Appendix to

False Alarm? Estimating the Marginal Value of Health Signals

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We investigate the marginal value of information in the context of health signals after checkups. Although underlying health status is similar for individuals just below and above a clinical threshold, treatments differ according to the checkup signals they receive. For the general population, whereas health warnings about diabetes increase healthcare utilization, health outcomes do not improve at the threshold. However, among high-risk individuals, outcomes do improve, and improved health is worth its cost. These results indicate that the marginal value of health information depends on setting appropriate thresholds for health warnings and targeting individuals most likely to benefit from follow-up medical care.

Key words: health, signals, information, value, prevention, diabetes
JEL Classification: I10

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Online Appendix (Not for Publication)

Appendix I: Definitions of variables

Outcome variables	Definition
■ Any DM Visit	▪ Indicator variable for diagnosis of diabetes (or at least rule-out diagnostic testing for diabetes) within 1 year of the index checkup ▪ "Diagnosis" is defined by the following 2 conditions: (1) The individual has a claim that includes DM as one of the conditions and (2) Consultation days > 0. ▪ "DM" includes all diseases categorized as ICD10 codes E10~E14.
■ Number of DM visits	▪ Consultation days for DM within 1 year of the checkup
■ OGTT examination	▪ Indicator variable for conducting an oral glucose tolerance test (OGTT) within 1 year of the checkup
■ DM-related outpatient medical spending	▪ Total spending on outpatient claims that include "DM" as one of the conditions + Total spending on pharmacy claims that include a "DM drug" as one of the drugs. ▪ "DM drugs" are drugs categorized as ATC code A10.
■ Number of total visits	▪ Consultation days (for any diseases) within 1 year of the checkup
■ Total medical spending	▪ The sum of total spending on all types of claims
■ Walk or Exercise ■ Smoke ■ Drink everyday ■ Eat after dinner	▪ Self-report of health habits as measured in the health survey associated with the checkup a year after the index check-up ▪ "Walk or Exercise" = 1 if the individual reports exercising enough to work up a sweat for 30 minutes or more per day & 2~7 days per week. ("Walk or Exercise" = 0 otherwise.) ▪ "Drink everyday" = 1 if he/she drinks an alcoholic beverage every day. ("Drink everyday" = 0 otherwise.) ▪ "Smoke" = 1 if he/she has a habit of smoking. ("Smoke" = 0 otherwise.) ▪ "Eat after dinner" = 1 if he/she eats a midnight snack 3 days or more per week. ("Eat after dinner" = 0 otherwise.)
■ FBS / HbA1c / BMI / SBP	▪ The values of FBS / HbA1c / BMI / SBP measured at the checkup a year after the index checkup
■ Risk for all-cause mortality	▪ The predicted risk of death from any cause within 5 years after the index checkup, based on the risk factors measured at the index checkup, as calculated from the Hong Kong University – Singapore (HKU-SG) risk prediction model developed by Quan et al. (2019); see Appendix II.

Appendix II: Implementing the Hong Kong University – Singapore (HKU-SG) risk score for all-cause mortality

Measurement of long-run health outcomes utilizes a risk prediction model suitable for estimating all-cause mortality in our sample of adult Japanese with potential risk factors for diabetes. Quan et al. (2019) develop risk prediction scores for individuals residing in high-income East Asia by analyzing detailed clinical data for more than 1 million individuals over age 20 with type 2 diabetes in Hong Kong and Singapore. Based on more than 6 million person-years of follow-up between 2006 and 2016, the authors relate risk factors in a given year to the probability of mortality in the next five years. We use this Hong Kong University – Singapore (HKU-SG) risk score as our outcome measure because the only risk prediction model calibrated on Japanese individuals with type 2 diabetes (Tanaka et al. 2013) does not include an estimate of all-cause mortality, and other common risk prediction models such as the UK Prospective Diabetes Study (UKPDS) or the Risk Equations for Complications Of type 2 Diabetes (RECODe) are based on older treatment technology (UKPDS) or calibrated for Western populations (UKPDS and RECODe), and have been demonstrated to be less accurate for East Asian populations (Quan et al. 2019).

The Quan et al. model was developed using Cox proportional hazard models with the data for 678,750 participants from Hong Kong, and then validated with data for 386,425 participants from Singapore. The resulting HKU-SG risk scores for mortality utilize data on the following risk factors: age, duration of diabetes, gender, smoking, body mass index, systolic and diastolic blood pressure, HbA1c, LDL cholesterol and pre-existing conditions (atrial fibrillation, chronic kidney disease, ischemic heart disease and cerebrovascular disease).

We calculated the HKU-SG mortality risks that formed the basis of our net value analyses as follows. From the JMDC data, we first identified individuals considered to be at high risk for diabetes, defined as those with elevated blood pressure (SBP >= 130 mg/dl or DBP >= 85 mg/dl) and cholesterol (total triglyceride >= 150 mg/dl or HDL < 40 mg/dl). We then focus on individuals with FBS close to the "diabetic type" threshold (121<=FBS<=130) and with at least one post-checkup observation of HbA1c. This resulted in a total of 802 unique individuals. Finally, we pulled age, duration of diabetes (calculated as the difference between the date of the checkup and the first diagnosis of diabetes), gender, smoking status, history of atrial fibrillation (ICD 10 I48), chronic kidney disease (ICD 10 N18, N19, N26.9), cerebrovascular disease (ICD 10 I63), and ischemic heart disease (ICD 10 I20-I25), SBP, DBP, HbA1c, BMI and LDL values at the time of the checkup from the beneficiary and claims files of the JMDC data (see below for more detail). After merging all demographic, behavioral and clinical variables, we obtained an analytical dataset of 603 individuals with data for one pre- and one post-checkup observation.

We focus on non-DM patients who were not diagnosed as DM within the 6 months before the index check-up in our analysis. Therefore most are incident cases with duration of diagnosis equal to zero. Patients without two separate non-suspect (i.e. suspicion flag[1]=0) diagnoses of diabetes in two or more years are assigned a duration of diagnosis of 0 in all years.

[1] The JMDC claims data includes a "suspicion flag" to demarcate claims in which the physician may

Atrial Fibrillation and other pre-existing conditions

We used JMDC's disease data files to determine whether an individual had a prior history of Atrial Fibrillation (AF). For each individual, we identified the earliest year he or she had a non-suspect diagnosis of AF (I48 Atrial fibrillation and flutter). Then, for each observation for which a HKU-SG risk score was calculated, we identified whether the earliest year of AF was prior to the current year. If so, we set the dummy variable AF to 1, and 0 otherwise. Coding proceeded similarly for the other pre-existing conditions used in the HKU-SG risk scores-- chronic kidney disease, ischemic heart disease and cerebrovascular disease—by using the same condition codes as used in the Hong Kong data to develop the model.

BMI (Body Mass Index)

Height and weight are available in the JDMC checkup data and are reported in centimeter and kilograms. We calculated the BMI using the standard formula, weight (kg) / [height (m)]2 after converting height in centimeters to meters.

All other variables (age, gender, systolic and diastolic blood pressure, smoking status, LDL cholesterol and HbA1c) were taken directly from the patient demographic file or the checkup file.

Estimating reduction in mortality risk

We took the following steps to calculate the reduction in all-cause mortality from of the mandatory checkup for a hypothetical high-risk individual. First, we took the average of all continuous variables (age, duration of diabetes, SBP, DBP, HbA1c, BMI and LDL) separately in the pre- and post-checkup observations. Because the HKU-SG risk score requires an input of 0 or 1 for binary variables (gender, smoking status, history of atrial fibrillation, chronic kidney disease, cerebrovascular disease and ischemic heart disease), we expanded the 1 observation of the average values (the hypothetical average person) 10,000,000 times, and we randomly distributed the 0s and 1s over the resulting 10,000,000 observations using a uniform distribution such that the average of the binary variables equals the percentage of the variables with value 1. For example, if gender = 1 corresponds to female, and females represented 20% of the original sample of 603, there would be 10,000,000 x 0.2 or 2,000,000 randomly assigned observations with gender = 1.

To assess the impact on all-cause mortality of a reduction of 0.311 in HbA1c values with a standard deviation of 0.116, we calculated the following numbers: (1) The HKU-SG mortality rate at baseline for a hypothetical representative high-risk person, with the average HbA1c derived from the data as approximately 5.9. (2) The HKU-SG mortality rate in the post-period, with the average HbA1c defined as 5.9 – 0.311. (3) The HKU-SG mortality rate in the post-period, with the average HbA1c defined as 5.9 + (-0.311 – 1.96 * 0.116). (3) The HKU-SG mortality rate in the post period,

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suspect a given condition but has not definitively diagnosed it, such as a diagnostic rule-out test for a given medical condition like diabetes. We use "non-suspect" to describe claims lacking this suspicion flag (i.e. SUSPECT==0).

with the average HbA1c defined as 5.9 + (-0.311 + 1.96 * 0.116). The 10,000,000 mortality rates calculated in (1) to (4) were averaged to capture the hypothetical representative high-risk person. By calculating (2) – (1), we obtained the change in all-cause mortality for the hypothetical high-risk person. We calculated (3) – (1) for the lower bound of the 95% confidence interval, and (4) – (1) the upper bound. These calculations yield the results reported in section 5.4.[2]

We also calculated alternative monetary values for the reduction in risks due to the lower HbA1c, taking into consideration that the Quan model calculates five-year all-cause mortality rates. In this method, we determined the value in the mortality rate reduction as follows: We calculated (1) the baseline value as (0.0036367 (i.e., baseline mortality rate))*(value of dying immediately + value of dying after 1 year, value of dying after 2 years + value of dying after 3 years + value of dying after 4 years)/5 + (1-0.0036367)*(value of living all five years). For all values of life in future years, we discounted at 3% annually to derive the net present value. As before, we re-calculated this values for (2) the new mortality rate (0.035497) given the reduction in HbA1c for high-risk individuals, as well as the (3) lower and (4) upper bounds of the new mortality rates 0.036131 and 0.034874. We used these figures to calculate the value of the reduction in mortality risk ((2)-(1)) and the confidence interval ([(3)-(1),(4)-(1)]) as described previously.

[2] Additional robustness checks using the Tanaka et al. (2013) risk model and cardiovascular risk prediction scores of the World Health Organization provide broadly similar results, confirming lack of cost-effectiveness for the general population and the benefit of targeting high risks.

Appendix III: Comparing our results to those of two similar studies with Korean and US data

In this section, we highlight the similarities and differences between our study and two closely related ones that also cite ours, Kim et al. (2019) on health screening in Korea and Alalouf et al. (2019) on marginally diagnosed patients in the United States. Each study has strengths for assessing impacts of exceeding a diabetes threshold in the context of different OECD-country health systems. Our study provides information on the short- and longer-run (up to 5-year) effects of mandatory checkups among a working-age population who enjoy universal health coverage. The Kim et al. (2019) study may be most relevant for understanding the effects of voluntary subsidized screening programs, in light of self-selection of individuals into baseline screening and follow-up care, as well as observing the 3- or 4-year outcomes for those who self-select into continued screening. The US study reveals the effects of exceeding the threshold for patients receiving regular medical care (not a health checkup or screening program) among commercially-insured individuals in the US, following individuals up to 6 years after they exceed the HbA1c threshold.

Our study and Kim et al. (2019) use FBS values from screening or checkup results, based on lab reports linked to claims data. Our Japan sample includes working-age adults. The Korean sample also includes older, unemployed or retired individuals, with more women than in the Japan sample. Alalouf et al. (2020) use A1c values from an initial blood test, analyzing medical claims (Optum) and EHRs (from UCLA) to follow patients for six years after the blood test where they crossed the HbA1c threshold for diabetes. They also analyze Health Risk Assessment survey data for the small subset of Optum enrollees who complete such a survey in a given year.

We focus most on the already-published study that includes both the pre-diabetes and diabetes thresholds, Kim et al. (2019). At the lower "pre-diabetes" threshold, utilization clearly increases in Japan but not in Korea. At the higher threshold corresponding to "diabetic type," the Korean study finds that crossing the threshold increases use of DM medications and improves some intermediate health outcomes (such as BMI and waist circumference), although the effect attenuates over time and is no longer statistically significant after 3 or 4 years.

One reason for the differences in response at the lower threshold may be that the multiple thresholds in the Korean checkup report—with only a "yellow light" and no free secondary exam at the lower threshold, compared to a "red light" and free second exam at the 126 threshold—lead individuals to infer that the "pre-diabetes" signal is not serious enough to make a physician visit. On the other hand, because most Japanese reports only include the "pre-diabetes" threshold (see Figure 2), people may take it more seriously and visit physician offices. In addition, differences in the samples may contribute to the differing results. For example as noted, we have about five times more observations around the pre-diabetes threshold than the Korean sample does. Since the estimated effects only hold among such "marginal" individuals, differences in sample size around the thresholds matter.

In section 5.3 we report results on the longer-run effects of crossing both DM thresholds on health outcomes. In particular, we show that our results for the general population continue to hold at 5 years: there is no evidence that additional care for DM at either the pre-diabetes or diabetic type thresholds improves health outcomes for the general population in the longer-term. These results are consistent with those of Kim et al. for the long-run (5 years after screening for our sample; 3 or 4 years after baseline screening for the Kim et al. sample), but in our sample this is not a dissipation of the short-term results, since we can rule out any short-term impacts as well. Jointly these findings suggest that any health improvement from incremental medical utilization for the general population

may dissipate over time, reinforcing how challenging it can be to use screening to prompt sustained improvements in lifestyle, treatment, and outcomes.

Perhaps more strikingly, when we focus on high-risk individuals (who by definition exceed thresholds for three biomarkers), we find that exceeding the threshold of FBS=126 mg/dl leads to lower FBS and HbA1c values. These findings among high-risk individuals are discussed in more detail in section 5.4. Although Kim et al. find that crossing the 126 threshold leads to greater anti-diabetic medication use, we do not find evidence that crossing the diabetic-type cutoff increases utilization of DM medications either at the extensive margin (Any DM drug) or at the intensive margin (DM drug spending) among high risks. Moreover, as noted, we find that both the likelihood and number of DM visits *decrease* three years after the index checkup (see Figure A38), suggesting that health improvements operate primarily through individual's health behavior.

Kim et al. (2019) do not look at the individuals who exceeded both cholesterol and FBS thresholds (only examining each separately) nor do they recreate the predicted risk based on multiple risk factors like FBS and cholesterol, so we cannot compare our results for high-risk individuals directly to theirs. This might be possible in a future study using a larger sample from Korea, where a larger number of individuals exceeded the higher threshold for multiple risk factors. Nevertheless, it is striking that among the self-selected individuals who participate in screening both at baseline and 3 or 4 years later, improvements dissipate; whereas in the Japanese sample, with more individuals at that threshold and less influence of self-selection, high risk individuals' health improvements continue when followed-up in the same "long-run" timeframe (3 to 5 years in our paper, 3 to 4 years in Kim et al. (2019) round 3 screening.

Indeed, Kim et al.(2019) also provide an important acknowledgment of the potential limitations of data from widespread screening across heterogeneous providers, and how non-response to a biomarker value slightly above a threshold could be perfectly rational. The reports themselves may not provide accurate actionable data for all thresholds. For example, Kim et al. (2019) excluded analysis of the 70% of FBS baseline screening results performed outside major hospitals, because of concerns about the data from other settings; they also did not analyze response for the most common chronic disease, hypertension, because they observed noticeable clustering at multiples of 5 (see p.5 Footnote 9 in Kim et al. (2019).

Finally, we calculate the cost-effectiveness of preventive care by using a risk score that predicts the impact of reduced blood sugar level on mortality. Since neither of the other studies does so, we are unsure whether this result generalizes. Despite these differences, consistent economic insights flow from the results of both studies: namely, only high-risk individuals (FBS>=126 with elevated blood pressure and cholesterol in Japan, FBS>=126 with "red light" in Korea) exhibit meaningful health improvements from health checkups. This suggests that targeting follow-up interventions at high-risk groups are likely to be more cost effective.

Alalouf et al. (2019) use A1c values from an initial blood test, combined with medical claims and electronic health records to follow patients for six years after the blood test where they crossed the HbA1c threshold for diabetes. Similar to both of the other studies, they find significant increases in healthcare utilization at the diabetes threshold (i.e., that "a marginally diagnosed patient with diabetes spends $1,097 more on drugs and diabetes-related care annually after diagnosis). However, the US patients they study do not exhibit changes in health behaviors. Like the Korean study, the US patients who cross the diabetic-type threshold experience improved blood sugar after the first year of

diagnosis, but the improvement dissipates thereafter, and other biomarkers like BMI, blood pressure, cholesterol show no improvement. Indeed, in the US sample of newly-diagnosed DM patients, diagnosis rates for complications increase, which the authors suggest may be due to more intensive screening.

The contrast in longer-term outcomes among the studies is especially of note. Comparing our study with that of Kim et al. (2019), this contrast might suggest that those who self-select into screening are not the ones who would most benefit from early warning from screening. In other words, the Japan setting is more appropriate for identifying the causal effect of screening on high-risk individuals, because mandatory screening provides information about crossing multiple health thresholds even for those who may not self-select into screening. Or the contrasting results could simply be a matter of sample size, or of differences between the Japanese working-age population and the Korean participants in screening. Further research on these questions would be valuable to help disentangle the mechanisms and long-term outcomes, such as 10- or 20-year mortality.

Appendix Ⅳ: Placebo Tests

As another check on inference, we re-estimate the models using placebo thresholds that range between 115 and 121, a range in which we do not expect any discontinuous increase or decrease in our outcome measure. We do not examine the thresholds below 115 and above 121 because those threshold values will include either the 110 or 126 threshold in the 5mg bandwidths, which will mechanically bias the estimates even when crossing the threshold does not affect outcomes. Figure A39 reports the placebo test results for utilization using our preferred specification of 5 mg/dl bandwidth. We find that in stark contrast to the impacts found at the 110 threshold, none of the placebo thresholds exhibit any robust effects on utilization. This result further strengthens confidence that our previous findings are not merely spurious. We also estimate the same model for health behaviors and health outcomes, finding no evidence that placebo thresholds affect these outcomes (not reported).[3]

Appendix Ⅴ: Effects on Those Who Did Not Receive the Signal in the Previous Year

One might expect that some people are not health conscious and may routinely ignore health warning signals. If we exclude these individuals, the effects of health signals on health outcomes and medical expenditures might be substantially larger. To explore such a possibility, we redo the analyses by excluding individuals whose FBS value exceeded the pre-diabetes threshold in the previous year.

In Figure A40, we report the impact on medical care utilization of crossing the pre-diabetes cutoff of FBS=110 mg/dl. As before, crossing the pre-diabetes threshold clearly increases medical care utilization. In fact, as expected, the impacts are slightly larger than those reported in Figure 4. For example, as shown in Figure A40, the probability of visiting a doctor for DM increases by approximately 6 percentage points among those who did not cross the threshold in the previous year, slightly higher than the 5-percentage-point increase found in Figure 4.

