

What Difference Does a Diagnosis Make? Evidence from Marginal Patients*

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Abstract

This paper explores the impact of receiving a diagnosis of diabetes among patients who are close to the diagnostic threshold using a regression discontinuity design. We find that a marginally diagnosed patient with diabetes spends \$1,097 more on drugs and diabetes-related care annually after diagnosis, but find no corresponding changes in self-reported health or healthy behaviors. These increases in spending persist over the 6-year period we observe the patients, despite many who are not initially diagnosed receiving a later diagnosis during this time frame. These marginally diagnosed patients experience improved blood sugar after the first year of diagnosis, but this improvement does not persist in subsequent years. Other clinical measures of health, such as BMI, blood pressure, cholesterol, and mortality show no improvement. The diagnosis rates for preventable disease-related conditions such as diabetic retinopathy, neuropathy, and kidney disease increase following a diagnosis, likely due to more intensive screening.

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Since the late 1990s, the criteria for diagnosing several chronic diseases have been relaxed, creating millions of new patients who were considered healthy under previous diagnosis guidelines. For example, new guidelines on diagnosing hypertension outlined by the American College of Cardiology and the American Heart Association in 2017 increased the number of patients with hypertension by over 40 percent, resulting in an additional 31 million Americans recommended to receive treatment for the disease (Muntner et al., 2018; Whelton et al., 2018). The trend towards diagnosing and treating progressively healthier patients has led some researchers in the medical field to express concern that such interventions may be, at best, wasteful, if not actually harmful and counterproductive (Welch et al., 2011). Yet, little is known regarding the implications for either health care spending or population health.

This paper explores the impact of a diagnosis on such "marginally" sick patients by exploiting a cutoff in the diagnosis criteria for a common chronic illness, diabetes mellitus. Diabetes is a condition characterized by the body's inability to regulate blood sugar and its diagnosis presents an ideal setting in which to explore the treatment of marginally diagnosed patients for several reasons. First, it is a common disease, making it an empirically relevant example; over 24 million individuals in the United States are currently diagnosed with diabetes, and annual spending on medical care related to diabetes and complications of diabetes is estimated at \$237 billion, with over \$50 billion spent on insulin and diabetes-controlling drugs alone (American Diabetes Association, 2018b). Second, diabetes is diagnosed using a sharp cutoff in blood sugar levels, which are smoothly distributed in the population, allowing us to estimate the effect of diagnosis using a regression discontinuity design that compares outcomes for patients with similar underlying health but with blood sugar levels falling on either side of this cutoff. Third, the blood test used to diagnosis diabetes is difficult to manipulate, making both self-selection by patients and strategic coding by providers extremely unlikely.

Marginally diagnosed patients are a particularly relevant group to study in the case of chronic illness, such as diabetes, because they represent a large fraction of the patients diagnosed with a given disease, due to the underlying distribution of health in the population (Welch et al., 2011). In our setting, the American Diabetes Association (ADA) recommends diagnosing diabetes in patients whose glycated hemoglobin (A1c) levels are at or above 6.5% (American Diabetes Association, 2018b). Most people have blood glucose levels below this level in the normal range (between 4% and 5.6%) and the share of the population decreases as the values become more extreme. As a result, even though spending is comparatively low among the "marginal" patients with diabetes whose A1c falls just above the

diagnostic threshold, they have an outsized impact on total costs due to their large representation among patients with diabetes. The distribution of A1c values among patients receiving an initial A1c test in our data makes it clear why patients near the cutoff are disproportionately represented among those with diabetes: over one quarter of all patients whose first A1c test puts them in the diabetes range have an A1c value within 0.1 percentage points of the cutoff, and over 15 percent have an A1c value of 6.5%, the lowest possible value one can receive and still be considered to have diabetes.

Our analysis is motivated by existing work in economics that evaluates the impact of diagnoses and subsequent care on health.¹ Most relevant to this paper, two recent papers use identification strategies similar to ours to examine the effects of diagnoses of specific chronic health conditions in Japan and Korea. [Iizuka et al. \(2021\)](#) find that Japanese patients with employer health insurance who exceed a pre-diabetes threshold have small but statistically significant increases in diabetes-related doctor visits and outpatient medical spending in the following year. They find no evidence, however, that this increased utilization leads to improvements in health over the short- or medium-term. In addition, the authors find no evidence that patients with test values above the diabetes threshold receive more care or see health improvements; however, among a subset of patients with other health conditions they do detect some improvements in blood sugar and BMI. Next, [Kim et al. \(2019\)](#) test for discontinuities at “medium risk” and “high risk” thresholds for diabetes under a Korean national health screening program. They find that high risk individuals are more likely to take diabetes medication and experience weight loss in the short-run. The authors find no effects on healthy behaviors, however, and the effects on weight loss appear to dissipate in the long-run (3-4 years after testing). They find no effects for individuals receiving a medium risk diagnosis for diabetes, and little evidence of effects of diagnoses of obesity or hyperlipidemia.

Our work builds on these studies in several ways. First, we contribute by examining the effects

¹One of the first studies in this literature documents that infants born near the diagnosis threshold for “very low birthweight” (birthweights of less than 1500g) receive more intensive medical care and experience a reduction in infant mortality ([Almond et al., 2010](#)). Follow up work has found evidence of longer-run effects of this diagnosis on health and human capital outcomes in the U.S., Chile, and Norway ([Bharadwaj et al., 2013](#); [Chyn et al., 2019](#)), indicating high cumulative returns to spending on this margin. More recent work examining other types of medical conditions also highlights that there may important effects on patient behavior, as well as psychological effects of diagnosis. For instance, among female students in New York City who receive BMI report cards with weight classifications, those with values of BMI just above an “overweight” threshold experience small *increases* in BMI and body weight during the subsequent year compared to those just below the threshold ([Almond et al., 2016](#)). However, individuals receiving a diagnosis of abdominal aortic aneurysm and told they will receive increased monitoring in a Swedish screening program have improved psychological well-being, compared to those just missing the diagnosis criteria but informed that they are at risk ([Dahlberg et al., 2016](#)). Other examples include: [Zhao et al. \(2013\)](#) find that individuals in China with systolic blood pressure above the hypertension diagnosis cutoff reduce their fat intake upon receiving a diagnosis; [Fukuma et al. \(2020\)](#) show that individuals in Japan with a cardiovascular risk factor whose waist circumference falls above a cutoff experience weight loss following lifestyle counseling; and, [Oster \(2018\)](#) documents that U.S. households in which someone was recently diagnosed with diabetes exhibit small reductions in their purchases of unhealthy food.

of a diabetes diagnosis for marginally diagnosed patients in the U.S. context, which is unique in its high medical spending and poor health outcomes when compared to other high income countries (Papanicolas et al., 2018). Similar to these authors, we aim to trace out the consequences of a marginal diagnosis over time in order to assess effects on both short- and long-term spending and health outcomes. Examining the long-run effects of a marginally diagnosed patient is tricky in the U.S. context, however, since it requires longitudinal data for individuals with information on lab values, in addition to medical claims. Since the U.S. does not have a national health system, the type of population-level administrative data often used in other settings (e.g. Korea in Kim et al., 2019) does not exist. In addition, national health surveys are not well-suited to study this question due to their lack of clinical data, small sample sizes, limited information on utilization and spending, or short windows of observation. Instead, we take advantage of longitudinal medical claims records from a large private insurer that includes laboratory test results from affiliated labs. With 61 million enrollees over our study period, this data source captures a sizeable share of the U.S. population with private health insurance coverage (nearly 30 percent of the privately insured population in the U.S. in 2018, calculated based on Berchick et al., 2019).

Using this data source, we are able to examine the impact of a diabetes diagnosis for the marginally diagnosed patient on different types of spending, use of care, and on clinical measures of health (blood sugar, cholesterol, and mortality) over a six year period. Although not capturing the full life course of disease, this observation period surpasses those used in existing studies and provides the opportunity to detect any early changes in utilization or health resulting from the diagnosis. We supplement these data with matched survey records that collect self-reported information on health and healthy behaviors, as well as electronic health records from a large health system to examine two additional clinical health measures (BMI and blood pressure).

Second, we build on existing work by examining additional policy-relevant outcomes such as diagnosis of diabetes-related complications and self-reported health. We also document changes in diabetes-related spending at the diagnosis threshold, which has implications for public policy given the large percent of the US population covered by government health programs.² Finally, our data allow us to conduct additional analyses documenting heterogeneity in the effects of a diabetes diagnosis across patients seeing different types of providers.

²Kim et al. (2019) do not examine spending and Iizuka et al. (2021) find no change in diabetes-related spending at the diabetes diagnosis cutoff in the whole population of patients, although do detect spending increases in the high risk subgroup.

Our work contributes to a broader literature in economics devoted to measuring the marginal impact of additional medical spending in the U.S. This work seeks to disentangle patient selection into care from the benefit of the care itself, usually with the goal of determining whether certain types of care reflect wasteful “flat of the curve” spending. In general, the results that have been previously documented on this topic are mixed, with some studies showing large benefits of additional medical spending (e.g. [Doyle, 2011](#); [Doyle et al., 2015](#)) and other papers showing limited or no benefit associated with additional spending (e.g. [Fisher et al., 2003a,b](#); [Frakes, 2013](#)). A limitation in the existing literature is that much of it focuses on care for the onset of acute conditions (such as heart attack or hip fracture) and mortality, with very little attention to treatment for chronic illnesses and more intermediate outcomes.

This paper contributes to this literature in three ways: first, we evaluate the marginal effects of diagnosis for a common chronic illness that affects a large share of the population. Understanding the marginal impact is particularly relevant given that treatment for chronic illnesses represents a substantial fraction of total medical spending (e.g. 86 percent of health care spending is for patients with one or more chronic illnesses, see [Gerteis et al., 2014](#)) and that over 100 million individuals in the United States are diagnosed with diabetes or pre-diabetes ([Centers for Disease Control and Prevention, 2017](#)). Second, our data permit us to observe a variety of intermediate outcomes, such as blood sugar, cholesterol, and disease complications, that may be more responsive to interventions than mortality. Finally, we are able to look at the effects of diagnosis over a longer time horizon to understand the dynamic nature of both health care utilization and health outcomes.

We find that patients with A1c values that fall right above the 6.5% threshold are 11 percentage points more likely to have a diabetes diagnosis appear on their health insurance claim in the first year following an initial A1c test.³ In addition, receiving a diagnosis at the cutoff is associated with approximately \$1,097 additional spending on recommended diabetes-related care and \$139 in endocrinology specialty care during that first year. Spending increases related to office-based care and laboratory tests are particularly large (representing most of the observed increase in spending), although we also detect increases in the probability of purchasing diabetes-related drugs and spending on vision screening. Notably, this elevated rate of spending for patients with A1c values just above the threshold persists for all six years that we observe patients; there is no evidence that patients with slightly lower

³We require individuals to be in the sample for at least one year prior to the initial A1c test in order to exclude those with previous diagnoses of diabetes.⁴ This also allows us to test for and rule out pre-test differences in utilization for patients on either side of the cutoff.

A1c values catch up, despite the natural progression of disease that leads many who were initially below the cutoff to be diagnosed at later points during our study period. It appears that receiving a “marginal” diagnosis sets patients on a path of persistently higher spending.

The evidence for health-related benefits is less obvious. We find that rates of diagnoses for complications related to diabetes (diabetic retinopathy, neuropathy, and diabetic kidney disease) increase for individuals right above the cutoff, likely due to increased interaction with the health care system and more intensive screening. We see no evidence that diagnosis rates for these complications fall over time among the marginally diagnosed group, nor do we find changes in the rates of serious, life-threatening complications related to diabetes (diabetic coma and ketoacidosis). We also find no evidence of changes in self-reported health or in healthy behaviors such as diet, exercise, drinking alcohol, or smoking following the initial lab test, even though clinical practice recommendations include lifestyle education and management for patients regarding diet, exercise, alcohol intake and smoking.

When we examine clinical measures of health, we find short-term improvements in blood sugar among marginally diagnosed patients, but these improvements do not persist past the first year, despite the persistence of higher levels of diabetes-related medical spending over the entire period. We also find no evidence of improvements in total cholesterol or mortality. Using electronic health records data available for up to three years following the initial lab test, we find no evidence of improvements in BMI or blood pressure during this period. While some of these estimates are imprecise, collectively they show little evidence of health improvements over the study period.

Finally, we find some suggestive evidence that patients of specialists are more likely to receive a diagnosis and experience a larger increase in spending (particularly spending related to laboratory tests and visits) when they receive a diagnosis as the result of crossing the cutoff, when compared to patients of primary-care physicians. These differences could be due to the different practice styles of the physicians, e.g. if specialists tend to favor more intensive intervention for diseases than primary care physicians. Alternatively, the differences may be due to unobserved heterogeneity in patient health across these two types of providers.

Taken together, our results imply that further relaxation of the diagnosis guidelines would result in higher costs with minimal health improvements in the short term. Our spending results suggest that relaxing the diagnosis threshold further, from 6.5 to 6.4, would increase diabetes-related spending by at least \$2.4 billion annually and generate only short-lived improvements in patient health over a 6-year period. At the same time, tightening the diagnosis criteria by moving the threshold from 6.5 to

6.6 would reduce spending by about \$1.8 billion annually.

1 Background

Many chronic illnesses are diagnosed by comparing the outcome of a laboratory test to a "cutoff" value specified in guidelines created by health or medical associations.⁵ To diagnose type 2 diabetes, physicians primarily rely on a measure of blood sugar called glycated hemoglobin A1c ("A1c"), which is collected via a blood draw. A1c measures the exposure of hemoglobin cells to plasma glucose (blood sugar) over the past three months. Normal A1c levels range from 4.0% to 5.6%. High A1c levels are considered a marker of diabetes, as they indicate poor control of glucose.

Although diabetes may be diagnosed using alternative tests of single or episodic glucose levels, A1c tests are considered the preferred diagnostic tool since they measure chronic glycemic exposure.⁶ The International Expert Committee recommended A1c as a superior method to diagnose diabetes in a 2009 consensus report, noting that it is convenient (does not require the patient to fast) and more stable (less fluctuation within and between days).⁷ Using data from cross-sectional epidemiological studies, this committee observed that the rate of any retinopathy, a long-term complication of diabetes, "increases substantially at A1c values starting between 6.0 and 7.0%." The committee also noted that when A1c levels were examined in 0.5% increments, the incidence of diabetes-specific "moderate" retinopathy noticeably increases at A1c levels \geq 6.5%.⁸ They concluded that this justifies assigning an A1c cutoff value of \geq 6.5% for the diagnosis of diabetes, although they note that "this cut point should not be construed as an absolute dividing line between normal glycemia and diabetes." The committee also emphasized that while there is evidence for a continuum of risk for the development of diabetes based on A1c levels, "there does not appear to be a specific level at which risk for diabetes clearly begins" ([The International Expert Committee, 2009](#)).⁹

⁵Interestingly, recent work suggests that additional discontinuities may also exist in terms of *who is tested* due to rules of thumb used by physicians for administering diagnostic tests. [Coussens \(2018\)](#) finds that, in the emergency department setting, physicians use heuristics based on patient age when determining whether to test for ischemic heart disease, resulting in a discontinuity in diagnosis for this condition.

⁶Other tests that can be used to screen for diabetes are the measurement of fasting plasma glucose (FPG) and plasma glucose during a two-hour oral glucose tolerance test (OGTT). The OGTT is not commonly used other than among pregnant women to screen for gestational diabetes.

⁷The IEC was convened in 2008 to consider the diagnosis of diabetes among nonpregnant individuals. Members were appointed by the American Diabetes Association, the European Association for the Study of Diabetes, and the International Diabetes Federation.

⁸The analysis included data on approximately 28,000 individuals from nine countries. The IEC also considered specificity and sensitivity and relied on a receiver operating characteristic curve analysis when determining the optimal cutpoint.

⁹A study by [Tsugawa et al. \(2012\)](#) examines the validity of the new diagnostic threshold by examining the association between A1c values and the 3-year incidence of retinopathy among a cohort of Japanese adults. The authors do find an increase in risk for those with A1c levels of 6.5-6.9% relative to 5.0-5.4%. However they do not find evidence of an explicit threshold effect of A1c.

Concordant with the IEC guidelines, the American Diabetes Association subsequently issued the recommendation of a diagnosis of diabetes if a patient's A1c is greater than or equal to 6.5% ([American Diabetes Association, 2010](#)).¹⁰ Once diagnosed, recommended care includes a comprehensive medical evaluation to form a care management plan, annual diagnostic tests (urinary albumin, lipid panel, glomerular filtration rate) to detect comorbid conditions or complications, A1c monitoring at least twice per year, antidiabetic medication, statin therapy (for those age 40 and above),¹¹ annual assessment for diabetic retinopathy by an ophthalmologist, annual comprehensive foot evaluation, and receipt of flu, pneumonia, and hepatitis B vaccines ([American Diabetes Association, 2017](#)). Patients are also advised to engage in regular exercise (2-3 times per week), decrease sedantary behavior, eat a healthful diet, and quit smoking if relevant. In addition, the ADA recommends that patients with diabetes receive more aggressive treatment for comorbid conditions. For example, patients with diabetes with blood pressure above 140/90 mmHg should have prompt initiation of drug therapy at the "maximum tolerated dose" to achieve blood pressure goals, while patients at high risk for kidney disease require additional monitoring and treatment.

Because individuals with A1c values falling just below or above the 6.5 threshold have similar underlying health, we can use the cutoff in diabetes classification to evaluate the impact of receiving a diabetes diagnosis on the health care utilization and associated costs, health, and behaviors for patients at the margin of being diagnosed. Patients whose A1c falls below 6.5, but at or above 5.7, are considered to have "pre-diabetes," with impaired glucose tolerance and at a higher risk of developing diabetes in the future. As such, they also receive some care aimed at lowering their risk for developing diabetes; specifically, the ADA recommends that the patients have their A1c tested annually and that the provider counsel them to make lifestyle changes such as losing weight and increasing exercise. The ADA also recommends that drug therapy should be discussed as an option for certain risk groups (e.g., those with a BMI of at least 35). Our analyses will document the average difference in utilization and spending for individuals on the margin of receiving diagnoses of pre-diabetes versus diabetes.

¹⁰Beginning in 2011, the ADA guidelines specify a value of 6.5% or higher on two separate tests be used to diagnose diabetes, unless the patient exhibits "unequivocal" hyperglycemia. However, in practice, we do not find that patients are receiving multiple tests. For example, in our data, less than 0.5% of patients who received an A1c value of 6.5 received a follow-up test within two weeks.

¹¹This guideline for statin therapy was recommended in 2013 by the American College of Cardiology and the American Heart Association and confirmed by the American Diabetes Association at the end of 2014.

2 Data

2.1 OptumInsight Claims

To assess the impact of a diagnosis on health care utilization and spending, self-reported health and healthy behaviors, and subsequent lab values (blood sugar and total cholesterol), we use the OptumInsight (Optum) database from 2009 to 2017.¹² Optum provides claims data from a large private health insurance company; over our sample period, 61 million patients are included in these data. The data include all claims associated with these patients that are paid for by the health insurance company. The claims data include procedure and diagnosis codes, as well as the date the procedure occurred and the cost of the claim (including the amount paid by the patient and by the insurance company); for pharmacy claims, the data include the national drug code, quantity dispensed, and cost. Additionally, the data contain some limited information on demographic characteristics of the patient, such as age and gender. Optum data are primarily composed of private or employer-sponsored health insurance plans, but includes some Medicare Advantage plans as well (see Table 1).

When an A1c test is used for diagnosis, the provider sends a blood sample to a lab for evaluation. In the Optum data, we observe the lab test results for laboratories that are affiliated with Optum. We do not observe test results for unaffiliated laboratories, although we do see spending associated with these tests. In nearly all cases, lab test results are rounded to the nearest 0.1 percent; for the small number of lab results that are reported with greater precision, we round to the nearest 0.1 percent so the data are comparable across all labs reported.

