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Knowing is not half the battle: Impacts of information from the National Health Screening Program in Korea☆

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ABSTRACT

Health screening provides information on disease risk and diagnosis, but whether this promotes health is unclear. We estimate the impacts of information provided by Korea's National Health Screening Program by applying a regression discontinuity design around different biomarker thresholds of diabetes, obesity, and hyperlipidemia risk using administrative data that includes medical claims, biomarkers, and behavioral surveys over four years after screening. Generally, we find limited responses to disease risk information alone. However, we find evidence for weight loss around the high risk threshold for diabetes, where information is combined with active prompting for a secondary examination for diagnosis and treatment.

1. Introduction

Health behavior is an important determinant for health, especially in industrialized countries where morbidity and mortality are primarily related to chronic or lifestyle diseases (Cawley and Ruhm, 2012). For instance, the World Health Organization (2009) identifies that the leading causes of mortality and morbidity in high income countries are modifiable risk factors, including overweight and obesity, physical inactivity, high blood pressure, high blood sugar, high cholesterol, and tobacco and alcohol use. However, people often resist engaging in healthy behaviors that have positive future health outcomes. One explanation is that individuals have imperfect information about the benefits of healthy behaviors or about their own health status (Kenkel, 1991; Sloan et al., 2003).[1] To address the lack of information, many developed countries provide public health screening.[2] These policies assume that

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[1] Other explanations include the following. Viewing health as one of many inputs into utility, rational individuals may find the marginal cost of healthy behavior to be higher than the marginal benefit of improved health (Grossman, 1972). Becker and Murphy (1988) suggest that people initiate addictive behaviors involving forward-looking maximization with time-consistent preferences. Thaler and Shefrin (1981) suggest that time-inconsistent preferences prevent individuals from adopting healthy behaviors—individuals may face internal competition between the farsighted desire to obtain better health and the nearsighted desire for immediate pleasure. Cognitive limitation or bounded rationality is also suggested as an alternative model to explain myopic behaviors (e.g., Suranovic et al., 1999).

[2] Under the Affordable Care Act, the U.S. requires almost all health plans to cover a set of preventive services including health screening at no cost and Medicare started covering annual wellness visits, including a wide range of health screening and counseling benefits, in 2011 (Chung et al., 2015). In 2011, the United Kingdom also implemented national screening for cardiovascular disease in adults aged 40–74 (Dalton and Soljak, 2012). Asian countries, including South Korea (Lee and Lee, 2010) and Japan (Kohro et al., 2008), and other European countries such as Austria (Hackl et al., 2015) also have national health screening programs for adults.

the information provided from screening will promote desirable health behaviors and early treatment that would prevent disease or reduce complications.[3]

We test this assumption in this paper by investigating whether individuals modify their health behavior in response to the disease risk classification information provided in their health screening report card.[4] In addition, we account for when this disease risk classification information is combined with further medical intervention—active prompting for a secondary examination and, if diagnosis is confirmed, treatment. Specifically, we apply a regression discontinuity design that takes advantage of the fact that disease risk classifications and prompting for a secondary examination for diabetes, obesity, and hyperlipidemia[5] vary discontinuously with levels of fasting blood sugar, body mass index (BMI), and low-density lipoprotein (LDL) cholesterol, respectively, at cutoffs that are arbitrary in the sense that individuals just below and just above a cutoff share otherwise similar characteristics.[6]

Our study setting is one of the world's largest health screening programs, the National Health Screening Program (NHSP) in Korea. The NHSP provides free general health screening to the entire population aged 40 and over. The NHSP includes a variety of tests for health screening including diabetes, obesity, and hyperlipidemia, and is combined with a survey that collects information on health behaviors. We use data on a 2% random sample of the population from administrative data provided by the National Health Insurance Service (NHIS) in Korea, which includes more than 350,000 screening participants observed from 2009 to 2013. The size of the dataset allows us to implement a regression discontinuity design with enough precision to estimate null impacts or rule out small impacts. Also, the richness of the dataset—longitudinal administrative data that includes medical claims, biomarkers, and a survey of health behavior over four years after screening—allows us to test the effect of screening on a range of behaviors and health outcomes, both in the short and long-term.

We find that providing disease risk classification information is, in general, not effective in inducing changes in behavior. For example, we find little to no differences in behavior around the medium risk thresholds for diabetes and obesity. In addition, we do not find changes in behavior around the high risk (disease suspected) thresholds for obesity and hyperlipidemia. Although we find an increase in the number of outpatient visits for those who were informed as high risk for hyperlipidemia, this does not translate to increased medical treatment or changes in behavior.

However, we do find increased diabetes medication and weight loss around the high risk (disease suspected) threshold for diabetes, where information is combined with prompting for a secondary examination and, if diagnosis is confirmed, treatment. Specifically, those just above the cutoff are prescribed 20.9 days more of diabetes medication (a 73.3% change), reduce BMI by 0.16 kg/m^2 (a 0.6% change), and reduce waist circumference by 1 cm (a 1.1% change) in the short-run. In the long-run, however, the observed short-run impacts are attenuated and no longer statistically significant. Our results suggest that information alone is not necessarily sufficient to lead to behavioral changes and better health outcomes, and that further medical intervention in addition to the disease risk classification information could increase the marginal benefits of screening.

Our study makes three important contributions. First, this paper complements the literature on how risk information affects health behaviors and health outcomes, by studying a setting where in some instances only risk information is provided and in other instances risk information coincides with diagnosis and medical treatment. In addition, our unique setting with three major lifestyle diseases (diabetes, obesity, and hyperlipidemia) and longitudinal administrative data allows us to have a comprehensive understanding on the role of information on disease risk. These distinctions are important because earlier papers, which focus on a specific disease through a relatively short period of time, have found mixed results which may have been conditional on whether only information was provided or whether information was synonymous with diagnosis and treatment. For instance, large impacts are found in individuals with confirmed Huntington Disease, a life threatening disease with no cure (Oster et al., 2013), and in newborns with Very Low Birth Weight classification, which is combined with medical treatment (Almond et al., 2010). Modest behavior changes are found with diagnosis of diabetes (Slade, 2012; Oster, 2015), HIV (Thornton, 2008), and hypertension (Zhao et al., 2013). However, limited effects are found for overweight classification (Almond et al., 2016; Prina and Royer, 2014), diabetes genetic risk group (Wu et al., 2016), and pre-diabetes status (Iizuka et al., 2017), none of which are combined with medical treatment.

Second, the quasi-experimental regression discontinuity design that we implement allows us to control for confounding factors that would make it difficult to disentangle the endogenous relationship between information on disease risk and outcomes. In fact, the use of suitable methods to control for endogeneity is particularly important to understand the behavior changes after a disease diagnosis because the relative risk of developing a disease is often correlated with past behaviors of individuals. Among quasi-experimental studies, our study is closest to papers that employ a regression discontinuity design based on diagnostic thresholds of birth weight for very low birth weight classification for newborns (Almond et al., 2010), systolic blood pressure for hypertension (Zhao et al., 2013), BMI for obesity (Almond et al., 2016), aorta size for abdominal aortic aneurysm (Dahlberg et al., 2016), and fasting blood sugar for pre-diabetes (Iizuka et al., 2017).

Lastly, this study provides evidence of the impact of risk information from screening on outcomes at a population level, based on a national health screening program. As Kim and Lee (2017) discuss, effects in the population-based screening setting might differ from those provided by clinical RCTs due to selection and crowd out. Thus, our setting provides rare practical evidence to inform national-level screening initiatives in other countries.

