bandwidth of 0.6. The variance in the averaged observable values increases with HbA1c due to increasingly smaller samples. By visual inspection, there does not appear to be any differences immediately above and below the cut-point[8].

5. Results

A parametric approach was used as the primary estimation method due to the sparseness of the sample around the cut-point. Equation 5, changes in exercise regressed on presence of a new diabetes diagnosis, was estimated using ordinary least squares (OLS) for comparison with the RD results. Equations 6 and 7 were estimated using two-stage least squares (2SLS) estimation where the predicted probability of a diabetes diagnosis were used to estimate the effect of a diabetes diagnosis on changes in exercise frequency and intensity. Equation 8, equivalent to equation 5 plus a function of the running variable, was estimated using OLS. Our preferred specification uses a second order polynomial as the functional form for the running variable in equations 6–8. We also report results using first, third, and fourth order polynomial functions. For robustness, we estimated the model using additional covariates, nonparametric estimation, as a falsification test, a cut-point at HbA1c equal to 6. For inference, standard errors were adjusted for heteroskedasticity using Huber-White estimator.

The main results are shown in Figure 3, which plots the averaged predicted changes in exercise frequency and intensity in the vertical axis against the average HbA1c values again using a bandwidth of 0.2. Panels 3(a) and 3(b) show the results of the sharp RD. There is a clear discontinuity in both exercise measures. Below the cut-point, there is a decline in frequency while above the cut-point, there is no change in frequency. With intensity, there is almost no change below the cut-point, and an increase above the cut-point. Panels 3(c) and 3(d) show the results of the fuzzy RD which assumes that the HbA1c readings induced a diabetes diagnosis among those above the cut-point and did not directly impact exercise behavior. Again, below the cut-point, there is a negative change in frequency and no change in intensity and above the cut-point, there is an positive change in both measures. The estimated effects in the fuzzy design are larger than that in the sharp design.

Table 3 reports the OLS, sharp RD, and fuzzy RD results using the entire sample, and also using subsamples stratified by education, income, and labor force status. The point estimates using the entire sample correspond to the plots in Figure 3 and show that the estimated effect of the cut-point is statistically significant for exercise intensity but less precisely estimated for frequency. However, when conditioned on a college degree, there is a statistically significant increase in exercise frequency. It also appears that the increase in frequency is larger for individuals with higher income and and those out of the labor force but these estimates are not precise. In contrast to the results for frequency, the estimated effects for exercise intensity is similar by education, income, and labor force status. These findings suggest that while all individuals increased exercise intensity, only those with more education or those less time constraints increased exercise frequency upon receipt of private health information.

[8]Parametric estimation using baseline observables as outcomes confirms that there is no statistically significant non-linearity at the cut-point. These results are available upon request.

While it does appear that being informed of one's HbA1c had an effect on exercise behavior, it is still unclear whether this was a direct response or whether the response was due to being diagnosed by a physician – should the mechanism be modeled as a sharp or fuzzy RD? If it were the former, then individuals who have not visited a doctor should respond to the cut-point. If it were the latter, then only those who have visited a doctor should respond to the cut-point. That is, for the sharp RD, limiting the sample to those who have visited a doctor should not alter the point estimates and, for the fuzzy RD, limiting the sample to those who have not visited a doctor should yield a null effect. To test this hypothesis, we estimated a set of models using only the subsample of individuals who visited a doctor[9]. These results are reported in Table 5. Conditioning on individuals who have visited a doctor improved the precision of the point RD estimates for change in exercise frequency. It also increased the magnitude of the point estimates on the sharp RD. Although not conclusive, these findings are suggestive that the behavioral response is through a diagnosis delivered by a physician.

5.1. Robustness

Estimating with a parametric approach allowed us to use the entire sample, but it may lead to biased estimates if the model misspecified. In Table 7, we examine the robustness of the results to changing the functional form of the running variable as well as inclusion of additional covariates for age, sex, and race/ethnicity. In the sharp RD, the discontinuity in the assignment variable remains even as we increase the flexible form of the running variable and include additional covariates does not affect the point estimates. In the fuzzy RD, there is an increase in the point estimates between linear/quadratic and cubic/quartic which corresponds with a decline in the first stage F-statistic. This suggests that increasing the flexible form of the running variable causes the assignment variable to lose its predictive power resulting in a weak instrument problem.

We also performed nonparametric estimation using local linear regression (LLR) following Hahn et al. (2001). In this approach, only data close to the cut-points are used for in a kernel estimation. The treatment effect for a fuzzy RD is

$$\beta = \frac{y^+ - y^-}{x^+ - x^-} \tag{9}$$

where $y^+ \equiv \lim_{z \to z_0^+} E[y_i | z_i = z]$, $y^- \equiv \lim_{z \to z_0^-} E[y_i | z_i = z]$, y is the outcome variable (exercise frequency or intensity), z is the running variable (HbA1c), z_0 is the cut-point, and x is the treatment variable (diabetes diagnosis). For a sharp RD, $x^+ - x^- = 1$ such that the treatment effect is

$$\beta = y^+ - y^- \tag{10}$$

The local linear estimator for y^+ is given by $\hat{a}$ where

$$(\hat{a}, \hat{b}) \equiv \underset{a,b}{argmin} \sum_{i=1}^{n} (y_i - a - b(z_i - z_0))^2 \, K\left(\frac{z_i - z_0}{h}\right) 1(z_i > z_0) \tag{11}$$

[9]The HRS survey question asks how many times the respondent has seen or talked to a medical doctor including emergency room or clinic visits. Responses were recoded as a dichotomous variable equal to 1 if number of times is 1 or more, and zero otherwise. Since a large portion of the sample reported visiting a doctor, the subsample of those who did not visit a doctor is too small for analysis.

where $K(\cdot)$ is a kernel function and $h > 0$ is the bandwidth. We followed Imbens and Kalyanaraman's (2011) algorithm for selecting the optimal bandwidth that balances between bias and precision in a RD design. Estimations using the optimal bandwidth along with smaller and larger bandwidths were also implemented.

LLR results are reported in Table 7. For the sharp RD, the LLR estimates are comparable to the parametric estimates, but estimated imprecisely at the smaller bandwidth. This is expected given the small sample size around the cut-point. As we increase the bandwidth, the LLR estimates become more precise. For the fuzzy RD, the LLR estimates are larger than the parametric estimates and very imprecise at the smaller bandwidth. As we increase the bandwidth, the standard error decreases and the estimates converge towards the parametric results. Taken together, the nonparametric findings at the larger bandwidths are roughly comparable to the parametric findings using linear/quadratic specifications.

