Public Cancer Screening: Impacts and Behavioral Responses*

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January 15, 2013

Job Market Paper

Abstract

This paper evaluates the impacts of and behavioral responses to cost-sharing in population-based public cancer screening using Korea's National Cancer Screening Program (NCSP), which provides free stomach and breast cancer screenings to those below the insurance contribution cutoff. Free cancer screening substantially increases the cancer screening take up rate, yielding more cancer detections. Nevertheless, the program was unsuccessful along other key dimensions. First, the initial increase in cancer detections was quickly crowded out by the decrease in cancer detections through other channels, such as private screening and diagnostic testing. Second, those who were induced to take up cancer screening by the cash incentive (compliers) were relatively healthy. These compliers' baseline cancer prevalence is as high as those who take up screening regardless of the availability of free cancer screening (always takers). Those who do not undergo screening regardless of the availability of free cancer screening (never takers) had the highest cancer mortalities, and thus stood to benefit the most from the screening they did not receive. Taken together, free public cancer screening has a limited impact on cancer- and all-cause mortalities. This analysis demonstrates that even when take up is significantly responsive, population based cancer screening can be ineffective due to the behavioral responses to cancer screening such as crowd out and self-selection. More broadly, my study suggests that the impact of health programs, even when they display large participation responses, crucially depend upon the potential behavioral responses of the agents involved.

*I would like to thank Cristian Pop-Eleches and Douglas Almond for the invaluable guidance and support. This project would not have been possible without the support of Sun-mi Lee at the National Health Insurance Corporation (NHIC) of Korea and Woojin Chung at Yonsei University. For useful feedback, I wish to thank to Jinook Jeong, Beomsoo Kim, Booyuel Kim, Soonman Kwon, Wojciech Kopczuk, Chulhee Lee, Wilfredo Lim, Benjamin Marx, Christine Pal, Eun-Cheol Park, Sangsoo Park, Leigh Linden, Miguel Urquiola, Eric Verhoogen, Tal Gross, Till von Wachter as well as seminar participants at Columbia University, Yonsei University, Seoul National University, Korea University, and the National Cancer Center of Korea. I appreciate my research assistant, Donghoon Lee, for the excellent work. This research is a part of the project "Impact Analysis of National Cancer Screening Program (NCSP)" initiated by the NHIC. The views expressed herein are mine, and do not reflect the views of NHIC. All errors are my own.

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1 Introduction

Cancer screening, a testing for cancer in the absence of symptoms, is often thought to play a central role in the fight against cancer.[1] For example, Cutler (2008) argued that cancer screening is the most important factor in explaining the recent cancer mortality reduction in the US. The stakes surrounding cancer screening are large. In 2008, there were 12.4 million new cancer diagnoses and 7.6 million deaths (13% of total deaths).[2] The US spends $10 to $15 billion annually on cancer screening; Korea spends around $400 million for public cancer screening (NCI (2007), NCC (2009)).

Despite its popularity, the effect of cancer screening is surprisingly poorly understood. Evidence on cancer screening from RCTs has been increasing in the last few years,[3] but evidence on population-based cancer screening is still extremely rare even though the effect of population-based cancer screening might differ from that in RCTs (Kadiyala and Strumpf (2011)). For example, the take-up rate in RCTs is close to 100%, which is far higher than in the population setting. If population-based cancer screening (unwittingly) encourages specific groups of people to take up screening, the effect on these selected people might differ from an experimental setting. The take-up rates in a population-based breast cancer screening program were 55.2%, 67.0%, and 73.8% in Korea, the US, and the UK, respectively (NCC (2009), NCI (2007), NHS (2008)).[4]

Moreover, at the time of past RCTs, cancer screening was not as popular as it is today. This means that a provision of cancer screening today could be crowded out more easily by outside options. Conceptually, the increase in cancer detections by cancer screening should be expected to erode completely over time. This erosion is predicted from the stylized framework where cancer is

[1] It is distinguished from the diagnostic testing that people undergo to detect cancer in the presence of relevant symptoms based on a doctor's recommendation.