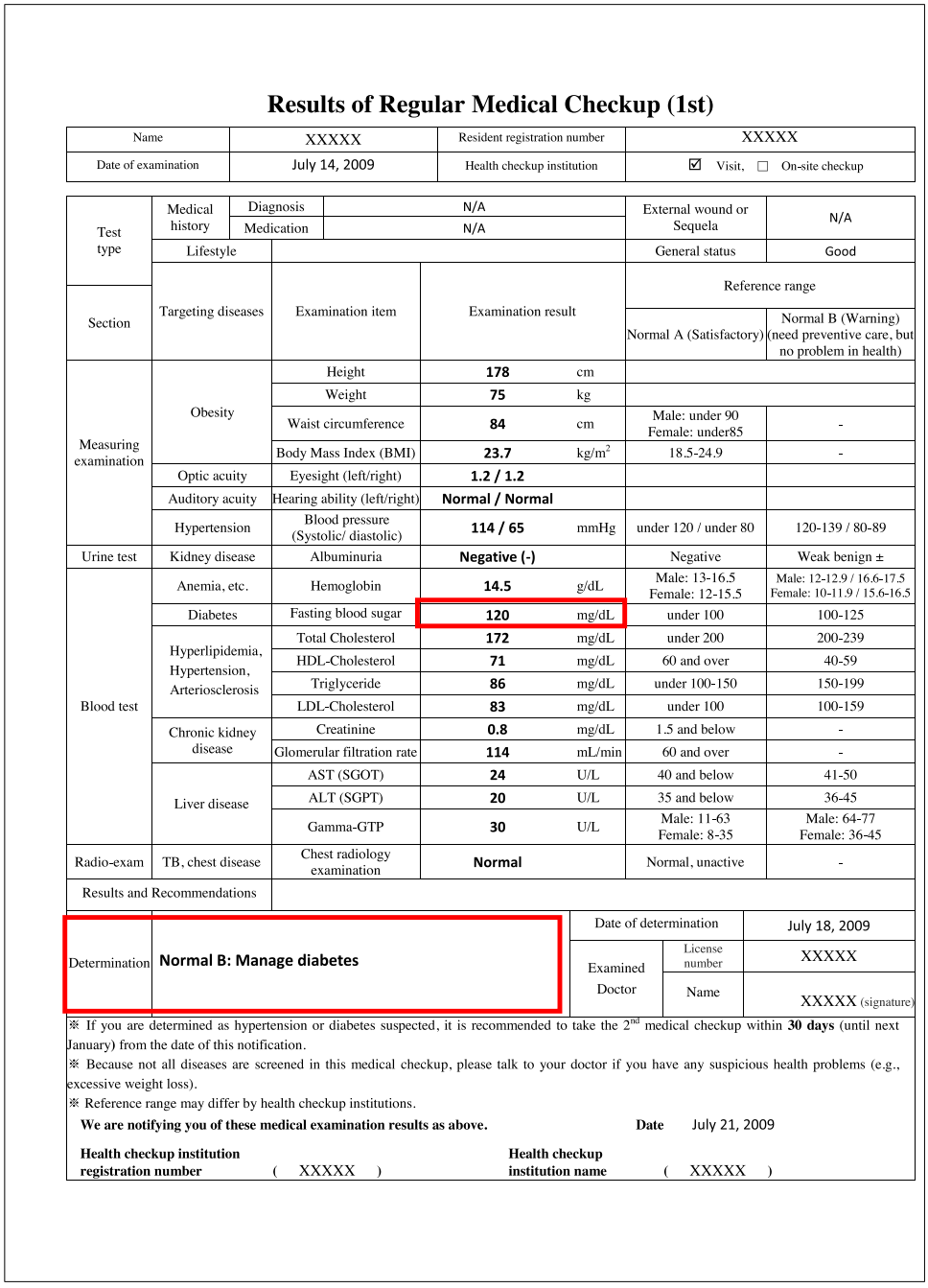
The remainder of the paper is organized as follows. Section 2 describes the institutional context and the screening program which creates the setting for our analysis. Section 3 describes the data and Section 4 presents the empirical framework. Section 5 describes and discusses the results. Section 6 concludes.

[3] Studies in other settings suggest that pure information could change health behavior. This includes studies exploring impacts of calorie posting on menus (Bollinger et al., 2011; Wisdom et al., 2010), and nutritional labeling (Variyam and Cawley, 2006).

[4] Our study investigates the relative impacts of different information and interventions from screening, which is distinct from the impact of screening versus not screening.

[5] Hyperlipidemia is a condition in which there are abnormally high levels of fats or lipids in the blood. Examples of lipids include cholesterol and triglycerides. In this study, the relative risk of hyperlipidemia is determined by the level of LDL cholesterol.

[6] For example, high risk for diabetes is defined as having a fasting blood sugar level of 126 mg/dL, meaning that an individual with a fasting blood sugar level of 126 mg/dL would be considered to have high risk for diabetes and would be prompted to take a secondary examination, while an individual with a fasting blood sugar level of 125 mg/dL would be considered to have medium risk for diabetes and would not be prompted to take the secondary examination. However, actual disease risk is not discontinuous at these thresholds—e.g., they tend to be set conservatively and have also changed over time (Welch et al., 2011).



Results of Regular Medical Checkup (1st)

Name	XXXXX	Resident registration number	XXXXX
Date of examination	July 14, 2009	Health checkup institution	☑ Visit, ☐ On-site checkup

Test type	Medical history	Diagnosis	N/A	External wound or Sequela	N/A
		Medication	N/A		
	Lifestyle			General status	Good

Section	Targeting diseases	Examination item	Examination result		Reference range: Normal A (Satisfactory)	Reference range: Normal B (Warning) (need preventive care, but no problem in health)
Measuring examination	Obesity	Height	**178**	cm		
		Weight	**75**	kg		
		Waist circumference	**84**	cm	Male: under 90 Female: under85	-
		Body Mass Index (BMI)	**23.7**	kg/m^2	18.5-24.9	-
	Optic acuity	Eyesight (left/right)	**1.2 / 1.2**			
	Auditory acuity	Hearing ability (left/right)	**Normal / Normal**			
	Hypertension	Blood pressure (Systolic/ diastolic)	**114 / 65**	mmHg	under 120 / under 80	120-139 / 80-89
Urine test	Kidney disease	Albuminuria	**Negative (-)**		Negative	Weak benign ±
Blood test	Anemia, etc.	Hemoglobin	**14.5**	g/dL	Male: 13-16.5 Female: 12-15.5	Male: 12-12.9 / 16.6-17.5 Female: 10-11.9 / 15.6-16.5
	Diabetes	Fasting blood sugar	**120**	mg/dL	under 100	100-125
	Hyperlipidemia, Hypertension, Arteriosclerosis	Total Cholesterol	**172**	mg/dL	under 200	200-239
		HDL-Cholesterol	**71**	mg/dL	60 and over	40-59
		Triglyceride	**86**	mg/dL	under 100-150	150-199
		LDL-Cholesterol	**83**	mg/dL	under 100	100-159
	Chronic kidney disease	Creatinine	**0.8**	mg/dL	1.5 and below	-
		Glomerular filtration rate	**114**	mL/min	60 and over	-
	Liver disease	AST (SGOT)	**24**	U/L	40 and below	41-50
		ALT (SGPT)	**20**	U/L	35 and below	36-45
		Gamma-GTP	**30**	U/L	Male: 11-63 Female: 8-35	Male: 64-77 Female: 36-45
Radio-exam	TB, chest disease	Chest radiology examination	**Normal**		Normal, unactive	-
Results and Recommendations						

Determination	**Normal B: Manage diabetes**	Date of determination		July 18, 2009
		Examined Doctor	License number	XXXXX
			Name	XXXXX (signature)

※ If you are determined as hypertension or diabetes suspected, it is recommended to take the 2nd medical checkup within **30 days** (until next January) from the date of this notification.

※ Because not all diseases are screened in this medical checkup, please talk to your doctor if you have any suspicious health problems (e.g., excessive weight loss).

※ Reference range may differ by health checkup institutions.

We are notifying you of these medical examination results as above. **Date** July 21, 2009

Health checkup institution registration number (XXXXX) **Health checkup institution name** (XXXXX)

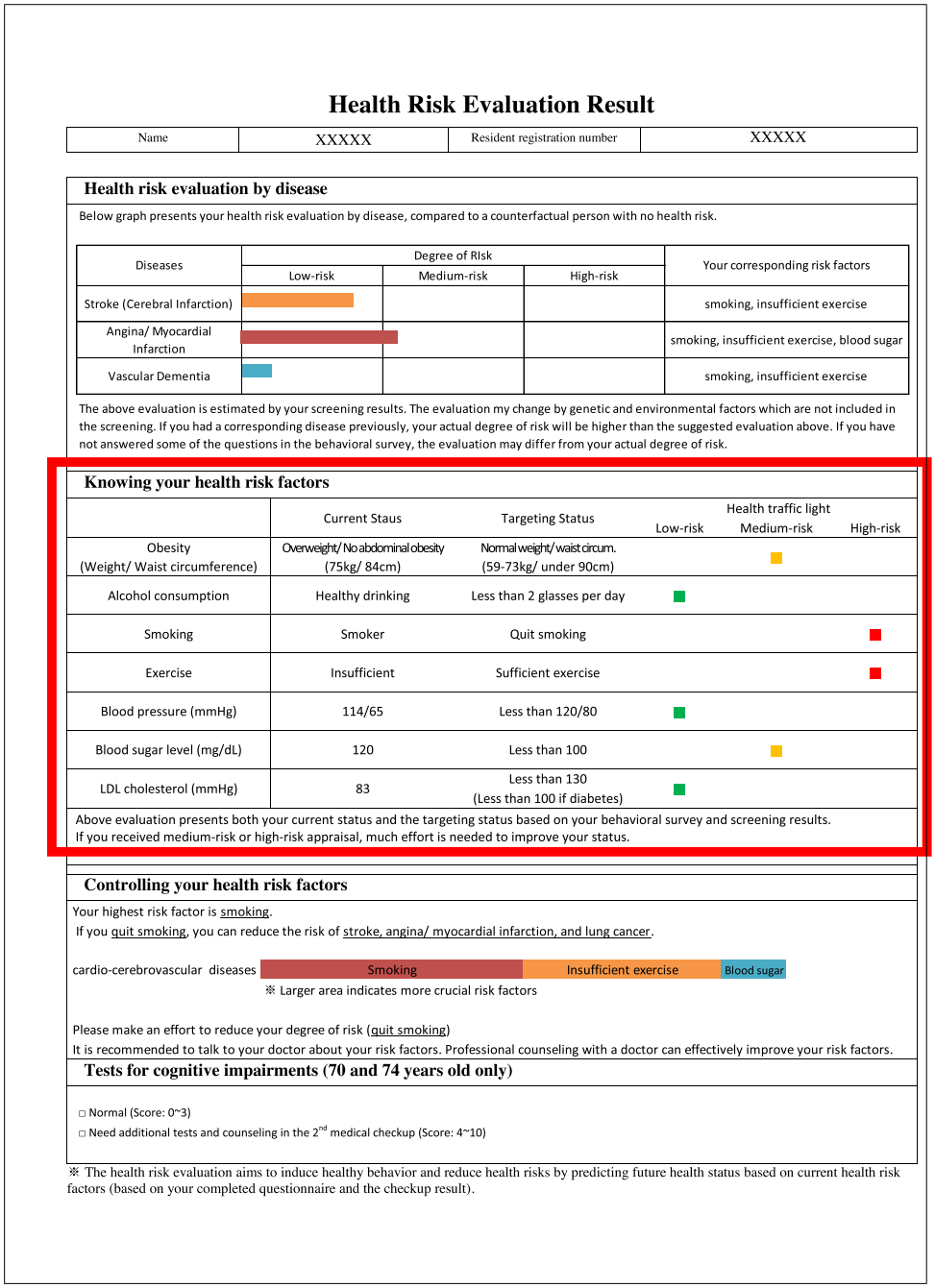
Fig. 1. (a) National Health Screening Program (NHSP) report card. (b) National Health Screening Program (NHSP) report card.
Notes: The report card is based on the 2009 standards. In the 2010 revision, BMI in the range "25.0–29.9" is classified as Normal B; and Normal A range for LDL cholesterol is "under 130" and Normal B range is "130–159".