As a falsification test, we changed the cut-point of the assignment variable to a HbA1c value of 6. Since HbA1c greater than 6 would not reveal information about health status, there should not be an effect on health behavior. Equations 6 – 8 were estimated using the new cut-point. Tables 8 and 9 shows that the point estimates are not statistically significantly different from zero when the cut-point is at 6. This supports the hypothesis that the health status information is conveyed upon reaching a HbA1c threshold where a diagnosis of diabetes is made by a physician.

We also examine the robustness of the results to trimming the range of HbA1c values. In theory, trimming the range should not materially affect the results if only the data around the cut-point are used to identify the effect. However, in the fuzzy RD, the number of observations used to estimate the first stage is already sparse. Therefore, restricting the upper range of HbA1c values will likely impact the results of the fuzzy RD. Tables 10 and 11 report the point estimates restricting the sample to HbA1c values within to 5 and 9, inclusive. The sharp RD for the overall sample show that exercise frequency increased by 1.77 compared to 1.08 for the unrestricted results shown in Tables 3 and 4. Only the estimates for the subsample of individuals in the labor force remain statistically significant. As expected, restricting the sample leads to a weak instrument problem making fuzzy RD results difficult to interpret.

As a final robustness check, we perform the same estimates using the ordinal values for exercise frequency and intensity. Exercise frequency responses were recorded on a scale of 1 through 5 where 1 refers to no participation and 5 is participation every day. The average frequency across light, moderate, and vigorous exercise was used as the measure of ordinal exercise frequency across all intensities. Exercise intensity responses were recorded on a scale of 0 to 3 where 0 refers to no participation and 3 refers to vigorous exercise participation. The maximum exercise intensity response was used as the measure of ordinal exercise intensity. A positive change in the ordinal exercise frequency or intensity reflect an increase in that measure. Table 4 reports the point estimates using ordinal changes in exercise frequency and intensity as outcomes. The sign and statistical significance of these results are comparable to the main results reported in Table 3. Therefore, the results are robust to using ordinal or cardinal measures of exercise.

6. Discussion

Studies have shown that a large part of the effect of education on health is through health behaviors[10] (Cutler and Lleras-Muney, 2006; Cutler et al., 2011). Previous studies that have examined the relationship between education and health behaviors have demonstrated that well educated individuals are more likely to use seat belts, less likely to smoke, more likely to exercise (Leigh, 1990; Kenkel, 1991; Sander, 1995; Jurges et al., 2011; de Walque, 2007; Cutler and Lleras-Muney, 2010). This study provides empirical evidence that education and income are important not only in disease prevention, as demonstrated in these studies, but also in preventing complications after disease onset. Diabetes is a chronic disease that if not well managed can lead to disability and death. Physical exercise can help manage the disease and prevent complications. The purpose of this study was to examine whether individuals who receive private health information in the form of a diagnosis adjust their exercise frequency or intensity.

The unconditional average change in the exercise frequency and intensity is negative for the overall sample which shows that exercise declines with age. Among those diagnosed with diabetes, there is an increase in both exercise frequency and intensity. This supports the hypothesis that those who received private health information modify their health production.

Results also show that individuals with more education and not in the labor force increased frequency more than other groups. The highest frequency observed was those with a college degree who exercise almost three more times per week (Table 5). Individuals out the labor force also increased their exercise frequency, by more than two times per week. In contrast, individuals in all subgroups by education, income, and education increased exercise intensity by about 0.7 METs. This corresponds to an upgrade in intensity from light to moderate, or from moderate to vigorous. Unlike in frequency, the increase in intensity is solely because those who received private health information are more likely to increase intensity, since there was no change in exercise intensity for the overall sample.

The rising prevalence of type 2 diabetes mellitus (Centers for Disease Control and Prevention, 2011), has raised the question of whether preventive screening should be expanded beyond the current recommendations of the U.S. Preventive Services Task Force (USPSTF). Currently, the USPSTF recommends screening for type 2 diabetes only for asymptomatic adults with high blood pressure. Outside of this group, the USPSTF concluded that there is inadequate evidence that early diabetes control as a result of screening leads to improve outcomes compared with initiating treatment after clinical diagnosis, particularly for outcomes such as severe visual impairment or end-stage renal disease which take years to become apparent. However, researchers have argued that expanding the screening to a greater number of asymptomatic adults can prevent disease onset (Gillies et al., 2008; Kahn et al., 2010; Villarivera et al., 2012). In our view, one way that expanding screening can improve outcomes is if a diagnosis of pre-diabetes leads to changes in health behaviors such as exercise, adopting a healthful diet, and stopping smoking. That is, the positive impact of early screening lies in its potential for altering health behaviors. There is limited empirical evidence

[10] A few papers countered the general consensus in the literature on education and health (Nayga, 2000; Albouy and Lequien, 2009; Tenn et al., 2010). We do not focus on the issue of reconciling the literature in this paper but note these studies for completeness.

regarding behavioral responses to private health information.

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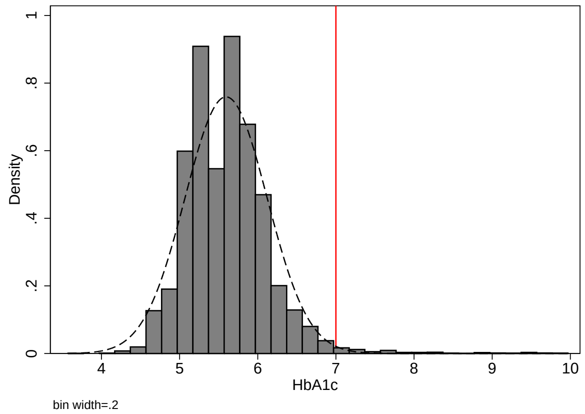
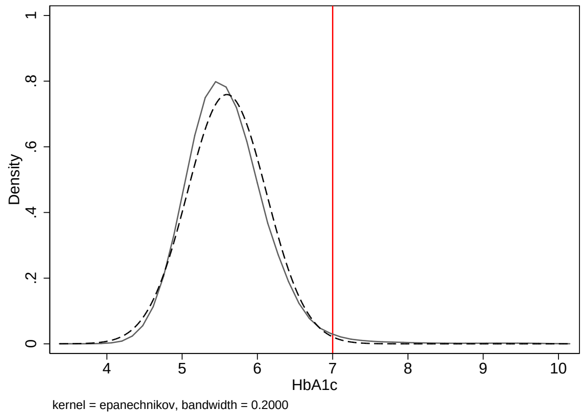
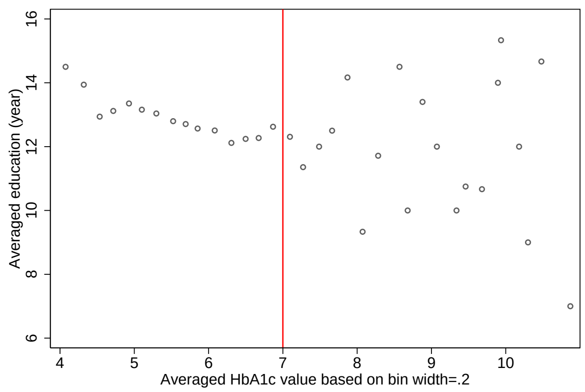