The data include unique patient identifiers that allow us to track patient spending and utilization over time. We are able to track patient spending if patients change insurance plans as long as the insurance plan is offered by an insurance company associated with Optum. If patients drop their insurance coverage, or switch to an insurance plan offered by a different company, we are no longer able to observe them in the data. However, Optum provides records of patients' enrollment, so we can distinguish patients who dropped coverage from patients who had no claims in a given year. We do not find any evidence of differential attrition from the sample based on A1c value relative to the diagnosis threshold (see Section 3.3). Therefore, as described in more detail below, we include patients in analyses for all years when they are enrolled in an Optum plan, regardless of whether they exit at a later point during the sample period. In Section 5, we examine the sensitivity of our estimates to

¹²Although OptumInsight data are available for earlier years, we use only individuals with the initial A1c test taken in 2009 or later because this was the first year that the A1c test was recommended for the diagnosis of diabetes.

restricting the analysis to members enrolled during the entire sample period.

To construct our sample, we pull all adult patients in Optum who have an A1c test at an Optum affiliated lab during our study period. From this group, we drop individuals who had a diagnosis of diabetes on their claim at any time before their first observed A1c test in order to eliminate patients who are receiving the test for monitoring, rather than the diagnosis of, diabetes.¹³ We also exclude individuals with a pregnancy-related diagnosis during the year prior to their first A1c test in order to drop cases associated with gestational diabetes, which has different treatment and diagnostic guidelines than type 2 diabetes (Vandorsten et al., 2013). We further restrict to patients who are in the sample at least 12 months prior to and 12 months following the initial lab test in order to observe their annual spending before and after the test. This leaves us with 142,541 patients in year 1 (the calendar year following the initial lab test). Figure A1 in the Appendix provides a diagram of our sample definition with patient counts for each exclusion criterion.

We observe patients for up to 6 years following their initial test. For subsequent years following the initial test, we require that patients are enrolled in an Optum plan for at least half the year to be included in the analysis. We define year relative to the date of the initial test. For example, if an individual was tested on March 1, 2010 we would consider the first year after the test to be March 2, 2010 through March 1, 2011. For patients enrolled in an Optum plan for less than a year, we scale their spending proportionally to their enrollment time in order to annualize the outcome. For example, if the patient is enrolled for 6 months and spends \$300, we double spending to \$600 to account for the fact that we observe only one half of the year's spending.

In our first stage analysis, we estimate the change in the diagnosis of diabetes at the A1c cutoff value of 6.5%. We define the diagnosis of diabetes as the presence of any claim with a diagnosis code for diabetes during the first year following the test. In later analyses, we also examine how the likelihood of diagnosis evolves over time by looking at the cumulative likelihood of diagnosis through year 2, year 3, etc. Our primary outcome measures look at spending for all types of care recommended for patients with diabetes by the American Diabetes Association (ADA). This includes doctor office visits and consultations related to diabetes; spending on diabetes-controlling drugs such as metformin; spending on two other types of drugs that are commonly prescribed for diabetes: statins and Angiotensin-converting enzyme (ACE) inhibitors; lab tests for relevant conditions; and spending related to vision testing for diabetic retinopathy. We examine total spending on recommended care as

¹³Although we are examining A1c tests starting in 2009 only, we have Optum claims dating back to 2001 and the entire period of claims data is used to implement this sample restriction.

well as each category individually. We also examine spending on endocrinology specialty care, which is not specifically recommended, but that may be affected by a diabetes diagnosis. In addition, we evaluate how receiving a diagnosis affects the quantity of care received by looking at the number of diabetes-related visits, the number of A1c or glucose lab tests, indicators that either of these two outcomes are positive, and an indicator for the presence of any spending on diabetes-controlling drugs.

Next, we evaluate changes in diabetes-related conditions and overall health at the cutoff. We group health outcomes into three categories: diabetes-related complications, lab results, and mortality. Diabetes-related complications are arguably the most consequential health outcome for the patients in the study. These complications are relatively common among diabetes patients ([Wexler, 2021](#)) and materially affect quality of life. We examine diabetic retinopathy, damage to the retina that can result in blindness; diabetic neuropathy, nerve damage that can result in, among other symptoms, pain, dizziness, and loss of feeling; diabetic kidney disease, chronic loss of kidney function that can result in end-stage renal disease; diabetic coma; and diabetic ketoacidosis, a complication in which the body burns fatty acids instead of glucose, and which can result in vomiting, abdominal pain, and death. Of these, diabetic coma and diabetic ketoacidosis are less common, but more severe. These complications were used by the IEC to determine diagnostic criteria for diabetes ([American Diabetes Association, 2010](#)), and we believe that any favorable impacts on the rate of these complications would provide the most direct evidence that treatment for marginal patients is beneficial.

We examine changes in individuals' A1c scores and total cholesterol from their baseline levels taken on the date of the first test (for A1c) or the year prior to the first test (for total cholesterol). Lab results, though they are less direct measures of patients' health and quality of life, are measured frequently, and may be more likely than complications to provide early evidence of the benefits of treatment. We estimate the effects of a marginal diagnosis on patients' A1c scores over time, as well as their cholesterol levels. High A1c scores are a risk factor for diabetes-related complications ([Inzucchi and Lupsa, 2020](#)), and high cholesterol is a risk factor for cardiovascular events (e.g. heart attack, stroke) ([Cholesterol Treatment Trialists' \(CTT\) Collaborators, 2012](#)). Clinical guidelines recommend managing levels of A1c to prevent or treat diabetes-related complications ([Inzucchi and Lupsa, 2020](#)). These lab results complement our estimates of the effects of a diagnosis on complications since changes in these scores are likely to manifest earlier than diabetes-related complications.

Individuals with initial A1c test values just above the diagnostic cutoff have a significantly greater number of A1c tests in subsequent years but are not more likely to have any A1c test (see Appendix

Table A1). To address this, we randomly select one A1c test per individual per year. For consistency across measures, we similarly select a random total cholesterol value in each year following the initial A1c test, although there does not appear to be a statistically significant larger number of tests for this measure at the diagnosis cutoff (see Appendix Table A1).

Finally, we examine differences in mortality at the cutoff. Any effect on mortality would be meaningful, but mortality is uncommon in our sample, and our power to detect effects is low. Since we require individuals to be in the sample for at least one year following the initial test, we examine mortality in years 2 and later. Additional details on the diagnosis and procedure codes used to construct the outcome variables may be found in Appendix Table A2.

Table 1 presents descriptive statistics for the Optum patients in the left panel. Of these patients, 52 percent are female, average age is 51.1 years, and 28 percent are enrolled in a Medicare Advantage plan with the remaining on individual private plans (such as those purchased from the Affordable Care Act health insurance exchanges) or employer-sponsored insurance. Women are slightly over-represented relative to men, likely because screening is recommended for women with a previous diagnosis of gestational diabetes.

2.2 Health Risk Assessment Data

A small subset of Optum enrollees completes a Health Risk Assessment (HRA) survey in any given year.¹⁴ This survey asks a wide range of questions about self-assessed health and behaviors and is typically administered by the insurance company at the behest of an employer. As such, patients who take the HRA are not necessarily representative of patients in the Optum database. The middle panel of Table 1 presents statistics for the HRA sample. Because the HRA tends to be administered for employers, the sample is composed almost entirely of individuals enrolled in private (non-Medicare) insurance plans. This sample is also somewhat younger (44.2 years old on average) and more female (55.4 percent). However, the characteristics of individuals who take the HRA appear to be balanced across the A1c threshold (see Section 5). Therefore, our estimates provide an internally valid measure of these self-assessed outcomes within the HRA subsample.

A full list of variables considered from the HRA is found in Appendix Section 2. In order to avoid conducting an excessive number of statistical tests, which might generate a large number of false positives, and to improve our statistical power, we construct four summary indices for the following

¹⁴Since HRA survey responses are typically observed only once per year, we do not impose the 6-month enrollment requirement described above for the Optum claims data; we include any patient with a survey response in any given year for analyses using the HRA data.

question domains: self-assessed health, physical and emotional well-being, healthy diet and exercise behavior, and smoking and drinking behavior. We do this by constructing a standardized z-score (subtracting the mean and dividing by the standard deviation) for each component and taking the average. This applies equal weight to each index component and is similar to the approach used in [Finkelstein et al. \(2012\)](#) and [Kling et al. \(2007\)](#). Positive values of the index indicate better outcomes (i.e., better health or lower rates of unhealthy behavior).

2.3 Electronic Health Records Data

We supplement our analysis of the Optum data with information on additional health outcomes from electronic health records (EHR) for patients receiving care in the University of California, Los Angeles health system. UCLA implemented its current EHR program CareConnect, which uses Epic Systems technology, on March 2, 2013. Our analysis uses UCLA data available after this date through 2016. Like the Optum data, the UCLA data allow us to follow individual patients over time. We are able to track a patient as long as they continue to have encounters within the UCLA health system, which includes two large hospitals and over 170 primary care and specialty practices. There are records for approximately 1.2 million distinct patients during this period and these data include clinical health measures recorded any time a patient visits a UCLA medical provider. We limit our sample to patients with a primary care provider (PCP) at UCLA in order to increase the likelihood that we observe their ongoing care. We explore differential attrition in [Section 3.3](#) below.

We construct an analytic sample using similar criteria to those used with the Optum data (see appendix for additional details and [Appendix Figure A2](#) for a flowchart). We present results for individuals with A1c tests conducted in 2013 and later, allowing for up to 3 years of follow up. Our outcomes of interest are two measures that are collected for a large percent of patients: body mass index and blood pressure. The data also include some information on utilization of services (number of encounters within the UCLA system), diagnoses, procedures, and prescription drugs, although they do not include cost measures.

Descriptive statistics from the UCLA data are presented in the third column of [Table 1](#). The individuals in the UCLA data are relatively similar to those in the Optum data, although the average age at first encounter is slightly lower at 47.2 years and small shares of the sample pay for care with Medicaid or out of pocket.

3 Empirical Strategy

We use a regression discontinuity (RD) design framework to analyze the impact of a diagnosis of diabetes across patients with similar underlying health. This is an example of a “fuzzy” regression discontinuity design since a diabetes diagnosis may depend on patient- and physician-specific factors separate from an A1c value. We estimate two versions of this model. The first version is a “reduced form” model that looks at the change in the outcome at the cutoff. The second version is an instrumental variables estimate of the effect of receiving a diagnosis of diabetes, using the diagnostic cutoff as an instrument for being diagnosed. To implement these analyses, we use local linear regression and the [Fuji et al. \(2009\)](#) optimal bandwidth selector, although we also assess the sensitivity of our results to alternative bandwidths and parametric regression methods (see discussion in Section 6.1).

If all patients with A1c values below the cutoff were not diagnosed with diabetes, and all patients above the cutoff did receive a diagnosis, the reduced form and IV estimates would be identical. However, the change in the prevalence of a diagnosis does not change from 0 to 1 at the 6.5% threshold. As will be seen in the analysis that follows, a non-trivial share of patients with an A1c value below the threshold receive a diabetes diagnosis within the first year. This may be due to physician discretion, but it may also be the result of a later positive test. Clinical guidelines recommend that physicians repeat the test in 3 to 6 months for patients with test values close to the threshold ([American Diabetes Association, 2018a](#)).

It is also the case that a sizeable share of individuals with values above the cutoff do not receive a diabetes diagnosis. This may also result from physician discretion in assigning a diagnosis, but it could also be due to measurement error. For instance, if physicians do not record the diagnosis of diabetes on the claim or medical record, or a patient does not seek additional care after learning about the diagnosis (and thus never generates additional claims), we would not be able to observe that the patient is diagnosed. That is, some patients may not appear to have received the diagnosis when, in fact, they did. In this case, our first stage would be attenuated and the IV estimate biased upwards, as it scales the reduced form estimate by the observed (not actual) change in diagnosis prevalence. To explore this further, we conduct a bounding exercise for the IV estimate in Appendix Table A3 that assumes that all patients with A1c values at 6.5 and above receive a diabetes diagnosis, regardless of whether we observe a diabetes diagnosis in their claims or medical record. This approach naturally results in a larger first stage and smaller IV estimates; however, our results still indicate that

meaningful increases in spending occur at the diagnosis cutoff.

3.1 Manipulation of the Forcing Variable

A potential concern about the validity of our design is whether or not patients or physicians can manipulate the test score in some way so as to generate selection across the threshold. However, due to the nature of the test, this is unlikely in our setting. The patient's A1c reflects the plasma glucose levels of the patient during the past 3 months, making the test difficult to manipulate with short term changes to diet or exercise. In addition, the test values are reported to Optum or recorded in the patient's medical record directly from the lab, making physician or patient manipulation impossible.

The absence of manipulation is also apparent in the first panel of Figure 1, which shows the sample size in the Optum data for each A1c value from the initial lab test. There are three noticeable features. First, the density is smooth across the threshold, with no apparent evidence of bunching on either side. Second, given the shape of the distribution of A1c values within the population of test takers, a substantial fraction of patients whose A1c is at or above the threshold fall very close to the threshold. Indeed, 15 percent of patients with A1c at or above 6.5% in the Optum data have an A1c of 6.5% exactly; over 25 percent have an A1c value of 6.5% or 6.6%.

We see similar patterns in the EHR data, presented in the second panel of Figure 1. The UCLA sample appears healthier overall, with more of the distribution falling in the normal A1c range. This could reflect differences in the underlying health of the UCLA population relative to the national population captured in the Optum database, or it could reflect more aggressive A1c testing within the UCLA health system. While these differences do not affect the internal validity of our estimates, they could affect the generalizability of the results to other settings.

3.2 Testing for Discontinuities in Baseline Characteristics

A second concern is that there are other changes that may occur at the diagnosis cutoff that affect the outcomes being studied. The regression discontinuity model relies on the assumption that patients with A1c values near the threshold differ only in the way they are treated by the medical system; i.e., that there are no systematic underlying differences between patients with A1c values just above and just below the 6.5% cutoff. We can assess this empirically by evaluating whether there are discontinuities in demographic characteristics, spending, and health measures at the cutoff in the year prior to the initial test. These variables are not expected to change at the diagnosis threshold, providing a check on the assumption behind our research design. If we find discontinuities in these characteristics,

it suggests that there may be pre-existing differences in individuals above and below the cutoff.

We conduct this test by evaluating whether age, gender, race (available in the EHR sample only), and insurance type (Medicare versus non-Medicare) change discontinuously at the cutoff (results in the top panel of Appendix Table A4). In the second panel, we conduct a similar test using spending measures observed in the year prior to the initial lab test. We examine total spending, spending on recommended care, statins, ACE inhibitors, and endocrinology specialty care. We operationalize this test by using each of these demographic, insurance, and spending characteristics as a dependent variable in our reduced form model for each of the study samples.

We do not find statistically significant discontinuities in any of the five demographic characteristics we consider, although we do find a statistically significant reduction in Medicare coverage and baseline total spending at the cutoff in the Optum sample. This indicates that individuals with A1c values just above the cutoff had less medical spending in the year prior to the test and were slightly less likely to have Medicare coverage. However, these discontinuities are not apparent when the data are plotted (see Appendix Figure A4). To evaluate whether these differential characteristics affect our results, we have re-estimated our spending models to include baseline spending and Medicare enrollment. The inclusion of these variables have little effect on our results, suggesting that the spending effects are not driven by differential baseline characteristics (see Appendix Tables A5 and A6). Furthermore, if we exclude the Medicare sample from our data, we find very similar effects as those observed using the full sample, but no discontinuity in baseline spending. Finally, we do not see any significant effects in the other four spending variables we examine as presented in the bottom panel of Appendix Table A4. Taken together this information suggests that there are not systematic differences in patient characteristics at the diabetes diagnosis threshold that are confounding our analysis.

We do, however, find evidence of pre-existing discontinuities in outcomes during the baseline year for the UCLA clinical health measures. For this reason, we have included baseline measures as control variables in our regression analyses with the UCLA data. In addition, the RD figures for this data source plot the residual from a regression on the pre-test outcome measures. We are unable to rule out, however, that there might remain some unobserved differences in the characteristics of individuals on either side of the cutoff.

3.3 Testing for Discontinuities in Sample Inclusion by Year

The sample sizes for our analyses decline with each year of observation for two reasons. First, the length of follow up for each patient depends on the timing of their initial A1c test. For example, if a patient has her initial test in 2016, we are only able to observe one post-test year (2017), so the patient will not be in the sample for regressions that estimate effects in year 2 and beyond. Second, both our Optum and UCLA samples are comprised only of patients who are associated with these organizations. Some patients leave Optum-associated plans or the UCLA health care system before the end of our study period. This effectively reduces the sample sizes and precision of our estimates for each year of follow-up.

This type of attrition should only be a concern for our research design, however, to the extent that patients on either side of the cutoff are differentially more likely to exit the sample over time. For example, if a diabetes diagnosis causes patients to switch out of Optum-associated plans or out of the UCLA health system, this could affect the interpretation of our outcomes for later years. We test for differential attrition and report the results in Appendix Table A7. Our dependent variable in these models is whether or not the individual appears in the sample in each subsequent year (i.e. years 2-6).

We find no significant discontinuities in the probability of attrition for either the Optum or UCLA sample, demonstrating that selective attrition out of the sample based on A1c relative to the diagnosis cutoff is unlikely. The results from these tests indicate that differential selection at the cutoff is not a threat to the internal validity of our estimates. We should note, however, that it is necessarily the case that the estimates of the long-term effects of diagnosis rely on the sample of patients who were tested during the earlier part of the sample period. To the extent that the treatment of diabetes (or pre-diabetes) has changed since 2009, this limits the generalizability of the results to individuals who are currently screened for diabetes. However, we have little reason to think that physician practice has meaningfully changed since 2009.¹⁵

¹⁵Practice guidelines for the treatment of diabetes have not changed considerably since then; essentially the only practice guideline that meaningfully changed was the recommendation to initiate statin therapy for all patients with diabetes age 40 and older regardless of cholesterol levels beginning in 2013.

4 Results

4.1 Short Run Effects: Year 1

We first analyze the impact of having an A1c value exceeding the 6.5% threshold on diabetes diagnosis and medical care spending in the first 12 months following the initial lab test. The first panel of Figure 2 plots the rates of diagnosis by A1c value for the year following the initial test. We see a large and discontinuous increase in diagnosis rates at the cutoff value of 6.5%. At the 6.5% value, diagnosis rates jump by over 10 percentage points. The second panel of Figure 2 shows average spending on all recommended diabetes care. Here, we observe a clear discontinuous increase in spending at the diagnosis threshold. The subsequent panels show the results for spending on specific types of diabetes-related care: office-based care (consultations and evaluation), vision care, lab test spending, and endocrinology specialty care. We observe noticeable jumps in all outcomes, although spending on endocrinology specialty care is particularly noisy.

Figure 3 displays similar graphs for two other measures of utilization: number of diabetes-related office visits and number of labs for glucose or A1c. The figure also displays graphs for spending on drugs that are commonly prescribed to patients with diabetes: antiglycemic medications such as metformin, statins, and ACE inhibitors. We observe noticeable jumps for the first two outcomes, but less evidence of an increase in prescription drug spending in the first year. Because the first-line diabetes controlling drug, metformin, is available as an inexpensive generic (about \$4 for a 30-day supply), it may be difficult to observe spending increases even if use of this drug increases. For that reason, we also examine an indicator that the patient has any spending for a diabetes-controlling drug; this indicator exhibits a small but less obvious jump at the diagnosis threshold. In the next two plots, we see some evidence of an increase in spending for statins and ACE inhibitors, with a larger jump for the latter drug.

Table 2 presents the local linear regression estimates associated with the outcomes in Figure 2. We see a statistically significant increase in the presence of a diabetes diagnosis of 10.8 percentage points (row 1). The next row shows the effect of crossing the diagnosis threshold on spending on recommended care, as defined by the ADA recommendations. At the cutoff of A1c equal to 6.5%, we observe a discontinuous increase in spending of \$208. We scale this increase in spending by the fraction of the sample who gain a diagnosis of diabetes at the cutoff with an IV estimate in column 2. This estimate shows that a diagnosis of diabetes is associated with approximately \$1,097 of additional

spending on recommended care.¹⁶

When we break this spending down into subcategories, we see that the spending increase in the first year is split primarily between office consultations and evaluations, which exhibit an increase of \$508 associated with a marginal diagnosis, and spending related to lab work, which experiences an increase of \$505. We also see a significant increase in spending related to screening for diabetic retinopathy, of \$28 in the first year. In addition, we estimate a marginally significant increase in spending on endocrinology specialty care (\$139) among the marginally diagnosed.