2. Institutional details

The National Health Screening Program (NHSP) in Korea has provided free general health screening since 1995. The NHSP consists of various tests and measurements including systolic and diastolic blood pressure, fasting blood sugar, cholesterol, hemoglobin, height, weight, waist circumference, and many others. During 2008–2009, to improve the precision and understanding of the screening results, the NHSP added waist circumference as a biomarker, broadened the lipid panel (to include HDL cholesterol, LDL cholesterol, and triglycerides), and added a "Health Risk Evaluation" section to the screening report. Before the screening, a survey is conducted of the screening participants regarding health behaviors such as exercise, alcohol consumption, and cigarette smoking. Free health screening through the NHSP is available every other year.[7]

A screening report is sent to the household by regular mail within two weeks after screening. The screening report consists

[7] Those born in odd-numbered (even-numbered) years are encouraged to undergo screening in odd-numbered (even-numbered) years. Age restrictions vary across insurance type as shown in Appendix Table A.1. Blue-collar workers with employee insurance are an exception in that they are eligible for screening every year. In addition to the free screening offered every one or two years, people are allowed to participate in the screening program through out-of-pocket expenditures at any time.



Health Risk Evaluation Result

Name	XXXXX	Resident registration number	XXXXX

Health risk evaluation by disease

Below graph presents your health risk evaluation by disease, compared to a counterfactual person with no health risk.

Diseases	Degree of RIsk			Your corresponding risk factors
	Low-risk	Medium-risk	High-risk	
Stroke (Cerebral Infarction)				smoking, insufficient exercise
Angina/ Myocardial Infarction				smoking, insufficient exercise, blood sugar
Vascular Dementia				smoking, insufficient exercise

The above evaluation is estimated by your screening results. The evaluation my change by genetic and environmental factors which are not included in the screening. If you had a corresponding disease previously, your actual degree of risk will be higher than the suggested evaluation above. If you have not answered some of the questions in the behavioral survey, the evaluation may differ from your actual degree of risk.

Knowing your health risk factors

	Current Staus	Targeting Status	Health traffic light		
			Low-risk	Medium-risk	High-risk
Obesity (Weight/ Waist circumference)	Overweight/ No abdominal obesity (75kg/ 84cm)	Normal weight/ waist circum. (59-73kg/ under 90cm)		■	
Alcohol consumption	Healthy drinking	Less than 2 glasses per day	■		
Smoking	Smoker	Quit smoking			■
Exercise	Insufficient	Sufficient exercise			■
Blood pressure (mmHg)	114/65	Less than 120/80	■		
Blood sugar level (mg/dL)	120	Less than 100		■	
LDL cholesterol (mmHg)	83	Less than 130 (Less than 100 if diabetes)	■		

Above evaluation presents both your current status and the targeting status based on your behavioral survey and screening results.
If you received medium-risk or high-risk appraisal, much effort is needed to improve your status.

Controlling your health risk factors

Your highest risk factor is smoking.
If you quit smoking, you can reduce the risk of stroke, angina/ myocardial infarction, and lung cancer.

cardio-cerebrovascular diseases: Smoking | Insufficient exercise | Blood sugar

※ Larger area indicates more crucial risk factors

Please make an effort to reduce your degree of risk (quit smoking)
It is recommended to talk to your doctor about your risk factors. Professional counseling with a doctor can effectively improve your risk factors.

Tests for cognitive impairments (70 and 74 years old only)

□ Normal (Score: 0~3)
□ Need additional tests and counseling in the 2nd medical checkup (Score: 4~10)

※ The health risk evaluation aims to induce healthy behavior and reduce health risks by predicting future health status based on current health risk factors (based on your completed questionnaire and the checkup result).

Fig. 1. (*Continued*)

of two pages. Fig. 1 shows a sample of the screening report from 2009, our baseline year. The first page of the screening report card (Fig. 1a) provides, for each biomarker, the exam result and two reference ranges—Normal A (Satisfactory) and Normal B (Warning; need preventive care, but no problem in health). If a biomarker falls outside the range of Normal A and Normal B, it is classified as Disease Suspected. Individuals are notified of which measurements are determined as Normal B or Disease Suspected in the bottom of the first page. For example, the red boxes in Fig. 1a indicate that a person has a fasting blood sugar level of 120 mg/dL, and thus determined as "Normal B: Manage diabetes."

The second page of the screening report card (Fig. 1b) informs screening participants of their "Health Risk Evaluation (HRE)." The HRE is designed to help individuals better understand and control their risk factors by visualizing the degree of risk. We focus on blood sugar, obesity, and LDL cholesterol in the "Knowing your health risk factors" section (within the red box, in the middle of the page) where the level of risk indicated by different "health traffic light" colors—low risk (green), medium risk (yellow), and high risk (red)—changes discontinuously based on the BMI, waist circumference, blood sugar, and LDL cholesterol ranges displayed on the first page. The cutoffs for the health traffic lights, summarized in Table A.2, are determined using the same or additional reference range cutoffs as those reported in the first page.

Those with a fasting blood sugar or blood pressure level outside the range of Normal A and B are offered a free secondary examination to confirm a diagnosis of diabetes or hypertension. Specifically, the secondary examination is encouraged in the screening report card as well as by direct contact from the medical institution at

which they took screening.[8] The secondary examination consists of confirmatory diagnostic tests, counseling with a physician, and recommendation for medical treatment if diagnosis is confirmed. For diseases other than diabetes and hypertension, individuals outside the range of Normal A and B are recommended in the screening report to seek further evaluation, but it is not covered by the NHSP.

Table 1 summarizes the study sample, cutoffs, and treatment (i.e., information obtained from the screening report) which change discretely around the cutoffs for each biomarker. We consider three biomarkers: fasting blood sugar, BMI, and LDL cholesterol which respectively determine the relative risk for diabetes, obesity, and hyperlipidemia.[9] First, we study diabetes screening by exploring the cutoffs 100 and 126 of fasting blood sugar (Panel A of Table 1). Those above the 100 cutoff receive a worse classification (medium risk/Normal B versus low risk/Normal A) compared to those below it. Those above the 126 cutoff receive a worse risk classification (high risk/diabetes suspected versus medium risk/Normal B) and are prompted to undergo the secondary examination. The 126 cutoff also coincides with the clinical guideline to prescribe diabetes medications if, upon secondary examination, the blood sugar level of 126 and above is confirmed and thus diagnosed as diabetes (Korean Diabetes Association, 2007, 2015; American Diabetes Association, 2015).

Second, we examine obesity screening by exploring the cutoffs 23 and 25 of BMI (Panel B of Table 1).[10],[11] The risk classification for obesity depends upon BMI and abdominal obesity (a waist circumference greater than 85 cm for females and 90 cm for males). For the health traffic light, the cutoff 23 divides low risk/Normal A and medium risk/Normal A for those who are not abdominal obese (below the waist circumference cutoff), while the cutoff 25 divides medium risk/Normal A and high risk/Normal B for those who are abdominal obese (at or above the waist circumference cutoff). Therefore, we restrict our sample to people with or without abdominal obesity depending on the BMI cutoffs we are investigating. In Korea, the diagnosis cutoff for a diagnosis of obesity is BMI over 25 with abdominal obesity. The basic treatment for obesity is healthy diet and regular physical exercise. Drug treatment or weight loss surgery for obesity is only recommended for special cases including those with cardiovascular complications, extreme obesity, or sleep apnea (Korean Endocrine Society and Korean Society for the Study of Obesity, 2010).