(a) Histogram

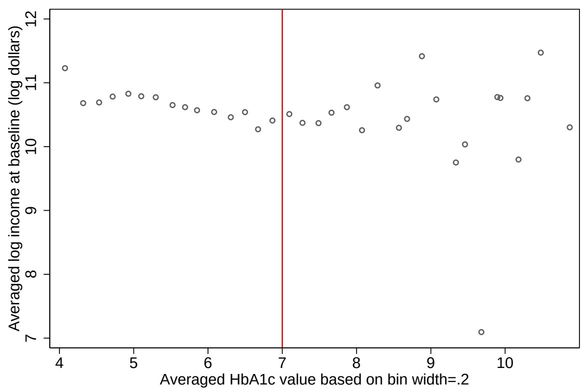


(b) Kernel Density

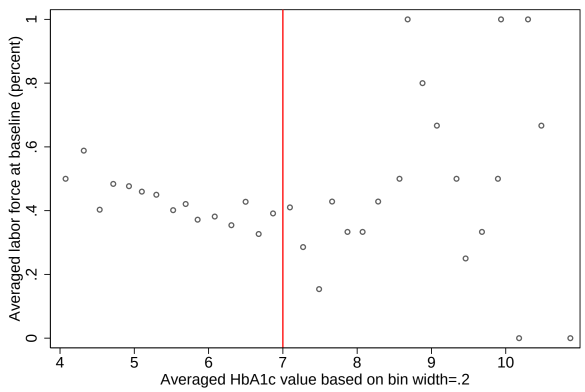
Figure 1: HbA1c values. Dashed curve denotes normal distribution).



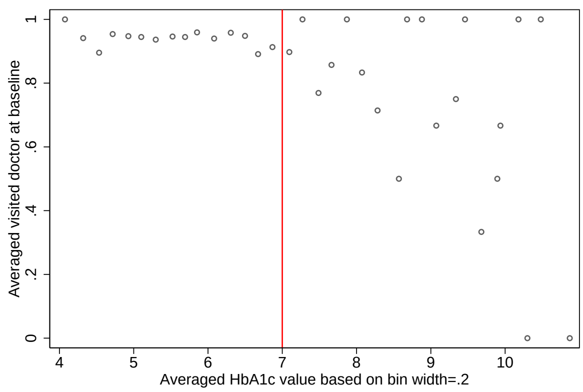
(a) Education



(b) Income

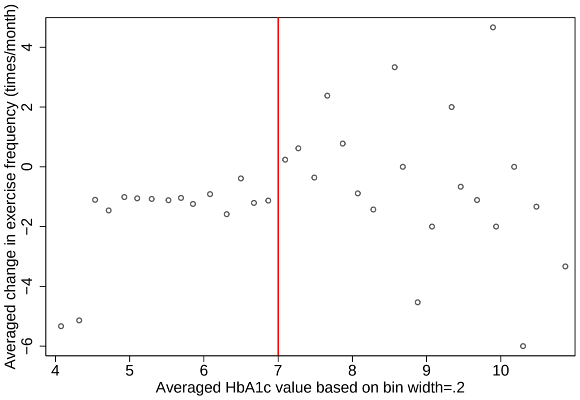


(c) Labor Force Participation

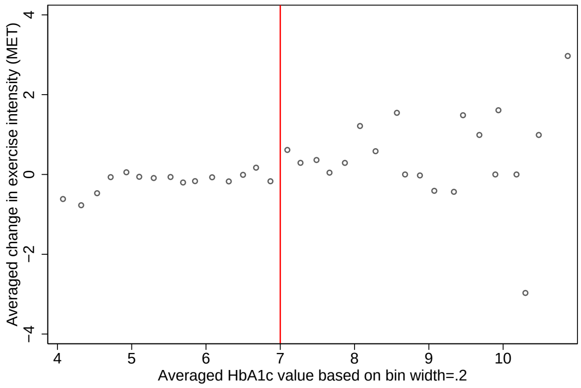


(d) Visited Doctor

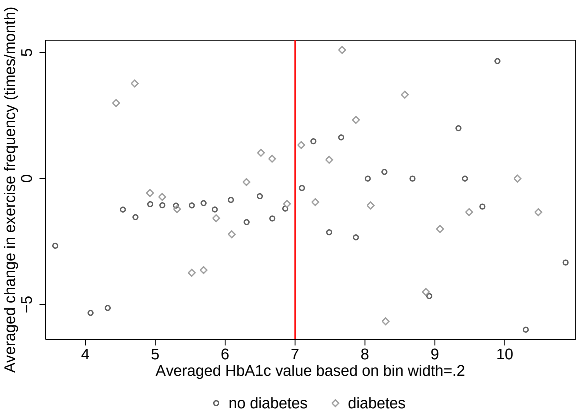
Figure 2: Observables at baseline. Open circles are unconditional averages (bandwidth=0.2).