Table 3 presents similar results for the additional measures of utilization and drug spending. We find that a diagnosis of diabetes is associated with about 3 additional office visits for diabetes-related care in the 12 months following diagnosis and about 0.4 more A1c or glucose labs. A diagnosis of diabetes also significantly increases the probability that a patient takes a diabetes-controlling drug by 4.3 percentage points. We also find increases in total spending on ACE inhibitors, but no significant effect on spending on statins or the amount spent on diabetes-controlling drugs.

We next examine complications related to diabetes and health outcomes in the Optum data. Figure 4 shows the effect of receiving an A1c value above the diabetes diagnosis cutoff on the incidence of preventable conditions associated with diabetes: diabetic retinopathy (eye damage), diabetic neuropathy (nerve damage), diabetic kidney disease, ketoacidosis, and diabetic coma. The incidences of diabetic neuropathy and diabetic kidney disease appear to increase at the A1c cutoff. This is not necessarily surprising given that the ADA guidelines stipulate that much of the recommended care for diabetes involves screening for these conditions. Changes at the cutoff in rates of ketoacidosis and diabetic coma are substantially noisier and harder to discern; these conditions are more serious and also very rare.

The remaining panels display the results for the direct health outcomes we measure in the Optum data: change in A1c from the initial test value, change in total cholesterol from pre-test values, and mortality. There appears to be a larger negative value in the difference between current and initial A1c levels, indicating greater improvement relative to the initial test for those above the cutoff relative to those just below.¹⁷ We see no visible evidence of a change in mortality.

The associated estimates are reported in Table 4. We find statistically significant increases in the

¹⁶Note that because the bandwidth selector chooses a different bandwidth for every outcome based on the variance of that outcome, the “first stage” varies across rows.

¹⁷Recall that those right below or right above the cutoff are equally likely to receive *any* A1c test, but those right above the cutoff tend to receive *more* A1c tests in a given year (see Appendix Table A1). We address this by selecting one A1c test result at random for those with more than one A1c value available.

diagnoses of retinopathy, neuropathy, and diabetic kidney disease, but no change in the two most life-threatening (and rare) complications associated with diabetes, ketoacidosis and diabetic coma. Although unable to completely rule out changes, the positive sign of the point estimates does not suggest avoidance of these conditions.

The bottom three rows of Table 4 present the results for the health outcomes derived from the Optum lab data. First, we look at the change in A1c from the initial test for patients who received an A1c test from an Optum-affiliated laboratory (i.e., for patients for whom we can observe the lab result, approximately 33 percent of the sample, see Appendix Table A1). We see that A1c relative to the prior year falls by about 0.06 percentage points for patients at the cutoff, and is associated with a reduction in A1c of about 0.34 percentage points for the marginally diagnosed. For context, metformin, a drug commonly provided to newly diagnosed patients with diabetes, typically lowers A1c by a bit over 1 percentage point in clinical trials (Hirst et al., 2012), so a reduction in A1c of 0.34 is within the range of what might be expected with the initiation of drug therapy. We find no effect on changes in total cholesterol (relative to levels observed prior to the initial test), although the confidence intervals do not rule out clinically meaningful effect sizes. We also do not detect effects on mortality; and, while the confidence intervals include negative estimates, the direction of the point estimates do not suggest mortality benefits. This may be unsurprising since the marginally diagnosed are the healthiest group of diabetic patients and likely carry a much lower risk of short-term health complications.

The results from the Optum claims data demonstrate substantial increases in spending associated with the A1c 6.5% cutoff value, indicating that patients with otherwise similar underlying health are treated differently depending on where their A1c falls relative to the diagnostic guideline. Next, we evaluate whether these additional interventions affect other clinical measures of health reported on the UCLA electronic health record. We examine the effect of a diabetes diagnosis on BMI, systolic, and diastolic blood pressure. Since patients often have more than one reading for each of these measures during a given year, we use the average value. We also create binary variables indicating that BMI falls in the "normal," "overweight," or "obese" range, and that blood pressure falls in the "high blood pressure" range.¹⁸

The figures associated with these outcomes, as well as a plot for the diagnosis of diabetes for this

¹⁸We define high blood pressure as 140/90 millimeters of mercury (mm Hg) and higher, which was the definition at the start of our project. The guideline for diagnosis by the American Heart Association and the American College of Cardiology has since been updated to 130/80 mm Hg, although 140/90 mm Hg is the cutoff used for Stage 2 Hypertension (American College of Cardiology, 2017).

sample, are presented in Figure 5.¹⁹ Despite a large increase in diabetes diagnoses, there is no visible change in any of the clinical health measures at the cutoff. Table 5 presents the regression discontinuity estimates from this analysis. In the first row, we find a significant increase in the diagnosis of diabetes at the cutoff A1c value of 29 percentage points. In the subsequent rows, we show that the diabetes diagnosis is not associated with changes in any of the health outcomes. The estimated coefficients are small relative to the control mean and statistically insignificant. We are able to rule out very small changes in BMI (larger than -.343, or -1.2% of the sample mean).

Finally, we examine the effect of diabetes diagnosis on measures of self-reported health and healthy behaviors in the Optum Health Risk Assessment (Figure 6 and Table 6).²⁰ As with the other two samples, we observe a significant increase in the incidence of diabetes diagnosis in this sample (by 16 percentage points). However, we do not find any statistically significant changes in self-reported health or healthy behaviors associated with the diagnosis of diabetes. In fact, the direction of the coefficient estimates suggest that the marginally diagnosed report worse subjective health and healthy behaviors. Results for the components of these indices also indicate no effect of diagnosis on self-reported health or behaviors; these are reported in Appendix Table A8.

4.2 Medium Run Effects: Years 2 through 6

The initial effects of a diabetes diagnosis may not persist if, for example, those with A1c values directly below the cutoff gain a diagnosis relatively soon after the initial test. Therefore, we first examine the likelihood of later diagnosis in each year. We also examine the persistence of spending and health effects by re-estimating our IV model using outcomes from years 2 to 6 following the initial test. These estimates demonstrate how a diagnosis in year 1 affects spending in subsequent years.

Figure 7 shows how diagnosis and spending evolves over time, in years 2 through 6 following the initial lab test. The first panel shows the reduced form estimates on the probability of ever being diagnosed with diabetes by each subsequent year. After the initial year, the difference in diagnosis rates across the threshold closes somewhat but does not entirely disappear until year 6; we observe significantly higher diagnosis rates 3 years after the initial test and positive point estimates for the first 5 years.

The second panel of Figure 7 shows the effect of diagnosis in year 1 on spending on subsequent

¹⁹Note that graph (a) in Figure 5 differs from Figure 2(a) in that it estimates the change in diabetes diagnoses specific to the UCLA EHR sample.

²⁰Note that graph (a) in Figure 6 differs from Figure 2(a) and Figure 5(a) in that it estimates the change in diabetes diagnoses specific to the Optum HRA sample.

years (i.e. IV estimates). In contrast to the diagnosis estimates, which show convergence between the marginally diagnosed and marginally undiagnosed, we see fairly stable impacts of a year 1 diagnosis on spending on recommended care in each subsequent year, with little evidence that the gap in spending between those above and below the threshold closes. The estimates become less precise due to some individuals leaving the sample over the study period, but we see consistently positive effects for all years and a statistically significant effect even five years after the initial test. Our estimated effects on spending related to lab and office-based care are similarly stable over time. Spending on vision care for retinopathy screening appears to increase over time, with higher spending observed in later years. In contrast, spending on endocrinology specialist care is not consistently higher in the years following the initial test.

We document similar results when examining the effect of a diabetes diagnosis on our other utilization measures in Figure 8. The increased number of diabetes-related office visits and glucose/A1c labs remain stable, for the most part, for all 6 years following the test. The effect of a diagnosis on spending on diabetes-controlling drugs increases over time, as does the probability a patient takes any diabetes-controlling drug. In contrast, we do not find any evidence that statin or ACE inhibitor spending are larger in years 2-6 as a result of diagnosis.

Overall, our results using claims data show large increases in spending and use of care among those marginally diagnosed in year 1. These spending increases stay relatively stable or, in the case of drug spending and vision care, appear to grow larger over time. This pattern is consistent with physicians delaying pharmacologic treatment if first recommending lifestyle changes, or starting with the inexpensive first-line therapy (metformin) and later switching to more expensive drug therapies. These results also support the hypothesis that receiving a diagnosis puts a patient on a path to persistently higher spending.

Next, we examine how the impact of a diabetes diagnosis affects the diagnosis of complications related to diabetes and health as measured in the Optum dataset. These results, displayed in Figure 9, show significantly higher diagnoses of neuropathy and diabetic kidney disease in years 1 and 2. Subsequent years show neither statistically significant increases nor reductions in the rates of complications related to diabetes. Note that because we have smaller samples in later years, however, we lose precision for many estimates starting in year 4 or year 5 after the initial test. Because, ketoacidosis and diabetic coma are rare conditions, we are unable to estimate an effect of diabetes diagnosis on these conditions after five years (for ketoacidosis) or four years (for diabetic coma) due to insufficient

variation to compute the optimal bandwidth. The estimates show no change in these conditions, although the effects for later years have large confidence intervals. Finally, the last three panels of Figure 9 show the effects on changes in A1c, total cholesterol, and mortality in the years following the test. In contrast to the spending effects, which persisted over the entire period, the improvement in A1c observed in the first year does not continue in subsequent years. We also do not observe any changes in total cholesterol or mortality in subsequent years.

We also use the EHR data to evaluate whether improvements in clinical health emerge in later years. For these measures, we observe only 3 years of data after the initial test. Effects are similar across all three years, indicating no health improvements associated with a diabetes diagnosis for marginal patients (Figure 10). Finally, we look at the impact of a diagnosis on the self-reported outcomes in the health risk assessment survey. We continue to find no statistically significant effect on these outcomes in subsequent years, but our confidence intervals are large. These results are reported in the Appendix in Figure A3.

To summarize, we find that the diagnosis of diabetes for individuals with A1c values just above the diagnosis cutoff leads to greater spending on diabetes-related medical care. This spending increase is not only present in the year following the test but persists over time. Our point estimates suggest that a diagnosis of diabetes is associated with a cumulative \$8,107.86 in additional spending on recommended care over 6 years, in present value terms.²¹

In terms of health benefits associated with this spending, we see only minimal improvements in health over our observation period. We find a short-term improvement in A1c during the year following the initial test. This change in A1c appears short-lived with no evidence of additional A1c improvement over the following 5 years. We find no evidence of changes in other clinical health measures (total cholesterol, BMI, blood pressure, or mortality), nor do we find changes in patient-reported health or health behaviors. The coefficient estimates are not only small in size, but often take the opposite direction of a health benefit.

We only observe patients for 6 years following the initial diagnosis of diabetes; and, it may be the case that additional improvements in health manifest in year 7 or later. Indeed, we find strong evidence that receiving a diagnosis of diabetes is associated with early diagnosis of several complications associated with diabetes, such as retinopathy, neuropathy, and diabetic kidney disease; since these complications were detected earlier, we might expect patients to experience improved health

²¹We arrive at \$8,107 by aggregating the IV estimates of the effect of a diagnosis on recommended care over the 6 years for which we have estimates, assuming additional spending related to a diagnosis is \$0 for subsequent years.

trajectories over a longer time horizon. There may also be additional value to patients of learning about these conditions or their diabetes diagnosis (see additional discussion in [Iizuka et al., 2021](#)), in general, which is not captured in our analysis.

5 Specification Checks

In this section, we conduct several analyses to probe the robustness of our results to different sample and model specification choices.

5.1 Sensitivity to Specification and Bandwidth Choices

First, we assess the robustness of our results to using a quadratic model and alternative bandwidths in the local linear model, reported in Appendix Tables [A9-A12](#). The quadratic regression is given by:

$$y_i = \alpha + \beta A1c_{6.5i} + \gamma_0 c + \gamma_1 c^2 + \gamma_2 A1c_{6.5} c + \gamma_3 A1c_{6.5} c^2 + \epsilon_i \quad (1)$$

where we include a quadratic function in the A1c value c centered at 6.5 that is allowed to differ on the two sides of the cutoff point. Following recent guidance on implementation of RD designs with discrete running variables, we do not cluster the standard errors by the running variable, but rather estimate robust standard errors ([Kolesár and Rothe, 2018](#)).

In the first column, we re-report the results from our main reduced form specification to facilitate comparison. We then report the results from a model that estimates the RD effect using a quadratic in initial lab value that is allowed to vary at the cutoff. Results with this model are very similar to our baseline estimates for most outcomes in the Optum data ([Appendix Tables A9-A10](#)). We no longer find a decrease in A1c associated with diabetes diagnosis in the first year, however. Subsequent columns show the results for larger (twice) and smaller (one half) multiples of the optimal bandwidth in the local linear regression estimation. Results are very similar both quantitatively and qualitatively when alternative bandwidths are used, although larger bandwidths tend to result in somewhat larger estimates. For our estimates of the change in A1c from its baseline value, however, we find a larger decline under a smaller bandwidth, suggesting that the difference in values is most apparent for those individuals closest to the threshold. The estimates for preventable conditions, clinical health measures, and self-reported health measures ([Appendix Tables A11-A12](#)) look, for the most part, similar across specifications.

5.2 Sensitivity to Sample Inclusion Criteria

We also examine the sensitivity of our results to our sample inclusion criteria. In particular, we require that individuals be enrolled in an Optum plan for at least 1 year prior to their initial A1c test so that we can adequately assess whether they have previously been diagnosed with diabetes. It may be the case, however, that some individuals in our sample were misclassified as having no diabetes diagnosis prior to their first test when, in fact, they had already been diagnosed. This might be the case if, for example, they were diagnosed before entering the Optum data. In Appendix Tables [A13](#) and [A14](#), we conduct our analysis but only include those who were enrolled in an Optum plan for 2 years prior to the initial test. Approximately 70 percent of our main analytic sample met this criterion. Our spending results are very similar, indicating that our initial sample definition likely performed well at excluding those who were already diagnosed with diabetes. When we implement similar sample criteria in the UCLA data, we estimate a larger first stage with a 41 percentage point increase in diagnosis, but still find no evidence of health effects (Appendix Table [A15](#)). Omitted here in the interest of space, results on self-reported health and healthy behaviors are also similar under this sample refinement.

5.3 Bounding Exercise for IV Estimates

Next, we conduct a bounding exercise to determine a lower bound on the treatment effect of receiving a diabetes diagnosis on spending. If doctors are not recording the diabetes diagnosis on their submitted claims (Optum) or on the electronic health record (EHR), some individuals with A1c values above the diagnosis cutoff may in fact receive a diagnosis even though it is not visible in the data. This would result in an underestimation of the first stage (i.e., the effect of an A1c above the cutoff on diagnosis) and an overestimation of the treatment effect of receiving a diagnosis on other outcomes (e.g., the effect of receiving a diagnosis on spending). In Appendix Table [A3](#), we re-estimate our IV models assuming that everyone with an A1c value above 6.5 receives a diagnosis of diabetes, even if we do not observe it on the claim or EHR. That is, the variable indicating the individual has received a diabetes diagnosis is coded to be one for all individuals with A1c 6.5 or higher. This assumption results in a much larger first stage of about 56 percentage points, and smaller effects for the marginally diagnosed on spending outcomes. Although these lower bounds are, naturally, much smaller than the IV estimates reported in Table [2](#), the estimates indicate that a diagnosis of diabetes increases spending by at least \$242 in the first year following the initial A1c test.

5.4 Exploring Differences in Utilization and Health Samples

We next conduct additional analyses to compare the UCLA EHR and Optum data results. Since these are very different samples, the lack of health effects in the EHR data may be less likely to translate to the Optum setting if the treatment patterns for diabetes diagnosis are very different. While, the UCLA EHR data do not contain information on spending (making it difficult to produce similar estimates as those presented in Table 2 for the Optum sample), they do contain some information on utilization that can be used to assess changes at the cutoff. The effect of a diabetes diagnosis on such utilization measures are presented in Appendix Table A17. We find that a diagnosis of diabetes is associated with 4.5 additional ambulatory encounters for diabetes care, 0.4 additional A1c labs, and a 14 percentage point increase in the probability of taking a diabetes-controlling drug during the first 12 months following the initial test. These estimates are similar to those in the Optum sample and indicate a clear increase in utilization following diagnosis. In addition, the EHR data allow physicians to note health problems of patients on a “problem list.” In addition to seeing a higher probability of having a diabetes diagnosis associated with an encounter, we see a higher probability that diabetes is on a patient’s problem list at the diagnosis cutoff. The probability of a diabetes diagnosis on the problem list increases by 31 percentage points for the marginally diagnosed.

5.5 Sensitivity to Removing Attriters

Although we find no evidence of sample attrition associated with the diagnosis cutoff, it could be the case that individuals who remain in our sample all six years vary systematically from those we only observe for one or two years. As a result, the effects we estimate in years 2-6 following the initial lab test may reflect changes in the underlying sample rather than time-varying treatment effects. We examine this by comparing the results obtained from our main (unbalanced) sample, from those we obtain when we restrict the sample to only those who remain enrolled all 6 years (balanced). The results of this exercise are presented in Figures 11 and 12, which plot the coefficient in each year for the unbalanced panel (black) against those obtained in the balanced panel (red). We provide results just for the spending and utilization outcomes, given the low rates of mortality and some of the preventable conditions, and the relatively small size of the balanced panel. Although the balanced panel has much larger confidence intervals, the point estimates indicate that diagnosis rates and spending are similar across the two samples. Similar analysis of the UCLA (Figure 13) data shows that results remain null for all three years in the version of the sample that uses a balanced panel. Based on these

analyses, there do not appear to be systematic differences in the effect of diabetes diagnosis across the groups that remain in the sample continuously and the main sample.

6 Additional Analyses

We next undertake some additional analyses to further explore and understand our main findings.

6.1 Changes in Overall Utilization

We explore whether the increase in diabetes-related care occurs during separate encounters or visits, or whether it alternatively changes the focus or style of treatment that occurs during interactions with the health care system that would take place regardless of the diagnosis. For example, diabetes and non-diabetes patients may have the same number of office visits, but diabetes patients receive information and treatment specific to their illness, whereas non-diabetes patients receive more general information on their health. We assess this in two ways.

First, we look at the total number of office visits for evaluation and management and total spending on this category, including visits unrelated to diabetes. These results are presented in the first panel in Appendix Table A16. We find no significant change in the total number of office visits or total spending on office visits, despite the fact that we see increases in visits and spending for diabetes-related care. This suggests that, at least for office visits, diabetes-related care could be delivered in the context of existing health care interactions, either representing additional care received during the same encounter or crowding out visit time that would have otherwise been focused on other problems or diseases. However, our standard errors are large enough that we cannot rule out annual increases in total office spending smaller than \$188 or increases in office visits smaller than 0.6.

Next, we examine diabetes-related care that more clearly represents new utilization by focusing on the elements of recommended care that are *not* identified by a diagnosis code: spending on statins, ACE inhibitors, diabetes-controlling drugs, endocrinology specialist care, and spending on glucose labs. Among this subset of recommended care, we find that diagnosis results in a statistically significant increase in spending of about \$250 in the first year, which represents about one-quarter of our main spending estimate. Thus, we find clear evidence of an increase in some types of “new” utilization associated with a diabetes diagnosis.

6.2 Heterogeneity by Provider Type

Next, we conduct additional analyses to explore whether patients of different types of providers experience difference changes in outcomes upon being diagnosed with diabetes. We identify the provider who ordered lab analysis for the A1c test among patients by finding outpatient visits within one week of the observed lab that contains a procedure code for an A1c test. If no outpatient visit exists, but we do observe an office visit for the patient in the week the lab is processed, we assign the provider at that office visit as the one who ordered the A1c lab.²² Using these patient-provider linkages, we focus on two broad groups of providers: primary care physicians (those with a specialty of family medicine or internal medicine), and specialists (those with other specialties). We then conduct an RD analysis within each subgroup defined by the provider's specialty.