Lastly, we examine the cutoff 160 of LDL cholesterol among those without a previous history of hyperlipidemia or diabetes (Panel C of Table 1).[12] The cutoff 160 divides Medium Risk/Normal B and High Risk/Hyperlipidemia Suspected. Medical treatment is recommended at the 160 cutoff for people with confirmed diagnosis, which is based on additional risk factors.[13]

To summarize the expected outcomes, only those with biomarkers above the high risk cutoffs (blood sugar 126, BMI 25, and LDL cholesterol 160) are recommended for further medical evaluation to confirm diagnosis through the screening report. Therefore, we expect possible changes in health behavior as well as diagnosis and treatment around the high risk cutoffs. However, we expect only possible changes in health behavior at the lower risk, pre-disease cutoffs (i.e., blood sugar 100 and BMI 23 cutoff).

3. NHIS data

Our analysis uses the NHIS's National Sample Cohort (NHIS-NSC) data that is a 2% random sample of the Korean population (Lee et al., 2015). Our empirical analysis requires data on take-up and the results from general screening, and future health behaviors and health outcomes. The NHIS database consists of three parts—eligibility information, medical claims, and screening information. Eligibility data such as gender, age group, income bracket, and type of insurance as well as disease-specific medical claims data are available regardless of screening participation. However, information from screening, such as self-reported health behaviors, self-reported previously diagnosed diseases, and biomarkers, are available only for screening participants.[14]

Our study sample consists of those who participated in the NHSP in 2009 or 2010. We define 2009–2010 screening as the baseline or round 1 screening because most people are eligible for screening in only one of these years, and combine the 2009 and 2010 samples for our main analysis to increase statistical power.[15] In our data, 352,245 individuals participated in the baseline screening. Among eligible individuals, the baseline screening participation rate was about 66% in 2009 and 68% in 2010 (NHIS, 2009, 2010).

Table 2 reports the baseline summary statistics of variables for individuals who participated in the baseline screening during 2009–2010. Of those baseline screening participants, about 77% and 53% participated in round 2 (after 1 or 2 years) and round 3 (after 3 or 4 years), respectively.[16]

While our analysis is based on voluntary screening participants, we are able to measure some of the characteristics of the screening non-participants. To shed light on external validity, we compare the characteristics of screening participants and non-participants (Table A.3). We find that screening participants are more likely to have employee insurance, have higher income, and have lower total medical expenditure compared to those who are eligible but did not take screening during 2009–2010.

[8] Unfortunately, our data do not support individual level information on the secondary examination. According to the statistical yearbook of the NHIS, the participation rate for the secondary examination among eligible individuals was 37% in 2009 and 39% in 2010 (NHIS, 2009, 2010). The secondary examination report card is shown in Fig. A.1. Individuals are informed about diet control, exercise, and need for medical treatment.

[9] We considered studying other disease risk classifications such as hypertension. However, blood pressure readings suffer from clustering at multiples of five and ten, and hence are not suitable for a regression discontinuity analysis which requires smooth density around the cutoffs.

[10] The World Health Organization (WHO, 2000) introduced the classification of obesity based on BMI thresholds of 18.5, 25, 30, 35 and 40 in 2000. Modifications of the WHO definitions are used across different countries, especially in Asia.

[11] We do not study the underweight classification—and thus the BMI threshold of 18.5—in this paper because a classification of underweight is fundamentally different from a classification of overweight or obese. We do not assess the BMI threshold of 30 for individuals without abdominal obesity because the sample size around this threshold is small.

[12] We do not focus on the lower cutoffs for LDL cholesterol because these cutoffs were not consistent throughout our baseline period (i.e., 100 in 2009 and 130 in 2010).

[13] Risk factors that determine treatment include the following five conditions: currently smoking, hypertension, low HDL ($\leq$40 mg/dL), family history of coronary artery disease, and age (45 or older for men and 55 or older for women). The recommended treatment cutoffs of LDL cholesterol are 160, 130, or 100 mg/dL for those with 0–1 risk factors, 2+ risk factors, or coronary artery disease, respectively (Lorenzo et al., 2007; Korean Society of Lipidology and Atherosclerosis, 2009). Using our baseline screening data, we estimate that 63.1% of those classified as high risk for LDL cholesterol fall into the 0–1 risk factor category, and their treatment for hyperlipidemia would be determined by the 160 cutoff.

[14] In addition, we do not observe the actual risk classifications that individuals receive in their screening report card. However, we are able to reconstruct the risk classifications (i.e. Normal A, Normal B, and Disease Suspected in the first page of screening report; and low risk, medium risk, and high risk in health traffic lights) for each individual following the NHSP rules and using biomarker information.

[15] For those who took screening in both years, we only use 2009 observations to avoid duplication. As mentioned in Section, blue-collar workers with employee insurance are eligible for screening every year.

[16] The observed participation rate in round 3 screening is lower than in round 2 screening because for the 2010 cohort we have data after 3 years but not 4 years from the screening.

Table 1
Study sample, cutoffs, and treatments.

Running variables	Samples	Cutoffs			Treatments: Treatment group (at or just above cutoff)		Treatments: Comparison group (just below cutoff)	
Panel A. Diabetes screening								
Fasting blood sugar (mg/dL)	No previous diagnosis	126	Information	1st page 2nd page	Diabetes suspected High risk	■	Normal B Medium risk	■
			Secondary examination		Yes		No	
		100	Information	1st page 2nd page	Normal B Medium risk	■	Normal A Low risk	■
			Secondary examination		No		No	
Panel B. Obesity screening								
BMI (kg/m^2)	Abdominal obesity	25	Information	1st page 2nd page	Normal B High risk	■	Normal A Medium risk	■
			Secondary examination		No		No	
	No abdominal obesity	23	Information	1st page 2nd page	Normal A Medium risk	■	Normal A Low risk	■
			Secondary examination		No		No	
Panel C. Hyperlipidemia screening								
LDL cholesterol (mg/dL)	No previous hyperlipidemia diagnosis and no diabetes	160	Information	1st page	Hyperlipidemia suspected		Normal B	
				2nd page	High risk	■	Medium risk	■
			Secondary examination		No		No	

Notes:
1. “Normal A,” “Normal B,” and “Disease suspected” refer to the results reported in the first page of the screening report. “Low risk,” “Medium risk,” and “High risk” refer to the risk classifications used in health traffic lights in the second page
2. In the case of fasting blood sugar, the analysis sample is further restricted to those who took baseline screening in general hospitals (excluding those who took screening in private clinics and public health centers) in order to avoid potential manipulation around the threshold. See text for further details.
3. In the case of LDL cholesterol, the analysis sample is further restricted to those with triglycerides less than or equal to 400 mg/dL and those without diabetes because LDL cholesterol is not reported in the screening results if the triglycerides are abnormally high (i.e. >400 mg/dL) and cutoffs for risk classification are different for those with diabetes (see Appendix Table A.2).
4. “Abdominal obesity” is defined as waist circumference being 85 cm or above for females and 90 cm or above for males.
5. “No diabetes” is defined as having no previous diabetes diagnosis or fasting blood sugar level greater than or equal to 126 in the baseline screening result.

Table 2
Baseline statistics.

Variables (N = 352, 245)	Mean	Std. Dev.
Male	0.51	0.50
Age 50 or older	0.46	0.50
Insurance type		
Self-employed insurance	0.23	0.42
Employee insurance	0.76	0.42
Medical care assistance	0.003	0.06
Average income decile	6.17	2.83
BMI (kg/m^2)	23.71	3.24
Height (cm)	163.28	9.23
Weight (kg)	63.47	11.58
Waist circumference (cm)	80.23	9.17
Blood sugar (mg/dL)	97.81	24.19
LDL cholesterol (mg/dL)	114.23	39.01
Basic exercise	0.36	0.48
Number of drinks per week	6.90	13.86
Number of cigarettes per day	3.80	7.75
Self-reported diabetes diagnosis	0.09	0.28
Self-reported hyperlipidemia diagnosis	0.05	0.22
Previous year diabetes medication days	13.46	64.79
Previous year obesity medication days	0.01	1.42
Previous year hyperlipidemia medication days	11.08	52.65
Previous year total medical expenditure (USD)	522.5	1641.0
Round 2 screening participation	0.77	0.42
Round 3 screening participation	0.53	0.50

Notes: This table reports the baseline characteristics of the study sample. In the analysis, we restrict our sample as summarized in Table 1. Baseline (or round 1) is defined as the screening in 2009 and 2010, taking the observation in 2009 if one took screening in both years. Round 2 screening is defined as the screening 1 or 2 years after the baseline, taking the earlier observation if an individual participated in both years. Similarly, round 3 screening is defined as the screening 3 or 4 years after the baseline, taking the earlier observation if an individual participated in both years.