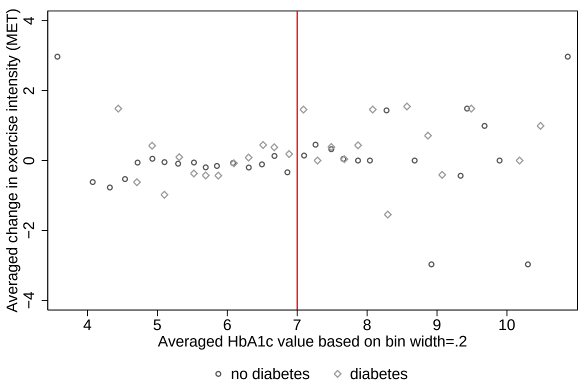
(a) Sharp RD: ΔExercise Frequency



(b) Sharp RD: ΔExercise Intensity

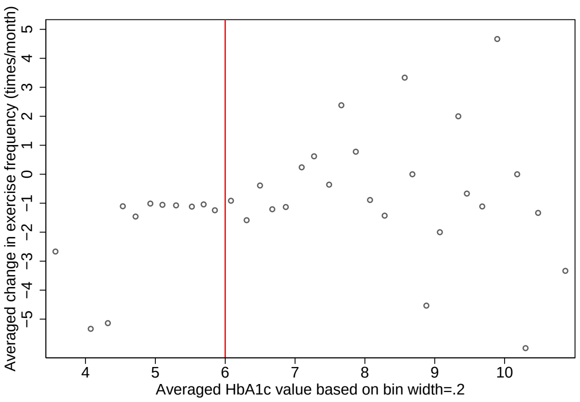


(c) Fuzzy RD: ΔExercise Frequency

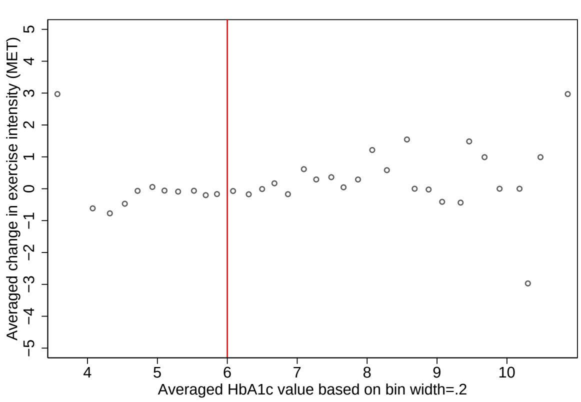


(d) Fuzzy RD: ΔExercise Intensity

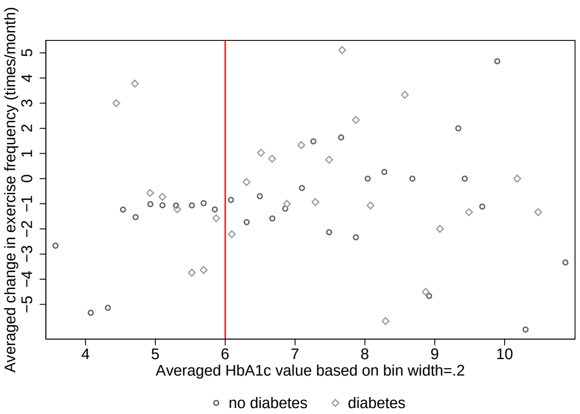
Figure 3: Changes in exercise frequency and intensity. Open circles and diamonds are unconditional averages.



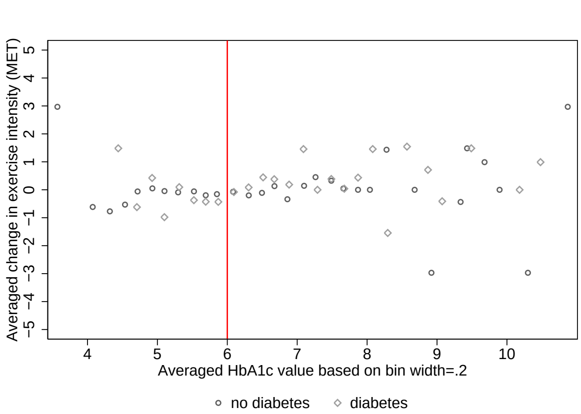
(a) Sharp RD: ΔExercise Frequency



(b) Sharp RD: ΔExercise Intensity

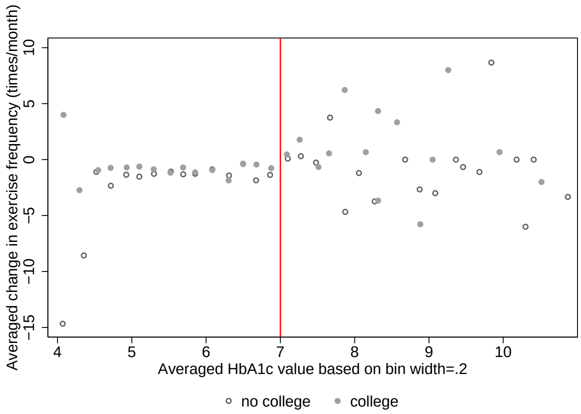


(c) Fuzzy RD: ΔExercise Frequency

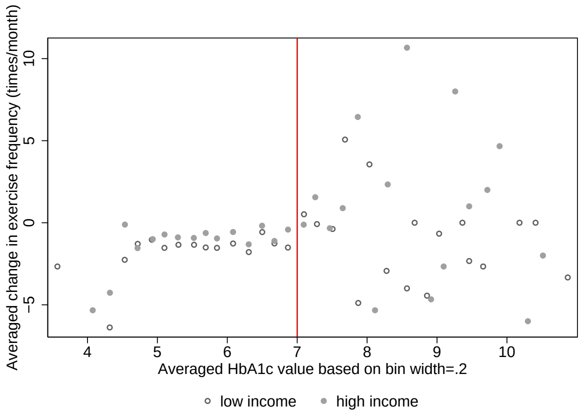


(d) Fuzzy RD: ΔExercise Intensity

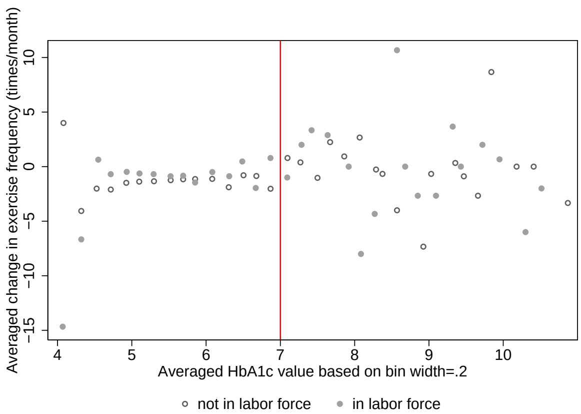
Figure 4: HbA1c cut-point at 6: Changes in exercise frequency and intensity. Open circles and diamonds are unconditional averages.