The results of this heterogeneity analysis are found in Table 7. As may be seen from the first row of this table, an A1c value above the cutoff is more likely to result in a diabetes diagnosis for patients of specialists versus primary care doctors. The point estimates also indicate that patients diagnosed by specialists experience somewhat higher spending as a result (\$1458 vs \$1200), which appears to be accounted for by higher spending on office-related diabetes care (\$637 vs \$531) and on diabetes-related labs (\$637 vs \$550). However, our estimates are not precise enough to reject that the changes at the cutoff are similar. Furthermore, it is not clear from this analysis whether differences in the effect at the cutoff by provider specialty reflect provider-specific factors (such as providers' practice style or preferences) or underlying differences in the patient population.²³ More work is needed to understand the interplay between provider guideline adherence and patient outcomes.

7 Conclusion

The distribution of health in the population is such that many individuals with a chronic illness are near the margin of being diagnosed. This paper explores the impact of a diagnosis on such "marginal" patients using longitudinal medical claims records for a large private insurer that includes clinical data. We find that individuals whose blood glucose levels are just above the threshold for a diabetes diagnosis have significantly higher spending on recommended care than similar patients whose blood glucose levels fall just below this cutoff. Receiving such a diagnosis appears to put patients on a path

²²We are able to successfully link about 60% of our sample to providers using this method. Additional details on how we link providers to lab orders are found in Appendix Section 4.1.

²³Indeed, we see that spending on recommended care is higher even among patients of specialists who do not cross the diagnosis cutoff threshold, as evidenced by the differences in the "control mean" of those whose A1c falls between 5.9 and 6.4.

of persistently higher spending and utilization of diabetes-related care. Even after 5 years, patients whose initial test put them above the diagnosis cutoff have spending that is significantly higher than those with lab tests just below this cutoff.

We can use our estimated increase in diabetes-related spending in a back-of-the-envelope calculation to explore how tightening the diagnosis threshold, from 6.5% to 6.6%, would affect total U.S. spending on diabetes-related care. The ADA estimates that 1.4 million individuals are newly diagnosed with diabetes each year. If we assume that the distribution of A1c values among the population being tested is similar to that observed in the Optum data, this suggests that 15.4 percent, or 216,000, of these individuals have A1c values of 6.5%. Moving the diagnosis threshold to 6.6% would, therefore, be expected to decrease diabetes-related spending over the next 6 years for each of these individuals, for a total reduction in spending of \$1.75 billion ($=\$8,107.86 \times 216,000$).²⁴

Among these marginally diagnosed patients, this additional spending appears to be associated with only minimal improvements in health over our observation period. We see a reduction in A1c in the first year following diagnosis, but this improvement does not persist through years 2 through 6 and is somewhat sensitive to model specification. We do not detect any improvements in blood pressure or BMI as measured on electronic health records, nor in total cholesterol or mortality rates. We also do not detect any changes in self-reported measures of health or healthy behaviors. We do find evidence that receiving a diagnosis of diabetes is associated with diagnosis of several complications associated with diabetes (retinopathy, neuropathy, and diabetic kidney disease), which may have repercussions for quality of life or health over a longer time horizon.

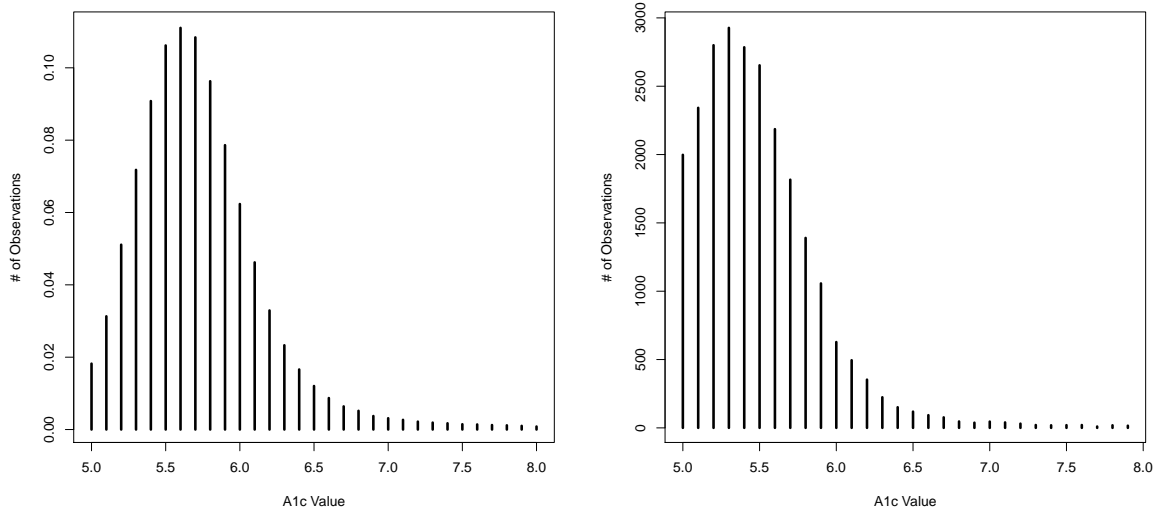
The length of our analysis is limited by attrition over time in the sample, which is particularly large in year 5 and year 6 following the initial A1c test. In the absence of population-level data on health care utilization and clinical health measures in the U.S., it will be difficult to assess these types of longer-term consequences. Current efforts underway to longitudinally link electronic health records across health systems, as well as to link all-payer claims databases and EHR records within specific states, may enable researchers to better examine this question at some point in the future. Until then, the fact that we find minimal effects on intermediate measures of health such as blood sugar, blood pressure, cholesterol, and BMI reduces our optimism about the likely magnitude of longer term health improvements.

Overall, results suggest that the effects of increased spending on relatively healthy diabetes pa-

²⁴This calculation examines spending for the initial 6 years following a diagnosis since our analysis follows spending during this amount of time only.

tients are likely modest, and would indicate that future revisions of diagnosis guidelines for chronic diseases should exercise caution when relaxing these guidelines to include healthier populations.

Figure 1: Sample size by A1c Value, Optum and EHR



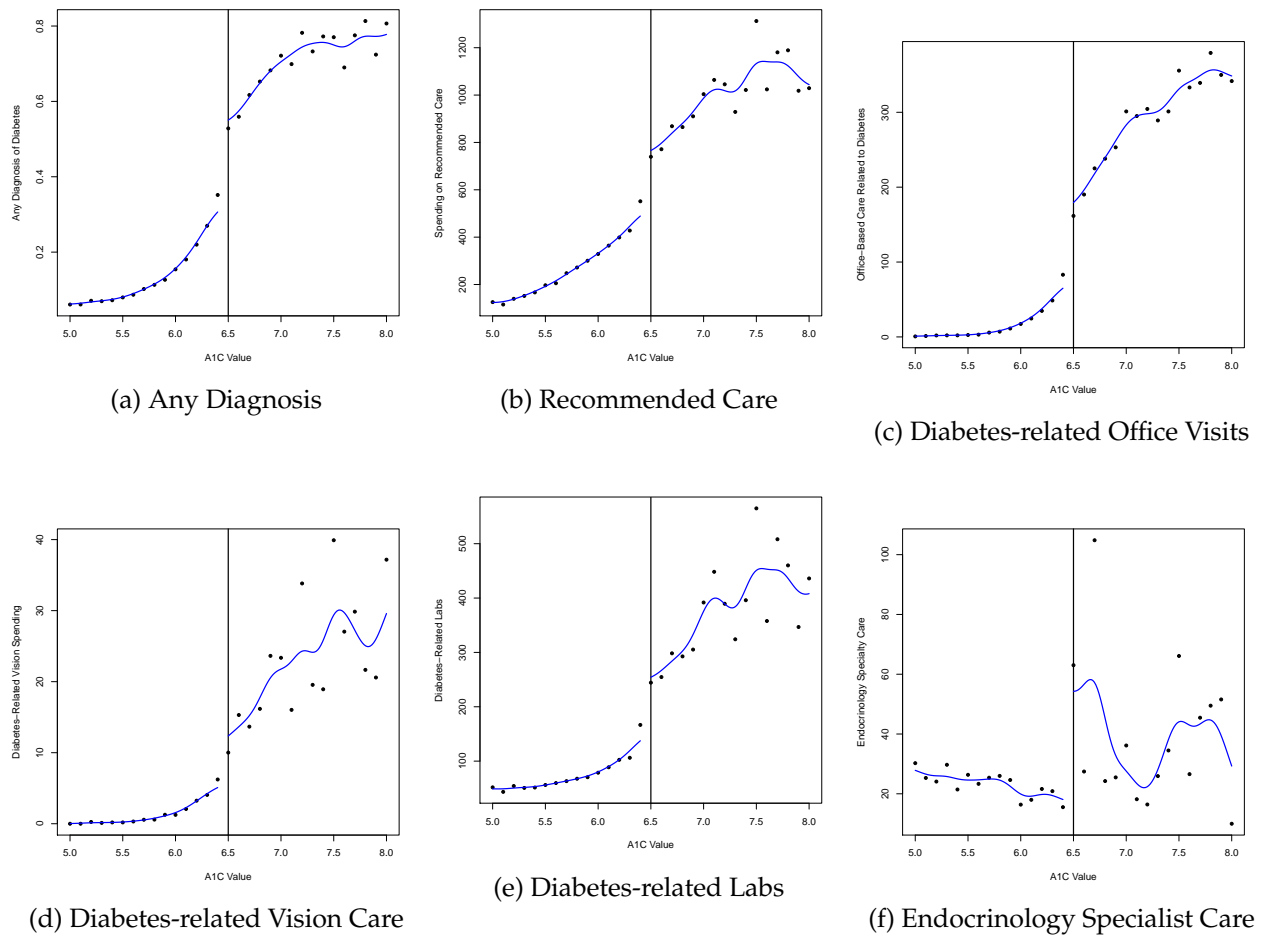
Source: Authors' calculations from the Optum claims data (left panel) and UCLA EHR data (right panel). Horizontal axis indicates each value of A1c. Vertical axis indicates sample size within each A1c bin.

Table 1: Demographic Statistics, Optum, HRA and UCLA EHR Data

	Optum	Health Risk Assessment	UCLA EHR
Female	0.523	0.554	0.612
Age	51.13	44.22	47.15
White	N/A	N/A	0.654
Black	N/A	N/A	0.048
Hispanic	N/A	N/A	0.111
Asian	N/A	N/A	0.105
Medicare	0.281	0.006	0.181
Private	0.719	0.994	0.749
Medicaid	0	0	0.016
Self-Pay	0	0	0.046
N	142,541	16,916	23,882

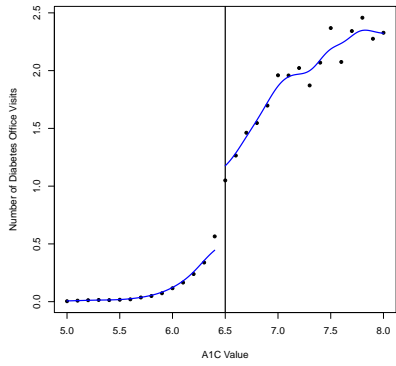
Note: Authors' calculations from Optum claims, Health Risk Assessment, and UCLA EHR data. This table contains descriptive statistics for patients with an A1c test who meet all sample criteria described in the text.

Figure 2: Diabetes Diagnosis and Spending in 12 Months Following Initial Lab Test

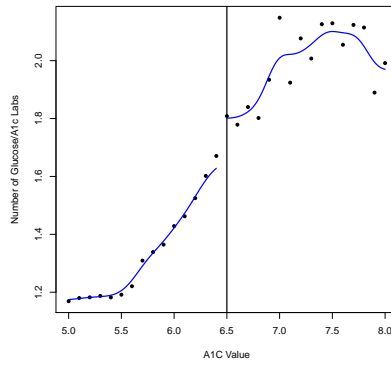


Source: Authors' calculations from the Optum claims data. Horizontal axis displays the test value. Vertical axis displays within test value averages of outcome variable. Vertical line at 6.5 is the diagnosis cutoff for diabetes.

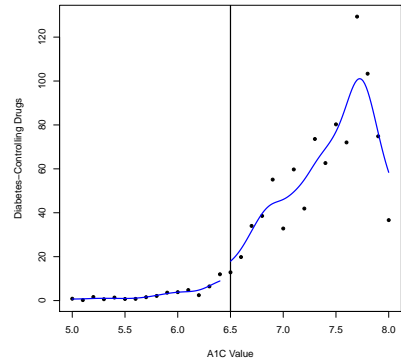
Figure 3: Drug Spending and Other Utilization Measures in 12 Months Following Initial Lab Test



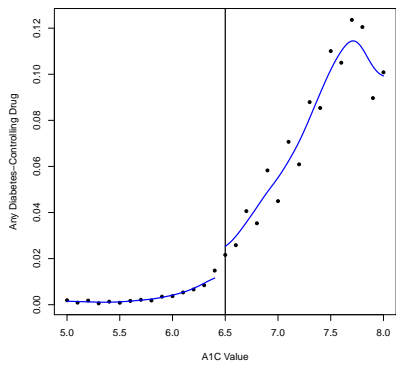
(a) # of Diabetes-Related Office Visits



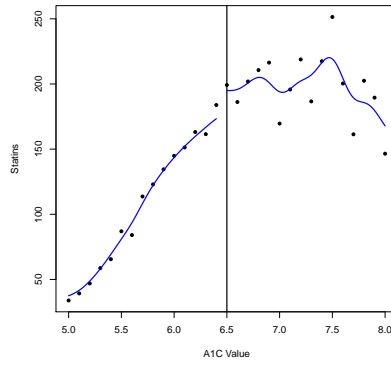
(b) # Glucose/A1c Labs



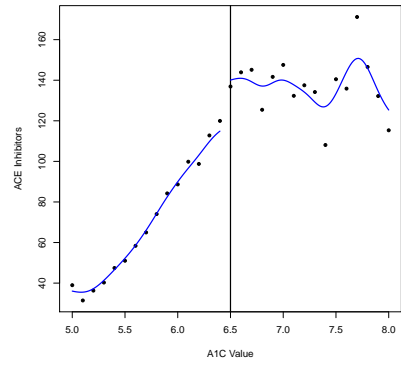
(c) Diabetes-Controlling Drugs



(d) Any Diabetes-Controlling Drug Spending



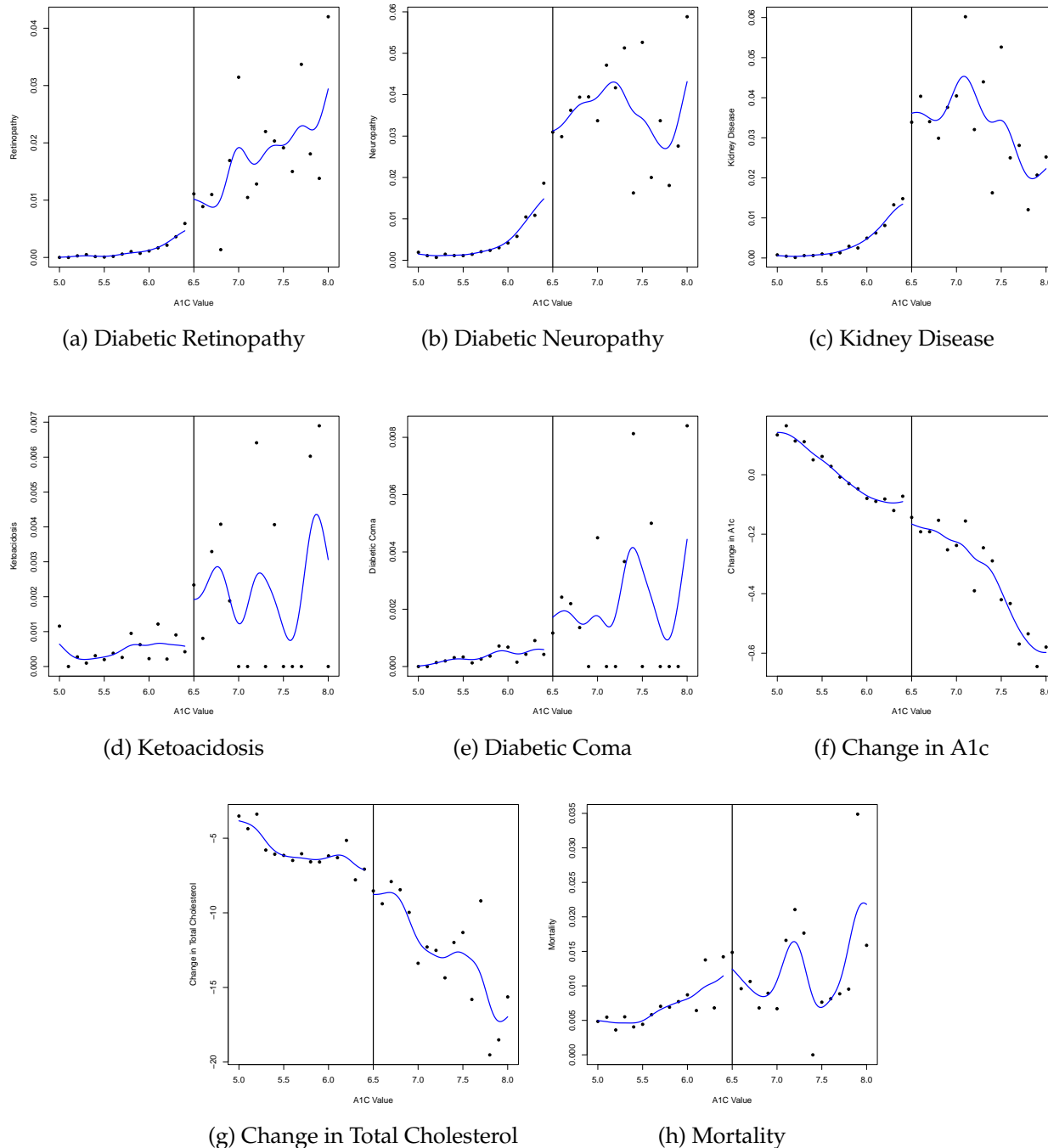
(e) Statins



(f) ACE Inhibitors

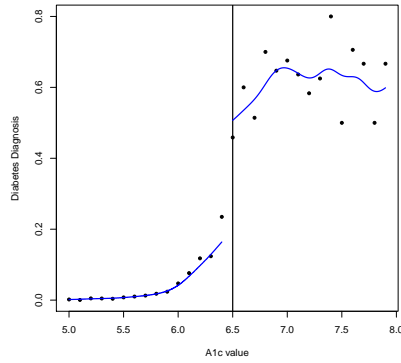
Source: Authors' calculations from the Optum claims data. Horizontal axis displays the test value. Vertical axis displays the average within test value averages of outcome variable. Vertical line at 6.5 is the diagnosis cutoff for diabetes.

Figure 4: Diagnosis of Complications Related to Diabetes and Optum Health Outcomes in 12 Months Following Initial Lab Test

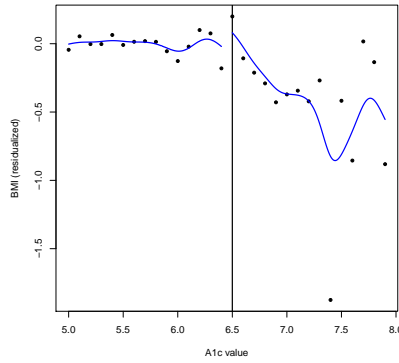


Source: Authors' calculations from the Optum claims data. Horizontal axis displays the test value. Vertical axis displays range value averages of outcome variable. Vertical line at 6.5 is the diagnosis cutoff for diabetes.