Outcome variables, described in Table 3, are measures of health care utilization (outpatient visits and prescription medications for diabetes, obesity, and hyperlipidemia), biomarkers (changes in fasting blood sugar, BMI, waist circumference, and LDL cholesterol), and health behaviors (physical exercise[17], number of drinks per week, and number of cigarettes per week).[18] We define outcomes in the second and third round as short- and long-run outcomes, respectively.[19]

4. Empirical framework

4.1. Setup of the empirical analysis

We implement a regression discontinuity design by taking advantage of the fact that risk classification thresholds and prompting for a secondary examination vary discontinuously with the running variables—fasting blood sugar, BMI, and LDL cholesterol. For each biomarker, we estimate the following equation:

$$Y_{ict} = \beta \cdot 1\{M_{ic} \geq \tau\} + f(M_{ic}) + \theta_c + \psi_t + \epsilon_{ict}, \quad (1)$$

where Y_{ict} is the outcome of interest for individual i, screening cohort c (=2009 or 2010), t years after screening offer. $1\{M_{ic} \geq \tau\}$ is an indicator function of individual i's running variable (M_{ic}) being greater than or equal to the cutoff, $f(M_{ic})$ is a flexible function of the running variable, θ_c is the cohort-fixed effect, ψ_t is the year-fixed effect, and ϵ_{ict} is the idiosyncratic error term.[20] Errors are clustered by the unique value of the running variable as suggested by Lee and Card (2008).

Modeling $f(M_{ic})$ and bandwidth selection are important decisions in a regression discontinuity design. We use a non-parametric approach to model the function $f(M_{ic})$ by approximating it via a polynomial function of M_{ic} over a narrow range of data. In the main analysis, we estimate the discontinuity parameter β using a local linear regression with uniform kernel. Our preferred bandwidth is 10 mg/dL for blood sugar and LDL cholesterol, and 1 kg/m^2 for BMI because we believe these are narrow enough to compare observations below and above the cutoff and wide enough to be precise.[21] However, we report a series of robustness checks with different polynomial degrees and bandwidths to show how sensitive our findings are to these parameters. We also estimate our main outcomes after controlling for additional baseline characteristics, including gender, age, residential area, insurance type, and baseline amount of medical expenditure.

4.2. Validity of regression discontinuity design

A critical assumption to our identification strategy is that individuals just below a threshold are comparable to individuals just above a threshold. One way this assumption could be violated is if the running variables could be precisely manipulated around the cutoff. However, the running variables used in our analysis are unlikely to suffer from manipulation because BMI is a continuous function of two measurements that are observed, and fasting blood sugar and LDL cholesterol are based on laboratory measurements.

To test this assumption, we first examine whether the density functions of the running variables are smooth around the threshold (Lee and Lemieux, 2010). Fig. A.2 illustrates the density of the three running variables. To the naked eye, the densities of fasting blood sugar in Panel (a) and LDL cholesterol in Panel (b) appear smooth at the treatment cutoffs.[22] Panels (c) and (d) respectively present the

[17] Exercise is measured as an indicator function of engagement in "basic exercise." An individual is engaging in "basic exercise" if, in the survey, one answered as engaging in 3 or more days of vigorous exercise, or 5 or more days of moderate exercise, or 5 or more days of mild exercise during the last week. Vigorous exercise is defined from the question "During the last week, how many days did you exercise vigorously for more than 20 min until you were almost out of breath? (example: running, aerobics, cycling in high speed, mountain hiking, etc.)"; moderate exercise is defined from the question "During the last week, how many days did you exercise in a moderate level for more than 30 min until you had to breathe a little faster than usual? (example: fast walking, tennis, bicycle riding, cleaning, etc.)"; and mild exercise is defined from the question "During the last week, how many days did you walk for a total of more than 30 min, including separate 10-min walks? (examples: light exercise, walking to work, walking for leisure, etc.)."

[18] Since information on biomarkers and health behaviors are observed only for screening participants, we also look at future screening take-up to account for potential selection-bias in these future outcomes (it is also an important health behavior in itself). As shown in Columns 4 and 10 of Table A.7, we do not find differences in future screening rates between those below and above the cutoffs.

[19] Specifically, short-run outcomes are measured in round 2 screening—1 or 2 years after the baseline, taking the earlier observation if an individual participated in both years. Similarly, long-run outcomes are measured in round 3 screening—3 or 4 years after the baseline, taking the earlier observation if an individual participated in both years. On the other hand, because medical claims data are observed regardless of screening participation, short- and long-run health care utilization is defined as follows. For outpatient visits, we use the total number of outpatient visits for a disease of interest during the year and 1 year after the baseline screening take-up (short-run outcome) and 2 and 3 years after the baseline screening take-up (long-run outcome). For prescription medications, we examine the sum of the prescribed number of days for each medication in the year of and year after the baseline screening (short-run) and 2 and 3 years after the baseline screening (long-run).

[20] The year-fixed effect is not included in the regression for future screening participation, outpatient visits, and medication because we aggregate these outcomes over consecutive years.

[21] We fix our bandwidth choice in our main analysis because the MSE optimal bandwidth choices suggested by Calonico et al. (2014) or Imbens and Kalyanaraman (2012) are often too large in our case to evaluate two different cutoffs per running variable.

[22] For fasting blood sugar, we restrict our sample to individuals who took screening at general hospitals (where laboratory test results are automatically recorded), since we observed slight heaping around the 126 cutoff for individuals who took screening elsewhere (e.g., smaller institutions such as private clinics and public health centers), where test results are more likely to be recorded manually by staff). We

Table 3
Outcome variable descriptions and data sources.

Category	Variables	Data source	Short-run (Round 2)	Long-run (Round 3)
Health care utilization	**Number of disease-specific outpatient visits** **Number of days on disease-specific prescription medication**	Health insurance claims data	Year of and 1 year after screening	2 and 3 years after screening
Biomarkers	**Change in waist circumference** Change in fasting blood sugar Change in BMI Change in LDL cholesterol	NHSP program data	Next screening, 1 or 2 years after baseline screening	Next screening, 3 or 4 years after baseline screening
Health behaviors	**Change in engaging in basic exercise** Change in number of drinks per week Change in number of cigarettes per day	NHSP survey data	Next screening, 1 or 2 years after baseline screening	Next screening, 3 or 4 years after baseline screening

Notes. Bolded variables are those presented in the main text; results for other variables are presented in the Appendix. The reference point for variables measured as a change is the baseline (Round 1) screening level.

densities of BMI for the no abdominal obesity and abdominal obesity samples, and we do not observe extraordinary spikes around the BMI thresholds in either case. We conduct the McCrary test to formally test for the smoothness of the densities at the treatment cutoffs (McCrary, 2008). The *t*-statistics of the McCrary test at the treatment and placebo cutoffs, using several different bandwidths, are reported in Table A.5. While some discontinuities at the treatment cutoffs are statistically significant, they are not disproportionately larger than those at the placebo cutoffs. Similar to Chetty et al. (2009), we show this formally by presenting the cumulative distribution function of the absolute value of the t-statistics at multiple cutoffs (Fig. A.3), with vertical lines depicting the treatment cutoffs. The figures show that for each biomarker, the magnitude of the t-statistic at the treatment cutoff is no larger than the 80th percentile of all cutoffs, suggesting that the discontinuity in the density at the cutoff is not an outlier relative to the placebo cutoffs.

Another way to test the validity of our model is by testing the smoothness of observable baseline characteristics around the cutoffs. As reported in Figs. A.4–A.6 and Table A.6, with very few exceptions, we do not find differences between individuals just below and just above the cutoff in their observable characteristics, including basic demographics, baseline health outcomes, and health behaviors. Two of the 55, or 3.6%, of the discontinuity estimates at the cutoffs are statistically significant at the 5% level of significance, suggesting that our sample is balanced around the cutoffs. Nonetheless, we estimate regressions that control for these observable baseline variables, finding that the results from the regressions including the control variables are similar to those from the regressions without them.[23]

In summary, our analyses of the density of the running variables and distribution of observable characteristics around the thresholds support our identifying assumption that individuals just below a threshold are comparable to individuals just above.

5. Estimation results

In this section, we present evidence on the impact of and behavioral responses to risk information from diabetes, obesity, and hyperlipidemia screening in Sections 5.1, 5.2, and 5.3, respectively. We discuss the results in Section 5.4.

5.1. Results from diabetes screening

We first examine the responses to information on diabetes risk obtained from diabetes screening by comparing individuals just below and just above the fasting blood sugar cutoffs of 100 and 126. As described in Section 2 (and Table 1), the 100 cutoff is the medium risk and Normal B threshold, while the 126 cutoff is the high risk, Diabetes Suspected, and prompt for a secondary examination threshold.

Panels A and B of Fig. 2 illustrate short-run and long-run outcomes against fasting blood sugar level, respectively. In the figures, the scatter plot indicates the mean of the outcome variable within 1 point bins. The solid lines represent the fitted values from Eq. (1) using a local linear regression with a bandwidth of 10 mg/dL and a uniform kernel, which are plotted separately below and above the cutoff. The regression analogs are presented in Table 4.