[2] Cancers are the second leading cause of death in developed countries and one of the three leading causes of death for adults in developing countries. In terms of mortality, lung cancer is the most common cause of death (1.31 million deaths), followed by stomach (780,000), liver(699,000), colorectal (610,000), and breast (460,000) cancer (Boyle and Levin (2008))

[3] Mammography for breast cancer and fecal occult blood test (FOBT) for colorectal cancer were the only screenings with evidence from RCTs before 2008. Recently, RCTs on the PSA test for prostate cancer (Andriole et al. (2009), Schröder et al. (2009)), low dose computed tomography (CT) (Gross (2011)) and chest X-ray (Oken et al. (2011)) for lung cancer, and sigmoidoscopy (Atkin et al. (2010)) and colonoscopy (Zauber et al. (2012)) for colorectal cancer have been published.

[4] Interestingly, even evidence from RCTs is mixed and controversial. For example, four out of the eight RCT studies on breast cancer screening reported breast cancer mortality reductions, while the other four reported no impact. Furthermore, only three out of eight studies were adequately randomized, and no adequately randomized study showed a reduction in breast cancer mortality (Schopper and de Wolf (2009)). Evidence on prostate cancer is also mixed. One in the US found no prostate cancer mortality reduction (Andriole et al. (2009)), while a European study found a 20% prostate cancer mortality reduction (Schröder et al. (2009)).

eventually detected sometime before death (e.g., through diagnostic testing) and screening per se does not cause cancer. Therefore, the actual effectiveness of cancer screening on health outcomes would depend upon the difference between the timing of cancer detection by screening and that of detection without screening. If cancer detection is quickly crowded out by diagnostic testing, for example, screening would be ineffective. Previous analyses have often ignored both the erosion prediction and the important interplay between initial screening and subsequent testing and detection. Sustained "effects" of screening on cancer detection may be an artifact of endogenous coding, where deaths with but not from cancer are seen to respond (Black, Haggstrom, and Welch, 2002).

In this paper, I evaluate the impacts of and behavioral responses to cost-sharing in population-based public stomach and breast cancer screenings. I use a regression discontinuity (hereafter RD) design that takes advantage of the National Cancer Screening Program (NCSP) in Korea, which provides free cancer screening to those under the insurance contribution cutoff and charges a 50% copayment to those above.[5] I investigate a dynamic aspect of cancer detections through various channels by utilizing data covering the all cancer detections regardless of detection channels. Furthermore, I explore the characteristics and cancer mortality of those induced to take up cancer screening by the program (compliers). Specifically, I compare them to other sub-populations such as those who take up screening regardless of the availability of free cancer screening (always takers) and those who do not take up screening regardless of the availability of free cancer screening (never takers) to shed light on why population-based estimates may depart from RCTs.

I reach two conclusions. First, I find that cancer screening take up increases by around 10 percentage points - more than doubling - when the price of cancer screening decreases from 50% copayment to zero. This also results in significantly more detections in the short-run. However, this detection bump quickly erodes over time through decreases in cancer detections via other channels such as private screening and diagnostic testing. This finding means that public cancer screenings were provided to those who would have taken testing through other channels of cancer detection. Second, I find that there is no difference in baseline cancer prevalence between compliers and always-takers. Moreover, I find that never takers are significantly less healthy compared to compliers and always takers in terms of cancer mortality. This finding implies that the population-based public cancer screening provision did not reach people more in need of cancer screening during the study

[5]Insurance contribution is a fixed percentage of basic salary for those with employee insurance.

period.

Taken together, despite its large effect on screening take up and initial increase in cancer detections, subsidizing cancer screening had a limited impact on cancer- and all-cause mortalities up to 6 years after cancer screening because of behavioral responses such as crowd out and selection. My results also imply that the finding from RCTs might be quite different from that in population-based programs due to behavioral responses. To be more successful, cancer screening programs should promote a sufficiently high take up rate in order to reach people in need of cancer screening. Given that cancer screening is already popular, additional provision of cancer screening should be considered with care because such screening can be easily crowded out.

The rest of this paper is organized as follows. Section 2 briefly discusses the previous literature and contribution of my study. Section 3 explains the institutional details. Section 4 describes the data and presents the descriptive statistics. Section 5 shows the estimation strategy. Section 6 presents the results. Finally section 7 provides the conclusions.