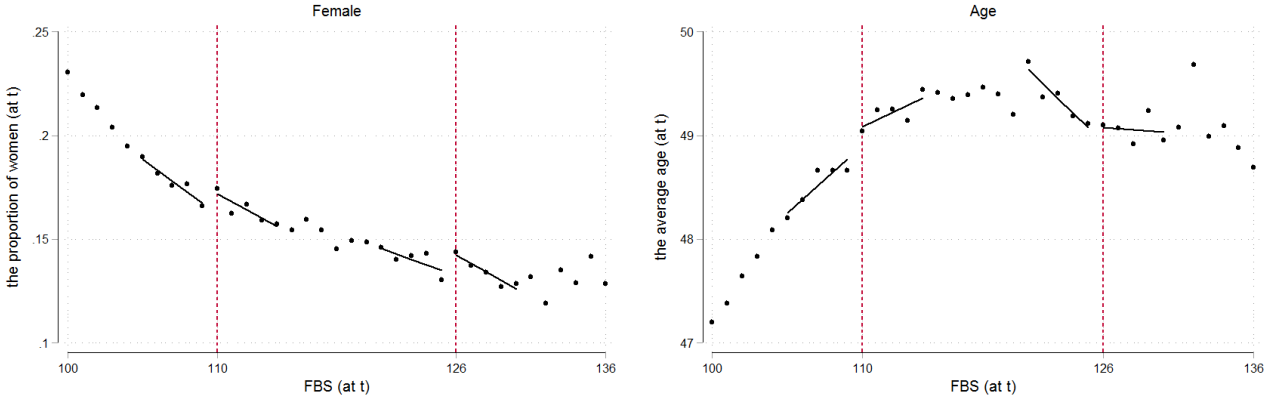
The results for health outcomes reported in Figure A41 are similar to our previous results; there is no evidence that the moving above the pre-diabetes threshold affects health outcomes. These results are confirmed by local-linear regressions (not reported). Thus, as expected, individuals who did not receive the warning in a previous year respond more to a checkup result outside the normal range; however, the additional medical care utilization still does not seem to improve health outcomes. These results lend further support to our conclusion that preventive DM care around the prediabetes threshold of FBS=110 mg/dl is neither effective nor cost effective.

We now turn to the results for the diabetic type threshold. For medical care utilization, as shown in Figure A42, we continue to find that the probability of a DM visit increases at the threshold; but other utilization variables are not affected very much in this case. Turning to health outcomes shown in Figure A43, a notable departure from our previous analyses is that we find some evidence that

[3] The results are available upon request.

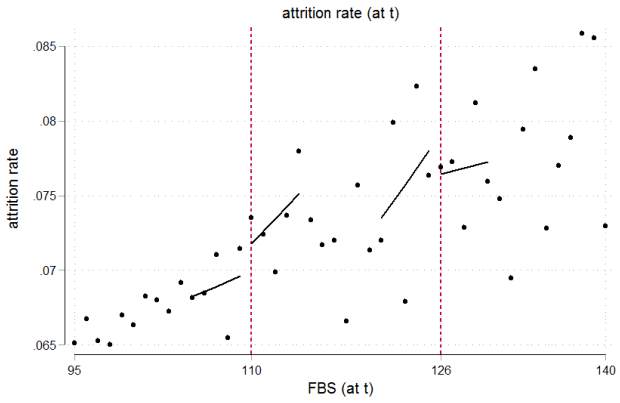
crossing the diabetic type threshold reduces FBS values by about 3 mg/dl (which is about a 3% reduction from the mean at FBS=125) when the individual did not cross that threshold in the previous year; for the majority of local-linear regressions and some quadratic regressions, the RD coefficients are significantly negative at the 5% confidence level. For all other health outcomes, however, the effects are not distinguishable from zero. Thus, crossing the diabetic type threshold appears to have some influence on health outcomes for those who did not exceed the threshold in the previous year, although the results are not robust across bandwidths and for alternative health outcomes.

Figure A1. Covariates Balance



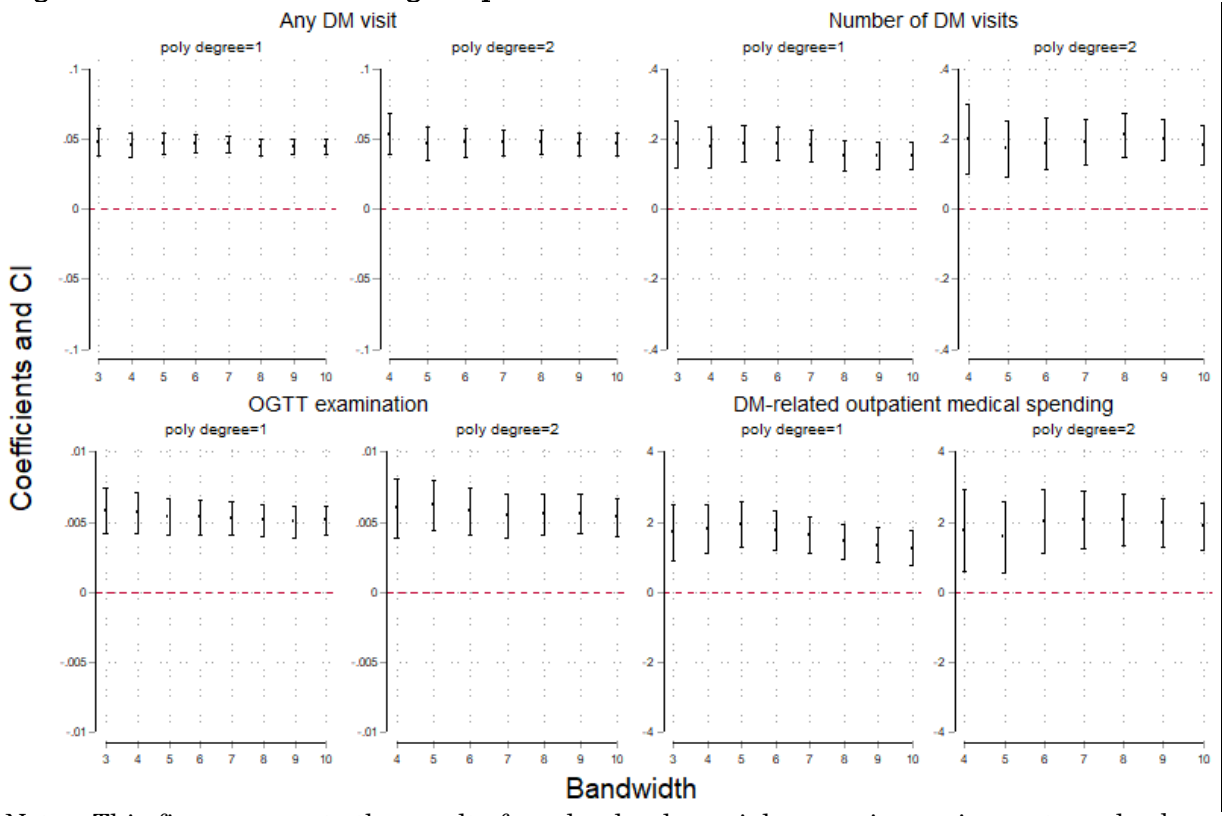
Notes: The scatter plot shows the mean of the covariate within 1 point bins of the FBS value. The vertical lines indicate the two threshold values for DM diagnosis. We fit the values using a linear function within 5 mg/dl of FBS values before and after the thresholds.

Figure A2. Attrition rate



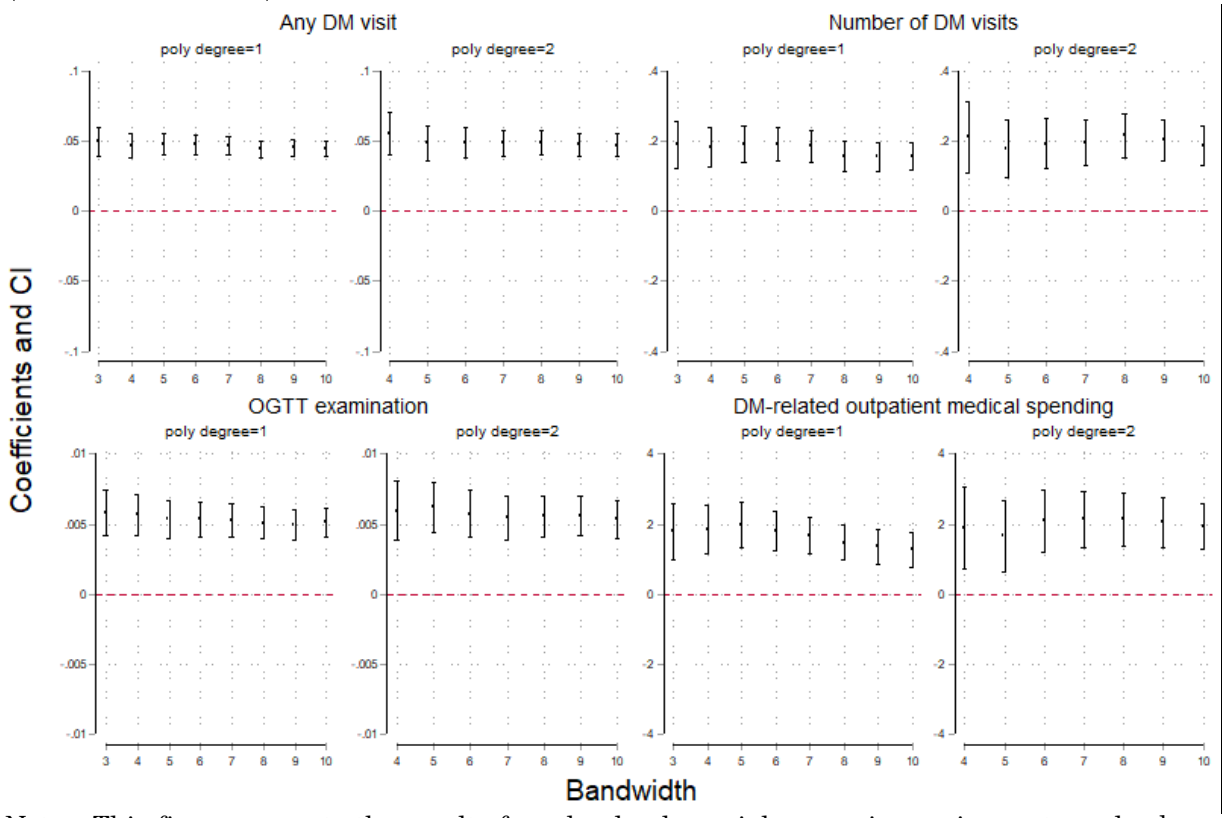
Notes: The scatter plot shows the mean of attrition within 12 months after a checkup, using 1 point bins of the FBS value. The vertical lines indicate the two threshold values for DM diagnosis. We fit the values using a linear function within 5 mg/dl of FBS values before and after the thresholds.

Figure A3. Effects of exceeding the pre-diabetes threshold (FBS=110) on medical care utilization



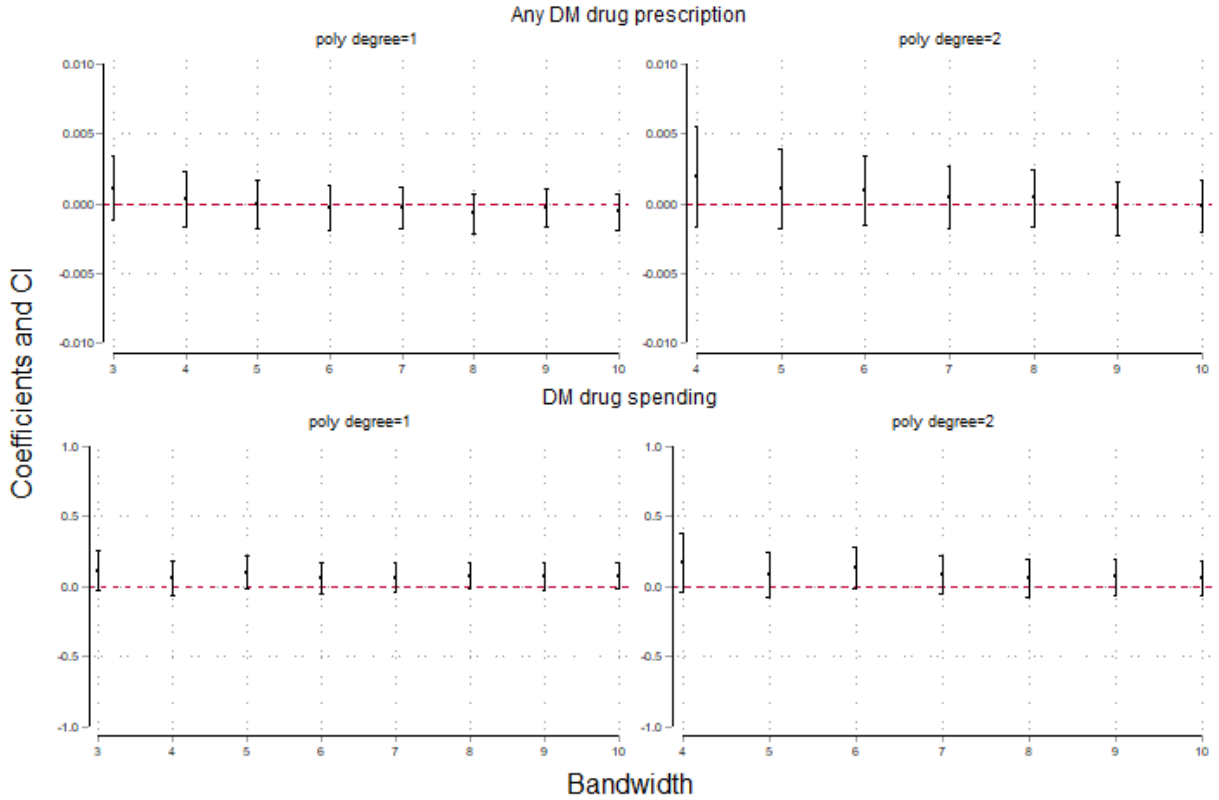
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and covariates. Only the coefficients and 95% CIs for the FBS≧110 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A4. Effects of exceeding the pre-diabetes threshold (FBS=110) on medical care utilization (without covariates)



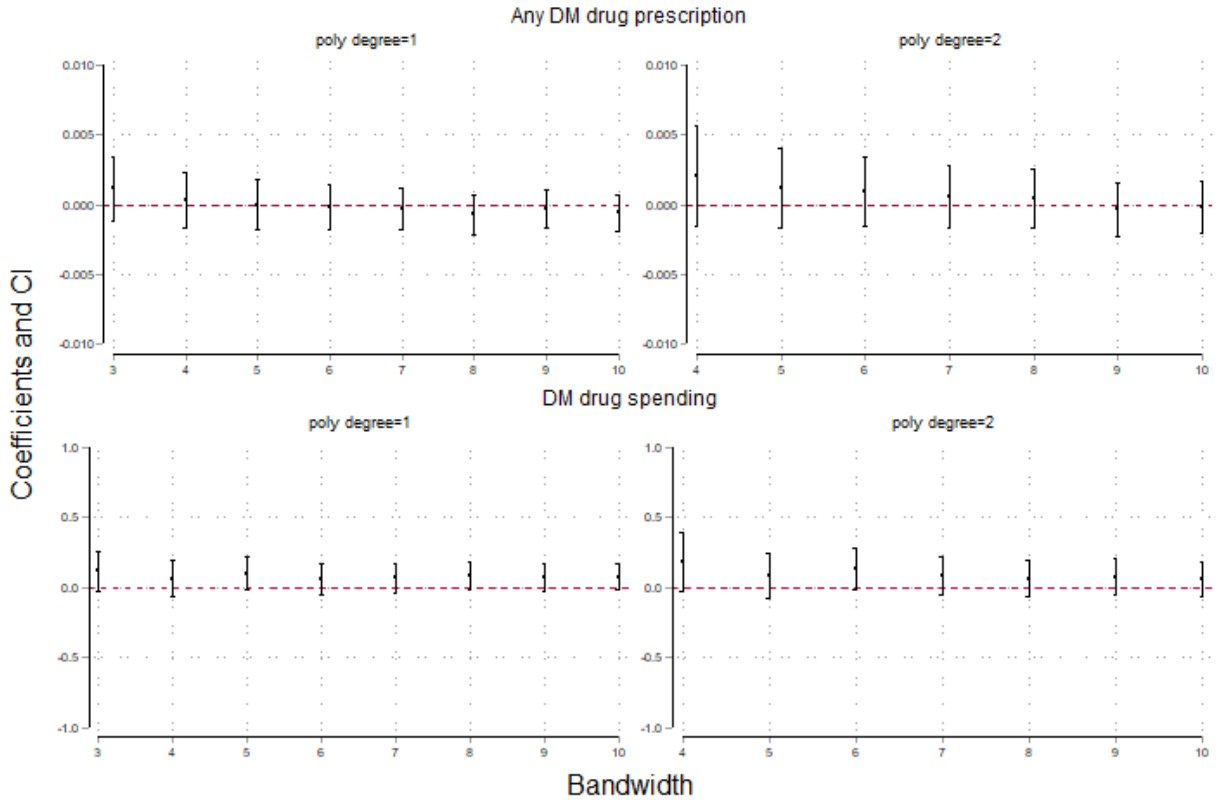
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and without covariates. Only the coefficients and 95% CIs for the FBS≧110 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A5. Effects of exceeding the pre-diabetes threshold (FBS=110) on DM medication



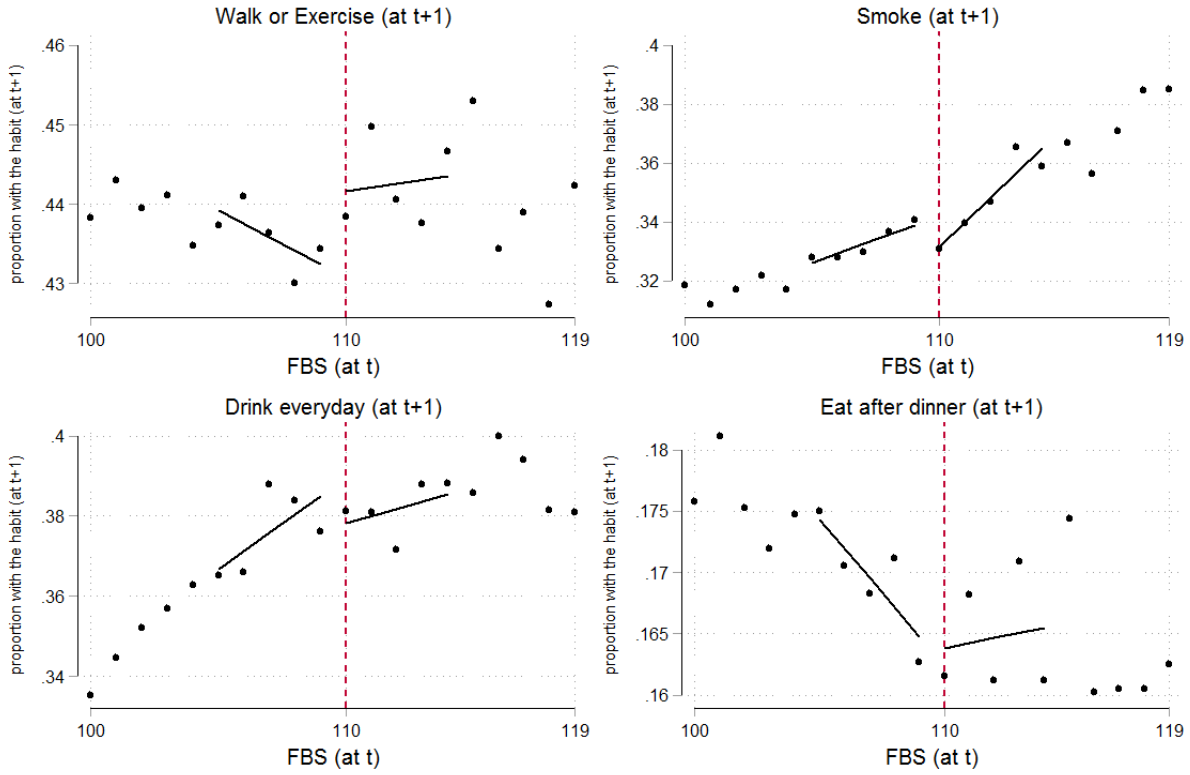
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and covariates. Only the coefficients and 95% CIs for the FBS≧110 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A6. Effects of exceeding the pre-diabetes threshold (FBS=110) on DM medication (without covariates)