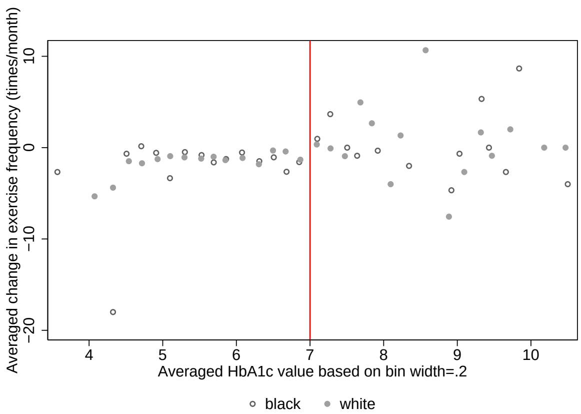
(a) Education



(b) Income

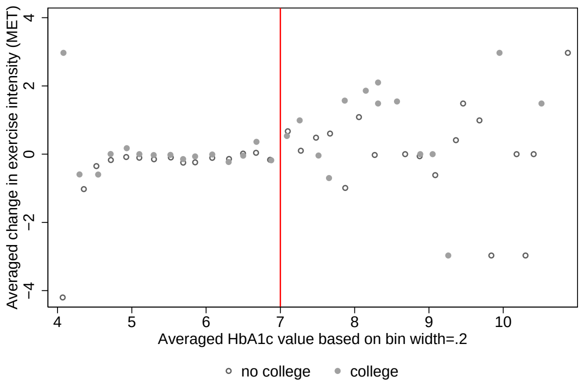


(c) Labor Force Status

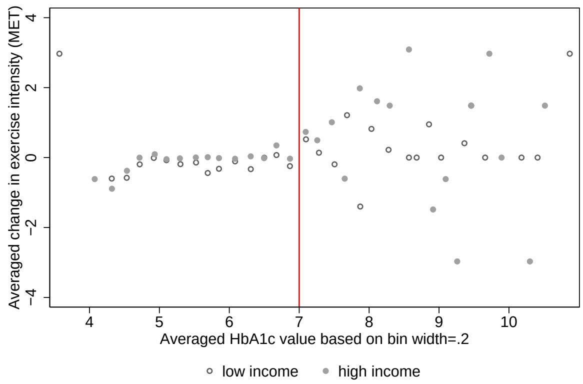


(d) Race

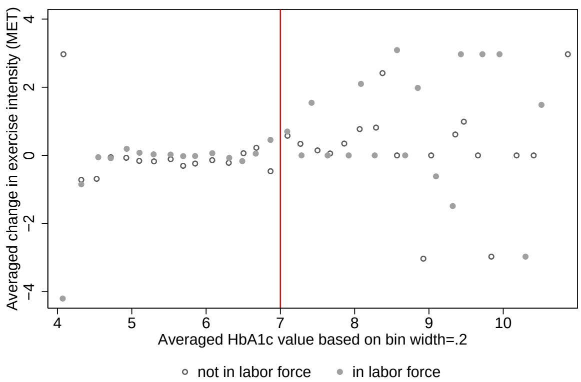
Figure 5: Changes in exercise frequency. Open and solid circles are unconditional averages.



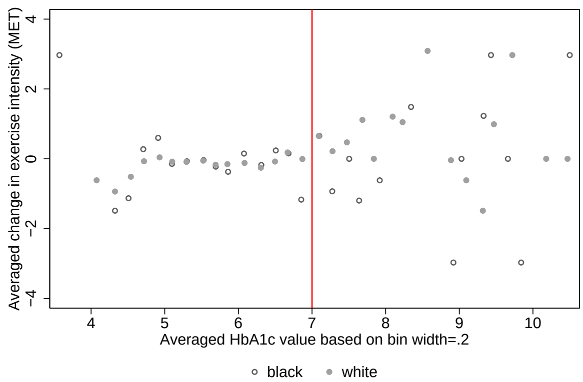
(a) Education



(b) Income



(c) Labor Force Status



(d) Race

Figure 6: Changes in exercise intensity. Open and solid circles are unconditional averages.

Table 1: The Distribution of HbA1c $\geq$ 7 by Diabetes Diagnosis

		No Diabetes	Diabetes	
		$\Delta D_i = 0$	$\Delta D_i = 1$	Total
HbA1c<7	$Z_i = 0$	8,808	307	9,115
HbA1c≥7	$Z_i = 1$	76	62	138
	Total	8,884	369	9,253

Table 2: Summary statistics.

		College Degree		Income		Labor Force		Race	
	All	Low	High	Low	High	Out	In	Black	White
Exercise frequency	9.14	8.14	10.29	7.64	10.41	8.36	10.47	7.23	9.42
ΔExercise frequency	-1.09	-1.23	-0.92	-1.37	-0.85	-1.28	-0.78	-1.13	-1.16
Exercise intensity	5.02	4.70	5.39	4.51	5.45	4.69	5.57	4.75	5.06
ΔExercise intensity	-0.09	-0.14	-0.02	-0.19	0.00	-0.16	0.04	-0.08	-0.09
ΔDiabetes	0.04	0.05	0.03	0.04	0.04	0.04	0.03	0.05	0.03
HbA1c	5.60	5.65	5.56	5.66	5.56	5.63	5.55	5.78	5.57
HbA1c≥7	0.01	0.02	0.01	0.02	0.01	0.02	0.01	0.03	0.01
Age	69.43	70.77	67.93	72.51	66.85	73.73	62.17	68.29	70.08
Female	0.61	0.64	0.58	0.68	0.55	0.64	0.56	0.64	0.61
Black	0.11	0.13	0.09	0.16	0.07	0.11	0.11	1.00	0.00
Hispanic	0.08	0.11	0.04	0.12	0.05	0.07	0.09	0.00	0.00
Married	0.66	0.61	0.71	0.43	0.85	0.60	0.75	0.47	0.68
High School	0.36	0.68	0.00	0.41	0.32	0.39	0.31	0.31	0.38
College	0.47	0.00	1.00	0.29	0.61	0.40	0.58	0.36	0.50
Labor force	0.37	0.29	0.47	0.20	0.52	0.00	1.00	0.39	0.36
Income	65593	43641	90737	19949	104066	48009	95307	41263	71748
Weekly wage	869	562	1083	389	1017	.	869	681	914
Observations	9253	4925	4290	4232	5021	5813	3440	1022	7318

Exercise frequency is the average frequency across light, moderate, and vigorous exercise measured as times per month.

Exercise intensity is the maximum intensity among light, moderate, and vigorous exercise measured as metabolic equivalents (MET).

Table 3: By education, income, labor force status: Estimated treatment effects on changes in exercise frequency and intensity.

		College Degree		Income		Labor Force	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	No	Yes	Low	High	Out	In
	ΔExercise Frequency						
OLS	0.0746	0.211	-0.0885	0.487	-0.291	0.254	-0.218
	(0.329)	(0.430)	(0.513)	(0.484)	(0.446)	(0.401)	(0.579)
Sharp RD	1.081	0.156	2.463**	0.651	1.280	1.372	0.121
	(0.736)	(0.990)	(0.991)	(1.044)	(1.034)	(0.860)	(1.449)
Fuzzy RD	4.655	0.681	10.55*	2.688	5.749	6.869	0.397
	(3.331)	(4.303)	(5.803)	(4.397)	(4.981)	(4.745)	(4.760)
	ΔExercise Intensity						
OLS	0.137	0.173	0.0986	0.158	0.134	0.0616	0.336*
	(0.101)	(0.128)	(0.167)	(0.145)	(0.142)	(0.124)	(0.172)
Sharp RD	0.596***	0.544**	0.650*	0.602**	0.538	0.478*	0.859**
	(0.214)	(0.275)	(0.345)	(0.261)	(0.351)	(0.252)	(0.410)
Fuzzy RD	2.569**	2.365*	2.785*	2.486*	2.416	2.395*	2.826**
	(1.023)	(1.286)	(1.691)	(1.342)	(1.543)	(1.439)	(1.331)
Observations	9253	4925	4290	4232	5021	5813	3440
F-stat	19.45	11.93	7.364	10.67	8.648	10.67	9.054
P-value (Endog)	0.00816	0.0603	0.0733	0.0356	0.137	0.0612	0.0610

Frequency is measured as times per month. Intensity is measured as metabolic equivalents (MET).