Panel A of Fig. 2 shows that at the 126 cutoff there is a clear deviation from the overall trend in the short-run number of prescribed days of diabetes medication, which indicates that individuals who are classified as high risk for diabetes and receive prompting for a secondary examination take more diabetes medications during the year of or the year after the baseline screening, compared to those who are classified as medium risk. The discontinuity estimates in Table 4 report that high risk individuals are prescribed 20.9 days more of diabetes medication (a 73.3% increase) (Panel A.1, Column 2) than medium risk individuals.[24] These results are not surprising because if diabetes was confirmed at the secondary examination, medical treatment was recommended.[25]

In addition to the impact on diabetes medication days, we find a short-run decrease in waist circumference of 0.96 cm (a

do not implement this restriction for BMI and LDL cholesterol because we did not observe heaping for these biomarkers. Among baseline screening participants, 30% took screening in general hospitals. We compare characteristics between screening participants at general hospitals and those elsewhere (Table A.4). Screening participants at general hospitals are more likely to have employee insurance, have higher income, and have lower total medical expenditure compared to those who took screening elsewhere.

[23] Results are available upon request.

[24] Even though we see a short-run impact on medications whose action is to control blood sugar level, we need not observe a corresponding short-run impact on fasting blood sugar level (Fig. A.7(a). This is because diabetes medication is not recommended on the day of the screening and the half-life of diabetes medications is short. Therefore, effects of the medication will not be reflected in blood sugar results. Specifically, the half-lives of biguanide and sulfonylurea, which are the most common types of diabetes medications, are 4–8.7 h (Dunn and Peters, 1995) and 2–10 h (Prendergast, 1984), respectively.

[25] According to the statistical yearbook of the NHIS, among the participants of the secondary examination, 51% and 40% were diagnosed as having diabetes in 2009 and 2010, respectively (NHIS, 2009, 2010). Considering the fact that the participation rate of the secondary examination was 37% in 2009 and 39% in 2010, we estimate that 18.9% (=37%*51%) and 15.6% (=39%*40%) of those above the 126 cutoff were ultimately diagnosed with diabetes in 2009 and 2010, respectively.

Table 4
Impact of risk information.

	(1) Short-run impact	(2)	(3)	(4)	(5) Long-run impact	(6)	(7)	(8)
	Disease-specific # of outpatient visits	Disease-specific # of medication days	Change in waist circumf.	Change in basic exercise	Disease-specific # of outpatient visits	Disease-specific # of medication days	Change in waist circumf.	Change in basic exercise
Panel A.1 Diabetes risk information: high risk cutoff at fasting blood sugar of 126								
RD estimate	0.636[+]	20.866[**]	−0.955[**]	−0.026	0.653	8.281	−0.100	0.012
	(0.325)	(4.587)	(0.248)	(0.029)	(0.720)	(10.272)	(0.301)	(0.047)
Mean of the Dep. Var. in levels at [116, 126)	1.27	28.49	83.92	0.40	2.24	55.50	83.68	0.41
Observations	4639	4639	3641	3540	4598	4598	2654	2560
Panel A.2 Diabetes risk information: medium risk cutoff at fasting blood sugar of 100								
RD estimate	−0.013	0.163	−0.241[*]	0.007	0.004	0.374	−0.159[*]	0.009
	(0.030)	(0.924)	(0.091)	(0.008)	(0.086)	(1.205)	(0.069)	(0.011)
Mean of the Dep. Var. in levels at [90, 100)	0.11	2.01	80.20	0.38	0.18	3.29	80.68	0.38
Observations	51,569	51,569	41,497	40,370	51,332	51,332	29,370	28,317
Panel B.1 Obesity risk information: high risk cutoff at BMI of 25								
RD estimate	0.007	0.097	−0.358	−0.018	0.003	0.119	−0.418	−0.016
	(0.005)	(0.117)	(0.236)	(0.023)	(0.003)	(0.108)	(0.267)	(0.027)
Mean of the Dep. Var. in levels at [24, 25)	0.001	0.01	86.33	0.37	0.002	0.02	86.23	0.38
Observations	15,395	15,395	11,731	11,569	15,208	15,208	7461	7320
Panel B.2 Obesity risk information: medium risk cutoff at BMI of 23								
RD estimate	−0.001	0.0004	0.212[**]	0.011	0.0004	−0.008	0.082	0.009
	(0.001)	(0.009)	(0.080)	(0.008)	(0.001)	(0.027)	(0.125)	(0.013)
Mean of the Dep. Var. in levels at [22, 23)	0.002	0.02	77.81	0.38	0.002	0.04	78.25	0.39
Observations	81,950	81,950	64,032	62,864	81,424	81,424	44,605	43,588
Panel C Hyperlipidemia risk information: high risk cutoff at LDL cholesterol of 160								
RD estimate	0.169[**]	1.811	0.052	0.006	0.126	1.692	0.344	0.050
	(0.054)	(1.584)	(0.118)	(0.017)	(0.103)	(2.537)	(0.232)	(0.029)
Mean Dep. Var. in levels at [150, 160)	0.91	25.25	81.87	0.38	1.48	48.73	82.16	0.38
Observations	25,903	25,903	19,995	19,676	25,740	25,740	13,505	13,219

Notes. This table reports estimates of β from local linear regression of Eq. (1) using a uniform kernel. For Panels A.1–A.2, the running variable is baseline fasting blood sugar; and bandwidth of 10 mg/dL is used. For Panels B.1–B.2, the running variable is baseline BMI, and bandwidth of 1 kg/m^2 is used. For Panel C, the running variable is baseline LDL cholesterol, and bandwidth of 10 mg/dL is used. Shown in parentheses are standard errors which are clustered at the unique value of the running variable. The outcome variables used in columns (1), (2), (5) and (6) are disease-specific; hence, it is the number of outpatient visits or medication days for diabetes in Panels A.1–A.2, for obesity in Panels B.1–B.2, and for hyperlipidemia in Panel C.

[*] Statistical significance at the 5% level.

[**] Statistical significance at the 1% level.

[+] Statistical significance at the 10% level.

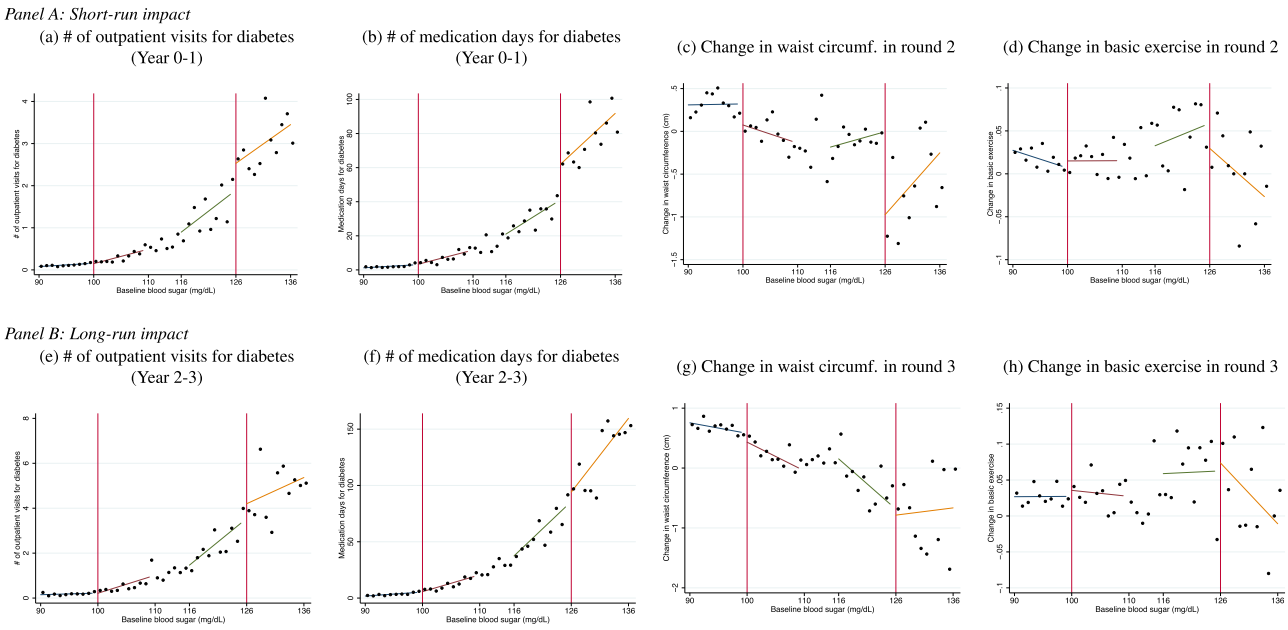


Fig. 2. Impacts of risk information: diabetes screening.
Notes: The running variable is baseline fasting blood sugar. The scatter plot indicates the mean of the dependent variable within 1 point bins. Around two cutoffs, 100 and 126, the solid lines are the fitted values from the local linear regression of the dependent variable using a uniform kernel with a bandwidth of 10 mg/dL.