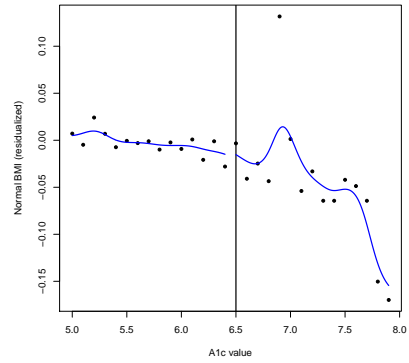
Figure 5: Clinical Measures of Health in 12 Months Following Initial Lab Test



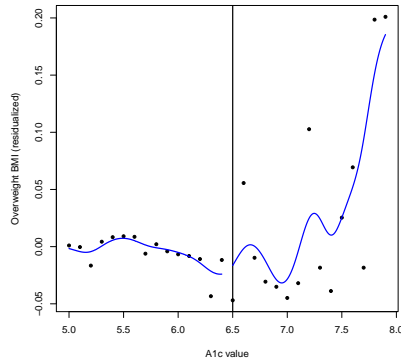
(a) Diagnosis of Diabetes



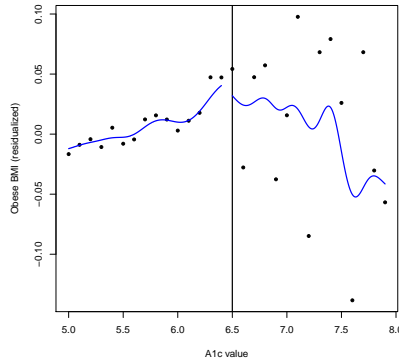
(b) BMI



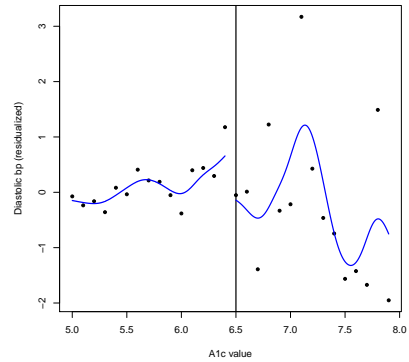
(c) BMI in normal range



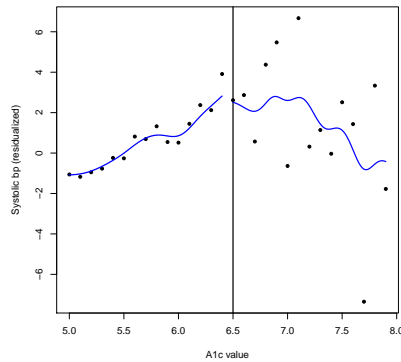
(d) Overweight



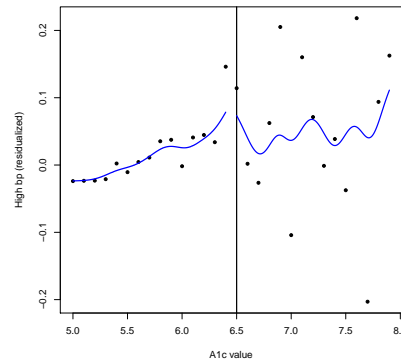
(e) Obese



(f) Diastolic BP



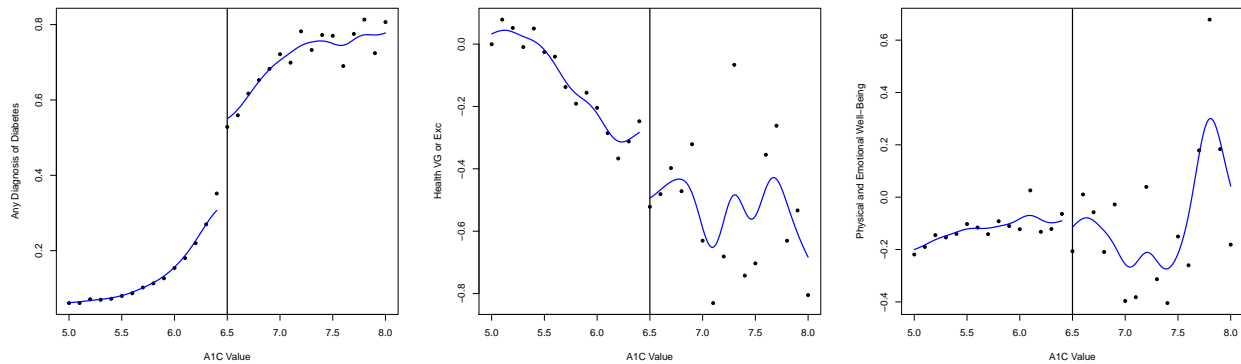
(g) Systolic BP



(h) High BP

Source: Authors' calculations from the UCLA Electronic Health Record data. Horizontal axis displays the test value. Vertical axis displays within test value averages of outcome variable. Vertical line at 6.5 is the diagnosis cutoff for diabetes. Note that all panels except panel (a) use data that is first residualized by regressing the outcome on the previous year's value. The resulting error term is then binned by test value and the average within each test value is plotted.

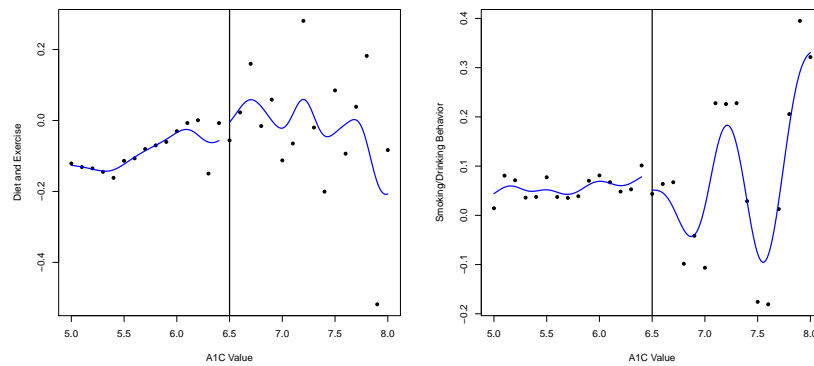
Figure 6: Self-Reported Health and Behavior in 12 Months Following Initial Lab Test



(a) Diabetes Diagnosis

(b) Health VG or Exc

(c) Physical and Emotional Well-Being

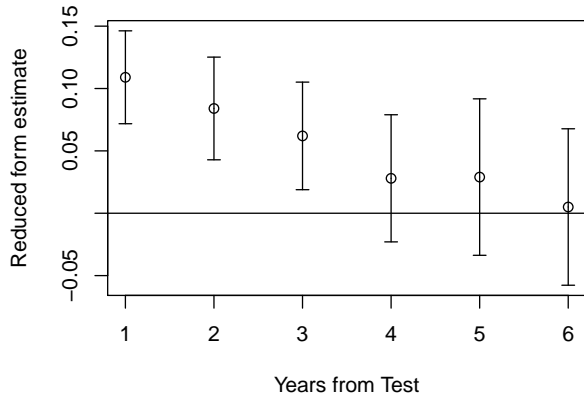


(d) Diet and Exercise

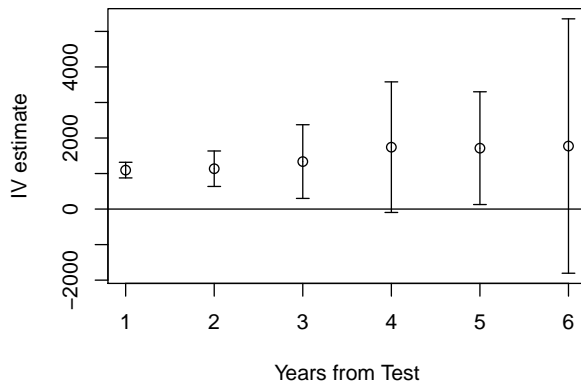
(e) Healthy Smoking and Drinking Choices

Source: Authors' calculations from the Optum Health Risk Assessment data. Horizontal axis displays the test value. Vertical axis displays within test value averages of outcome variable. Vertical line at 6.5 is the diagnosis cutoff for diabetes.

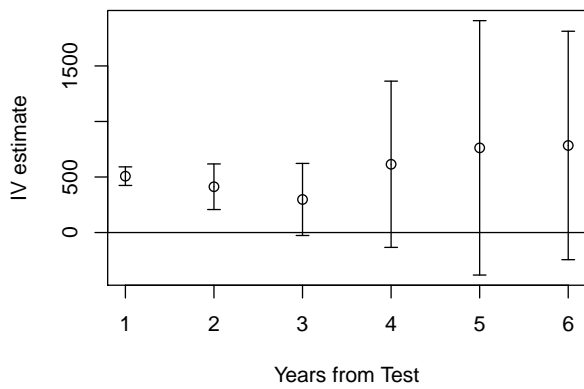
Figure 7: Optum Diagnosis and Spending Outcomes by Year After Initial Lab Test



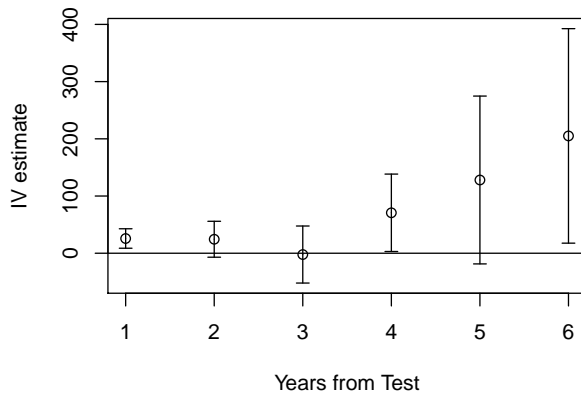
(a) Any Diagnosis of Diabetes



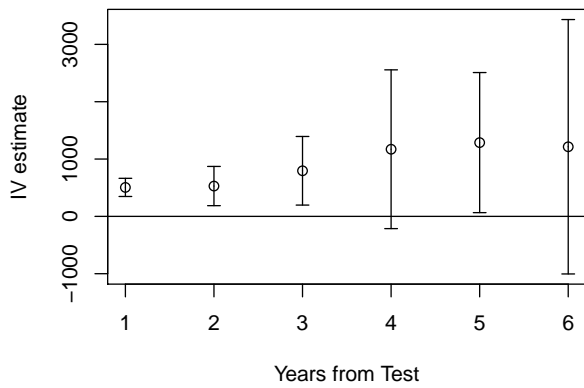
(b) Recommended Care



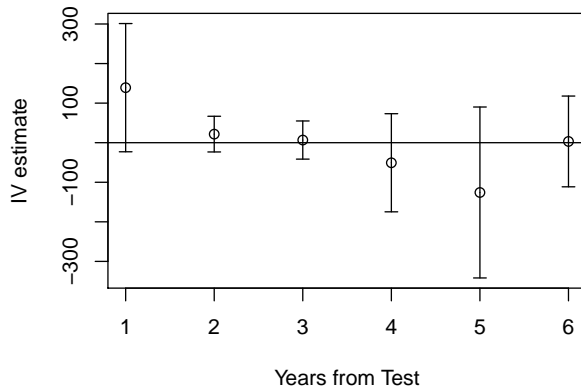
(c) Diabetes-related Office Visits



(d) Diabetes-related Vision Care



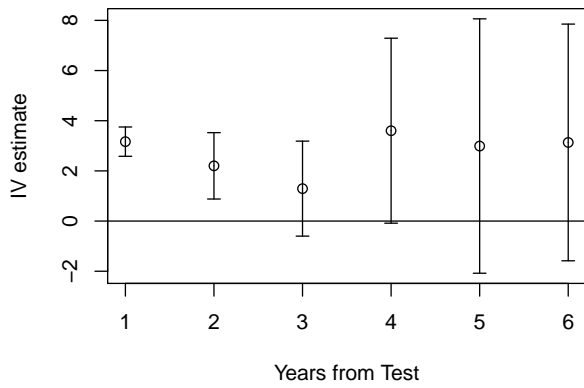
(e) Diabetes-related Labs



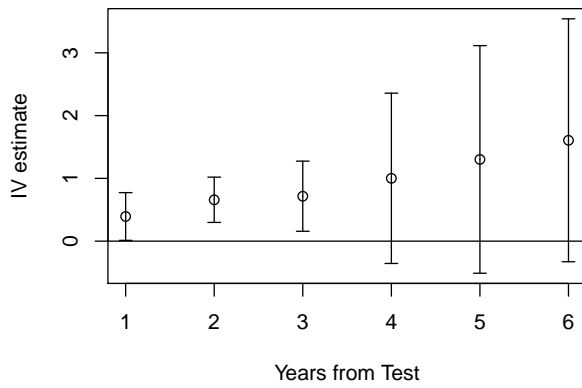
(f) Endocrinology Specialist Care

Source: Authors' calculations from the Optum claims data. Horizontal axis indicates the year relative to the initial lab test. Vertical axis indicates size of the regression discontinuity effect estimated using local linear regression. 95 percent confidence intervals displayed.

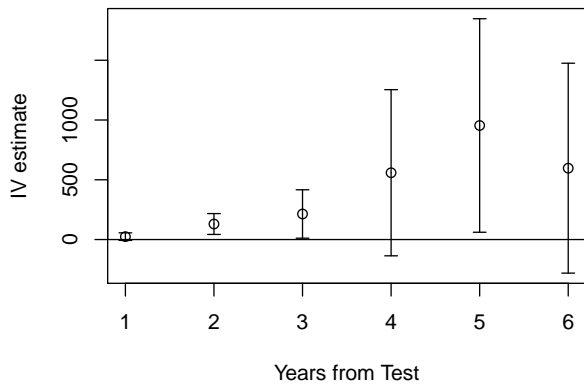
Figure 8: Optum Utilization Outcomes by Year After Initial Lab Test



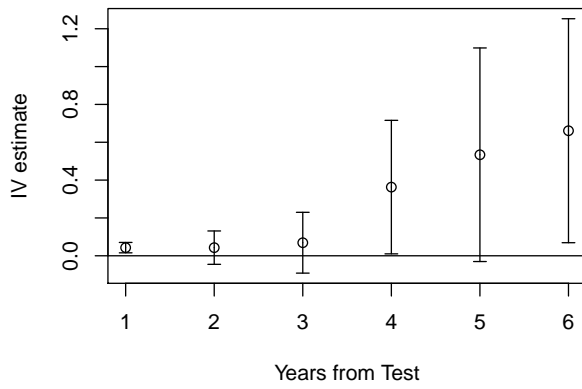
(a) # of Diabetes-Related Office Visits



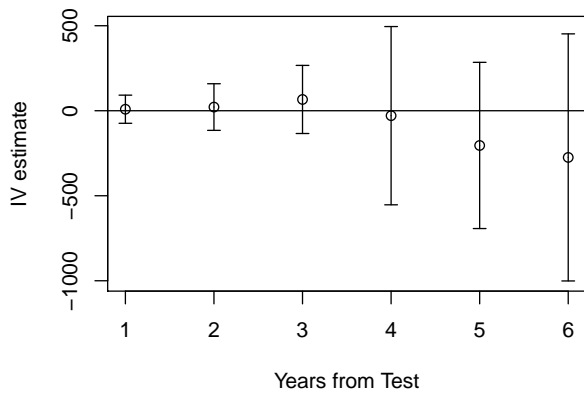
(b) # Glucose or A1c Labs



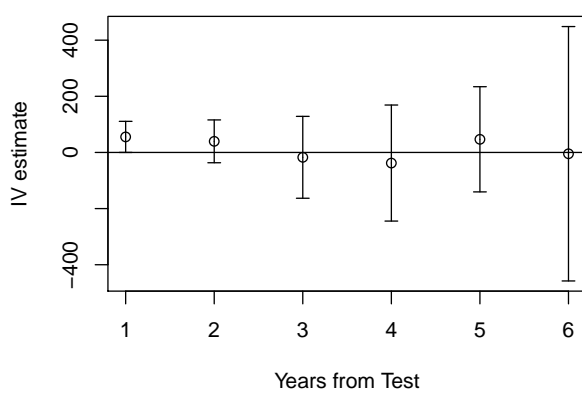
(c) Diabetes-Controlling Drugs



(d) Any Diabetes-Controlling Drug



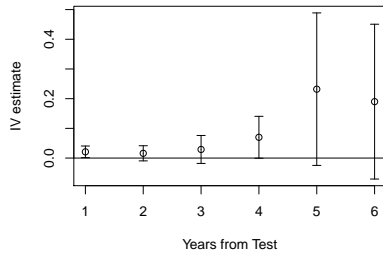
(e) Statins



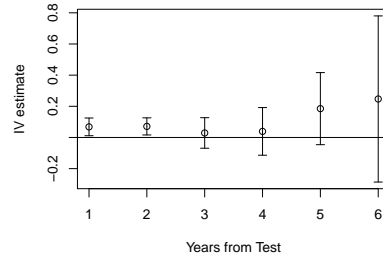
(f) ACE Inhibitors

Source: Authors' calculations from the Optum claims data. Horizontal axis indicates the year relative to the initial lab test. Vertical axis indicates size of the regression discontinuity effect estimated using local linear regression. 95 percent confidence intervals displayed.

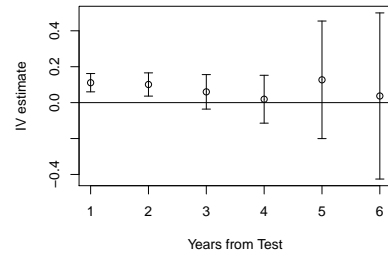
Figure 9: Incidence of Complications by Year After Initial Lab Test