Quadratic functional form for HbA1c values used in RD specifications.

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Weak instrument test statistic is robust Kleibergen-Paap Wald rk F statistic.

Endogeneity test H_0: ΔDiabetes is exogenous.

Table 4: By age, gender, race: Estimated treatment effects on changes in exercise frequency and intensity.

		Age		Gender		Race	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Less than 65	65 and above	Male	Female	Black	White
			ΔExercise Frequency				
OLS	0.0746	-0.591	0.405	0.0101	0.136	0.229	0.0513
	(0.329)	(0.548)	(0.409)	(0.486)	(0.449)	(0.939)	(0.384)
Sharp RD	1.081	0.770	1.133	1.503	0.710	2.179	1.286
	(0.736)	(1.133)	(0.954)	(1.221)	(0.938)	(1.806)	(0.936)
Fuzzy RD	4.655	3.219	4.974	10.79	2.441	20.37	4.878
	(3.331)	(5.097)	(4.285)	(10.51)	(3.294)	(25.56)	(3.791)
			ΔExercise Intensity				
OLS	0.137	0.0698	0.176	0.218	0.0765	-0.180	0.0969
	(0.101)	(0.176)	(0.124)	(0.146)	(0.141)	(0.317)	(0.116)
Sharp RD	0.596***	0.485	0.622**	0.482	0.696**	-0.0194	0.809***
	(0.214)	(0.328)	(0.269)	(0.338)	(0.276)	(0.499)	(0.300)
Fuzzy RD	2.569**	2.031	2.729**	3.459	2.392**	-0.181	3.068**
	(1.023)	(1.420)	(1.334)	(2.936)	(1.047)	(4.663)	(1.260)
Observations	9253	3157	6096	3595	5658	1022	7318
F-stat	19.45	5.685	13.17	2.881	17.29	0.795	14.98
P-value (Endog)	0.00816	0.153	0.0290	0.184	0.0135	0.998	0.00958

Frequency is measured as times per month. Intensity is measured as metabolic equivalents (MET).

Quadratic functional form for HbA1c values used in RD specifications.

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Weak instrument test statistic is robust Kleibergen-Paap Wald rk F statistic.

Endogeneity test H_0: ΔDiabetes is exogenous.

Table 5: Sample that visited doctor: Estimated treatment effects on changes in exercise frequency and intensity.

		College Degree		Income		Labor Force	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	No	Yes	Low	High	Out	In
	ΔExercise Frequency						
OLS	0.000378	0.0768	-0.0698	0.371	-0.304	0.273	-0.489
	(0.338)	(0.447)	(0.516)	(0.507)	(0.451)	(0.411)	(0.595)
Sharp RD	1.717**	0.784	2.956***	1.471	1.645	2.219**	0.123
	(0.786)	(1.112)	(0.961)	(1.119)	(1.100)	(0.901)	(1.596)
Fuzzy RD	6.997*	3.016	13.61**	6.111	6.543	10.69*	0.371
	(3.590)	(4.360)	(6.772)	(5.131)	(4.825)	(5.510)	(4.815)
	ΔExercise Intensity						
OLS	0.135	0.142	0.145	0.152	0.136	0.0982	0.252
	(0.102)	(0.128)	(0.168)	(0.145)	(0.143)	(0.124)	(0.175)
Sharp RD	0.701***	0.668**	0.720**	0.833***	0.507	0.603**	0.879*
	(0.234)	(0.318)	(0.339)	(0.285)	(0.376)	(0.276)	(0.452)
Fuzzy RD	2.857***	2.570*	3.317*	3.462**	2.017	2.902*	2.657**
	(1.060)	(1.316)	(1.815)	(1.670)	(1.414)	(1.553)	(1.300)
Observations	8548	4447	4067	3798	4750	5441	3107
F-stat	18.90	12.50	6.291	8.705	10.08	9.938	9.570
P-value (Endog)	0.00476	0.0452	0.0485	0.00848	0.194	0.0344	0.0793

Frequency is measured as times per month. Intensity is measured as metabolic equivalents (MET).

Quadratic functional form for HbA1c values used in RD specifications.

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Weak instrument test statistic is robust Kleibergen-Paap Wald rk F statistic.

Endogeneity test H_0: ΔDiabetes is exogenous.

Table 6: Sample that visited doctor: Estimated treatment effects on changes in exercise frequency and intensity.

		Age		Gender		Race	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Less than 65	65 and over	Male	Female	Black	White
	ΔExercise Frequency						
OLS	0.000378	-0.791	0.381	-0.170	0.151	0.0920	0.0175
	(0.338)	(0.566)	(0.420)	(0.498)	(0.462)	(1.000)	(0.386)
Sharp RD	1.717**	0.796	1.900*	2.262*	1.265	3.266*	1.766*
	(0.786)	(1.276)	(1.002)	(1.340)	(0.988)	(1.912)	(0.972)
Fuzzy RD	6.997*	3.025	8.046*	14.27	4.169	21.75	6.506
	(3.590)	(5.199)	(4.681)	(11.44)	(3.438)	(21.08)	(3.969)
	ΔExercise Intensity						
OLS	0.135	0.0157	0.195	0.215	0.0780	-0.239	0.122
	(0.102)	(0.180)	(0.124)	(0.145)	(0.144)	(0.319)	(0.116)
Sharp RD	0.701***	0.490	0.754***	0.455	0.888***	-0.0196	0.876***
	(0.234)	(0.378)	(0.290)	(0.377)	(0.296)	(0.559)	(0.313)
Fuzzy RD	2.857***	1.863	3.192**	2.872	2.927***	-0.131	3.226**
	(1.060)	(1.393)	(1.411)	(2.655)	(1.099)	(3.711)	(1.253)
Observations	8548	2828	5720	3256	5292	933	6893
F-stat	18.90	5.945	12.41	3.292	16.26	1.314	14.58
P-value (Endog)	0.00476	0.205	0.0150	0.272	0.00390	0.978	0.00821

Frequency is measured as times per month. Intensity is measured as metabolic equivalents (MET).

Quadratic functional form for HbA1c values used in RD specifications.

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Weak instrument test statistic is robust Kleibergen-Paap Wald rk F statistic.

Endogeneity test H_0: ΔDiabetes is exogenous.

Table 7: Alternate specifications: Estimated treatment effects on changes in exercise frequency and intensity.