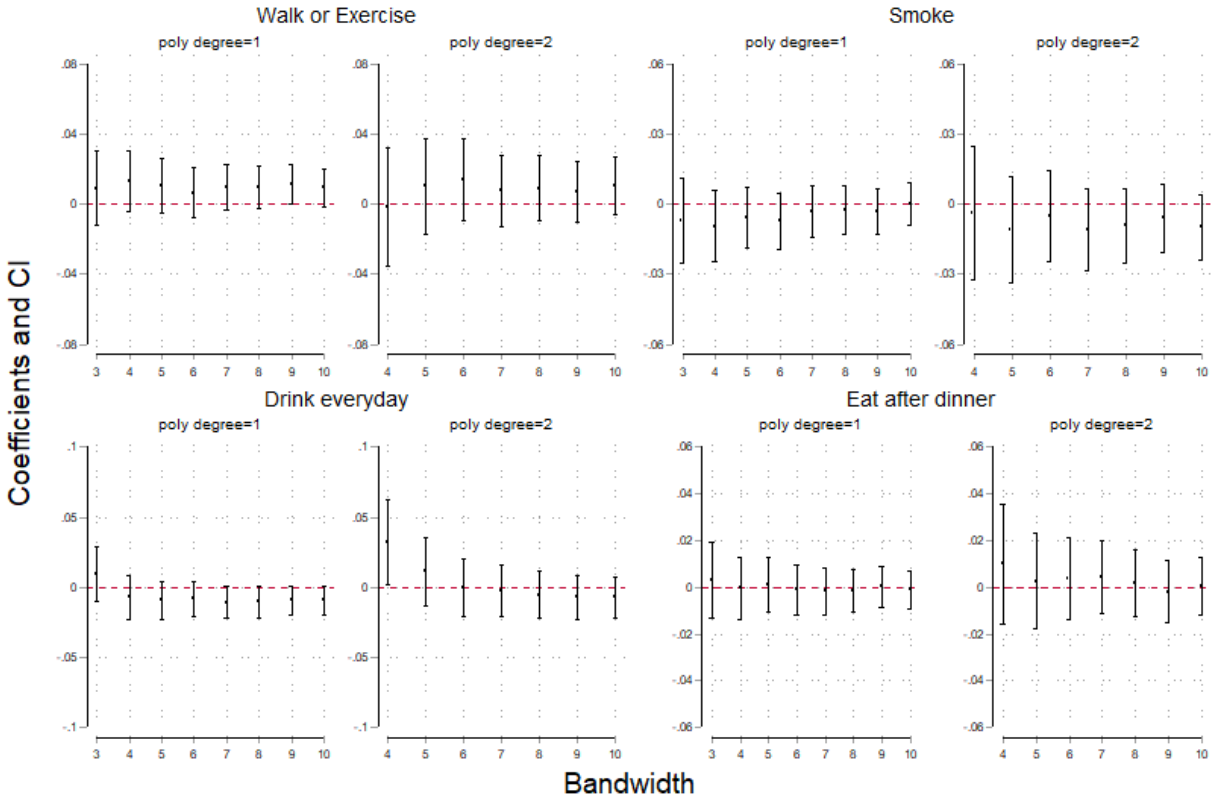
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and without covariates. Only the coefficients and 95% CIs for the FBS≧110 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A7. Effects on health behavior of exceeding the pre-diabetes threshold (FBS=110)



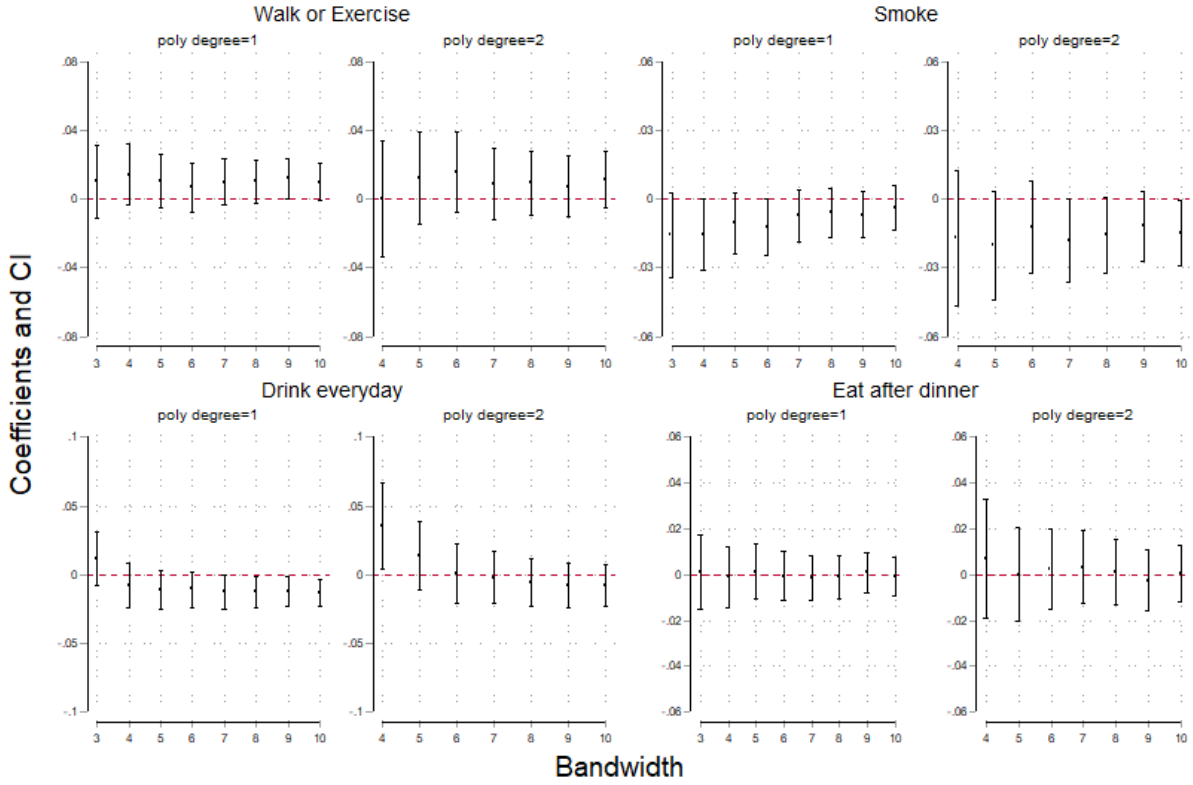
Notes: The scatter plot shows the mean of health behavior variable within 1 point bins of the FBS value. The vertical line indicates the FBS=110 mg/dl threshold. We fit the values using a linear function within 5 mg/dl of FBS values around the threshold.

Figure A8. Effects of exceeding the pre-diabetes threshold (FBS=110) on health behavior



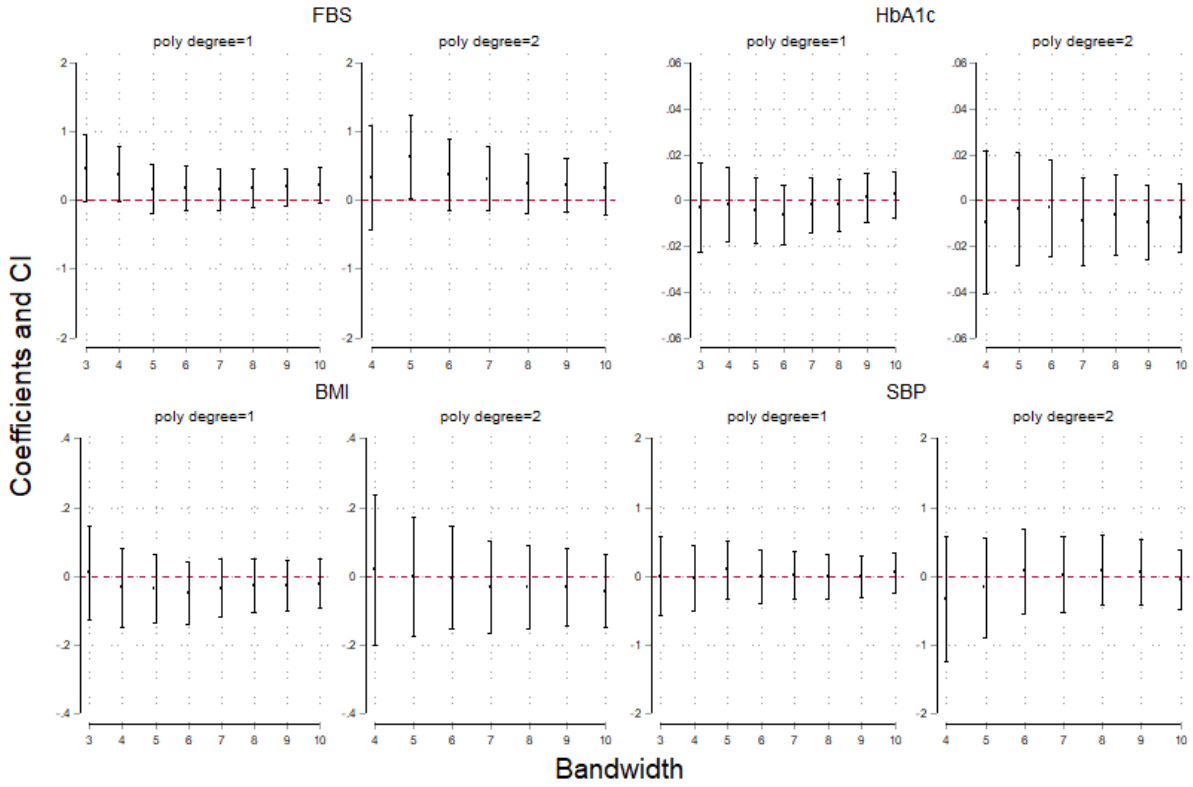
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and covariates. Only the coefficients and 95% CIs for the FBS≧110 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A9. Effects of exceeding the pre-diabetes threshold (FBS=110) on health behavior (without covariates)



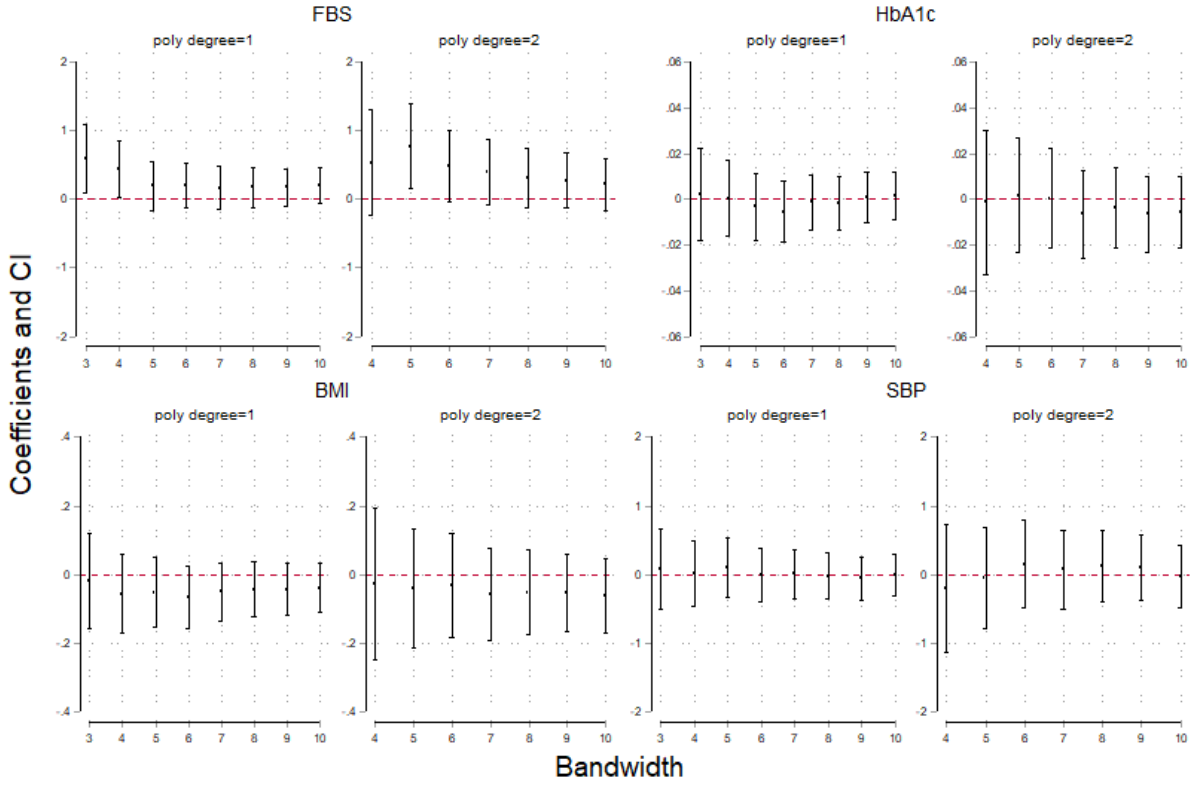
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and without covariates. Only the coefficients and 95% CIs for the FBS≧110 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A10. Effects of exceeding the pre-diabetes threshold (FBS=110) on intermediate health outcomes



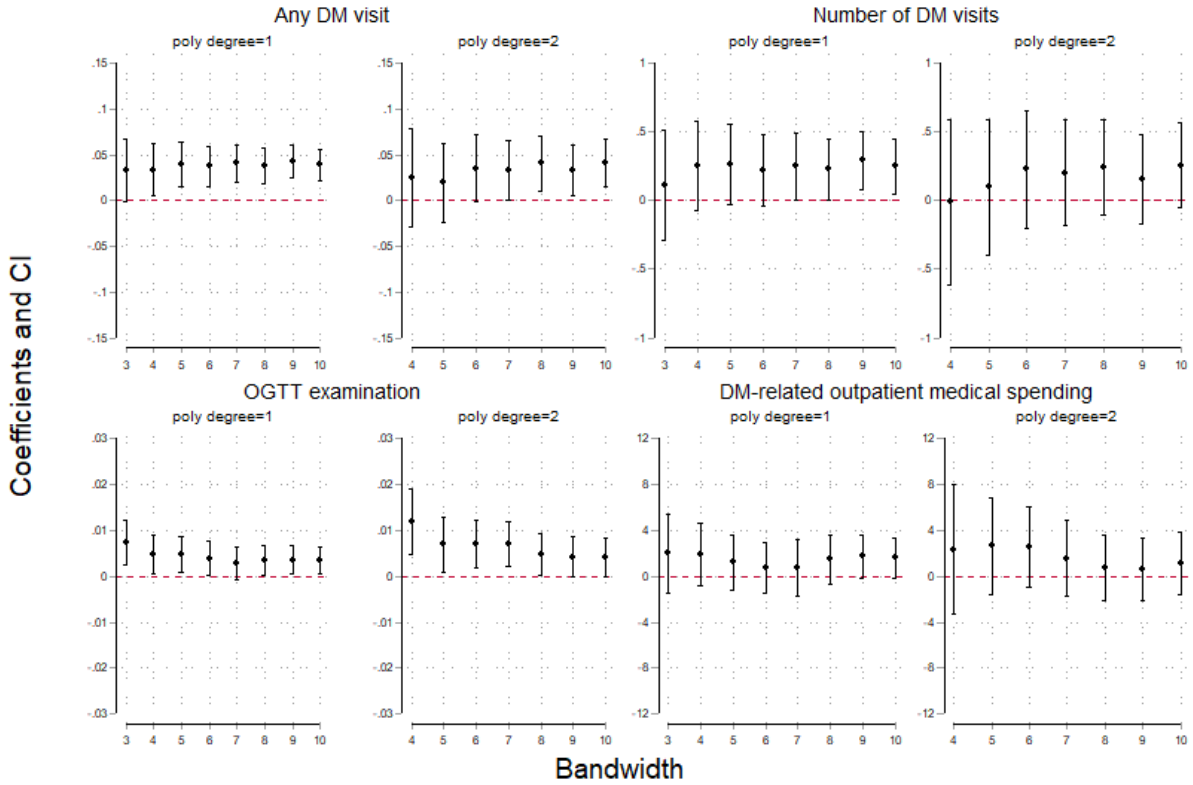
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and covariates. Only the coefficients and 95% CIs for the FBS≧110 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A11. Effects of exceeding the pre-diabetes threshold (FBS=110) on intermediate health outcomes (without covariates)



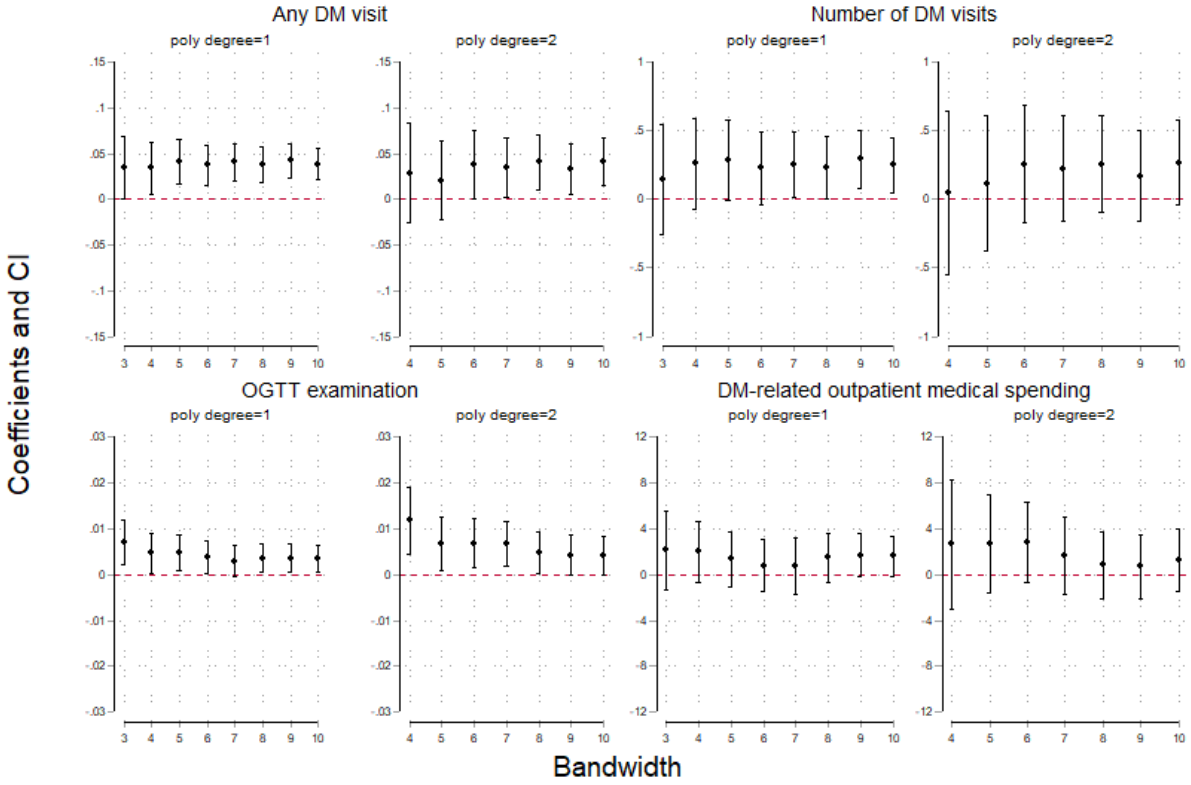
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and without covariates. Only the coefficients and 95% CIs for the FBS≧110 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A12. Effects of exceeding the diabetic-type threshold (FBS=126) on medical care utilization