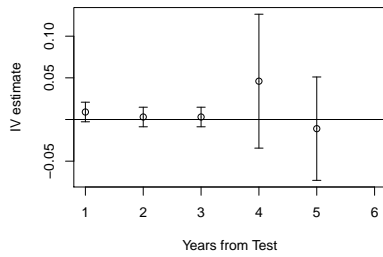
(a) Diabetic Retinopathy



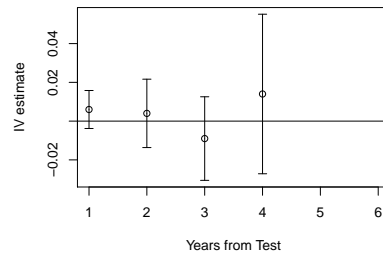
(b) Diabetic Neuropathy



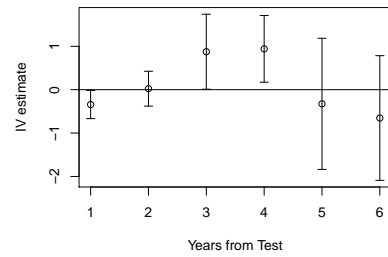
(c) Kidney Disease



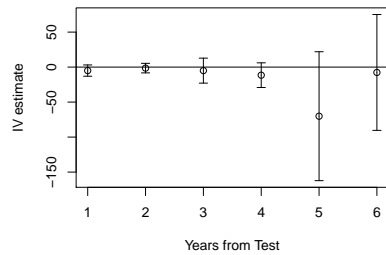
(d) Ketoacidosis



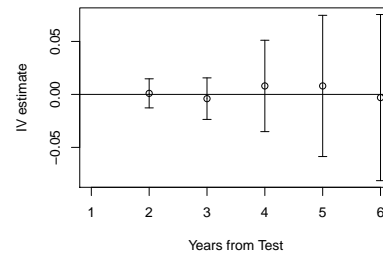
(e) Diabetic Coma



(f) Change in A1c



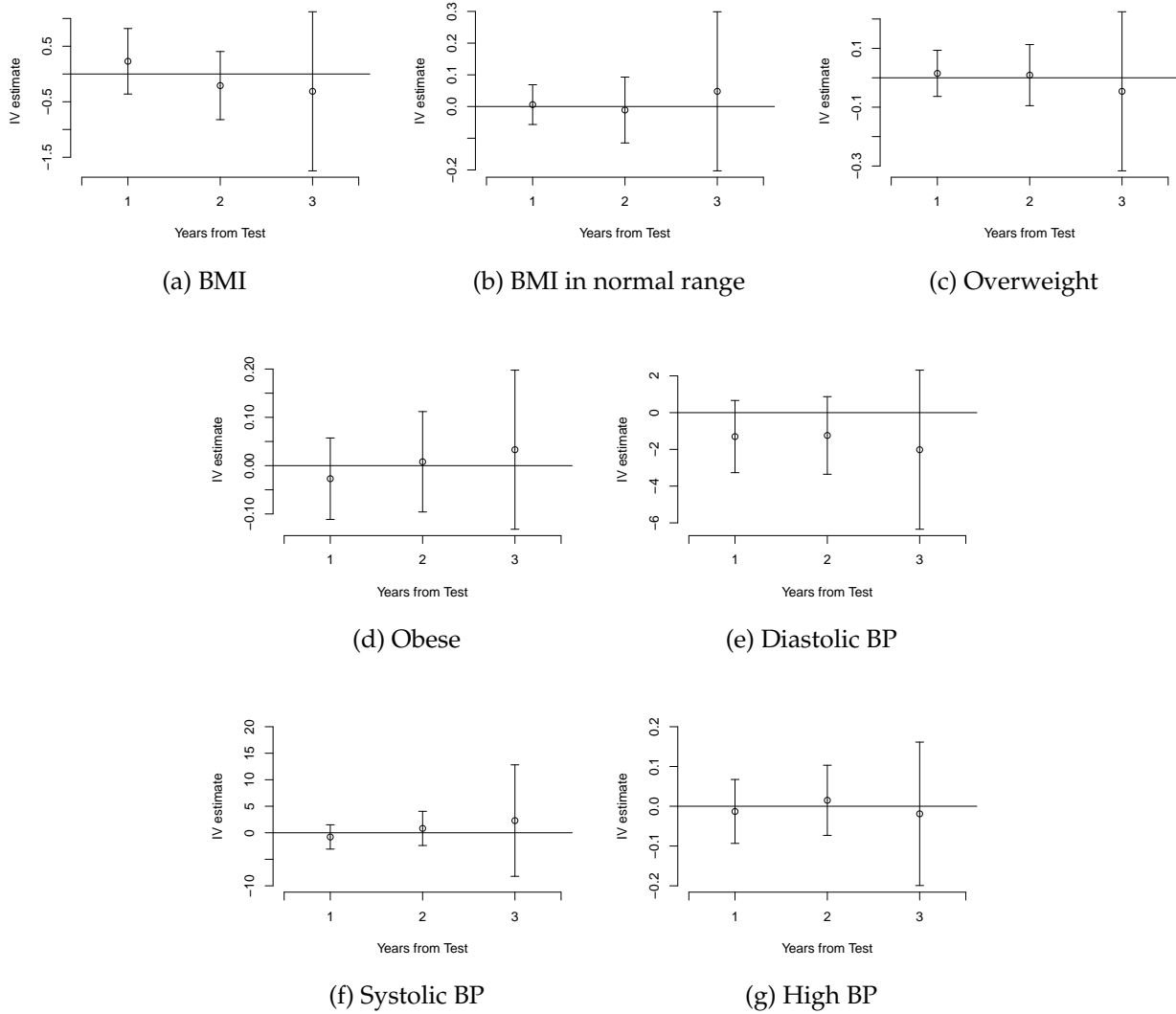
(g) Change in Total Cholesterol



(h) Mortality

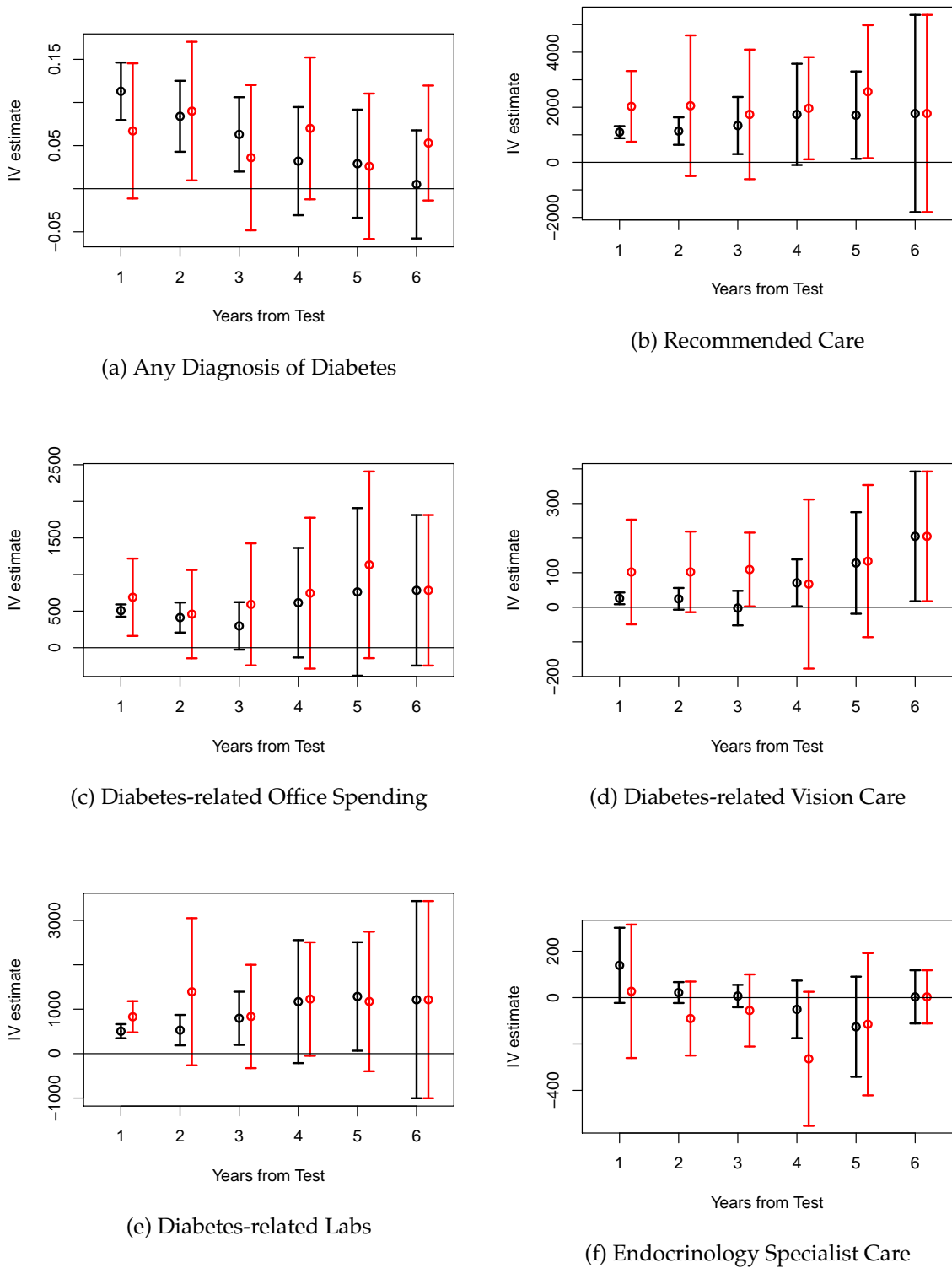
Source: Authors' calculations from the Optum claims data. Horizontal axis indicates the year relative to the initial lab test. Vertical axis indicates size of the regression discontinuity effect estimated using local linear regression. 95 percent confidence intervals displayed. Note that ketoacidosis and diabetic coma are rare conditions. Because we have smaller samples in later years, we are unable to estimate an effect of diabetes diagnosis on these conditions after five years (for ketoacidosis) or four years (for diabetic coma) following the initial test due to insufficient variation to compute the optimal bandwidth.

Figure 10: Diagnosis and Health Outcomes in 12 Months Following Initial Lab Test, UCLA EHR Data



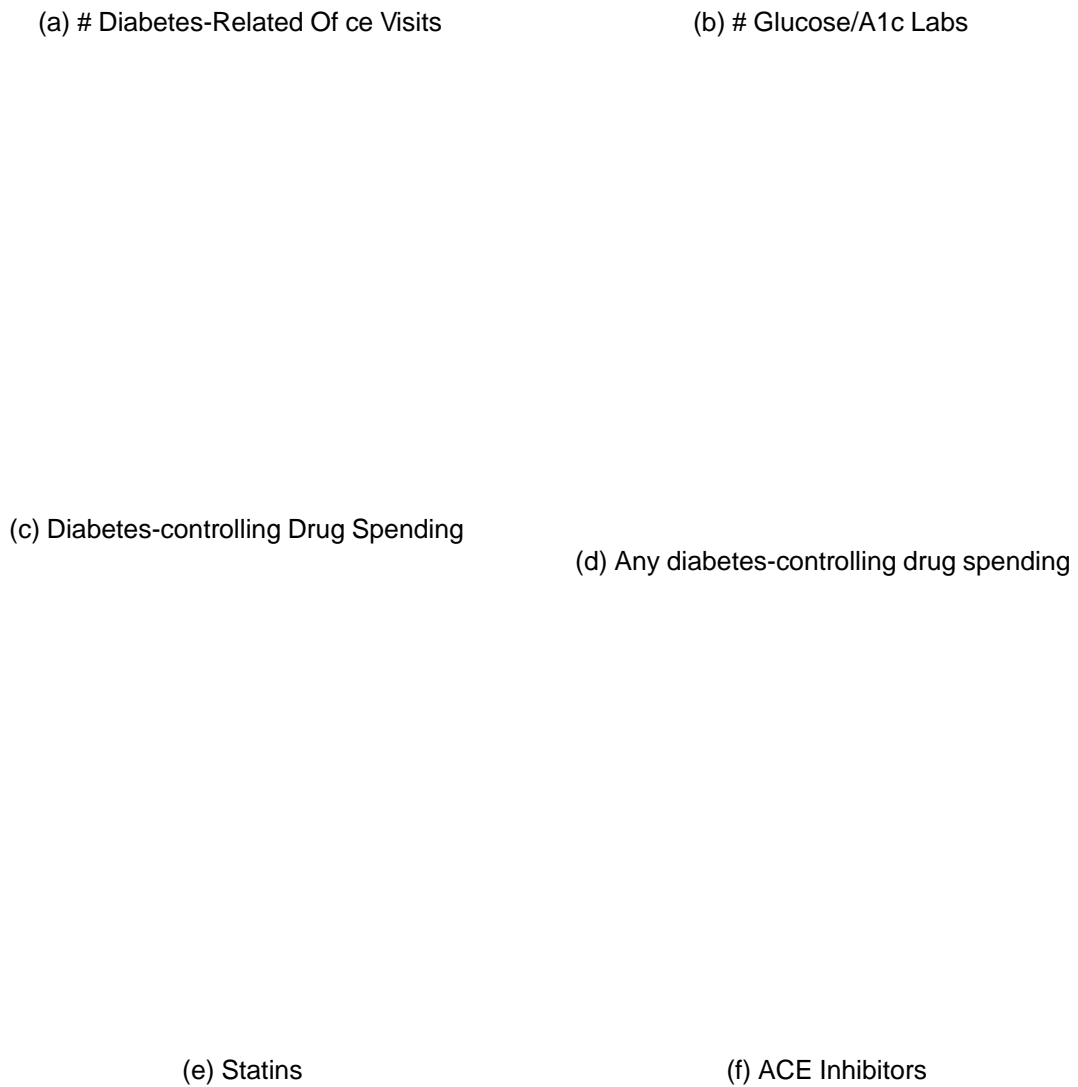
Source: Authors' calculations from the UCLA EHR data. Horizontal axis indicates the year relative to the initial lab test. Vertical axis indicates size of the regression discontinuity effect estimated using local linear regression. 95 percent confidence intervals displayed.

Figure 11: Optum Spending Outcomes Using a Balanced (red) vs. Unbalanced (black) Panel



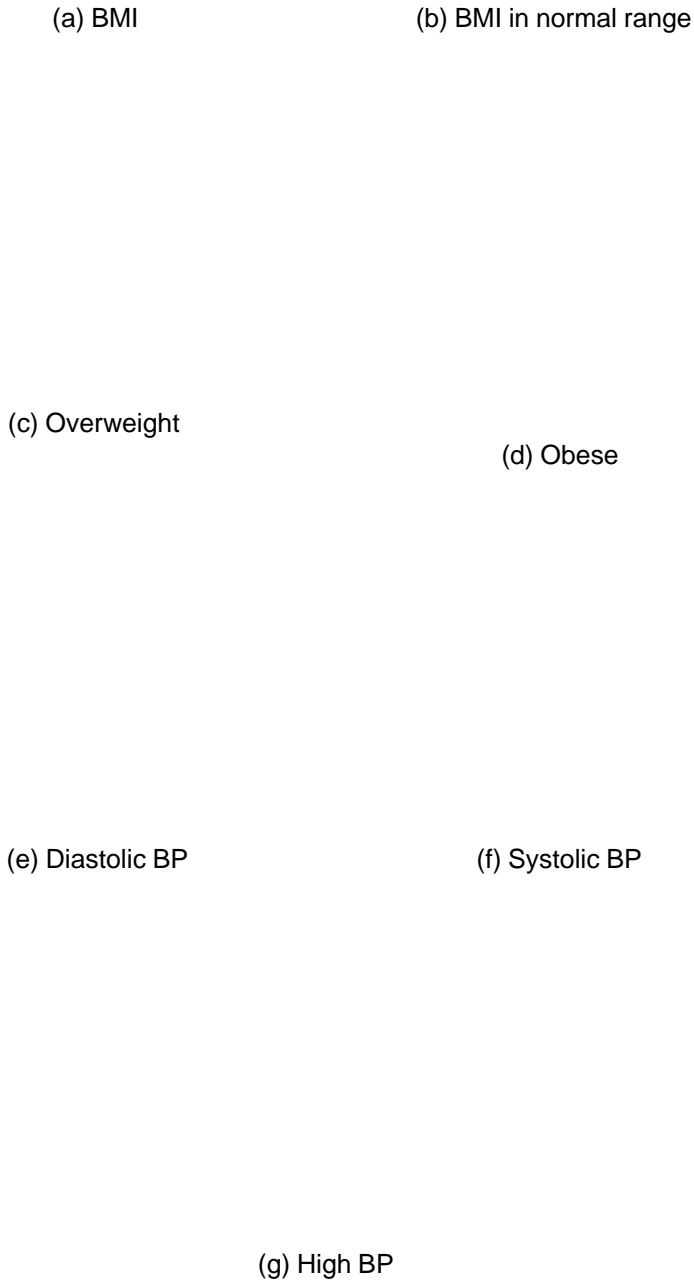
Source: Authors' calculations from the Optum Health Risk Assessment claims data. Horizontal axis indicates the year relative to the initial lab test. Vertical axis indicates size of the regression discontinuity effect estimated using local linear regression. 95 percent confidence intervals displayed.

Figure 12: Optum Utilization Outcomes Using a Balanced (red) vs. Unbalanced (black) Panel



Source: Authors' calculations from the Optum claims data. Horizontal axis indicates the year relative to the initial lab test. Vertical axis indicates size of the regression discontinuity effect estimated using local linear regression. 95 percent confidence intervals displayed.

Figure 13: UCLA EHR Outcomes Using a Balanced (red) vs. Unbalanced (black) Panel



Source: Authors' calculations from the Optum claims data. Horizontal axis indicates the year relative to the initial lab test. Vertical axis indicates size of the regression discontinuity effect estimated using local linear regression. 95 percent confidence intervals displayed.

Table 2: RD Estimates of Effects of Diabetes Diagnosis on Spending by Category in First 12 Months Following A1c Test

	Control Mean (Std Dev)	Reduced Form Estimate	IV Estimate of Effect of Diagnosis
Diabetes Diagnosis	0.183	0.108*** (0.019)	NA
Spending on ADA-Recommended Care	362.03 (718.09)	207.609*** (22.912)	1,096.894*** (112.295)
Spending on Office-Based Care Related to Diabetes	26.17 (122.28)	79.112*** (6.912)	507.661*** (42.690)
Spending on Diabetes-Related Vision Services	2.26 (27.92)	5.483*** (1.446)	28.215*** (7.360)
Spending on Diabetes-Related Labs	89.10 (353.69)	78.650*** (13.891)	505.367*** (80.798)
Endocrinology Specialist Care Spending	19.95 (313.62)	38.741* (23.024)	139.092* (82.668)

Notes: Control means calculated using observations with A1c test values below 6.5 and greater than or equal to 6. Coefficient estimates from local linear regression with optimal bandwidth calculation from Fuji, Imbens, and Kalyanaraman (2009). Asterisks denote level of statistical significance: * > 0.10, ** > 0.05, *** > 0.01.

Table 3: RD Estimates of Effects of Diabetes Diagnosis on Drug Spending and Other Utilization Measures in First 12 Months Following A1c Test

	Control Mean (Std Dev)	Reduced Form Estimate	IV Estimate of Effect of Diagnosis
Number of Diabetes-Related Office Visits	0.177 (0.775)	0.450*** (0.045)	3.166*** (0.298)
Number of A1c or Glucose Labs	1.46 (1.01)	0.063* (0.032)	0.393** (0.194)
Spending on Diabetes-Controlling Drugs	4.37 (97.04)	5.264 (3.497)	24.379 (16.183)
Any Spending on Diabetes Drugs	0.005	0.009*** (0.003)	0.043*** (0.014)
Spending on Statins	151.21 (436.84)	2.073 (9.799)	8.939 (49.50)
Spending on ACE Inhibitors	96.00 (299.36)	13.767** (7.020)	55.420** (28.258)

Notes: Control means calculated using observations with A1c test values below 6.5 and greater than or equal to 6. Coefficient estimates from local linear regression with optimal bandwidth calculation from Fuji, Imbens, and Kalyanaraman (2009). Asterisks denote level of statistical significance: * > 0.10, ** > 0.05, *** > 0.01.

Table 4: RD Estimates of Effects of Diabetes Diagnosis on Subsequent Diagnoses of "Preventable" Conditions, Subsequent A1c, and Mortality in First 12 Months Following A1c Test

	Control Mean (Std Dev)	Reduced Form Estimate	IV Estimate of Effect of Diagnosis
Diabetic Retinopathy	0.0018	0.004** (0.002)	0.021** (0.010)
Diabetic Neuropathy	0.007	0.010** (0.004)	0.068*** (0.029)
Kidney Disease	0.0063	0.018*** (0.004)	0.111*** (0.026)
Ketoacidosis	0.0006	0.002 (0.001)	0.009 (0.006)
Diabetic Coma	0.0006	0.001 (0.001)	0.006 (0.005)
Change in A1c from Previous Year	-0.0564 (0.460)	-0.059** (0.027)	-0.342** (0.166)
Change in Total Cholesterol from Previous Year	-6.429 (32.62)	-1.471 (1.212)	-4.993 (4.114)
Mortality	0.005 (0.073)	0.0002 (0.001)	0.001 (0.007)

Notes: Control means calculated using observations with A1c test values below 6.5 and greater than or equal to 6. Coefficient estimates from local linear regression with optimal bandwidth calculation from Fuji, Imbens, and Kalyanaraman (2009). Asterisks denote level of statistical significance: * > 0.10, ** > 0.05, *** > 0.01.

Table 5: RD Estimates of Effects of Diabetes Diagnosis on BMI and Blood Pressure in First 12 Months Following A1c Test (UCLA EHR Results)

	Control Mean (Std Dev)	Reduced Form Estimate	IV Estimate of Effect of Diagnosis
Diabetes Diagnosis	0.080	0.292*** (0.041)	NA
BMI	28.47 (5.51)	0.137 (0.245)	0.430 (0.767)
Normal BMI	0.267	0.001 (0.025)	0.004 (0.070)
Overweight	0.343	0.004 (0.030)	0.010 (0.082)
Obese	0.356	-0.003 (0.026)	0.010 (0.083)
Diastolic blood pressure	76.13 (8.31)	-1.041 (0.710)	-4.016 (2.764)
Systolic blood pressure	129.34 (14.29)	-0.148 (0.910)	-0.384 (2.365)
High blood pressure	0.225	-0.009 (0.032)	-0.022 (0.080)

Notes: Control means calculated using observations with A1c test values below 6.5 and greater than or equal to 6. Coefficient estimates from local linear regression with optimal bandwidth calculation from Fuji, Imbens, and Kalyanaraman (2009). Models for all outcomes, with the exception of diabetes diagnosis, control for the baseline (pre-test) level of the outcome variable. Asterisks denote level of statistical significance: * > 0.10, ** > 0.05, *** > 0.01.

Table 6: RD Estimates of Effects of Diabetes Diagnosis on Self-Reported Health and Behaviors in First 12 Months Following A1c Test (Health Risk Assessment Results)

	Reduced Form Estimate	IV Estimate of Effect of Diagnosis
Diabetes Diagnosis	0.159*** (0.040)	NA
Self Reported Health Very Good or Excellent	-0.116 (0.083)	-0.728 (0.558)
Physical and Emotional Well-Being	-0.077 (0.058)	-0.292 (0.221)
Diet and Exercise	-0.003 (0.053)	-0.014 (0.289)
Healthy Smoking and Drinking Choices	-0.054 (0.060)	-0.323 (0.369)

Notes: Coef cient estimates from local linear regression with optimal bandwidth calculation from Fuji, Imbens, and Kalyanaraman (2009). Asterisks denote level of statistical signi cance: * > 0.10, ** > 0.05, ***> 0.01.