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔExercise Frequency			ΔExercise Intensity		
Parametric	Sharp RD	Fuzzy RD	F-stat	Sharp RD	Fuzzy RD	F-stat
Linear	1.10*	4.60	27.309	0.62***	2.58***	27.309
	(0.656)	(2.863)		(0.200)	(0.922)	
Quadratic	1.08	4.66	19.452	0.60***	2.57**	19.452
	(0.736)	(3.331)		(0.214)	(1.023)	
Cubic	2.01**	15.27	4.639	0.57**	4.33	4.639
	(0.873)	(9.388)		(0.268)	(2.654)	
Quartic	2.02**	14.25*	5.347	0.57**	4.03*	5.347
	(0.870)	(8.415)		(0.267)	(2.388)	
Linear + covariates	0.87	3.72	26.208	0.53***	2.28**	26.208
	(0.658)	(2.885)		(0.200)	(0.920)	
Quadratic + covariates	1.01	4.38	19.186	0.56***	2.45**	19.186
	(0.738)	(3.356)		(0.214)	(1.024)	
Cubic + covariates	1.88**	14.43	4.547	0.52*	4.03	4.547
	(0.872)	(9.200)		(0.267)	(2.602)	
Quartic + covariates	1.91**	13.63	5.241	0.53**	3.78	5.241
	(0.869)	(8.326)		(0.267)	(2.361)	
Nonparametric			Bandwidth			Bandwidth
LLR (larger)	1.57*	6.36*	5.33	0.64**	2.74**	3.94
	(0.808)	(3.528)		(0.266)	(1.248)	
LLR (optimal)	1.57*	8.51	2.66	0.58*	4.09	1.97
	(0.937)	(5.851)		(0.333)	(2.880)	
LLR (smaller)	0.90	13.63	1.33	0.72	25.00	0.99
	(1.209)	(24.839)		(0.447)	(83.825)	
Observations	9253	9253		9253	9253	

Frequency is measured as times per month. Intensity is measured as metabolic equivalents (MET).

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Weak instrument test statistic is robust Kleibergen-Paap Wald rk F statistic.

Additional covariates are for age, age-squared, and indicators for wave, female, black, and Hispanic.

Optimal bandwidth in LLR refers to Imbens and Kalyanaraman (2011).

Table 8: HbA1c cut-point at 6: Estimated treatment effects on changes in exercise frequency and intensity.

		College Degree		Income		Labor Force	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	No	Yes	Low	High	Out	In
	ΔExercise Frequency						
Sharp RD	-0.0267	-0.0992	0.0191	-0.0197	-0.00360	-0.438	0.671
	(0.245)	(0.334)	(0.364)	(0.355)	(0.341)	(0.305)	(0.414)
Fuzzy RD	-1.214	-4.011	1.257	-0.701	-0.233	-17.37	45.35
	(11.15)	(13.61)	(23.93)	(12.64)	(22.09)	(14.02)	(51.59)
	ΔExercise Intensity						
Sharp RD	0.0680	0.0832	0.0414	0.176*	-0.0247	0.0888	0.0132
	(0.0690)	(0.0942)	(0.102)	(0.101)	(0.0956)	(0.0872)	(0.113)
Fuzzy RD	3.095	3.366	2.727	6.281	-1.601	3.517	0.895
	(3.341)	(4.119)	(6.980)	(4.485)	(6.307)	(3.748)	(7.664)
Observations	9253	4925	4290	4232	5021	5813	3440
F-stat	6.877	4.369	1.678	5.216	1.823	5.795	1.103
P-value (Endog)	0.341	0.394	0.693	0.0855	0.786	0.310	0.940

Frequency is measured as times per month. Intensity is measured as metabolic equivalents (MET).

Quadratic functional form for HbA1c values used in RD specifications.

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Weak instrument test statistic is robust Kleibergen-Paap Wald rk F statistic.

Endogeneity test H_0: ΔDiabetes is exogenous.

Table 9: HbA1c cut-point at 6: Estimated treatment effects on changes in exercise frequency and intensity.

		Age		Gender		Race	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Less than 65	65 and over	Male	Female	Black	White
	ΔExercise Frequency						
Sharp RD	-0.0267	0.406	-0.249	0.382	-0.269	-0.0111	-0.154
	(0.245)	(0.437)	(0.297)	(0.409)	(0.306)	(0.628)	(0.286)
Fuzzy RD	-1.214	10.59	-17.01	14.81	-14.07	-0.507	-10.09
	(11.15)	(12.39)	(23.30)	(18.17)	(17.62)	(28.59)	(19.66)
	ΔExercise Intensity						
Sharp RD	0.0680	0.113	0.0467	0.0272	0.0957	0.400**	-0.0145
	(0.0690)	(0.122)	(0.0845)	(0.114)	(0.0865)	(0.193)	(0.0779)
Fuzzy RD	3.095	2.950	3.185	1.057	5.003	18.28	-0.951
	(3.341)	(3.391)	(6.120)	(4.456)	(5.231)	(22.24)	(5.136)
Observations	9253	3157	6096	3595	5658	1022	7318
F-stat	6.877	5.552	2.189	3.034	3.591	0.814	2.797
P-value (Endog)	0.341	0.357	0.596	0.846	0.272	0.0377	0.842

Frequency is measured as times per month. Intensity is measured as metabolic equivalents (MET).

Quadratic functional form for HbA1c values used in RD specifications.

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Weak instrument test statistic is robust Kleibergen-Paap Wald rk F statistic.

Endogeneity test H_0: ΔDiabetes is exogenous.

Table 10: Restrict sample to 5≤ HbA1c ≤9: Estimated treatment effects on changes in exercise frequency and intensity.

		College Degree		Income		Labor Force	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	No	Yes	Low	High	Out	In
	ΔExercise Frequency						
OLS	-0.0360	-0.00731	-0.0484	0.325	-0.356	0.0849	-0.229
	(0.347)	(0.446)	(0.553)	(0.500)	(0.480)	(0.419)	(0.620)
Sharp RD	1.770*	1.949	1.918	2.149	1.109	2.735**	-0.358
	(1.005)	(1.375)	(1.427)	(1.355)	(1.499)	(1.191)	(1.953)
Fuzzy RD	34.01	37.65	40.59	24.32	314.4	196.5	-2.462
	(49.14)	(68.56)	(104.0)	(29.24)	(10042.7)	(1208.5)	(14.12)
	ΔExercise Intensity						
OLS	0.117	0.129	0.113	0.113	0.139	0.0329	0.333*
	(0.106)	(0.134)	(0.176)	(0.152)	(0.148)	(0.129)	(0.183)
Sharp RD	0.460	0.514	0.410	0.328	0.547	0.632*	0.353
	(0.317)	(0.437)	(0.453)	(0.382)	(0.526)	(0.368)	(0.624)
Fuzzy RD	8.845	9.932	8.671	3.716	155.1	45.42	2.431
	(12.42)	(17.80)	(21.91)	(5.810)	(4920.2)	(276.2)	(4.094)
Observations	8272	4448	3794	3862	4410	5282	2990
F-stat	0.534	0.325	0.168	0.900	0.000971	0.0265	1.098
P-value (Endog)	0.154	0.250	0.373	0.404	0.306	0.100	0.605

Frequency is measured as times per month. Intensity is measured as metabolic equivalents (MET).