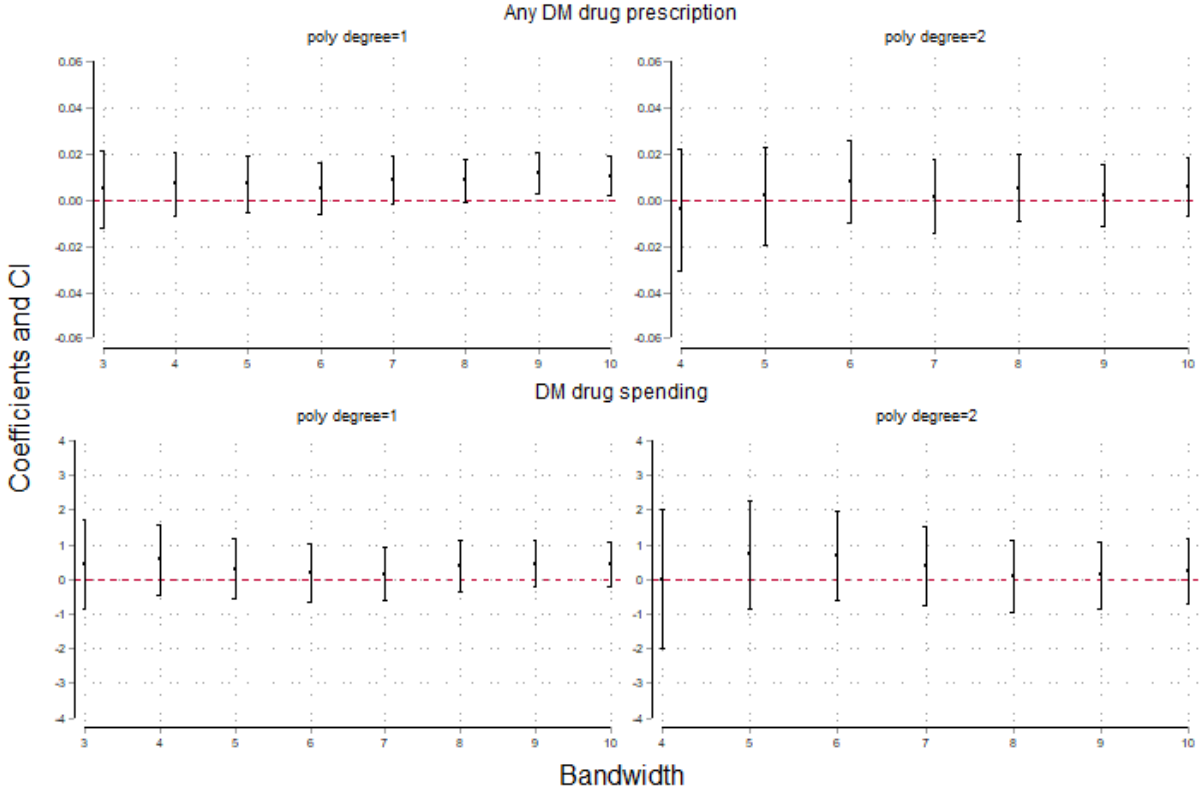
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and covariates. Only the coefficients and 95% CIs for the FBS≧126 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A13. Effects of exceeding the diabetic-type threshold (FBS=126) on medical care utilization (without covariates)



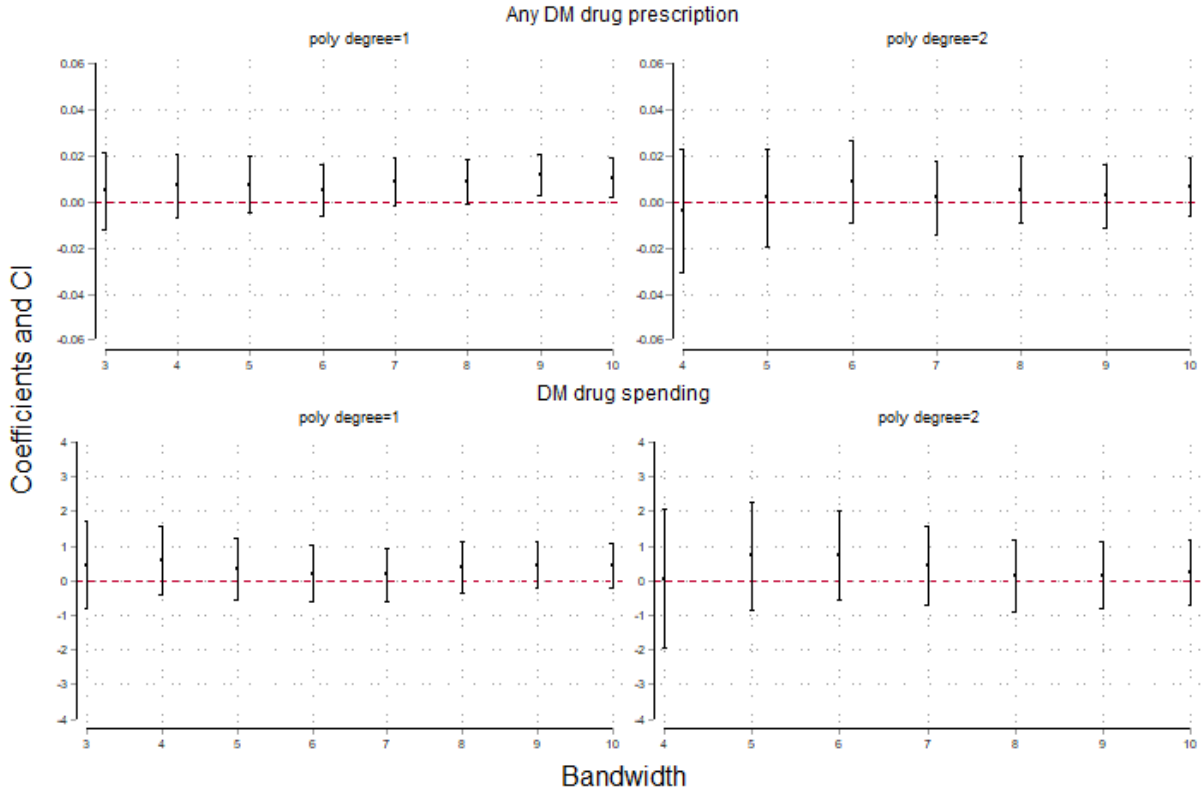
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and without covariates. Only the coefficients and 95% CIs for the FBS≧126 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A14. Effects of exceeding the diabetic-type threshold (FBS=126) on DM medication



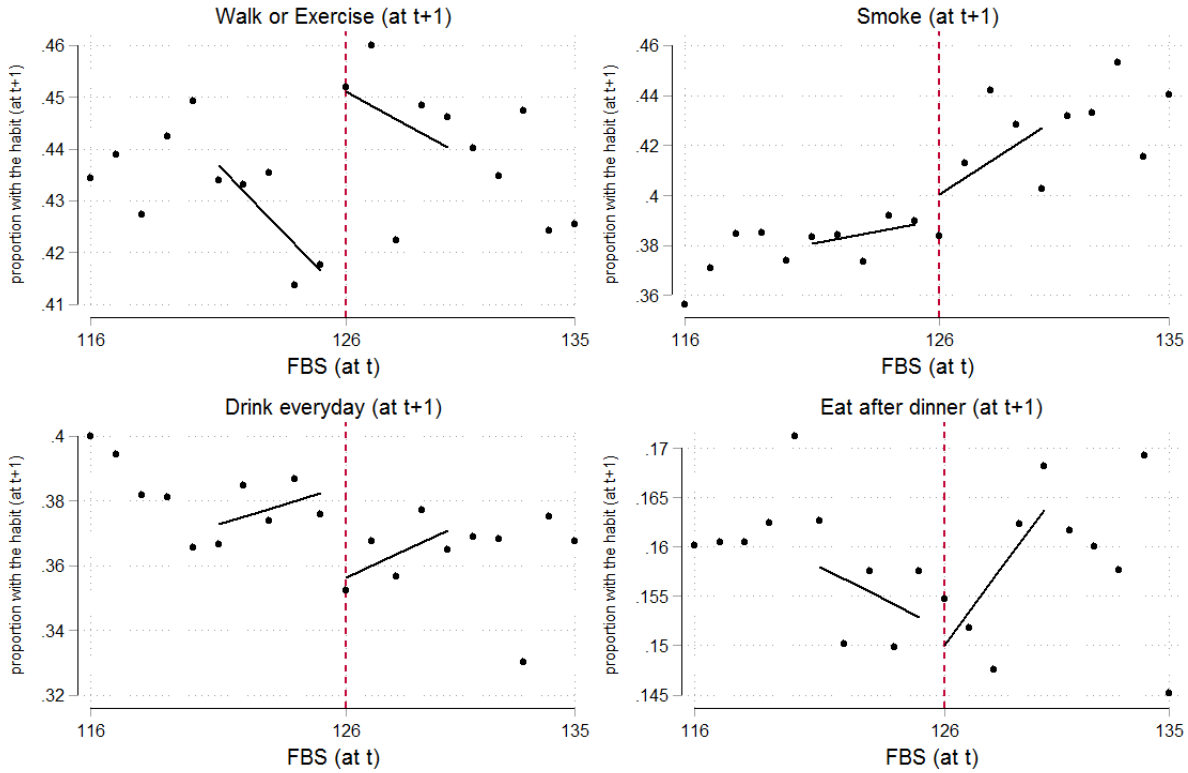
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and covariates. Only the coefficients and 95% CIs for the FBS≧126 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A15. Effects of exceeding the diabetic-type threshold (FBS=126) on DM medication (without covariates)



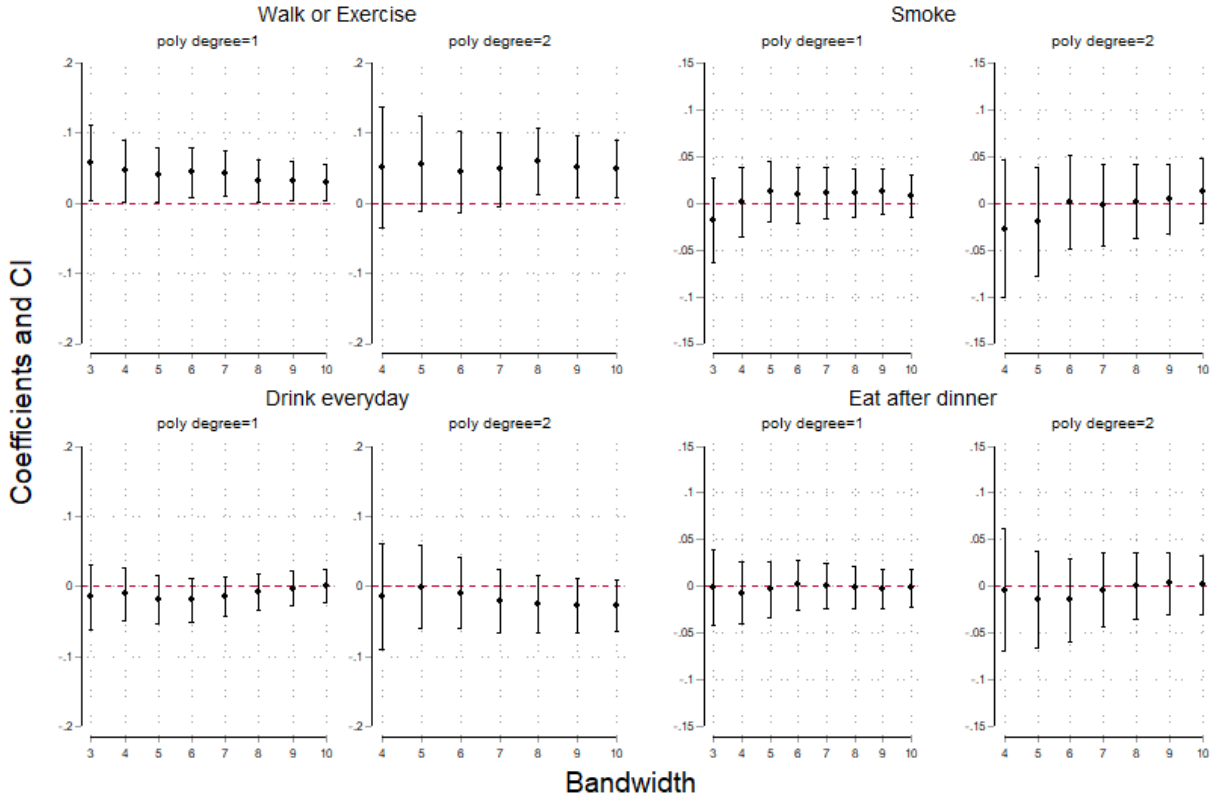
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and without covariates. Only the coefficients and 95% CIs for the FBS≧126 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A16. Effects on health behavior of exceeding the diabetic-type threshold (FBS=126)



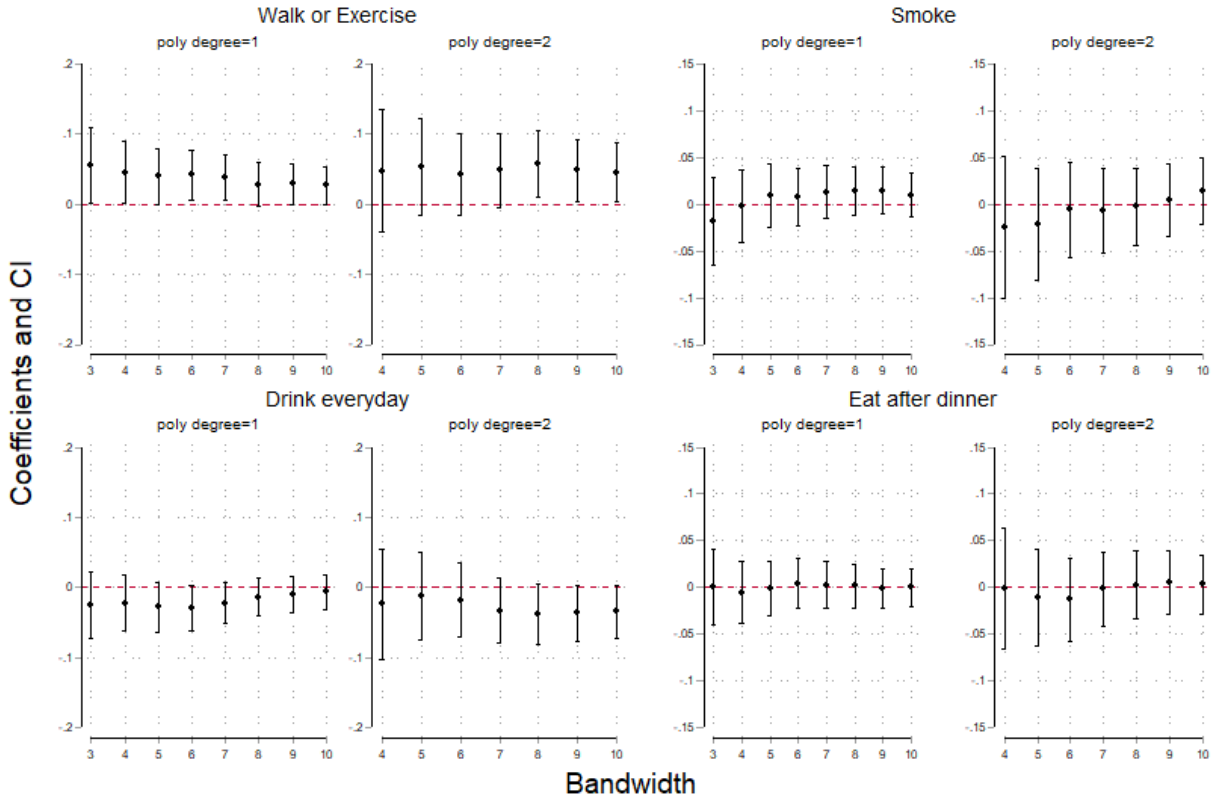
Notes: The scatter plot shows the mean of health behavior variable within 1 point bins of the FBS value. The vertical line indicates the FBS=126 mg/dl threshold. We fit the values using a linear function within 5 mg/dl of FBS values around the threshold.

Figure A17. Effects of exceeding the diabetic-type threshold (FBS=126) on health behavior



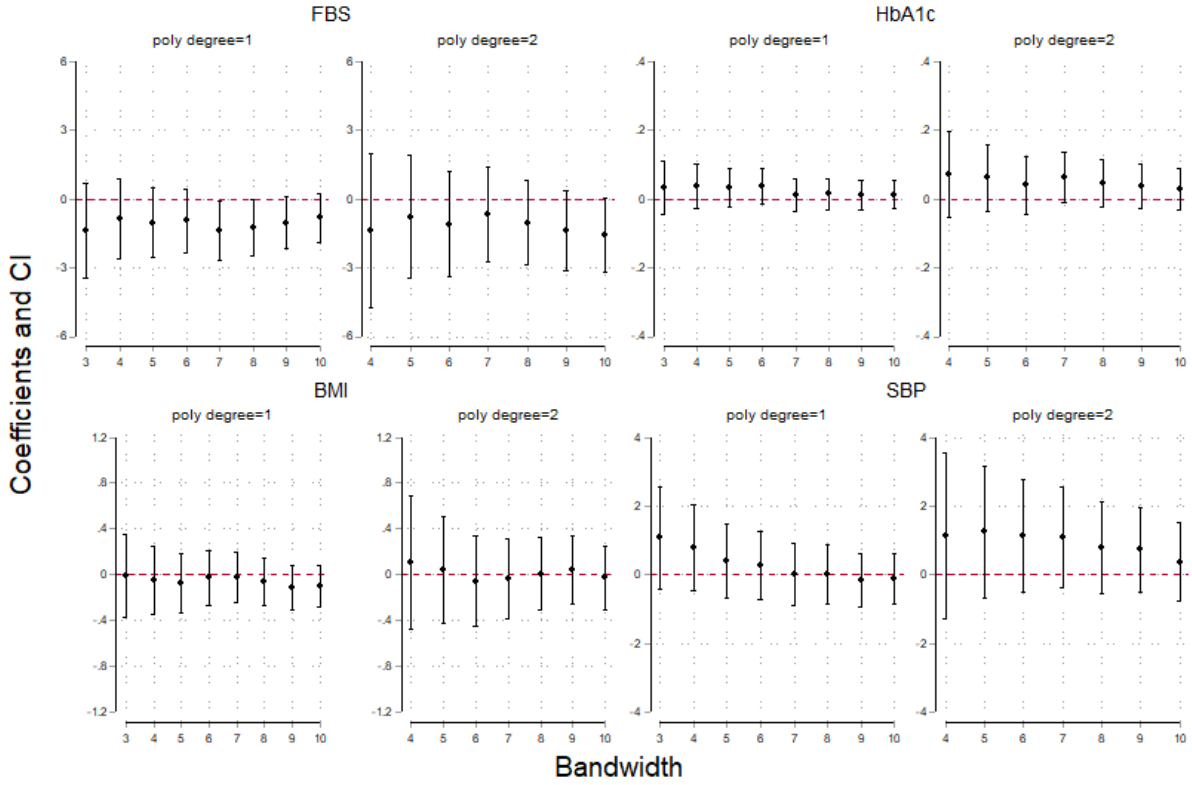
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and covariates. Only the coefficients and 95% CIs for the FBS≧126 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A18. Effects of exceeding the diabetic-type threshold (FBS=126) on health behavior (without covariates)