1.1% change) (Table 4, Panel A.1, Column 3).[26] Based on additional analyses, the change in waist circumference appears to be driven by behavioral improvement and not by diabetes medication. Specifically, there are certain types of diabetes medication (e.g., Metformin) that may lead to weight reduction. However, as shown in Table A.8, a decrease of waist circumference is driven by those who do not take diabetes medication (Panel A), not those who take medication (Panel B). A possible explanation is that individuals who were just above the 126 cutoff and who did not take medication either were associated with doctors who did not strictly follow medication treatment guidelines and who instead recommended lifestyle changes, or the individuals themselves were driven to substitute lifestyle changes for medication. In other words, these patients and/or their doctors could treat medication and behavior changes as substitutes.

If the reductions in waist circumference are not driven by diabetes medication, they should be due to changes in eating patterns or physical activity. Since we do not find changes in exercise around the cutoff, (Table 4, Panel A.1, Column 4), we speculate that the change is driven by changes in diet.

Additionally, by performing a subgroup analysis based on previous screening take up and results, we find evidence that the decrease in waist circumference is greater among those who did not take public health screening previously, compared to those who did (Table A.9, Columns 1 and 2). Among the previous screening takers, the decrease in waist circumference is greatest among those who previously received low risk results compared to those who received medium or high risk previously (Table A.9, Columns 3–5). These results suggest that the behavioral response is greater for those for whom the screening information is newer, in the sense that they either did not take public health screening previously or did take public health screening previously but were classified as having low risk previously.

In the long-run, the observed short-run impacts described above are attenuated, as shown in Panel B of Fig. 2 and Panel A.1 of Table 4. Specifically, we still observe an increase in medication days and decrease in waist circumference around the 126 cutoff, but the effects are smaller and no longer statistically significant.

Around the 100 cutoff, we do not find a meaningful impact on all outcomes, both in the short and long run. Even though the estimated coefficient on waist circumference in our main specification is statistically significant (Panel A.2 of Table 4), this appears to be spurious because it is not statistically significant in other specifications, as depicted in Fig. A.11(c).

5.2. Results from obesity screening

In this subsection, we examine the responses to information on obesity risk obtained from obesity screening by comparing individuals just below and just above the BMI cutoffs of 23 and 25. As described in Section 2 (and Table 1), 25 is the high risk and Normal B threshold for individuals with abdominal obesity, and 23 is the medium risk threshold for individuals without abdominal obesity. Fig. 3 presents graphical illustrations of short-run and long-run outcomes against baseline BMI, and Panels B.1 and B.2 of Table 4 report the corresponding discontinuity estimates at the cutoffs.

Around the 25 cutoff, information on obesity risk has no impacts. We do not observe changes in outpatient visits, medication, waist circumference, or physical activity. Around the 23 cutoff, individuals with medium risk have a 0.21 cm (a 0.27%) larger waist circumference than those with low risk (Column 3). Fig. A.13(c) shows that the regression results are robust to other specifications. If the increase in waist circumference is true, our finding is consistent with Almond et al. (2016) who study the impact of overweight classification and find a small but statistically significant increase in future weight among teenage girls in New York City, and also Hunger and Tomiyama (2014) who show an association that being labeled "too fat" at age 10 is a significant predictor of obesity at age 19 years.

Some possible explanations for this unexpected but consistent finding is that individuals close to this threshold who receive a medium risk classification are discouraged by the result and lose

[26] We also find a decrease in BMI of 0.158 kg/m^2, which is equivalent to a reduction of 0.42 kg (=0.158*(1.63)^2) for a person with the average height of 163 cm (Fig. A.7 and Table A.7)

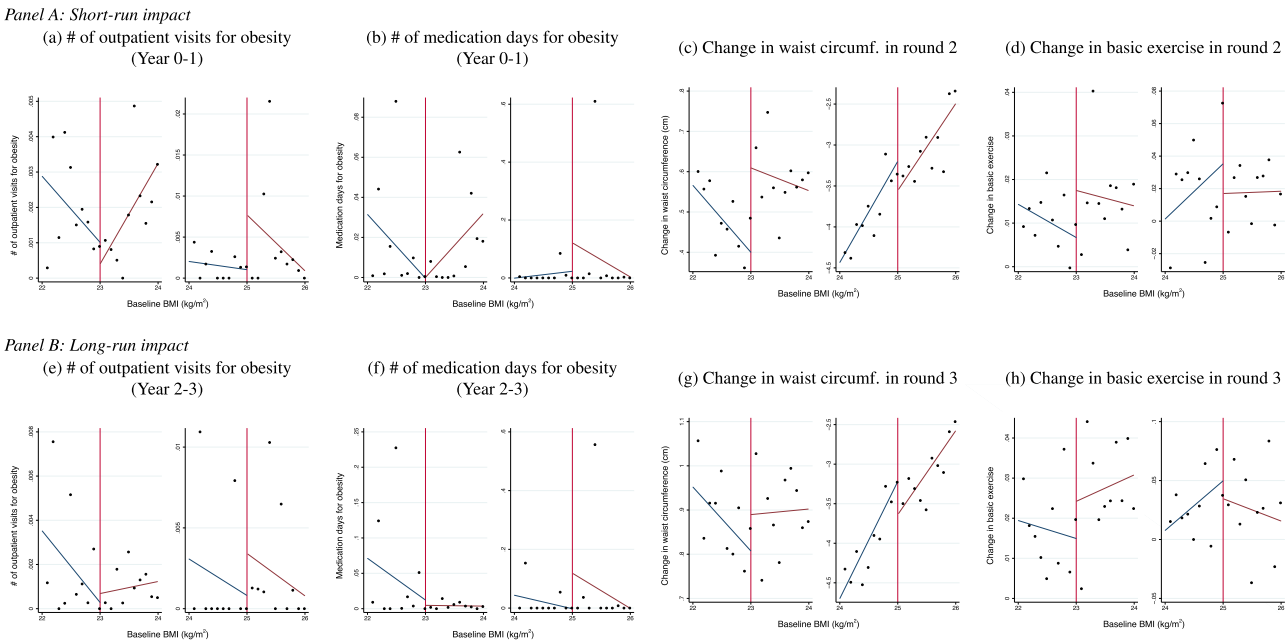


Fig. 3. Impacts of risk information: obesity screening.
Notes: The running variable is baseline BMI. The scatter plot indicates the mean of the dependent variable within 0.05 point bins. Around two cutoffs, 23 and 25, the solid lines are the fitted values from the local linear regression of the dependent variable using a uniform kernel with a bandwidth of 1 kg/m^2. For each panel, the left figure with cutoff 23 is based on the sample without abdominal obesity and the right figure with cutoff 25 is based on the sample with abdominal obesity.

motivation to pursue healthy behaviors, while those who receive a low risk classification react positively and continue maintaining reduced weight, or a combination of both these explanations. However, our results should be interpreted with caution. First, we do not find a similar negative impact around the high risk cutoff at 25. Second, we do not find a corresponding change in BMI (Fig. A.8 and Table A.7). Third, we do not find meaningful corresponding changes in health behaviors, including exercise, drinking, smoking, and blood sugar around the 23 cutoff (Panel B.2 of Table 4 and Table A.7).[27] However, the consistency of this finding across studies warrants future research into the reasons for these patterns.

5.3. Results from hyperlipidemia screening

We examine responses to information on hyperlipidemia risk obtained from hyperlipidemia screening by comparing individuals just below and just above the LDL cholesterol cutoff of 160. As described in Section 2 (and Table 1), the 160 cutoff is the high risk and Hyperlipidemia Suspected threshold. The discontinuity estimates are reported in Panel C of Table 4, and the corresponding graphical illustrations are presented in Fig. 4.

We find an increase in the number of outpatient visits around the 160 cutoff of 0.17 days (an 18.6% increase). This increase in outpatient visits for hyperlipidemia is consistent with high-risk individuals undergoing follow-up examinations to confirm disease (outside of the NHSP program which does not include secondary examinations for hyperlipidemia). However, the increase in outpatient visits did not result in increased medical treatment or changes in health behaviors.

One explanation for why increased outpatient visits did not translate into increased medical treatment, unlike the case for diabetes, is that doctors and/or patients do not strictly follow treatment guidelines when LDL cholesterol is just above the 160 cutoff. Studies indicate that it is common for physicians not to strictly follow clinical practice guidelines, due to lack of awareness, familiarity, and agreement (Cabana et al., 1999). A study in Israel reports that physicians recommended dyslipidemia medication only for 21% of clinical cases eligible for medical treatment and that only 62.6% of patients initiated the dyslipidemia medication when physicians recommended it (Vashitz et al., 2011). In addition, according to the 7th Korean National Health and Nutrition Examination Survey (KNHANES) in 2016, treatment rates for diabetes and hyperlipidemia patients are 67.2% and 49.1%, respectively.[28] Lastly, the 160 cutoff is not a sufficient condition for medication treatment; as discussed in Section 2, the 160 cutoff for treatment applies only to people with zero or one 0–1 risk factors.