Table 7: Heterogeneity in RD Estimates of Effects of Diabetes Diagnosis on Spending

	Primary Care		Specialist	
	Control Mean	Estimate	Control Mean	Estimate
Reduced Form RD Estimate Diabetes Diagnosis	0.196	0.121*** (0.025)	0.184	0.193*** (0.046)
IV Estimate of Effect of Diagnosis Spending on ADA- Recommended Care	778.3	1,200.072*** (185.481)	929.7	1,458.434*** (413.089)
Spending on Of ce-Based Care Related to Diabetes	76.49	531.150*** (79.383)	44.15	636.954** (266.801)
Spending on Diabetes- Related Vision Services	9.668	22.146* (12.059)	4.770	18.279 (18.682)
Spending on Diabetes- Related Labs	204	550.138*** (103.936)	216.7	636.954** (266.801)
Endocrinology Specialist Care Spending	15.61	89.584 (75.718)	59.63	168.179 (107.060)
Spending on Diabetes- Controlling Drugs	5.842	8.737* (5.229)	6.456	-14.025 (25.799)
Change in A1c	-0.0503	-0.111 (0.223)	-0.06816	-0.651 (0.504)

Notes: Control means calculated using observations with A1c test values below 6.5 and greater than or equal to 6. Coef cient estimates from local linear regression with optimal bandwidth calculation from Fuji, Imbens, and Kalyanaraman (2009). Asterisks denote level of statistical significance: * > 0.10, ** > 0.05, *** > 0.01.

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What Difference Does a Diagnosis Make? Evidence from Marginal Patients

Appendix

Mattan Alalouf Sarah Miller Laura R. Wherry

1 Additional Results

We include several additional results in the Appendix that are discussed in the text. These results are presented in Tables [A1-A17](#).

2 Health Risk Assessment Questions by Category

Alcohol and Tobacco Use

- How many alcoholic drinks do you consume per week?
- Do you currently use cigarettes?
- Do you currently use cigars or pipes?
- Do you currently use smokeless tobacco?

Diet and Exercise

- How many servings of high-fat foods do you consume per day?
- During a typical week, how many days do you do physical activity outside your job?
- Have you made changes recently to manage your weight?
- Have you made an effort recently to change physical activity?

Health Status

- How would you rate your health?

Physical and Emotional Well-Being

- In general, how often is stress a problem for you?
- In the past year, how much effect has stress had on your health
- In the past year, how many days have you missed an entire workday due to physical or mental health problems?
- In the past two weeks, how often did physical/emotional problems make it difficult to work the required hours?

- In the past two weeks, how often were you able to repeat the same motions working without difficulty caused by physical health?
- In the past two weeks, how often did physical/emotional problems make it difficult to concentrate on work?
- In the past two weeks, how often did physical/emotional problems make it difficult to handle your workload?
- In the past two weeks, how often did physical/emotional problems make it difficult to help people get work done?
- In the past two weeks, how often did physical/emotional problems make it difficult to feel capable?
- In the past four weeks, how much did your health problems affect your ability to do your regular daily activities?

3 Additional Details on UCLA EHR Data

For the purposes of this research project, de-identified medical records data were acquired through the Informatics Program of the UCLA Clinical and Translational Science Institute. The data were extracted from UCLA's Integrated Clinical and Research Data Repository (xDR), a large scale clinical data warehouse that includes a full copy of the CareConnect Clarity data warehouse linked to "legacy" data from older outpatient and hospital billing and managed care systems. Encounter data from xDR, which include hospitalizations, outpatient visits, and other encounter types, were used from the period January 1, 2006 to November 30, 2016. These data include information on the type of encounter, billing diagnoses, procedures completed (per billing data), and laboratory test results. Data on medication orders were only available starting in March 2, 2013 with the introduction of the CareConnect system at UCLA.

In contrast to Optum, the UCLA data include lab results for every lab ordered by a UCLA provider, including those processed by outside lab facilities. In addition, features of the medical records data that are unavailable in the Optum claims are the inclusion of vital sign data and problem lists, which are health conditions recorded by the physician during an encounter and are visible to the patient on the electronic patient portal and in printed visit summaries. The vital sign data and problem lists are only available starting in March 2, 2013 with the introduction of the current EHR CareConnect system at UCLA.

4 Construction of Analytic Samples

4.1 Optum Data

We identify each patient's initial A1c lab test in the Optum database. The database contains test descriptions and result values for lab tests provided by Optum affiliated laboratories. Patients who never receive A1c tests are not included in the analytic sample. We identified A1c tests as those with LOINC

codes 4548-4, 27353-2, 17856-6, and 17855-8. We used the test description text to drop remaining inappropriate tests. We include only patients who were 18 or older at the time of the initial test. We do not include patients whose first A1c test occurred before 2009.

We drop patients who have any inpatient, outpatient, or drug spending related to diabetes prior to the date of the first observed lab test (see Appendix Table A18). We treat inpatient and outpatient spending as related to diabetes if any of the associated ICD-9 diagnosis codes begin with “249,” or “250,” or if the associated ICD-10 codes begin with “E08,” “E09,” “E10,” “E11,” “E13.” Individuals with diabetes related lab tests (e.g. fasting plasma glucose, and random glucose tests) prior to the date of the first A1c test are also excluded. We also drop patients with pregnancy related diagnosis codes any time prior to the initial A1c test so that we can focus on standard diabetes diagnoses separately from gestational diabetes. We treat drug spending as related to diabetes if the prescription's National Drug Code (NDC) matches any of those in Appendix Table A19. We only observe the quarter in which a drug was prescribed, and we treat the first date of the quarter as the time of prescription.

We impose restrictions on how long patients must be present in the Optum data to ensure that we are identifying each patient's first A1c test. Without requiring that patients be present in the data prior to the date of the first test, we would likely mis-classify individuals with previously diagnosed diabetes (diagnosed and treated prior to their first Optum claim) with initial diabetes diagnoses. The Optum files provide records of insurance enrollment dates for each patient. We drop patients from our analysis if they were not enrolled in an Optum-covered insurance plan for at least 366 days prior to and following the date of the initial lab test. Many patients changed insurance plans during the sample period. We included these patients as long as they were covered under some Optum plan for the full 732 day period around the initial lab test, no matter how many times they switched plans. Some patients had brief breaks in coverage in the dates before and after the initial lab test. We dropped patients who had either had multiple breaks in coverage or had at least one break of more than 60 days.

We identify providers who ordered a patient's first A1c test by linking the first A1c test in the lab file to claims in the outpatient file. We link claims by date, patient, and procedure code. We consider a claim linked to the lab file for the same patient if the first date on the claim is within the seven days prior to the first date on the lab, and the procedure code is either 83036 or 83021 (hemoglobin A1c), or if the type of service code is “office visit.” When multiple claims link to a lab by this approach, we choose one claim to identify the provider using the following ranking: 1) claims where the procedure code is either 83036 or 83021 and the provider category is not in 0005, 0054, 0055, 0057, 1211, 1294, or 4834 (independent laboratory). 2) claims where the type of service code is “office visit,” and the provider category is not in 0005, 0054, 0055, 0057, 1211, 1294, or 4834. 3) claims where the provider category is in 0005, 0054, 0055, 0057, 1211, 1294, or 4834. If multiple claims meet one of these conditions, we select the claim with the first date closest to the first date of the A1c test in the lab file. If multiple claims meet one of these conditions and share the same first date, we select a claim at random.

For each provider linked to a patient in our analytic sample, we calculate the fraction of patients who had a claim with that provider for whom the provider ordered an A1c test. To calculate this measure, we use claims from the outpatient file. Claims with a procedure code of 83036 or 83021 are included as A1c tests. We determine the number of patients for whom the provider ordered at least one A1c test in the six months starting from the first date the provider ordered an A1c test for a patient

in our analytic file. We divide the number of patients with an A1c test by the number of patients who had any claim from the provider during that same six-month period.

4.2 UCLA EHR Data

The analytic sample was composed of all individuals with PCPs at UCLA aged 18 and older at the time of their first encounter with at least one A1c test for diabetes. Since LOINC codes were unavailable for the majority of labs, we identified A1c tests through text search of lab test descriptions to match the selection criteria used in the Optum data.

Since EHR vital records were only collected beginning in 2013, we exclude individuals with initial A1c tests that occurred prior to 2013. In order to preserve patient confidentiality, the EHR data have limited information available on dates of service. Each encounter is dated by the number of days relative to the patient's first encounter. In addition, we have information on the calendar year of the patient's last encounter. Therefore, we estimate the calendar year of the lab test by subtracting the difference in the number of days between the last encounter date and the lab test date divided by 365 from the calendar year of the patient's last encounter.

We required that each individual have at least one year of data prior to their initial diabetes test and that they have at least one encounter one year after the test date (i.e. remained in the data for at least one year following the test). Additional exclusions were made for individuals receiving a glucose test prior to the initial A1c test, individuals with diagnosis codes related to diabetes at any time prior to the test date, individuals with diagnosis codes related to pregnancy during the year prior to the test date, and anyone taking a drug for diabetes management prior to the test date. Similar to the Optum data, we have access to UCLA data prior to 2013 with information on encounters and labs dating back to 2006. We use this entire period to implement these sample exclusions, with the exception of the exclusion based on receipt of drugs for diabetes management. The last exclusion was only applied in 2013 or later since the prescription drug data are only available for these later years.

Figure A1: Details on Sample Construction: Optum

Figure A2: Details on Sample Construction: UCLA EHR

Figure A3: Optum Diagnosis and Spending Outcomes by Year After Initial Lab Test

(a) Health Very Good or Excellent

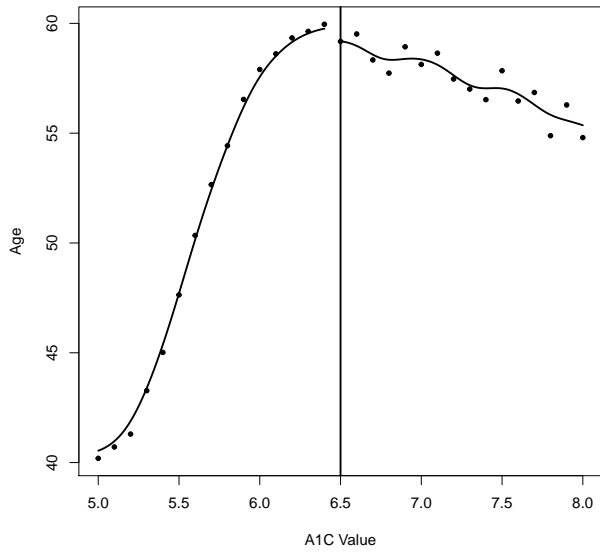
(b) Physical and Emotional Well-Being

(d) Diet and Exercise

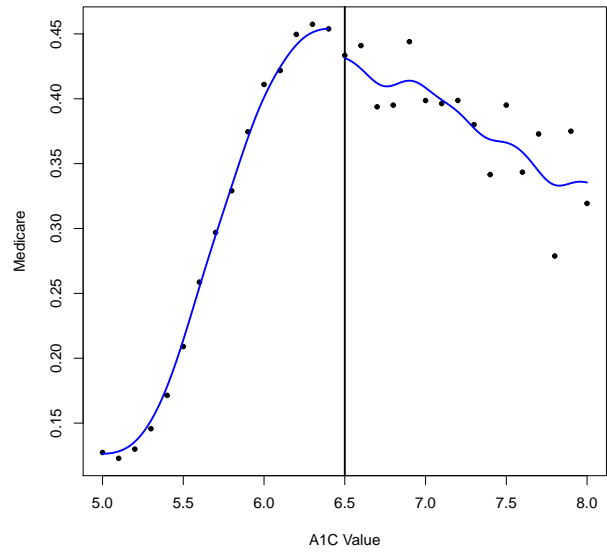
(e) Healthy Smoking and Drinking Choices

Source: Authors' calculations from the HRA survey data. Horizontal axis indicates the year relative to the initial lab test. Vertical axis indicates size of the regression discontinuity effect estimated using local linear regression. 95 percent confidence intervals displayed.

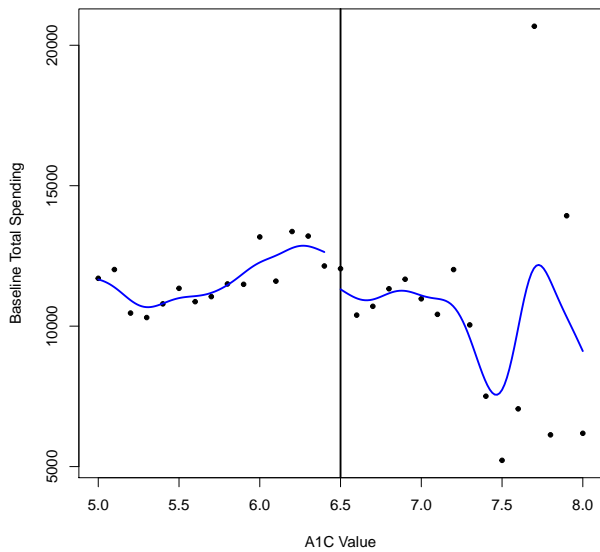
Figure A4: Optum Spending and Insurance Outcomes in Year Prior to Initial Lab Test



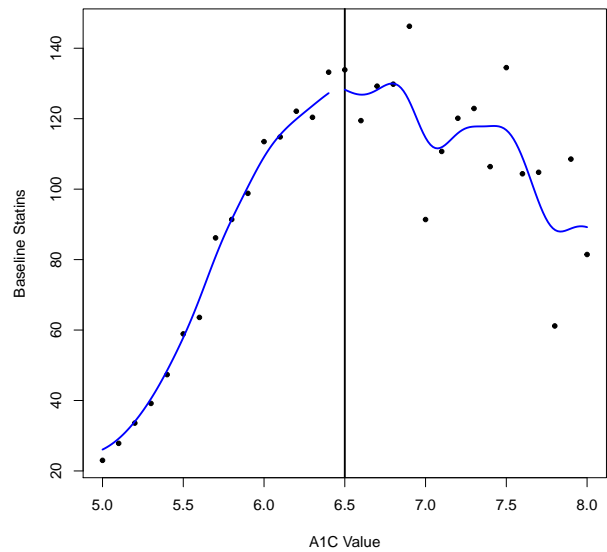
(a) Age



(b) Medicare Advantage



(d) Total Spending



(e) Spending on Statins

Source: Authors' calculations from Optum data. Horizontal axis indicates the year relative to the initial lab test. Vertical axis indicates size of the regression discontinuity effect estimated using local linear regression. 95 percent confidence intervals displayed.

Table A1: RD Estimates of Effects of Diabetes Diagnosis in First 12 Months

	Control Mean (Std Dev)	Reduced Form Estimate	IV Estimate of Effect of Diagnosis
Number of A1c Tests at Optum-Affiliated Lab	0.436	0.046** (0.019)	0.205** (0.081)
Any A1c Test at Optum-Affiliated Lab	0.326	0.004 (0.011)	0.018 (0.054)
Number of Cholesterol Tests at Optum-Affiliated Lab	0.509	0.024 (0.020)	0.120 (0.099)
Any Cholesterol Test at Optum-Affiliated Lab	0.369	0.003 (0.011)	0.019 (0.070)

Notes: Control means calculated using observations with A1c test values below 6.5 and greater than or equal to 6. Coefficient estimates from local linear regression with optimal bandwidth calculation from Fuji, Imbens, and Kalyanaraman (2009). Asterisks denote level of statistical significance: * > 0.10, ** > 0.05, *** > 0.01.

Table A2: Diagnosis and Procedure Codes Used to Measure Spending Outcomes

Description	ICD 9 Codes	ICD 10 Codes	CPT Codes
Diabetes Related DX	249, 250	E08, E09, E10, E11, E13	N/A
Preventable Conditions	2501, 2502, 2504, 2050, 2506	E101, E111, E100, E110, E102, E112, E103, E113, E104, E114	N/A
Diabetic Ketoacidosis	2501	E101, E111	N/A
Diabetic Coma	2502	E100, E110	N/A
Kidney Disease	2504	E102, E112	N/A
Diabetic Retinopathy	2505	E103, E113	N/A
Diabetic Neuropathy	2506	E104, E114	N/A
Consultations	N/A	N/A	99201-99215, 99241-99245
Nutritional Therapy	N/A	N/A	98960, 98961, 98962, 99078
Monitoring	N/A	N/A	95250, 95251
Self Management Training	N/A	N/A	98960, 98961, 98962, 99078
Recommended Care	N/A	N/A	All Codes in "Monitoring," "Consultations," "Nutritional Therapy," and "Self Management and Training"
A1c or Random Glucose Labs	N/A	N/A	82947, 83036
Preventable Conditions	2501, 2502, 2504, 2050, 2506	E101, E111, E100, E110, E102, E112, E103, E113, E104, E114	N/A

Table A3: Coding All Individuals with A1c of 6.5% or Higher As Receiving a Diagnosis

	IV Estimate of Effect of Diagnosis
Spending on ADA Recommended Care	242.314*** (30.471)
Spending on Office-Based Care Related to Diabetes	134.602*** (9.796)
Spending on Diabetes-Related Labs	126.778*** (21.583)
Spending on Diabetes-Related Vision Services	5.437*** (1.906)
Spending on Diabetes-Controlling Drugs	7.574* (4.352)
Spending on Statins	0.826 (11.404)
Spending on ACE Inhibitors	19.058* (9.950)
Endocrinology Specialist Care Spending	54.409* (31.843)
Change in A1c from Previous Year	-0.135** (0.067)
Mortality [^]	0.001 (0.002)

Notes: Coefficient estimates from local linear regression with optimal bandwidth calculation from Fuji, Imbens, and Kalyanaraman (2009). [^]Note that mortality is measured 2 years after the initial test as we require individuals to be present in the data and alive for the first 12 months after the initial test. Asterisks denote level of statistical significance: * > 0.10, ** > 0.05, *** > 0.01.

Table A4: Selection on Observable Characteristics at the Cutoff

	Female	Age	Black	Hispanic	Asian	Medicare
Optum	-0.019 (0.010)	-0.928* (0.556)	NA	NA	NA	-0.083*** (0.011)
UCLA EHR	-0.002 (0.035)	-0.998 (1.066)	-0.003 (0.022)	-0.001 (0.027)	-0.027 (0.026)	0.056 (0.037)
Health Risk Assessment	0.029 (0.026)	-1.185* (0.637)	NA	NA	NA	-0.001 (0.005)
Spending in Year Before Test:						
	Total spending	Recommended Care	Statins	ACE Inhibitors	Endocrinology	Specialty Care
Optum	-1,808.679** (808.22)	-13.21 (10.338)	-14.173* (7.902)	4.791 (5.787)	1.545 (1.916)	
Health Risk Assessment	251.64 (1,578.118)	-17.542 (30.655)	-42.771* (23.423)	26.489 (18.638)	-3.299 (3.240)	

Notes: Coefficient estimates from local linear regression with optimal bandwidth calculation from Fujii, Imbens, and Kalyanaraman (2009). Asterisks denote level of statistical significance: * > 0.10, ** > 0.05, *** > 0.01.

Table A5: RD Estimates of Effects of Diabetes Diagnosis in First 12 Months Following A1c Test, Controlling for Medicare Advantage Enrollment and Baseline Spending

	Control Mean (Std Dev)	Reduced Form Estimate	IV Estimate of Effect of Diagnosis
Diabetes Diagnosis	0.183	0.109*** (0.019)	
Spending on ADA Recommended Care	362.03 (718.09)	196.928*** (22.797)	1,025.114*** (108.940)
Spending on Office-Based Care Related to Diabetes	26.17 (122.28)	79.876*** (6.910)	505.539*** (42.050)
Spending on Diabetes-Related Labs	89.10 (353.69)	79.354*** (13.914)	502.903*** (79.820)
Spending on Diabetes-Related Vision Services	2.26 (27.92)	4.595*** (1.469)	27.031*** (8.559)
Endocrinology Specialist Care Spending	19.95 (313.62)	37.613 (22.987)	133.221 (81.415)
Number of Diabetes-Related Office Visits	0.177 (0.775)	0.456*** (0.045)	3.160*** (0.294)
Number of A1c/Glucose Labs	1.46 (1.01)	0.064** (0.032)	0.397** (0.192)
Spending on Diabetes-Controlling Drugs	4.37 (97.04)	4.843 (3.503)	22.096 (15.966)
Any Spending on Diabetes-Controlling Drugs	0.005	0.009*** (0.003)	0.041*** (0.014)
Spending on Statins	151.21 (436.84)	-7.354 (9.649)	-31.242 (41.094)
Spending on ACE Inhibitors	96.00 (299.36)	7.996 (6.966)	31.717 (27.601)

Notes: Control means calculated using observations with A1c test values below 6.5 and greater than or equal to 6. Coefficient estimates from local linear regression with optimal bandwidth calculation from Fuji, Imbens, and Kalyanaraman (2009). Asterisks denote level of statistical significance: * > 0.10, ** > 0.05, *** > 0.01.