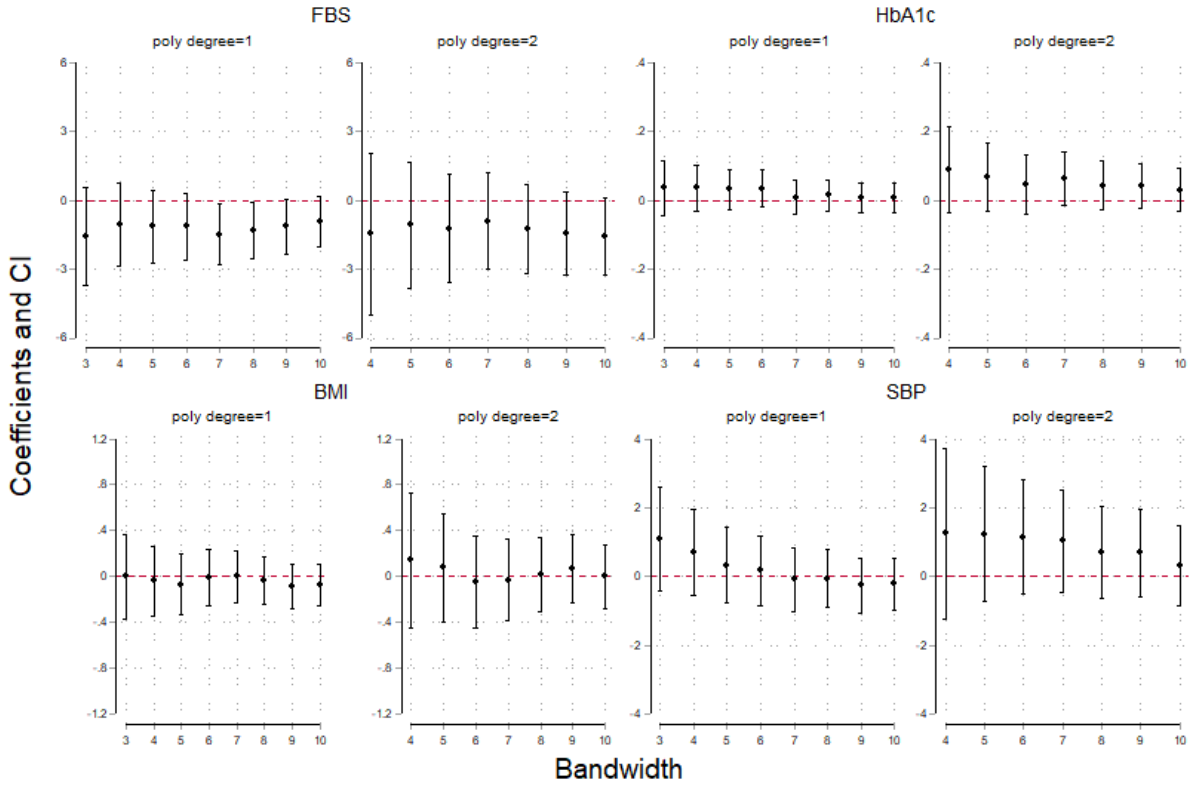
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and without covariates. Only the coefficients and 95% CIs for the FBS≧126 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A19. Effects of exceeding the diabetic-type threshold (FBS=126) on intermediate health outcomes



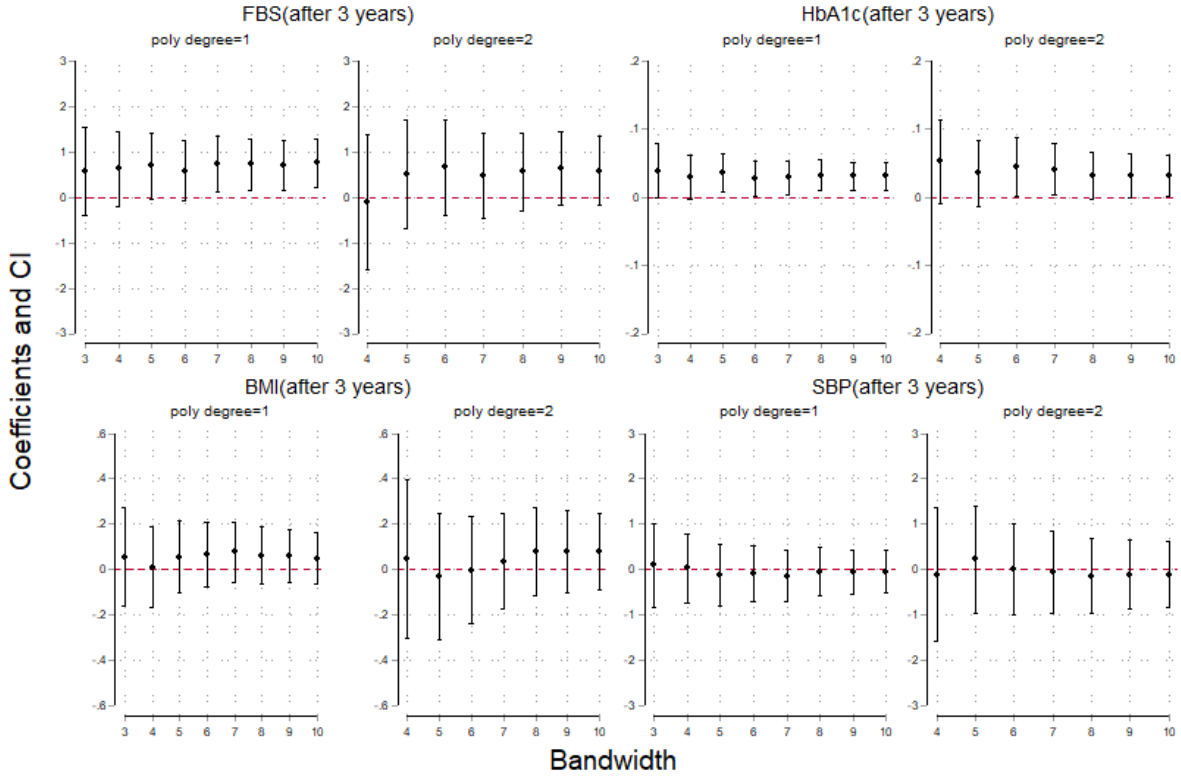
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and covariates. Only the coefficients and 95% CIs for the FBS≧126 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A20. Effects of exceeding the diabetic-type threshold (FBS=126) on intermediate health outcomes (without covariates)



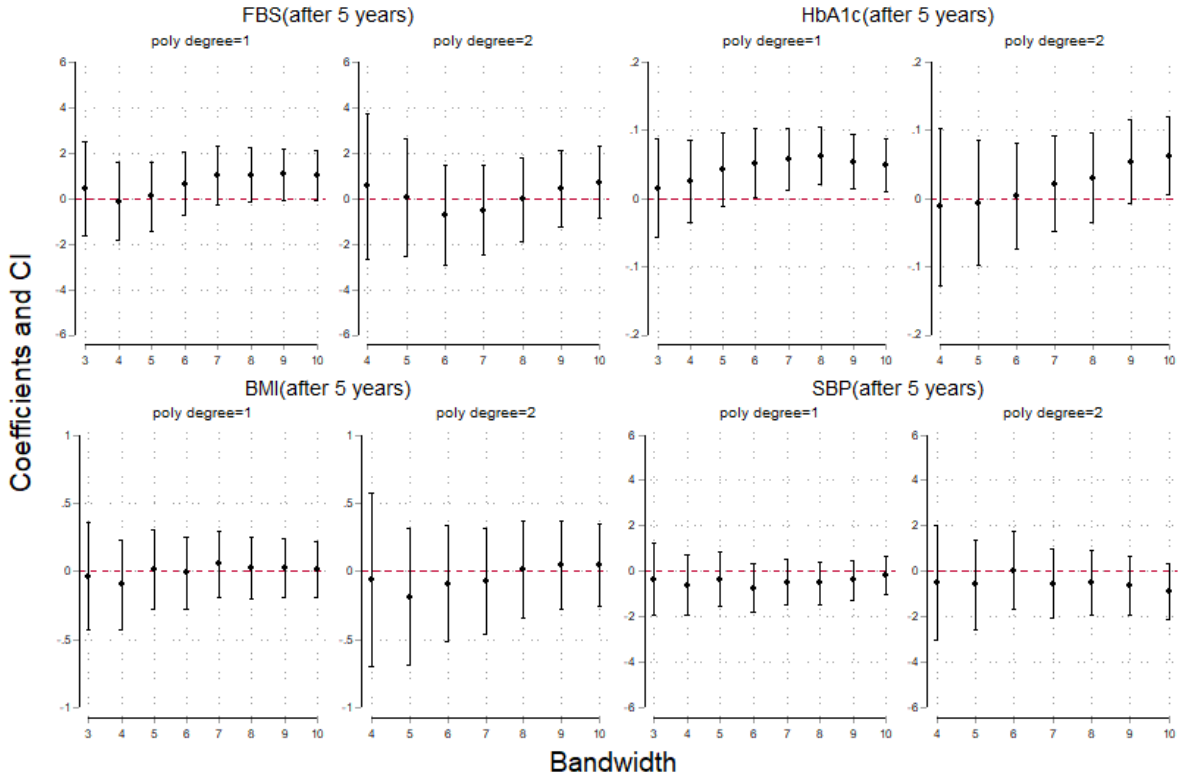
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and without covariates. Only the coefficients and 95% CIs for the FBS≧126 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A21. Longer-run Effects of exceeding the pre-diabetes threshold (FBS=110) on intermediate health outcomes (after 3 years)



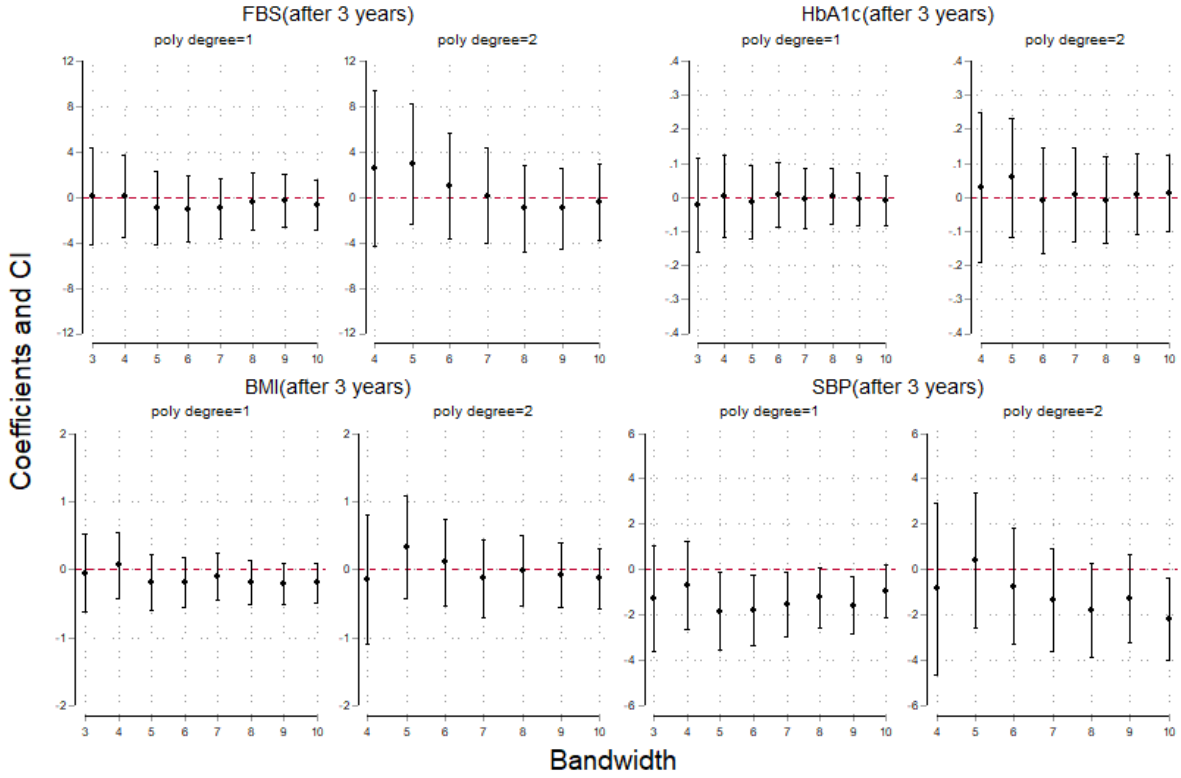
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and with covariates. Only the coefficients and 95% CIs for the FBS≧110 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A22. Longer-run effects of exceeding the pre-diabetes threshold (FBS=110) on intermediate health outcomes (after 5 years)



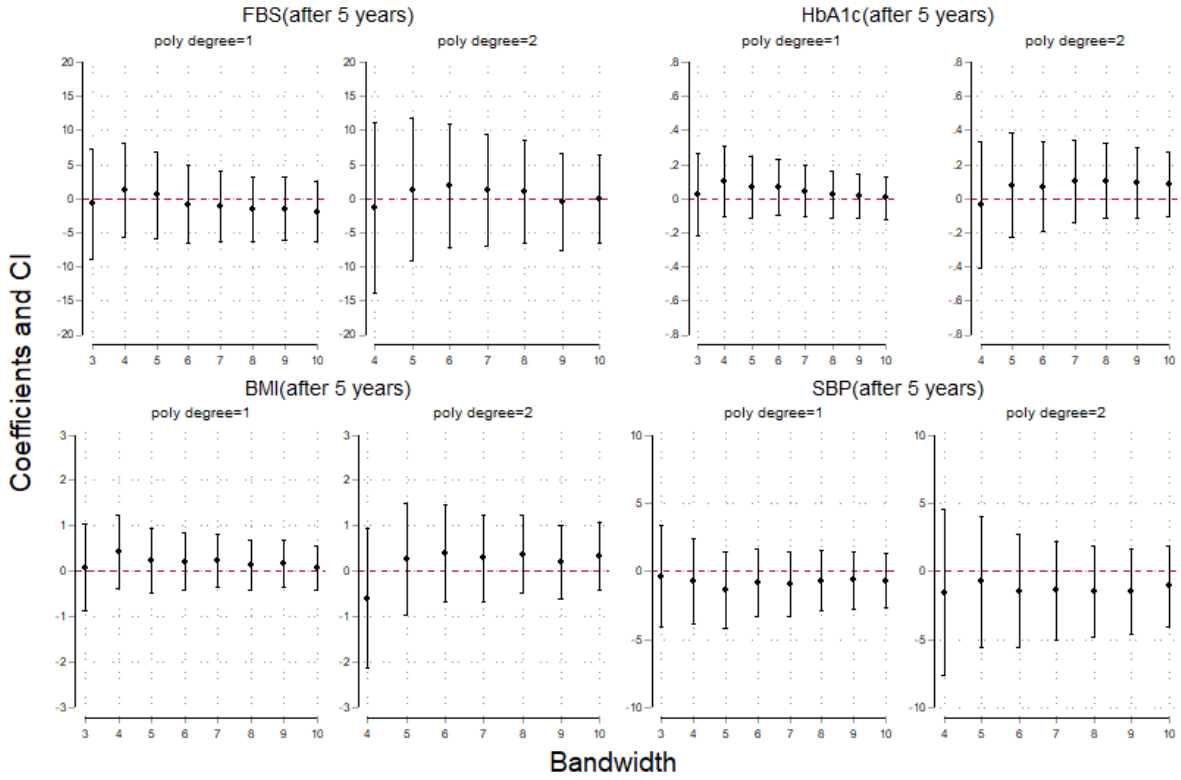
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and with covariates. Only the coefficients and 95% CIs for the FBS≧110 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A23. Longer-run effects of exceeding the diabetic-type threshold (FBS=126) on intermediate health outcomes (after 3 years)



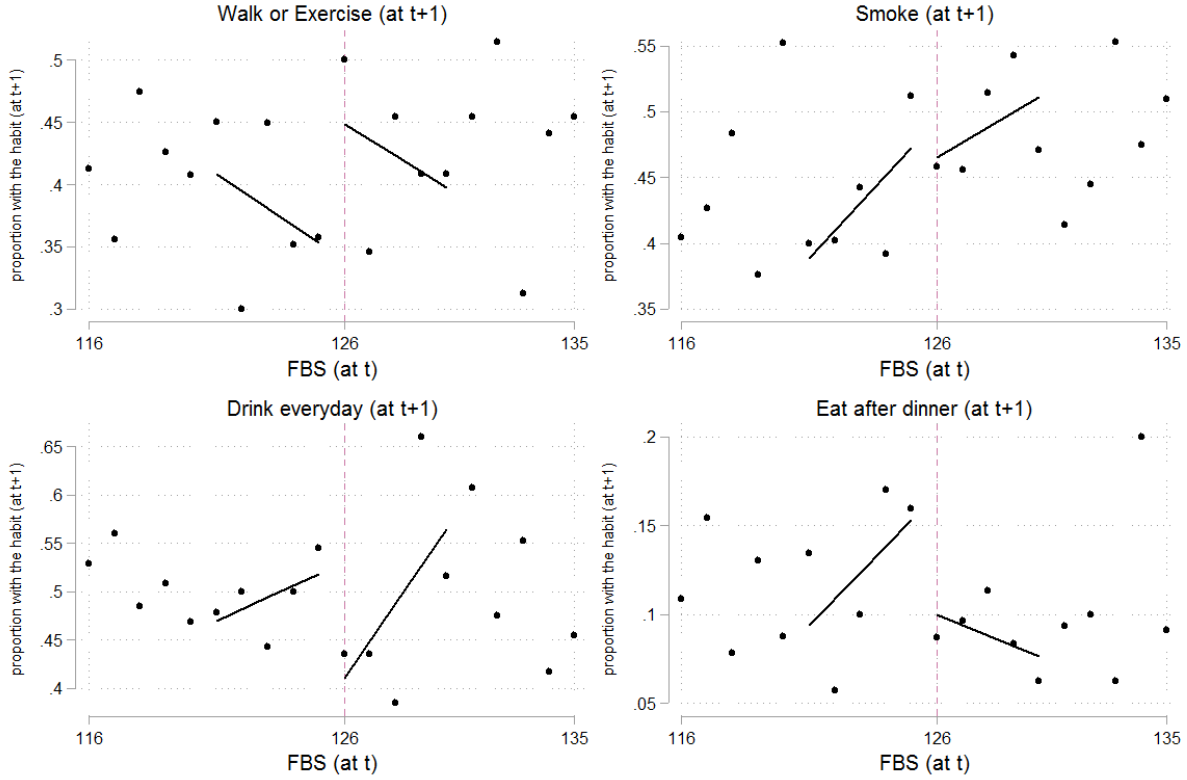
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and with covariates. Only the coefficients and 95% CIs for the FBS≧126 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A24. Longer-run effects of exceeding the diabetic-type threshold (FBS=126) on intermediate health outcomes (after 5 years)



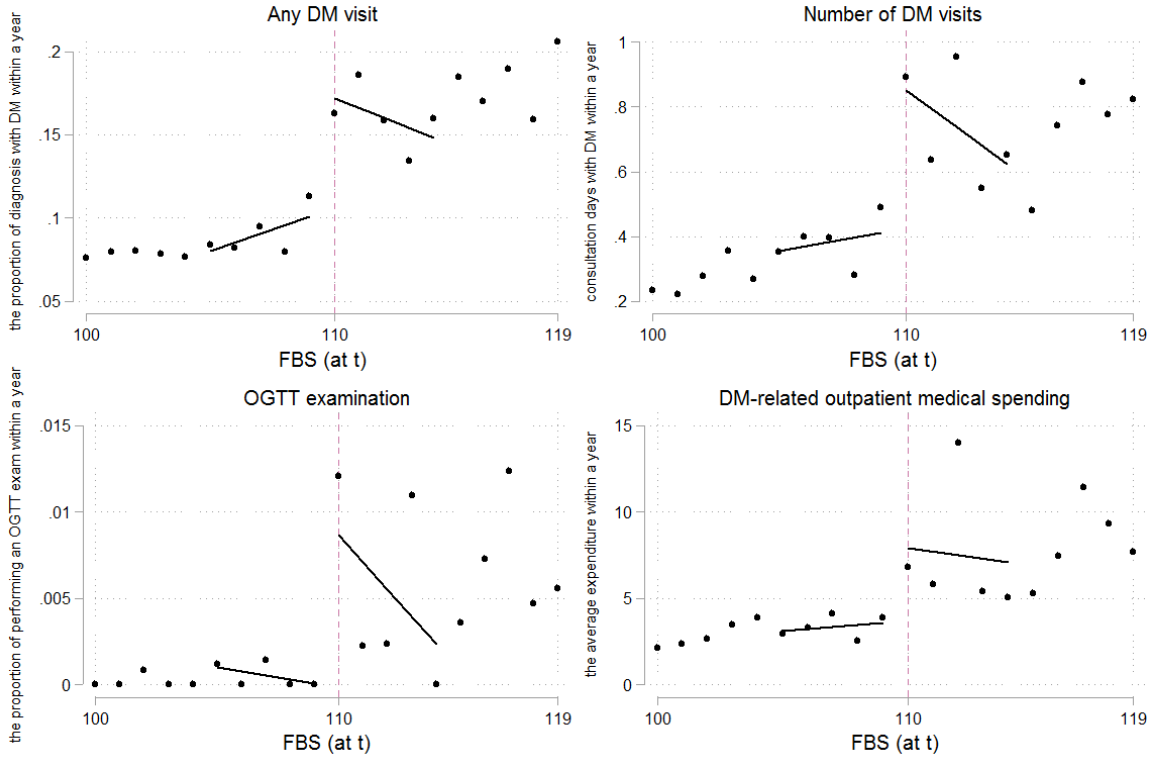
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and with covariates. Only the coefficients and 95% CIs for the FBS≧126 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A25. Effects of exceeding the diabetic-type threshold (FBS=126) on health behavior among high-risk individuals