5.4. Discussion

In the previous section, we find evidence for medication use and weight loss around the 126 threshold for diabetes, where individuals are classified as higher risk and prompted to undergo a secondary examination and, if diagnosis is confirmed, treatment. However, we find little to no differences around other risk classification thresholds, including the 160 threshold for LDL cholesterol, which is the diagnosis threshold for hyperlipidemia. In this subsection, we discuss several possible explanations for why people change behaviors only at the 126 cutoff for diabetes.

First, one of the most striking differences between the high risk classification for diabetes compared to the other classifications we study (including the medium risk classification for diabetes) is that those classified as high risk for diabetes receive further medical intervention in addition to the information on disease risk. Specifically, the 126 cutoff for diabetes was the only threshold where

[27] We are able to rule out more than a 0.016 percentage point change (=0.008*1.96) (or a 2% change at the mean of 0.38) in the probability of engaging in basic exercise in the short-run.

[28] Results are available at https://knhanes.cdc.go.kr/knhanes/eng/index.do.

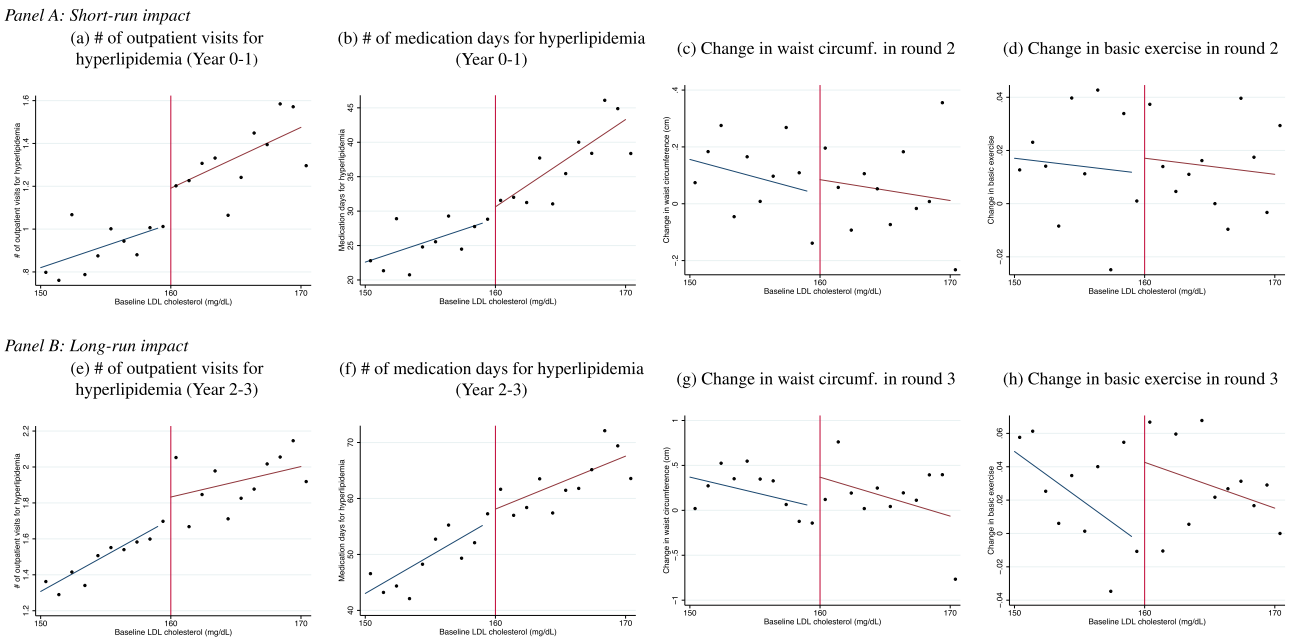


Fig. 4. Impacts of risk information: hyperlipidemia screening.
Notes: The running variable is baseline LDL cholesterol. The scatter plot indicates the mean of the dependent variable within 1 point bins. Around cutoff 160, the solid lines are the fitted values from the local linear regression of the dependent variable using a uniform kernel with a bandwidth of 10 mg/dL.

individuals were actively prompted to undergo a secondary examination where they had an opportunity to talk to a physician about their risk factors and treatment plans.[29] Moreover, this translated into an increase in diabetes medication use if diagnosis was confirmed. The fact that we do not find behavioral changes around other cutoffs suggests that the risk information alone is not a strong enough tool in itself to encourage people to engage in healthy behaviors.

Second, it is possible that individuals who understand that they are just above the risk classification cutoffs from the first page of the screening report may not take the information on disease risk seriously. In other words, individuals who are just above that cutoff may understand that their actual risk is not different from that for those just below the cutoff. If this holds true, we might expect this effect to be smaller for those with lower levels of education who might be less capable of inferring from the report how close they are to the boundary of a given risk classification. To test this, we conduct a subgroup analysis by income quintiles (a proxy for education level). We do not find any noticeable patterns of behavioral responses by level of household income (Figs. A.15–A.17).

Third, another explanation for the limited impact of obesity and hyperlipidemia risk information is that patients and/or doctors may consider risk information on diabetes more seriously than that for obesity and hyperlipidemia.[30] As discussed in Section 5.3, there is evidence to suggest that the lack of response is driven by doctors. First, we find that patients in our study increase outpatient visits as a result of the high hyperlipidemia risk classification, but that this does not result in increased medication prescriptions by physicians. Second, other survey data in Korea (KNHANES) shows that the physician adherence rate is higher for diabetes treatment than for hyperlipidemia treatment.

In summary, our results indicate that risk information alone is not sufficient for inducing a behavioral response. Moreover, our results are consistent with the explanation that further medical intervention (i.e., prompting for a secondary examination in our setting) in addition to information on disease risk is a vital complement to health screening. These results shed light on the mixed findings in previous literature that moderate behavioral changes are observed for diabetes (Slade, 2012; Oster, 2015) and hypertension (Zhao et al., 2013) where diagnosis is combined with further medical intervention, while no effects are found for overweight classification (Almond et al., 2016), which is unlikely to be combined with further medical intervention.

While our results indicate that the combination of information and medical intervention can be effective, we are unable to disentangle whether the impact is driven solely by medical intervention, or whether and how information and medical intervention are complementary. A next step for future research would be to understand the extent to which different interventions complement information and induce long-term behavioral modifications.

6. Conclusion

Using administrative data from the population based health screening program in Korea that includes more than 350,000 baseline screening takers and observations over four years after screening, this paper provides comprehensive evidence on short- and long-term impacts of information obtained from health screening on a rich set of biomarkers, behavior measures, and health care utilization. Specifically, we apply a regression discontinuity design that takes advantage of the fact that risk classifications and prompt-

[29] Moreover, and possibly related, the increase in outpatient visits among people just above the cutoff 160 of LDL cholesterol is smaller in magnitude (0.17 more outpatient visits) relative to that for the cutoff 126 of blood sugar (0.64 more outpatient visits).

[30] It seems plausible that people respond more to diseases where the perceived threat is greater. For example, Oster et al. (2013) explains that a large change in behaviors for those who are confirmed of Huntington's disease (HD) could be due to the fact that people with HD have a relatively short life expectancy and HD has no cure. The fact that the free secondary examination is offered for diabetes and not obesity or hyperlipidemia could cause individuals to perceive that diabetes is a more serious disease.

ing for a secondary examination vary discontinuously at various thresholds of fasting blood sugar, BMI, and LDL cholesterol, respectively.

When risk classification information alone is provided—around the medium risk threshold for diabetes, medium and high risk thresholds for obesity, and high risk threshold for hyperlipidemia—we find limited impacts to individual behaviors, health care utilization, and future health outcomes. However, we find evidence for significant behavioral responses when risk information is combined with prompting for a secondary examination that consists of confirmatory tests and counseling with a physician. Specifically, we find that those who are classified as high risk for diabetes and prompted for a secondary examination take more medications for diabetes and exhibit reduced waist circumference in the short run.

There are some limitations to this study. First, while we have a rich source of data covering several years, including as soon as one year after screening, it is possible that our estimates of null impacts could be missing very short-term behavior changes that happen shortly after receipt of screening results. However, to the extent that long-term behavior changes are important for the lifestyle diseases that are relevant to our study, the time period we study may be more relevant than the period immediately after screening. Second, an important component of the lifestyle diseases relevant to our study is food intake, which we do not observe. However, our administrative and self-reported data provide strong and relevant correlates to food consumption (e.g., waist circumference and BMI) that, combined with our other variables like exercise, help us to gain a thorough picture of relevant behavior changes.

Although the findings of this study specifically reflected the behavioral responses and health outcomes to the NHSP in Korea, this analysis still provides a number of implications for other health and social programs that provide information on disease risk. Our results suggest that information alone might not be sufficient to lead to behavioral changes, and that further medical interventions in addition to risk information may increase the marginal benefits of screening.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jhealeco.2019.01.003.

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