Table A6: RD Estimates of Effects of Diabetes Diagnosis in First 12 Months Following A1c Test, Controlling for Medicare Advantage Enrollment And Baseline Spending

	Control Mean (Std Dev)	Reduced Form Estimate	IV Estimate of Effect of Diagnosis
Diabetic Retinopathy	0.002	0.005** (0.002)	0.023** (0.010)
Ketoacidosis	0.007	0.001 (0.001)	0.009 (0.006)
Diabetic Coma	0.006	0.001 (0.001)	0.006 (0.005)
Diabetic Neuropathy	0.0006	0.011** (0.004)	0.075*** (0.029)
Kidney Disease	0.0006	0.019*** (0.004)	0.118*** (0.026)
Change in A1c from Previous Year	-0.056 (0.460)	-0.054** (0.025)	-0.293** (0.141)
Change in Total Cholesterol from Previous Year	-6.429 (32.62)	-0.928 (1.208)	-3.169 (4.123)
Change in Creatinine from Previous Year	0.014 (0.113)	0.004 (0.005)	0.02 (0.025)
Mortality	0.005	0.001 (0.001)	0.004 (0.007)

Notes: Control means calculated using observations with A1c test values below 6.5 and greater than or equal to 6. Coefficient estimates from local linear regression with optimal bandwidth calculation from Fuji, Imbens, and Kalyanaraman (2009). ^Note that mortality is measured 2 years after the initial test as we require individuals to be present in the data and alive for the first 12 months after the initial test. Asterisks denote level of statistical significance: * > 0.10, ** > 0.05, *** > 0.01.

Table A7: RD Estimates for Sample Attrition

	Optum		UCLA EHR	
	Control Mean	Reduced Form Estimate	Control Mean	Reduced Form Estimate
Year 2	0.754	-0.017 (0.012)	0.986	-0.009 (0.009)
Year 3	0.484	0.016* (0.0097)	0.207	-0.010 (0.042)
Year 4	0.300	0.003 (0.010)		
Year 5	0.200	-0.005 (0.009)		
Year 6	0.123	-0.001 (0.008)		

Notes: Control means calculated using observations with A1c test values below 6.5 and greater than or equal to 6. Coefficient estimates from local linear regression with optimal bandwidth calculation from Fuji, Imbens, and Kalyanaraman (2009). Asterisks denote level of statistical significance: * > 0.10, ** > 0.05, *** > 0.01.

Table A8: RD Estimates of Effects of Diabetes Diagnosis in First 12 Months Following A1c Test (Health Risk Assessment Results)

	Baseline Mean	Reduced Form Estimate	IV Estimate of Effect of Diagnosis
<i>Diet and Exercise</i>			
Eat 3+ Servings of High Fat Food per Day	0.193	-0.036 (0.031)	-0.138 (0.120)
Recently made Changes to Improve Weight	0.884	0.019 (0.044)	0.189 (0.467)
Engage in Physical Activity 3+ times per week	0.519	0.044 (0.042)	0.192 (0.195)
Recently Made Changes to Increase Physical Activity	0.903	0.008 (0.037)	0.051 (0.250)
<i>Physical and Emotional Well-Being</i>			
Health Interferes with Activities of Daily Life	0.131	0.012 (0.039)	0.135 (0.446)
Stress Intereferes with Health Quite a Bit or A Lot	0.101	0.005 (0.029)	0.026 (0.167)
Stress is a problem Sometimes, Almost Always or Always	0.371	0.022 (0.050)	0.174 (0.396)
<i>In the past 2 weeks, physical/emotional problems made it difficult... (some of the time or more)</i>			
...to feel capable	0.147	-0.014 (0.036)	-0.091 (0.237)
...to handle workload	0.089	-0.008 (0.028)	-0.043 (0.149)
...to help others with work	0.152	-0.001 (0.035)	-0.003 (0.157)
...to start work right away	0.069	-0.035 (0.022)	-0.16 (0.103)
...to concentrate at work	0.18	0.034 (0.041)	0.201 (0.248)
...to do repetitive tasks	0.151	-0.033 (0.034)	-0.13 (0.141)
...to work the number of hours required by your job	0.076	-0.007 (0.030)	-0.054 (0.235)
of days missed work due to physical or mental health problems	0.151	0.023 (0.036)	0.118 (0.192)
<i>Self-Reported Health</i>			
Health is Very Good or Excellent	0.514	-0.058 (0.041)	-0.363 (0.276)
<i>Smoking and Drinking Behavior</i>			
Currently Smoke Cigarettes	0.084	0.045* (0.027)	0.208 (0.130)
Currently Smoke Cigars	0.018	-0.006 (0.009)	-0.028 (0.040)
Currently Use Smokeless Tobacco	0.014	-0.003 (0.005)	-0.022 (0.044)
Number of Alcoholic Drinks Weekly	1.358	0.022 (0.181)	0.091 (0.758)

Notes: Coefficient estimates from local linear regression with optimal bandwidth calculation from Fuji, Imbens, and Kalyanaraman (2009). Asterisks denote level of statistical significance: * > 0.10, ** > 0.05, *** > 0.01.

Table A9: Alternative models and bandwidths: Spending and Utilization Outcomes

	Main model	Global quadratic model	Optimal Bandwidth x 2	Optimal Bandwidth x 0.5
Diabetes Diagnosis	0.108*** (0.019)	0.292*** (0.011)	0.161*** (0.013)	0.178*** (0.016)
Spending on ADA Recommended Care	207.609*** (22.912)	270.396*** (18.260)	268.938*** (18.671)	137.849*** (32.218)
Spending on Office-Based Care Related to Diabetes	79.112*** (6.912)	140.478*** (5.615)	115.549*** (5.566)	52.189*** (10.033)
Spending on Diabetes-Related Labs	78.650*** (13.891)	139.370*** (9.964)	114.484*** (10.831)	34.774* (20.660)
Spending on Diabetes-Related Vision Services	4.245*** (1.489)	9.249*** (1.279)	9.060*** (1.196)	3.214 (2.157)
Endocrinology Specialist Care Spending	38.741* (23.024)	30.525* (16.665)	33.576* (19.218)	44.18 (27.185)
Number of Diabetes-Related Office Visits	0.442*** (0.046)	0.899*** (0.034)	0.260*** (0.075)	0.673*** (0.035)
Number of A1c/Glucose Labs	0.063** (0.032)	0.102*** (0.024)	0.109*** (0.024)	0.06 (0.048)
Spending on Diabetes-Controlling Drugs	5.264 (3.497)	-1.01 (5.168)	8.232** (3.422)	-1.157 (4.627)
Any Spending on Diabetes-Controlling Drugs	0.010*** (0.003)	0.010*** (0.003)	0.013*** (0.003)	0.005 (0.004)
Spending on Statins	2.073 (9.799)	-13.013 (7.967)	-0.991 (8.209)	9.522 (13.486)
Spending on ACE Inhibitors	13.767** (7.020)	5.975 (5.825)	16.678*** (5.949)	13.999 (9.447)

Notes: Baseline means calculated using observations with A1c test values below 6.5 and greater than or equal to 6. Coefficient estimates from local linear regression with optimal bandwidth calculation from Fuji, Imbens, and Kalyanaraman (2009). ^Note that mortality is measured 2 years after the initial test as we require individuals to be present in the data and alive for the first 12 months after the initial test. Asterisks denote level of statistical significance: * > 0.10, ** > 0.05, *** > 0.01.

Table A10: Alternative model and bandwidths: Preventable Conditions and Optum Health Outcomes

	Main model	Global quadratic model	Optimal Bandwidth x 2	Optimal Bandwidth x 0.5
Diabetic Retinopathy	0.004** (0.002)	0.006*** (0.002)	0.006*** (0.002)	0.004 (0.003)
Ketoacidosis	0.002 (0.001)	0.001 (0.001)	0.001* (0.001)	0.001 (0.001)
Diabetic Coma	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Diabetic Neuropathy	0.010** (0.004)	0.018*** (0.003)	0.017*** (0.003)	0.004 (0.007)
Kidney Disease	0.018*** (0.004)	0.024*** (0.003)	0.023*** (0.003)	0.017*** (0.006)
Change in A1c from Previous Year	-0.062** (0.028)	0.061** (0.024)	-0.014 (0.019)	-0.105*** (0.039)
Change in Total Cholesterol from Previous Year	-5.26 (4.03)	-2.006* (1.172)	3.686 (2.757)	-5.212 (8.796)
Change in Creatinine from Previous Year	0.018 (0.025)	-0.004 (0.004)	-0.002 (0.012)	0 (0.061)
Mortality^	0.000 (0.001)	0.000 (0.0004)	0.000 (0.001)	0.000 (0.001)

Notes: Baseline means calculated using observations with A1c test values below 6.5 and greater than or equal to 6. Coefficient estimates from local linear regression with optimal bandwidth calculation from Fuji, Imbens, and Kalyanaraman (2009). Asterisks denote level of statistical significance: * > 0.10, ** > 0.05, *** > 0.01.

Table A11: Alternative model and bandwidths: Clinical Health Measures

	Main model	Global quadratic model	Optimal Bandwidth x 2	Optimal Bandwidth x 0.5
Diabetes Diagnosis	0.292*** (0.041)	0.300*** (0.041)	0.421*** (0.032)	0.210*** (0.061)
BMI	0.137 (0.245)	0.242 (0.271)	0.068 (0.196)	0.23 (0.302)
Normal BMI	0.001 (0.025)	-0.002 (0.030)	0.011 (0.021)	0.006 (0.032)
Overweight	0.004 (0.030)	0.025 (0.037)	-0.019 (0.026)	0.015 (0.041)
Obese	-0.003 (0.026)	-0.006 (0.028)	0.005 (0.020)	-0.027 (0.043)
Diastolic blood pressure	-1.041 (0.710)	-0.807 (0.737)	-0.628 (0.541)	-1.302 (1.004)
Systolic blood pressure	-0.148 (0.910)	-0.653 (1.213)	-0.089 (0.794)	-0.807 (1.173)
High blood pressure	-0.009 (0.032)	-0.019 (0.045)	0 (0.029)	-0.013 (0.041)

Notes: Control means calculated using observations with A1c test values below 6.5 and greater than or equal to 6. Coefficient estimates from local linear regression with optimal bandwidth calculation from Fuji, Imbens, and Kalyanaraman (2009). Models for all outcomes, with the exception of diabetes diagnosis, control for the baseline (pre-test) level of the outcome variable. Asterisks denote level of statistical significance: * > 0.10, ** > 0.05, *** > 0.01.

Table A12: Alternative model and bandwidths: Health Risk Assessment outcomes

	Main model	Global quadratic model	Optimal Bandwidth x 2	Optimal Bandwidth x 0.5
Diet and Exercise	-0.003 (0.053)	-0.014 (0.059)	0.002 (0.044)	0.07 (0.075)
Physical and Emotional Well-Being	-0.077 (0.058)	-0.023 (0.067)	-0.097* (0.050)	-0.044 (0.073)
Self Reported Health Very Good or Excellent	-0.116 (0.083)	-0.048 (0.090)	-0.115* (0.067)	-0.242** (0.121)
Healthy Smoking and Drinking Choices	-0.054 (0.060)	-0.1 (0.067)	-0.026 (0.050)	-0.03 (0.084)

Notes: Coefficient estimates from local linear regression with optimal bandwidth calculation from Fuji, Imbens, and Kalyanaraman (2009). Asterisks denote level of statistical significance: * > 0.10, ** > 0.05, *** > 0.01.

Table A13: RD Estimates of Effects of Diabetes Diagnosis in First 12 Months Following A1c Test Including Only Those Enrolled for at least 2 Years Prior to Initial Test

	Baseline Mean (Std Dev)	Reduced Form Estimate	IV Estimate of Effect of Diagnosis
Diabetes Diagnosis	0.172	0.108*** (0.022)	
Spending on ADA Recommended Care	351.46 (706.71)	211.666*** (26.851)	1,050.503*** (124.805)
Spending on Office-Based Care Related to Diabetes	25.13 (120.05)	70.649*** (9.316)	499.217*** (63.702)
Spending on Diabetes-Related Labs	80.22 (341.30)	80.121*** (14.223)	449.530*** (71.981)
Spending on Diabetes-Related Vision Services	2.17 (28.01)	3.953** (1.550)	16.988** (6.599)
Endocrinology Specialist Care Spending	19.65 (207.01)	33.653 (28.627)	111.773 (95.055)
Number of Diabetes-Related Office Visits	0.170 (0.770)	0.427*** (0.062)	3.223*** (0.444)
Number of A1c/Glucose Labs	1.48 (0.996)	0.054 (0.036)	0.28 (0.179)
Spending on Diabetes-Controlling Drugs	4.51 (99.59)	2.644 (4.371)	11.177 (18.462)
Any Spending on Diabetes-Controlling Drugs	0.005 (0.072)	0.006 (0.004)	0.027 (0.018)
Spending on Statins	151.7 (436.06)	21.72 (14.213)	117.688 (77.162)
Spending on ACE Inhibitors	94.79 (296.56)	15.313* (8.003)	54.366* (28.455)

Notes: Baseline means calculated using observations with A1c test values below 6.5 and greater than or equal to 6. Coefficient estimates from local linear regression with optimal bandwidth calculation from Fuji, Imbens, and Kalyanaraman (2009). Asterisks denote level of statistical significance: * > 0.10, ** > 0.05, *** > 0.01.

Table A14: RD Estimates of Effects of Diabetes Diagnosis in First 12 Months Following A1c Test Including Only Those Enrolled for at least 2 Years Prior to Initial Test

	Baseline Mean (Std Dev)	Reduced Form Estimate	IV Estimate of Effect of Diagnosis
Diabetic Retinopathy	0.002	0.004 (0.003)	0.021 (0.013)
Ketoacidosis	6e-04	0.001 (0.001)	0.008 (0.007)
Diabetic Coma	7e-04	-5e-04 (0.001)	-0.003 (0.006)
Diabetic Neuropathy	0.006	0.016*** (0.005)	0.097*** (0.030)
Kidney Disease	0.007	0.022*** (0.005)	0.121*** (0.029)
Change in A1c from Previous Year	-0.08 (0.441)	-0.085** (0.040)	-0.374** (0.186)
Change in Total Cholesterol from Previous Year	-6.691 (32.47)	-1.915 (1.478)	-5.663 (4.378)
Change in Creatinine from Previous Year	0.015 (0.113)	0.005 (0.005)	0.019 (0.020)
Mortality [^]	0.001	0.001 (0.001)	0.005 (0.007)

Notes: Baseline means calculated using observations with A1c test values below 6.5 and greater than or equal to 6. Coefficient estimates from local linear regression with optimal bandwidth calculation from Fuji, Imbens, and Kalyanaraman (2009). Asterisks denote level of statistical significance: * > 0.10, ** > 0.05, *** > 0.01.

Table A15: RD Estimates of Effects of Diabetes Diagnosis in First 12 Months Following A1c Test Including Only Those Enrolled for at least 2 Years Prior to Initial Test

	Control Mean (Std Dev)	Reduced Form Estimate	IV Estimate of Effect of Diagnosis
Diabetes Diagnosis	0.031	0.410*** (0.044)	–
BMI	28.49 (5.54)	0.321 (0.329)	0.872 (0.891)
Normal BMI	0.262	-0.001 (0.029)	-0.003 (0.070)
Overweight	0.337	0.02 (0.035)	0.049 (0.088)
Obese	0.363	-0.006 (0.028)	-0.017 (0.080)
Diastolic blood pressure	76.19 (8.43)	-0.677 (0.762)	-1.969 (2.189)
Systolic blood pressure	129.67 (14.10)	0.51 (1.117)	1.248 (2.745)
High blood pressure	0.23	0.009 (0.041)	0.021 (0.100)

Notes: Baseline means calculated using observations with A1c test values below 6.5 and greater than or equal to 6. Coefficient estimates from local linear regression with optimal bandwidth calculation from Fuji, Imbens, and Kalyanaraman (2009). Asterisks denote level of statistical significance: * > 0.10, ** > 0.05, *** > 0.01.

Table A16: Spending on Elements of Recommended Care Not Identified with a Diabetes Diagnosis Code

	IV Estimate of Effect of Diagnosis
Spending on All Office Care	22.23 (84.39)
Number of Evaluation and Management Visits	-0.339 (0.479)
Spending on Statins, ACE inhibitors, diabetes-controlling drugs, glucose labs and endocrinology specialty care	254.07** (102.30)

Notes: Coefficient estimates from local linear regression with optimal bandwidth calculation from Fuji, Imbens, and Kalyanaraman (2009). Asterisks denote level of statistical significance: * > 0.10, ** > 0.05, *** > 0.01.

Table A17: RD Estimates of Effects of Diabetes Diagnosis on Utilization in First 12 Months (UCLA EHR Results)

	Control Mean (Std Dev)	Reduced Form Estimate	IV Estimate of Effect of Diagnosis
Diabetes Diagnosis	0.08	0.292*** (0.041)	N/A
Diabetes Diagnosis on Problem List	0.03	0.126*** (0.032)	0.309*** (0.072)
Number of Ambulatory Encounters Related to Diabetes	0.27 (1.58)	2.035*** (0.204)	4.452*** (0.354)
Number of A1c Labs	0.73 (0.98)	0.152* (0.085)	0.397* (0.209)
Prescription for Diabetes-Controlling Drug	0.019	0.058*** (0.017)	0.136*** (0.039)

Notes: Control means calculated using observations with A1c test values below 6.5 and greater than or equal to 6. Coefficient estimates from local linear regression with optimal bandwidth calculation from Fuji, Imbens, and Kalyanaraman (2009). Asterisks denote level of statistical significance: * > 0.10, ** > 0.05, *** > 0.01.

Table A18: Diagnosis and Procedure Codes used in Sample Selection

Description	ICD 9 Codes	ICD 10 Codes	CPT Codes	LOINC Codes
Diabetes Related DX	249, 250	E08, E09, E10, E11, E13	N/A	N/A
Pregnancy Related Diagnosis	630-672, V22-V23	O00-O99	N/A	N/A
Diabetes Lab Tests	N/A	N/A	82947, 83036, 82947, 82952	1558-6, 20435-2, 20437-0, 20438-8, 2345-7, 74774-1, 4548-4, 27353-2, 17856-6, 17855-8

Table A19: Drugs used to Determine Diabetic Drug Spending and for Sample Selection

Diabetes Related Drugs by Generic Name
acarbose
albiglutide
alogliptin
alogliptin-metFORMIN
alogliptin-pioglitazone
canagliflozin
canagliflozin-metFORMIN
chlorproPAMIDE
dapagliflozin
empagliflozin
exenatide
glimepiride
glimepiride-pioglitazone
glimepiride-rosiglitazone
glipiZIDE
glipiZIDE-metFORMIN
glyBURIDE
glyBURIDE micronized
glyBURIDE-metFORMIN
insulin aspart
insulin aspart-insulin
insulin detemir
insulin glargine
insulin glulisine
insulin isophane
insulin lispro
insulin lispro-insulin lispro protamine
insulin regular
linagliptin
linagliptin-metFORMIN
liraglutide
metFORMIN-pioglitazone
metFORMIN-repaglinide
metFORMIN-rosiglitazone
metFORMIN-saxagliptin
metFORMIN-sitaGLIPtin
miglitol
nateglinide
pioglitazone
pramlintide
repaglinide
rosiglitazone
saxagliptin
simvastatin-sitaGLIPtin
sitaGLIPtin
TOLAZamide
TOLBUTamide