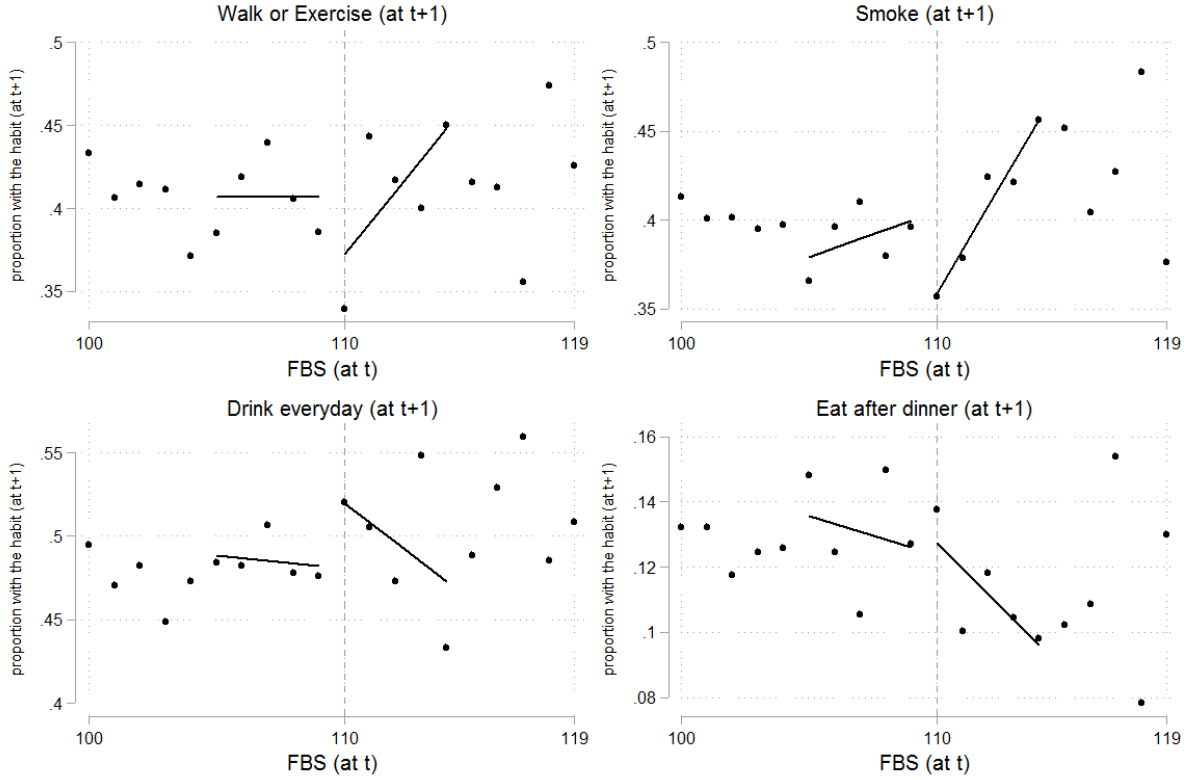
Notes: The scatter plot shows the mean of health behavior variable within 1 point bins of the FBS value. The vertical line indicates the FBS=126 mg/dl threshold. We fit the values using a linear function within 5 mg/dl of FBS values around the threshold.

Figure A26. Effects of exceeding the pre-diabetes threshold (FBS=110) on medical care utilization among high-risk individuals



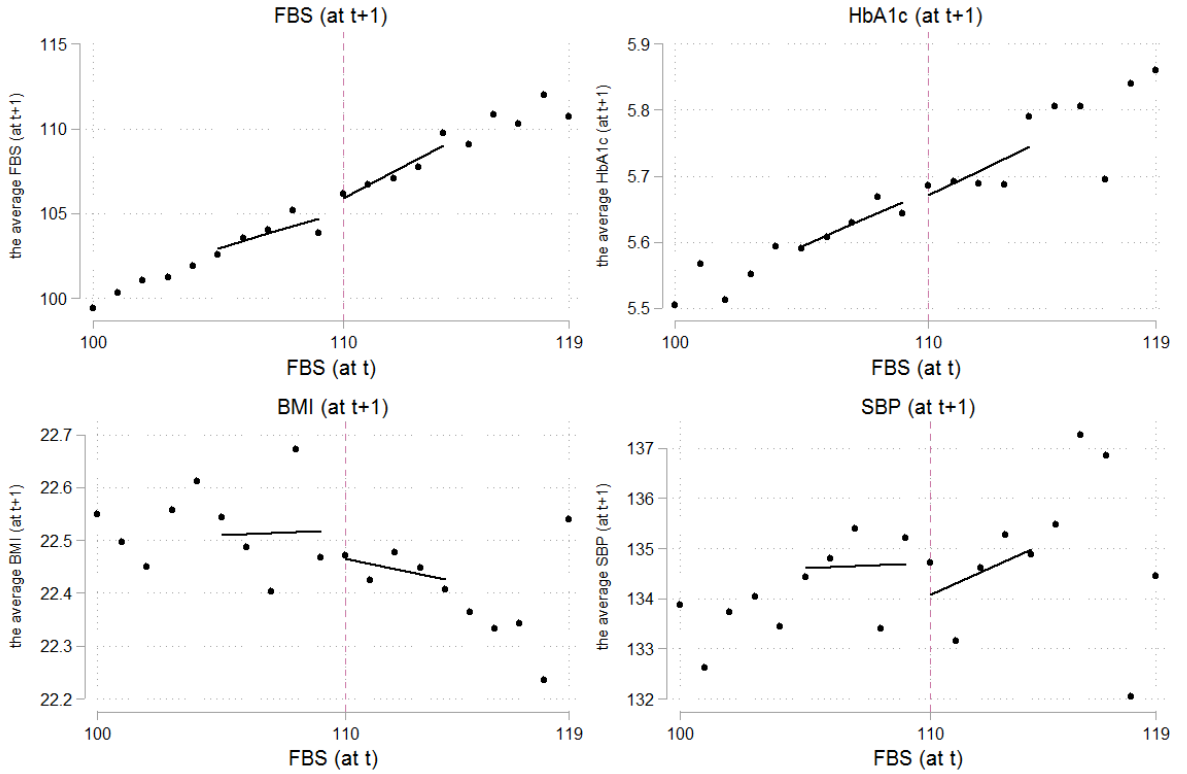
Notes: The scatter plot shows the mean of medical care utilization variable within 1 point bins of the FBS value. The vertical line indicates the FBS=110 mg/dl threshold. We fit the values using a linear function within 5 mg/dl of FBS values around the threshold.

Figure A27. Effects of exceeding the pre-diabetes threshold (FBS=110) on health behavior among high-risk individuals



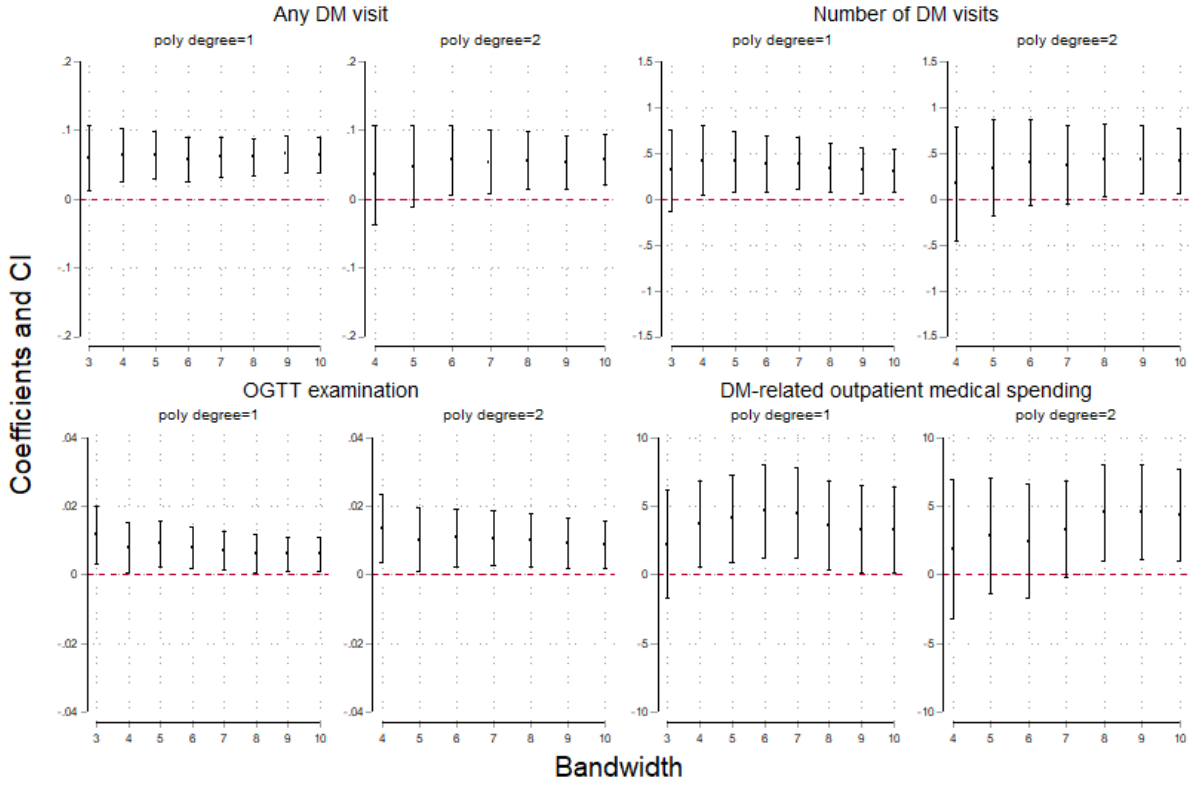
Notes: The scatter plot shows the mean of health behavior variable within 1 point bins of the FBS value. The vertical line indicates the FBS=110 mg/dl threshold. We fit the values using a linear function within 5 mg/dl of FBS values around the threshold.

Figure A28. Effects of exceeding the pre-diabetes threshold (FBS=110) on intermediate health outcomes among high-risk individuals



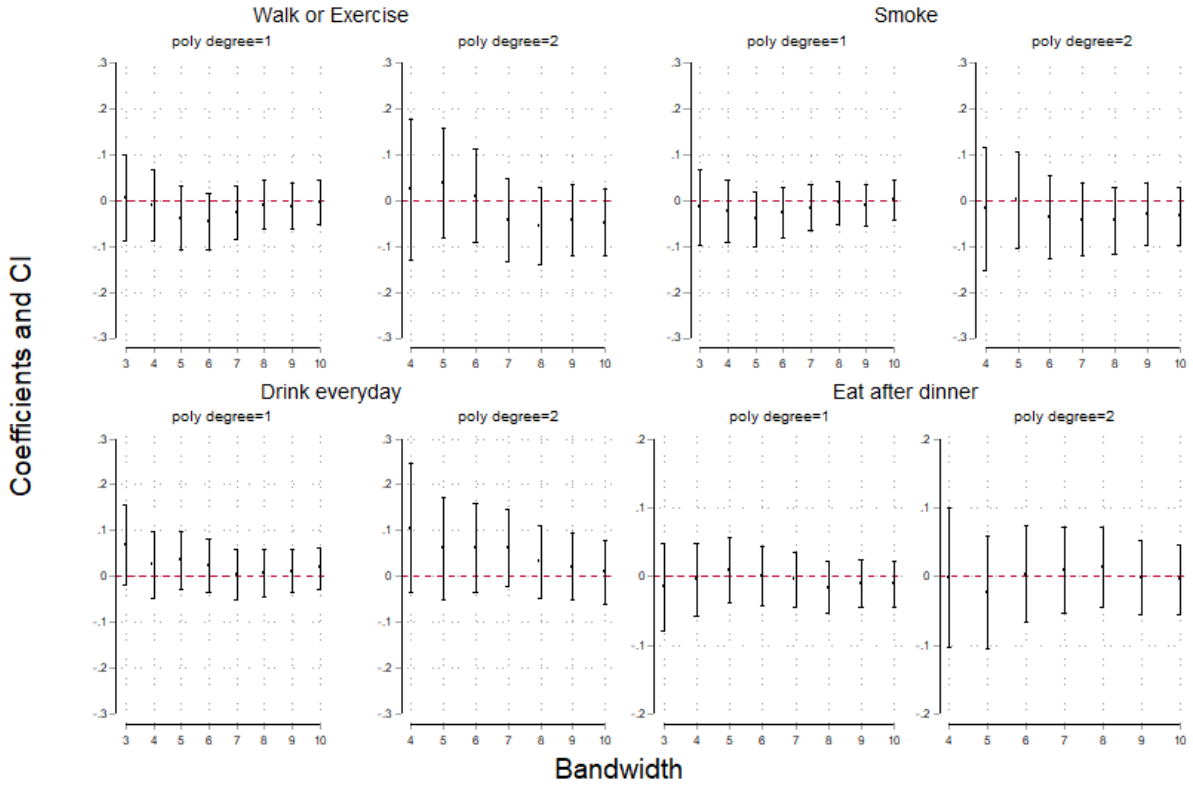
Notes: The scatter plot shows the mean of intermediate health outcome variable within 1 point bins of the FBS value. The vertical line indicates the FBS=110 mg/dl threshold. We fit the values using a linear function within 5 mg/dl of FBS values around the threshold.

Figure A29. Effects of exceeding the pre-diabetes threshold (FBS=110) on medical care utilization among high-risk individuals



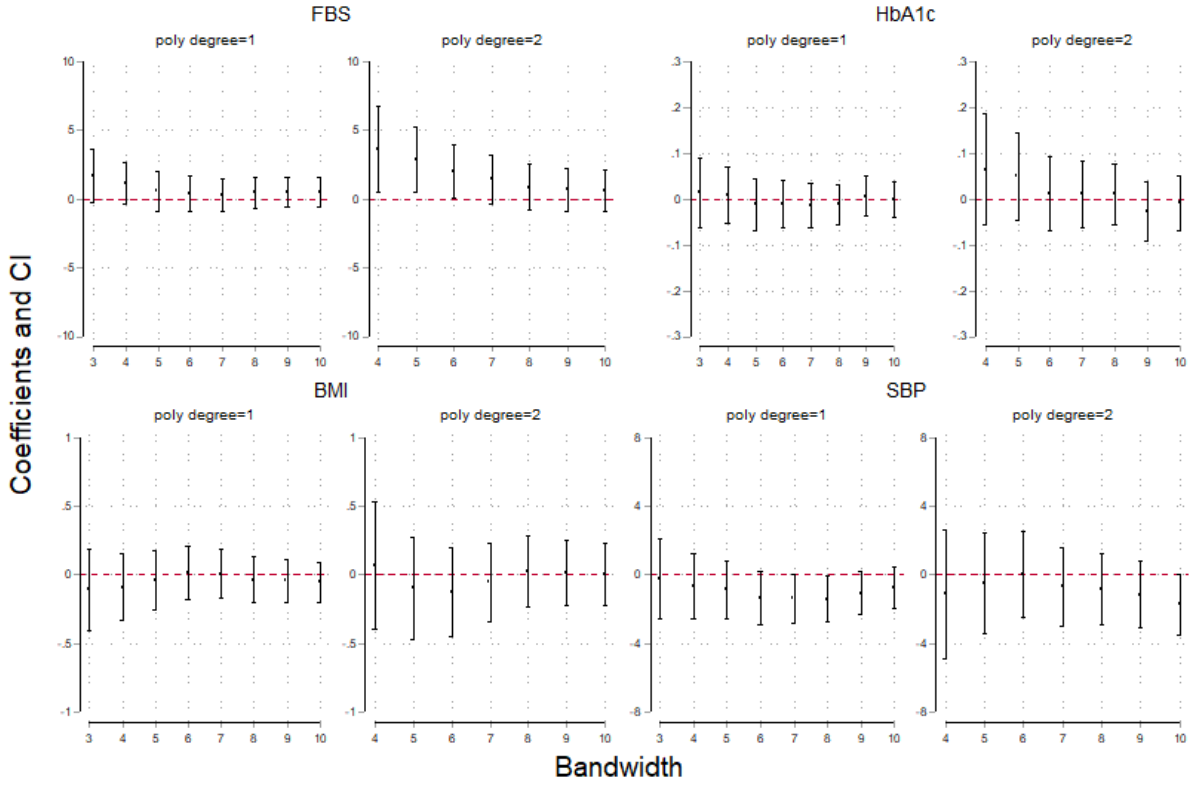
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and covariates. Only the coefficients and 95% CIs for the FBS≧110 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A30. Effects of exceeding the pre-diabetes threshold (FBS=110) on health behavior among high-risk individuals



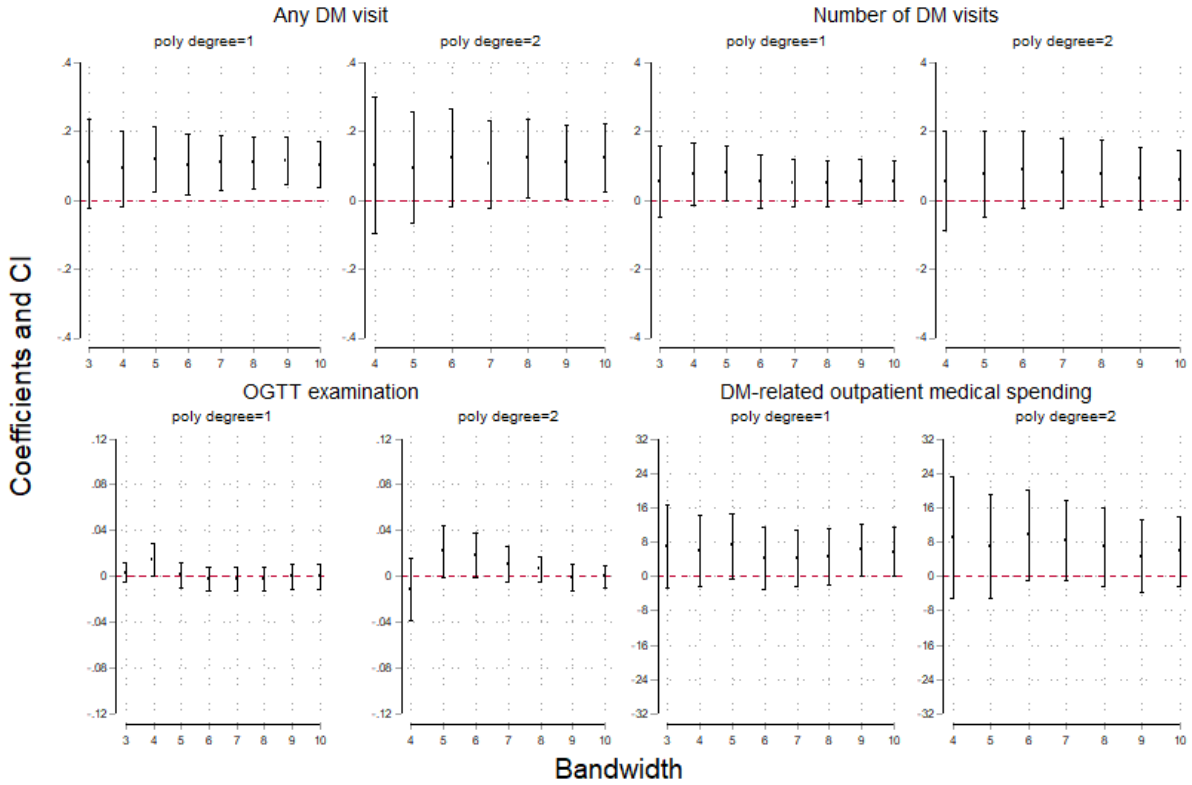
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and covariates. Only the coefficients and 95% CIs for the FBS≧110 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A31. Effects of exceeding the pre-diabetes threshold (FBS=110) on intermediate health outcomes among high-risk individuals