Quadratic functional form for HbA1c values used in RD specifications.

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Weak instrument test statistic is robust Kleibergen-Paap Wald rk F statistic.

Endogeneity test H_0: ΔDiabetes is exogenous.

Table 11: Restrict sample to 5≤ HbA1c ≤9: Estimated treatment effects on changes in exercise frequency and intensity.

		Age		Gender		Race	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Less than 65	65 and over	Male	Female	Black	White
				ΔExercise Frequency			
OLS	-0.0360	-0.683	0.261	-0.161	0.0756	0.291	-0.0445
	(0.347)	(0.609)	(0.421)	(0.519)	(0.466)	(0.990)	(0.409)
Sharp RD	1.770*	0.691	2.150*	0.724	2.385**	3.920*	1.539
	(1.005)	(1.625)	(1.232)	(1.862)	(1.133)	(2.312)	(1.289)
Fuzzy RD	34.01	-28.60	26.11	-9.930	19.18	24.17	-76.54
	(49.14)	(166.4)	(29.42)	(31.70)	(15.98)	(21.42)	(348.5)
				ΔExercise Intensity			
OLS	0.117	0.0485	0.156	0.249	0.0173	-0.221	0.0837
	(0.106)	(0.191)	(0.128)	(0.152)	(0.149)	(0.329)	(0.122)
Sharp RD	0.460	0.241	0.542	-0.0940	0.790**	0.471	0.627
	(0.317)	(0.453)	(0.400)	(0.504)	(0.399)	(0.583)	(0.439)
Fuzzy RD	8.845	-9.975	6.581	1.290	6.352	2.903	-31.17
	(12.42)	(60.59)	(7.472)	(6.897)	(4.916)	(4.415)	(143.4)
Observations	8272	2723	5549	3165	5107	941	6487
F-stat	0.534	0.0337	0.949	0.359	1.995	1.478	0.0517
P-value (Endog)	0.154	0.598	0.187	0.869	0.0547	0.408	0.162

Frequency is measured as times per month. Intensity is measured as metabolic equivalents (MET).

Quadratic functional form for HbA1c values used in RD specifications.

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Weak instrument test statistic is robust Kleibergen-Paap Wald rk F statistic.

Endogeneity test H_0: ΔDiabetes is exogenous.

Table 12: By education, income, labor force status: Estimated treatment effects on changes in ordinal exercise frequency and intensity.

		College Degree		Income		Labor Force	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	No	Yes	Low	High	Out	In
	ΔExercise Frequency						
OLS	0.0179	0.0245	0.0186	0.0570	-0.0111	0.0342	0.00164
	(0.0459)	(0.0607)	(0.0694)	(0.0696)	(0.0596)	(0.0569)	(0.0768)
Sharp RD	0.205**	0.106	0.343***	0.166	0.209	0.220**	0.130
	(0.0978)	(0.132)	(0.131)	(0.139)	(0.138)	(0.111)	(0.199)
Fuzzy RD	0.881**	0.463	1.467*	0.686	0.937	1.100*	0.429
	(0.449)	(0.574)	(0.753)	(0.610)	(0.642)	(0.629)	(0.645)
	ΔExercise Intensity						
OLS	0.0512	0.0682	0.0347	0.0571	0.0558	0.0263	0.125*
	(0.0458)	(0.0603)	(0.0704)	(0.0673)	(0.0620)	(0.0582)	(0.0702)
Sharp RD	0.273***	0.242*	0.311**	0.271**	0.246	0.182	0.471**
	(0.103)	(0.135)	(0.156)	(0.134)	(0.158)	(0.120)	(0.200)
Fuzzy RD	1.177**	1.053*	1.334*	1.118*	1.106	0.912	1.548**
	(0.479)	(0.605)	(0.797)	(0.652)	(0.685)	(0.639)	(0.696)
Observations	9253	4925	4290	4232	5021	5813	3440
F-stat	19.45	11.93	7.364	10.67	8.648	10.67	9.054
P-value (Endog)	0.0106	0.0849	0.0578	0.0574	0.131	0.128	0.0327

Frequency is measured as times per month. Intensity is measured as metabolic equivalents (MET).

Quadratic functional form for HbA1c values used in RD specifications.

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Weak instrument test statistic is robust Kleibergen-Paap Wald rk F statistic.

Endogeneity test H_0: ΔDiabetes is exogenous.

Table 13: By age, gender, race: Estimated treatment effects on changes in ordinal exercise frequency and intensity.

		Age		Gender		Race	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Less than 65	65 and above	Male	Female	Black	White
	ΔExercise Frequency						
OLS	0.0179	-0.0796	0.0674	0.0406	0.000801	-0.0565	0.0190
	(0.0459)	(0.0747)	(0.0575)	(0.0677)	(0.0624)	(0.140)	(0.0521)
Sharp RD	0.205**	0.130	0.221*	0.199	0.210*	0.202	0.248*
	(0.0978)	(0.140)	(0.125)	(0.165)	(0.124)	(0.214)	(0.134)
Fuzzy RD	0.881**	0.543	0.968*	1.427	0.722	1.887	0.941*
	(0.449)	(0.614)	(0.579)	(1.321)	(0.460)	(2.607)	(0.545)
	ΔExercise Intensity						
OLS	0.0512	0.0213	0.0693	0.106*	0.00610	-0.141	0.0492
	(0.0458)	(0.0748)	(0.0573)	(0.0637)	(0.0656)	(0.145)	(0.0518)
Sharp RD	0.273***	0.259	0.269**	0.242	0.305**	-0.0323	0.362**
	(0.103)	(0.159)	(0.128)	(0.162)	(0.132)	(0.197)	(0.150)
Fuzzy RD	1.177**	1.083	1.178*	1.739	1.048**	-0.302	1.371**
	(0.479)	(0.734)	(0.605)	(1.403)	(0.489)	(1.862)	(0.608)
Observations	9253	3157	6096	3595	5658	1022	7318
F-stat	19.45	5.685	13.17	2.881	17.29	0.795	14.98
P-value (Endog)	0.0106	0.116	0.0457	0.160	0.0209	0.929	0.0206

Frequency is measured as times per month. Intensity is measured as metabolic equivalents (MET).

Quadratic functional form for HbA1c values used in RD specifications.

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Weak instrument test statistic is robust Kleibergen-Paap Wald rk F statistic.

Endogeneity test H_0: ΔDiabetes is exogenous.