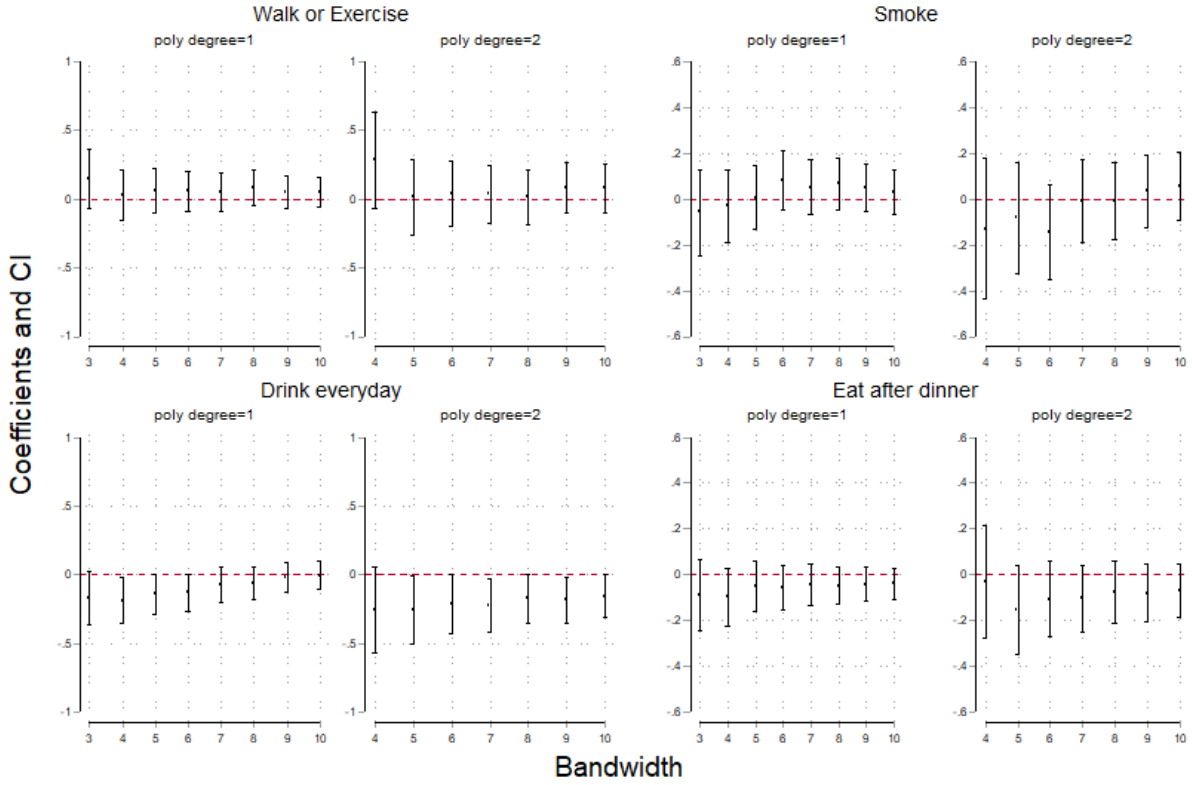
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and covariates. Only the coefficients and 95% CIs for the FBS≧110 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A32. Effects of exceeding the diabetic-type threshold (FBS=126) on medical care utilization among high-risk individuals



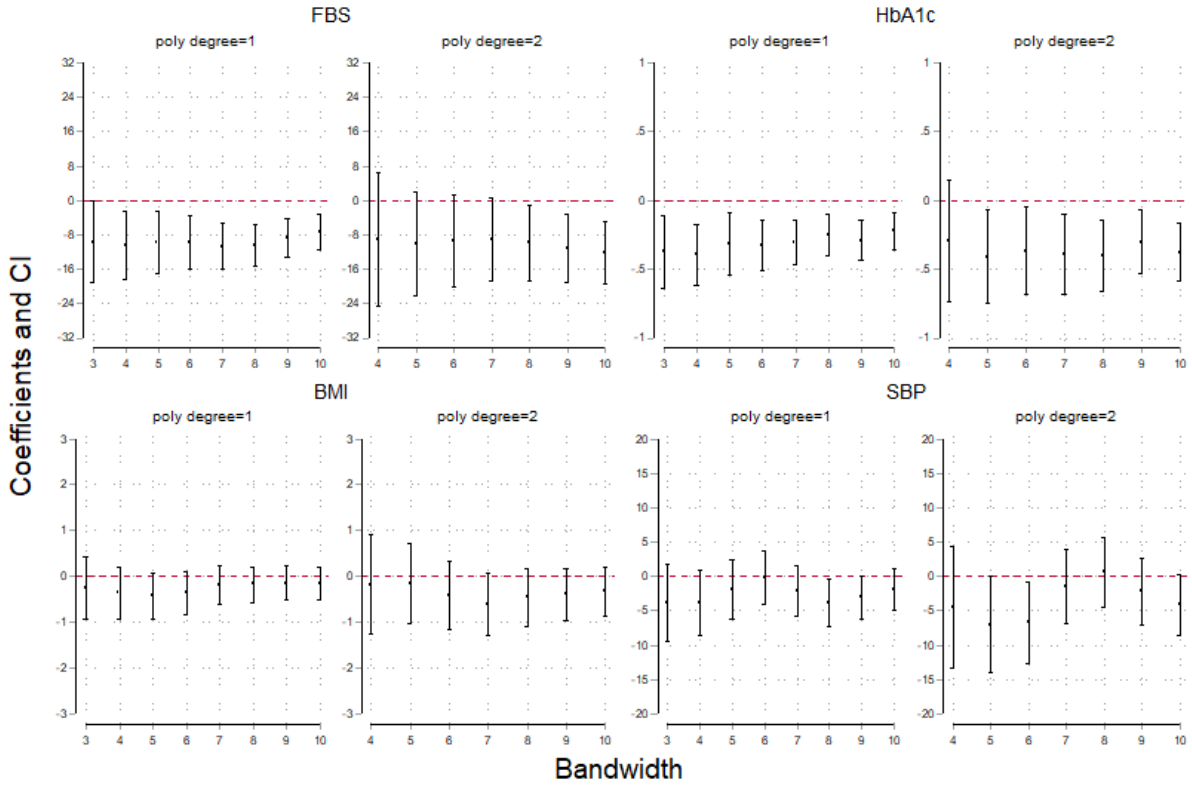
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and covariates. Only the coefficients and 95% CIs for the FBS≧126 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A33. Effects of exceeding the diabetic-type threshold (FBS=126) on health behavior among high-risk individuals



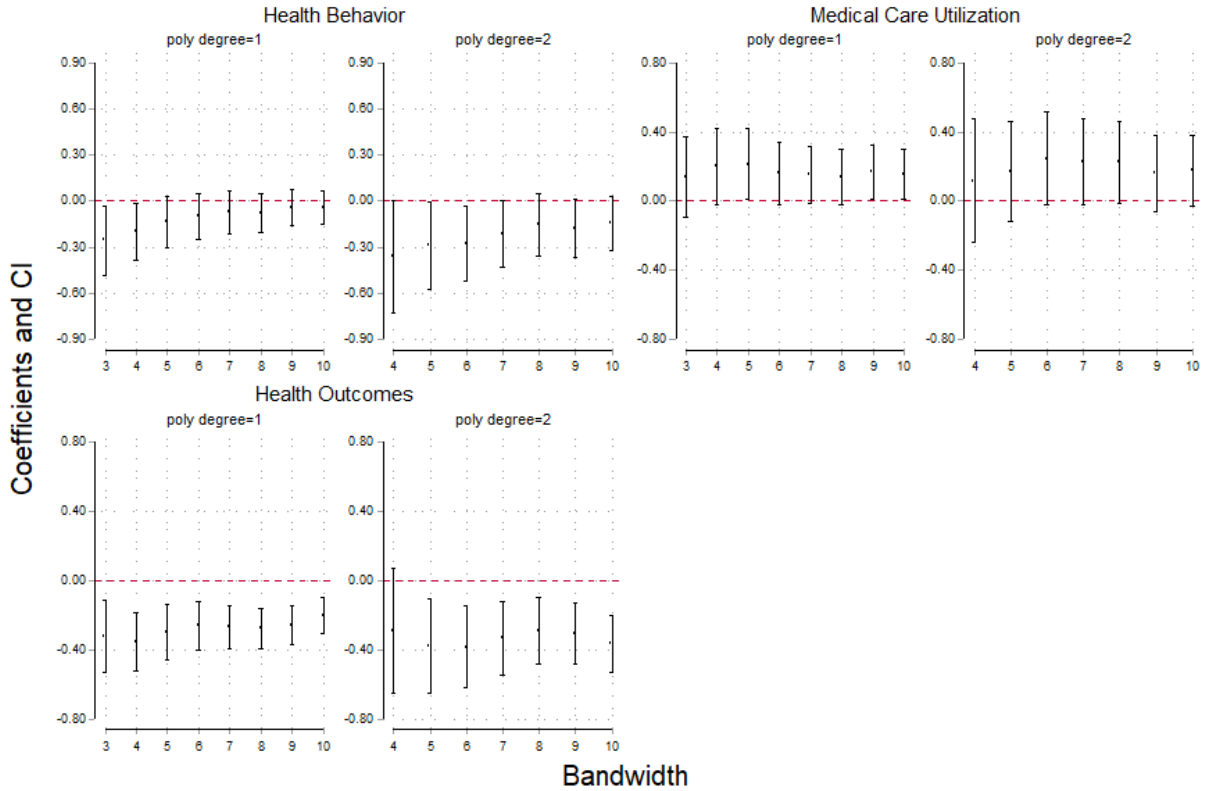
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and covariates. Only the coefficients and 95% CIs for the FBS≧126 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A34. Effects of exceeding the diabetic-type threshold (FBS=126) on intermediate health outcomes among high-risk individuals



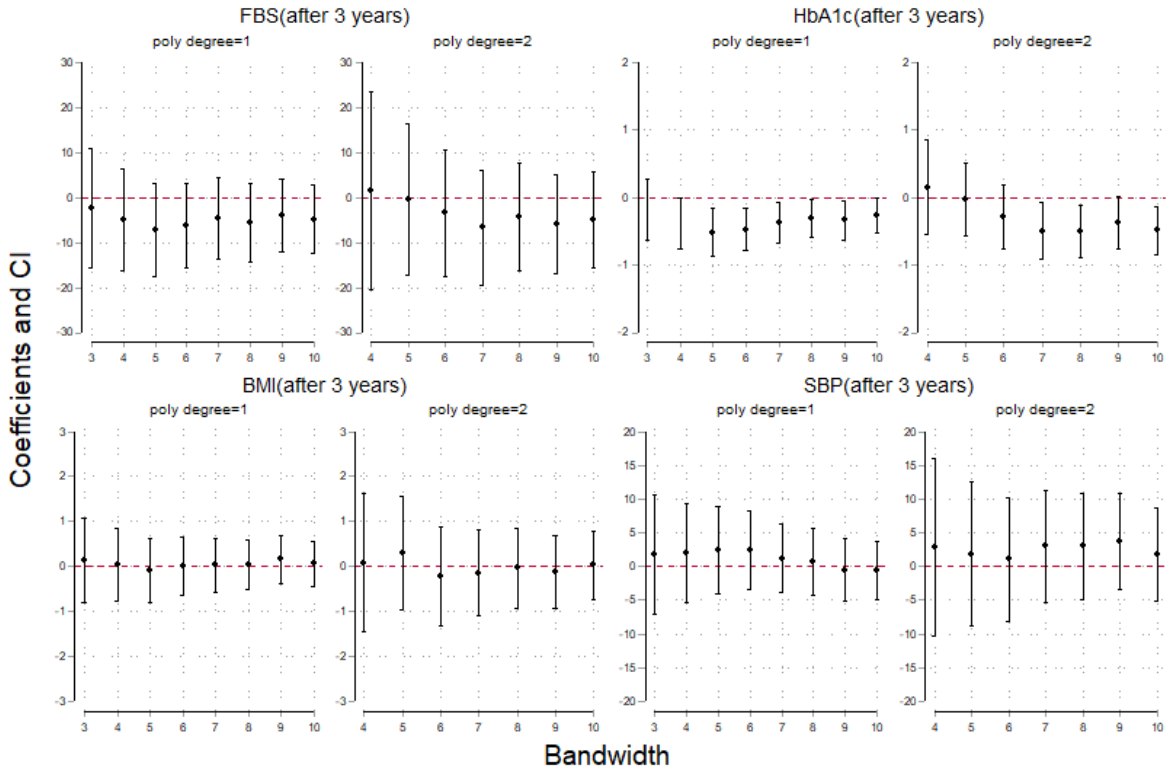
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and covariates. Only the coefficients and 95% CIs for the FBS≧126 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A35. Standardized treatment effect of the diabetic-type threshold (FBS=126) for high risks



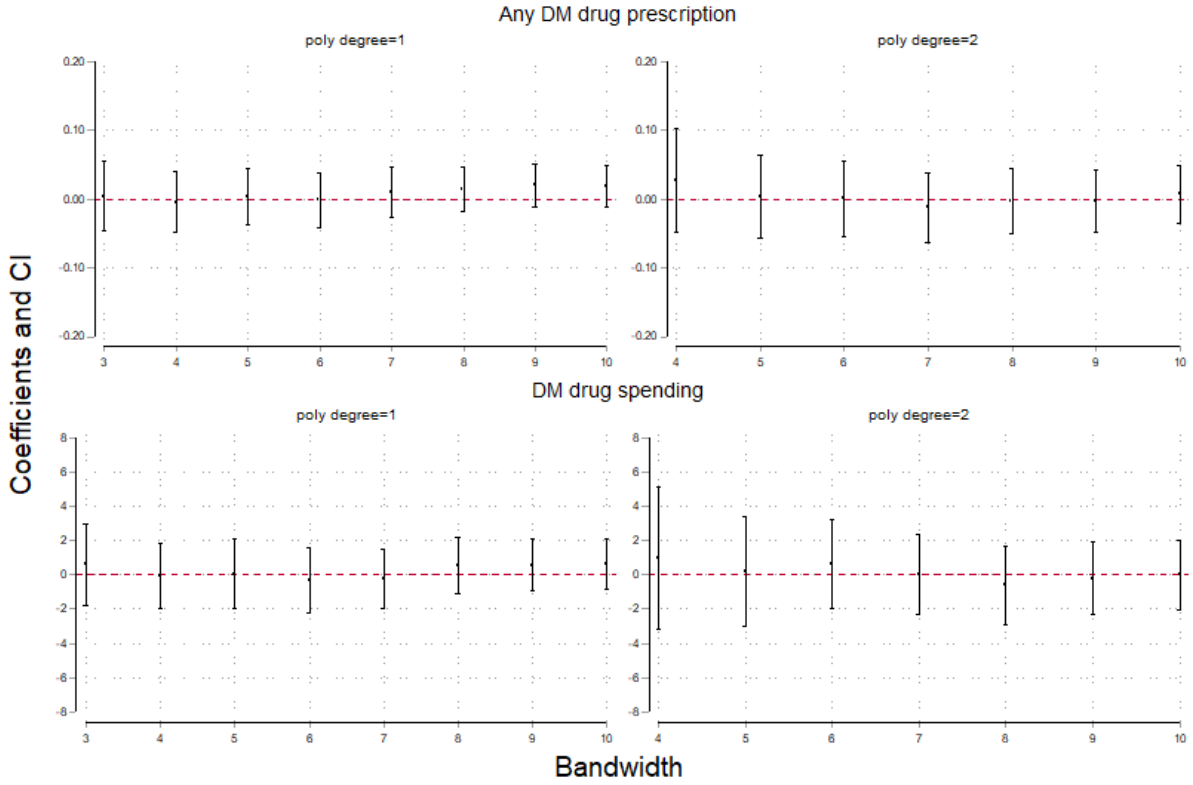
Notes: This figure presents the estimated standardized treatment effects. Only the coefficients and 95% CIs for the FBS≧126 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level. Individuals with FBS between 123 and 125 are chosen as the control group.

Figure A36. Longer-run effects of exceeding the diabetic-type threshold (FBS=126) on intermediate health outcomes among high-risk individuals (after 3 years)



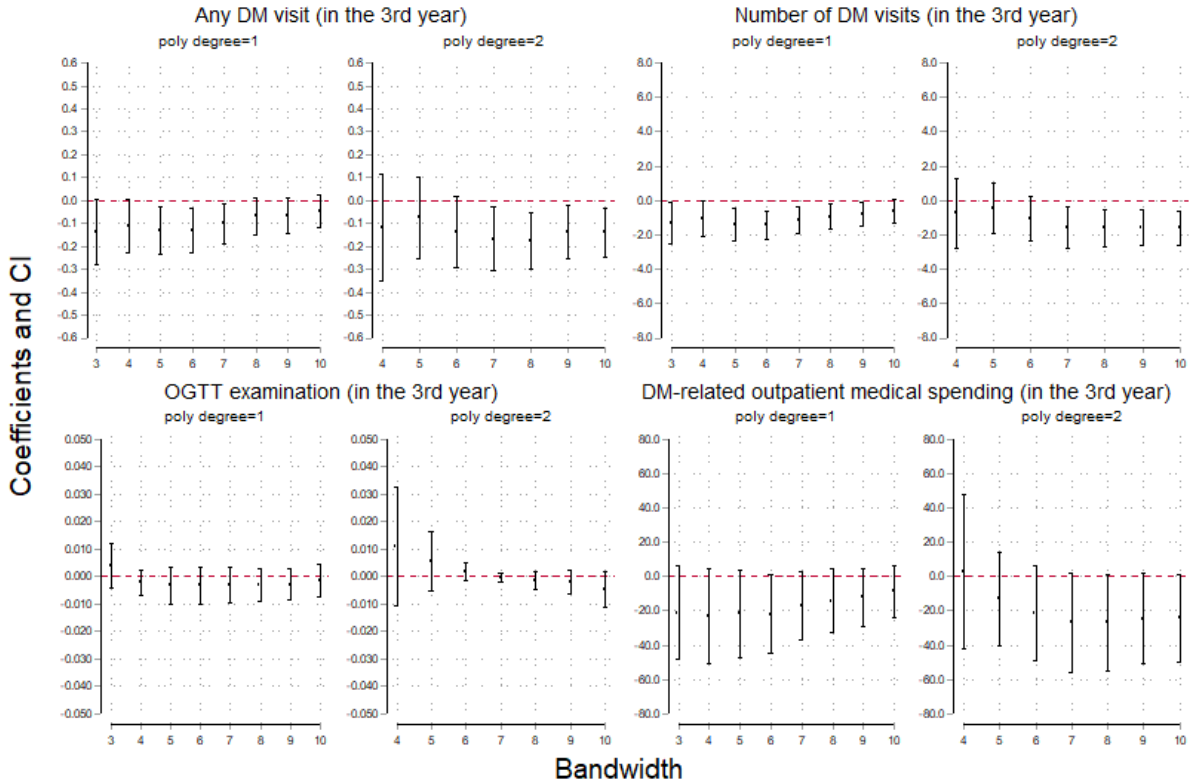
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and with covariates. Only the coefficients and 95% CIs for the FBS≧126 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A37. Effects of exceeding the diabetic-type threshold (FBS=126) on medications among high-risk individuals



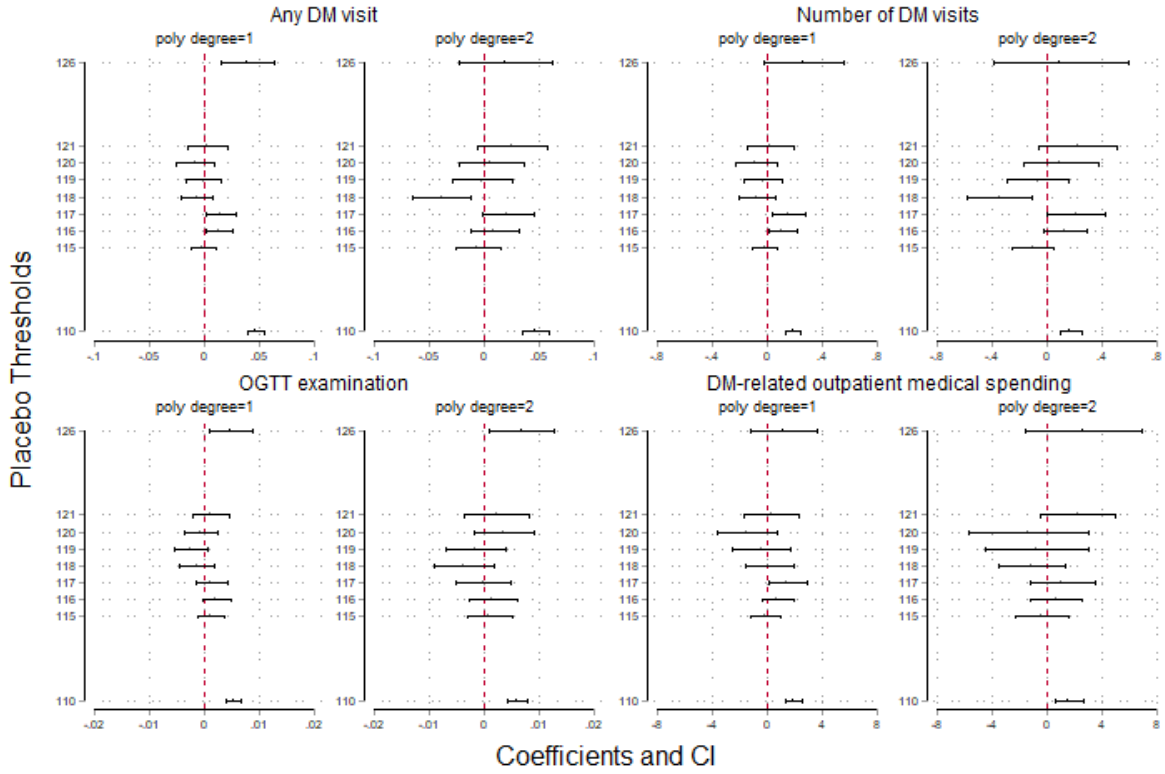
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and with covariates. Only the coefficients and 95% CIs for the FBS≧126 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A38. Longer-run effects of exceeding the diabetic-type threshold (FBS=126) on medical care utilization among high-risk individuals (in the third year)



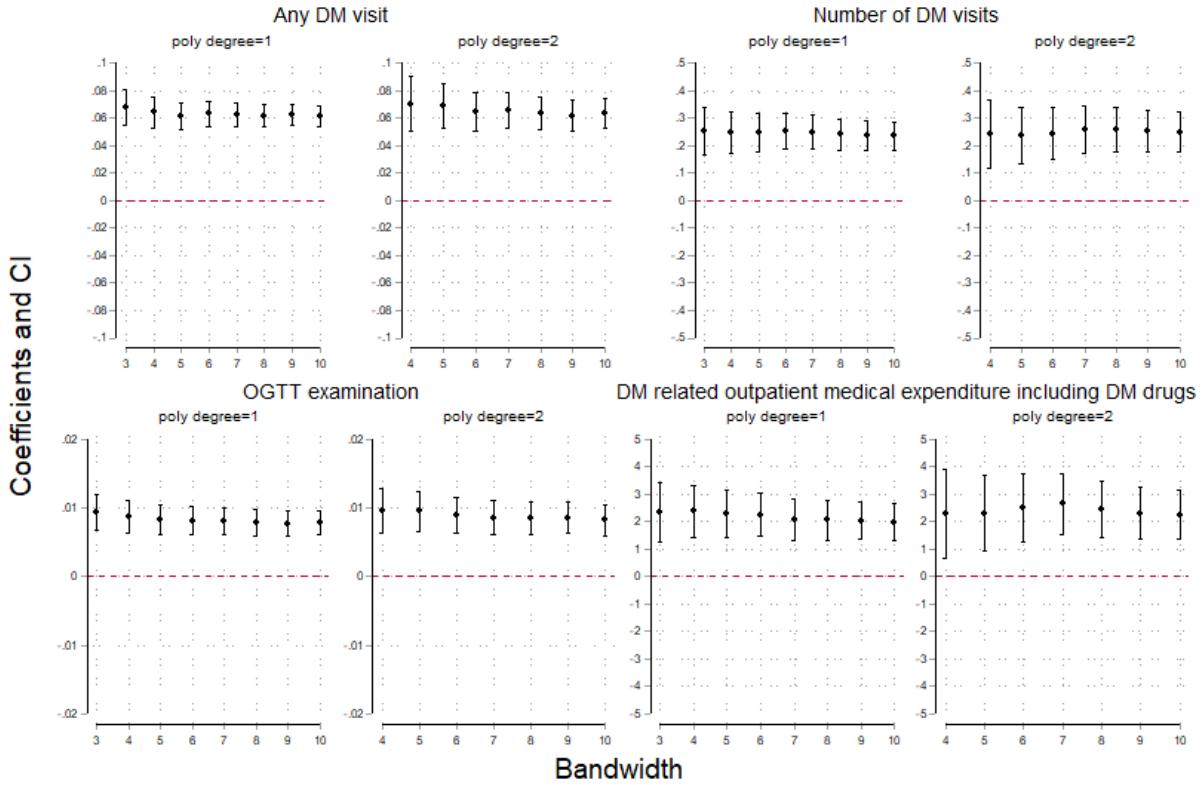
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and with covariates. Only the coefficients and 95% CIs for the FBS≧126 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A39. Effects of placebo signals (115≦FBS≦121) on medical care utilization



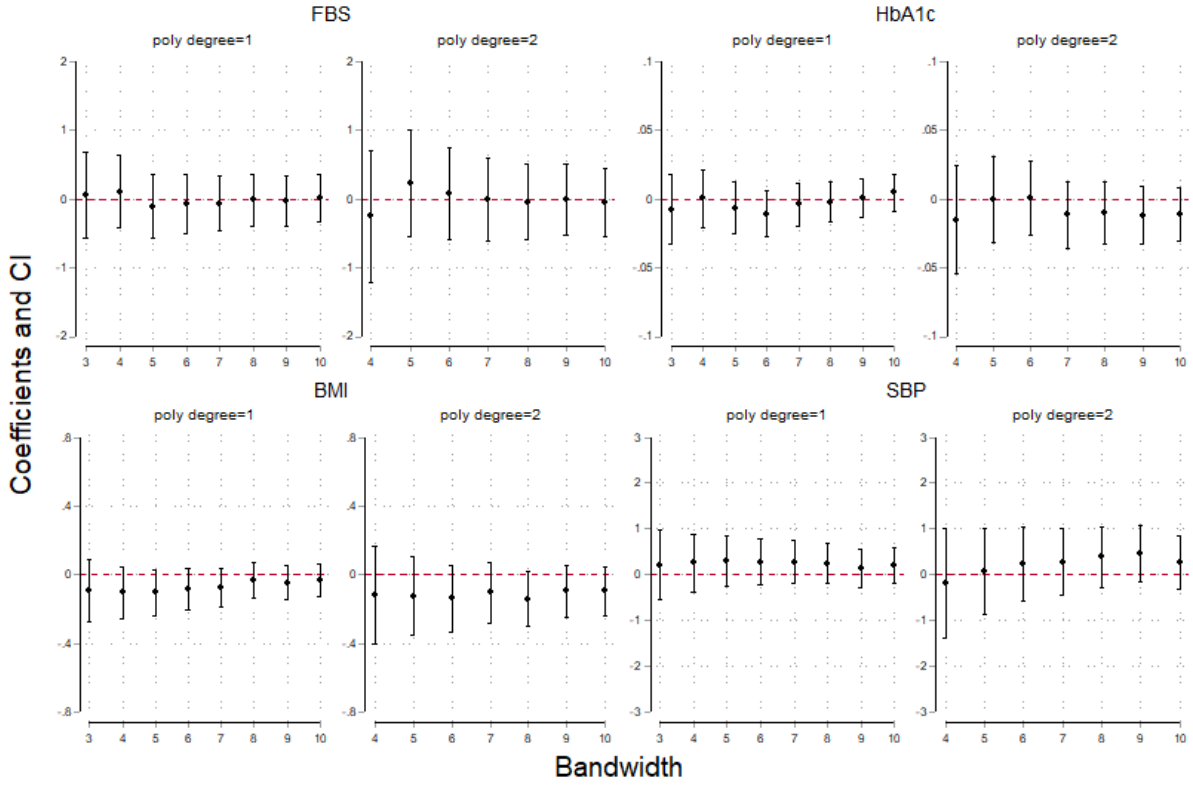
Notes: This figure presents the results from local polynomial regressions at placebo thresholds using rectangular kernel with our preferred bandwidth of 5mg/dl and covariates. The coefficients and 95% CIs are reported. To avoid contamination from actual thresholds at 110 and 126 mg/dl, the placebo thresholds are chosen from 115 to 121mg/dl. Standard errors, corrected for clustering at the person level.

Figure A40. Effects of exceeding the pre-diabetes threshold (FBS=110) on medical care utilization (for those who did not exceed the threshold in the previous year)



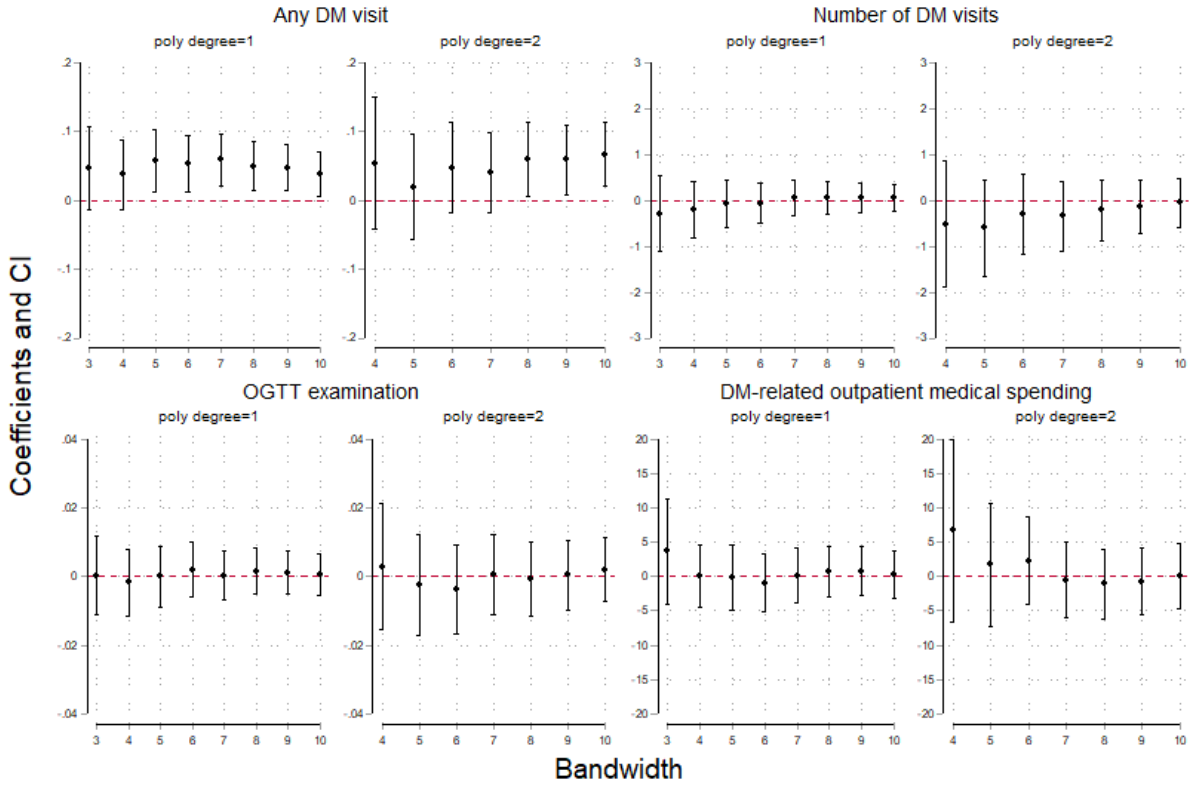
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and covariates. Only the coefficients and 95% CIs for the FBS≧110 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A41. Effects of exceeding the pre-diabetes threshold (FBS=110) on intermediate health outcomes (for those who did not exceed the threshold in the previous year)



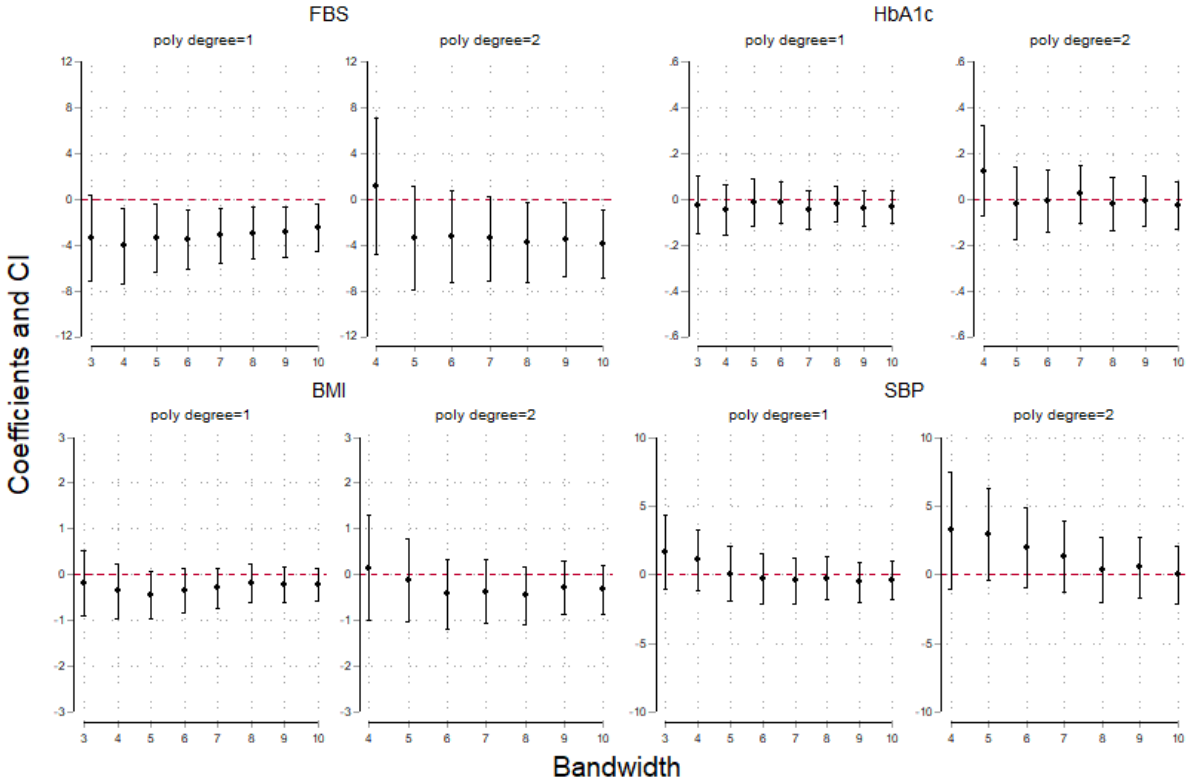
Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and covariates. Only the coefficients and 95% CIs for the FBS≧110 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A42. Effects of exceeding the diabetic-type threshold (FBS=126) on medical care utilization (for those who did not exceed the threshold in the previous year)



Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and covariates. Only the coefficients and 95% CIs for the FBS≧126 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Figure A43. Effects of exceeding the diabetic-type threshold (FBS=126) on intermediate health outcomes (for those who did not exceed the threshold in the previous year)



Notes: This figure presents the results from local polynomial regressions using rectangular kernel with different bandwidths and covariates. Only the coefficients and 95% CIs for the FBS≧126 mg/dl threshold are reported. Standard errors, corrected for clustering at the person level.

Table A1. McCrary test

Cutoff	Bandwidth				
	2	4	6	8	10
100	-0.776	**-2.786**	**-4.486**	**-7.756**	**-14.525**
101	-0.032	0.055	-1.303	**-4.015**	**-9.371**
102	1.349	**2.385**	1.828	-0.389	**-4.213**
103	-1.037	-0.126	0.384	-0.591	**-2.521**
104	0.707	-0.565	-0.401	0.117	-0.251
105	-1.171	-1.548	-1.439	0.282	1.394
106	0.880	0.839	1.384	**3.054**	**5.367**
107	-0.186	1.401	**2.972**	**4.519**	**7.729**
108	0.491	1.805	**3.362**	**5.215**	**8.763**
109	0.442	0.199	1.245	**3.749**	**7.618**
110	-1.424	**-2.176**	-1.471	1.358	**5.841**
111	0.724	0.338	0.605	**2.902**	**7.733**
112	0.226	1.647	**2.431**	**4.348**	**9.186**
113	0.330	1.110	**2.681**	**4.874**	**9.453**
114	-0.552	-0.260	1.549	**4.377**	**8.796**
115	0.531	0.400	1.609	**4.584**	**9.040**
116	-0.248	0.197	1.195	**3.867**	**8.462**
117	-0.047	0.720	1.505	**3.544**	**7.970**
118	0.923	1.009	1.570	**3.196**	**7.077**
119	-1.145	-1.279	-0.379	1.321	**4.653**
120	0.426	0.099	0.639	**2.069**	**4.913**
121	-0.059	1.198	1.493	**2.690**	**5.264**
122	1.283	1.035	1.456	**2.588**	**4.845**
123	**-2.465**	**-2.234**	-1.103	0.281	**2.375**
124	**2.248**	1.582	1.794	**2.644**	**4.248**
125	-1.200	0.241	0.561	1.323	**2.901**
126	1.010	0.585	0.706	1.141	**2.658**
127	-1.133	-1.120	-0.916	-0.298	1.177
128	0.996	0.161	-0.018	0.721	1.770
129	-1.131	-0.505	-0.046	0.697	1.574
130	1.143	1.497	**2.084**	**2.290**	**3.013**
131	-0.233	0.460	1.036	1.325	**2.021**
132	-0.333	-0.366	-0.353	0.099	0.726
133	0.663	-0.346	-0.822	-0.479	0.198
134	-1.348	-1.454	-1.570	-1.275	-0.460
135	1.141	1.118	1.067	1.003	1.578

Note: This table reports the results of McCrary's (2008) density test to detect manipulation of the running variable. We report t-values of the test for the null hypothesis that the density of FBS is continuous at the cutoff. Bold numbers indicate t-values greater than 2

Table A2. Permutation Test

	p-values	
	FBS at 110 mg/dl	FBS at 126 mg/dl
Individual test		
Age (at t)	0.153	0.519
Female (at t)	0.595	0.607
Walk or Exercise (at t)	0.947	1.000
Smoke (at t)	0.458	0.357
Drink every day (at t)	0.880	0.035
Eat after dinner (at t)	0.750	0.640
HbA1c (at t)	0.759	0.933
BMI (at t)	0.655	0.803
SBP (at t)	0.890	0.005
Joint test	0.474	0.749

Note: This table shows the results from a permutation test proposed by Canay and Kamat (2018) for the null hypothesis of continuity of the distribution of baseline covariates at the cutoff. The individual test reports the p-values for continuity of each of the nine covariates individually. The joint test reports the p-values for the nine-dimensional vector of covariates.