2 Contribution to Literature

This study contributes to the understanding of the causal effect of population-based cancer screening. Evidence on population-based cancer screening is extremely limited not only due to scarcity of exogenous variation in cancer screening take up but also due to lack of data. Access to population level data with information on cancer screening take up, cancer detections, and related outcomes for long term periods is extremely limited. An exception to this is Kadiyala and Strumpf (2011) who find that U.S. guidelines that recommend screening for breast and colorectal screening starting at age 40 and 50, respectively, generate discontinuous increases in screening rates that result in significant increases in early cancer detection at these ages.

This study has several distinct advantages that improve upon the previous literature. First, it provides reliable estimates on the causal effect of cancer screening by using plausibly exogenous variation in access to cancer screening. Current evidence on the causal effect is limited because the take up of cancer screening is associated with omitted variables (e.g., health-seeking behavior and genetic background) that are also related to health outcomes. I employ an RD design around insurance contribution cutoffs that determine free cancer screening eligibility. This design allows

comparison across people with very similar characteristics but sharply different cost-sharing, and thus cancer screening take up rates.

Second, this study finds evidence from a nationwide population-based cancer screening program. This setting provides a unique opportunity to examine selection to screening effects on various outcomes by exploring characteristics of compliers, always takers, and never takers. This selection can be a reason why effects in experimental settings differ from that in population-based cancer screening.

Third, taking advantage of a large administrative panel dataset covering all cancer detections, this study presents evidence on a dynamic aspect of cancer detections in response to a free public cancer screening offer. I measure not only the increase in cancer detections by public cancer screening, but also the crowd out of cancer detections by other channels over time. The unique setting of a public cancer screening program allows me to evaluate the dynamic feature of cancer detections through various channels. Especially, the crowd out could be timing and setting specific, which could be, at least partially, the reason for the mixed findings in the previous RCT literature.

This study also contributes to the understanding of the impact of cost-sharing of preventive health services. Cost-sharing is a double-edged sword; charging a non-zero price for health services could improve effectiveness by curbing unnecessary demand, but it may also reduce necessary demand, which could lead to worse health outcomes and higher medical expenditures in the future (selection effect). For example, Goldman, Joyce, and Zheng (2007) show that cost-sharing might reduce treatment compliance, which could lead to worse health outcomes and higher future medical expenditures.

In the context of preventive health care, the existence of a selection effect has not been made clear since individuals often are not aware of how much preventive health care they need. For this reason, price sensitivity in preventive health care is potentially different from other therapeutic health care. However, there is remarkably little evidence on the effects of cost-sharing in preventive health care. One of the few exceptions is evidence by Cohen and Dupas (2010), which shows that cost-sharing of insecticide-treated nets (ITN)s for malaria prevention decreases demand without inducing selection of people who are more vulnerable.

Baicker and Goldman (2011) explain that the overall cost-sharing effects consist of the own-price effect, the cross-price effect, and the effect on health. As many studies have already shown,

the demand for health care decreases due to cost-sharing (Newhouse et al. (1981), Manning et al. (1987), Newhouse and Group (1993), Hsu et al. (2006), Chandra, Gruber, and McKnight (2010)). In addition, a change in the price of a particular health care service may affect demand not only for that health service but also for a complementary or substitutable service. For example, Chandra, Gruber, and McKnight (2010) found "offset effects", specifically an increase in hospitalization in response to higher cost-sharing for outpatient or pharmaceutical use in Medicare. Lastly, the previous literature has found that greater utilization of health care is not related with better health outcomes for the average population (Manning et al. (1987), Wennberg and Cooper (1996)), but rather an increased cost-sharing is associated with adverse health outcomes for the vulnerable population (Swartz (2010)). Despite these findings, the evidence on the effect of cost-sharing on health is still scarce overall.

In the context of public cancer screening, I explore how much cost-sharing decreases demand for public cancer screening (own-price effect). In addition, I examine whether cost-sharing in cancer screening invites people who are more likely to have cancer to the screening, or just reduces screening take up without increasing the detection rate (selection effect). I also check whether changes in public cancer screening take up are crowded out by other sources of cancer detections such as private screening and diagnostic testing (cross price effect). Finally, I evaluate whether changes in public cancer screening take up have an impact on health outcomes (effect on health).

3 The National Cancer Screening Program (NCSP) in Korea

Korea provides universal health insurance coverage through the National Health Insurance (NHI) and the Medical Care Assistance (MCA). The NHI is available to 95% of the total population, and the MCA covers the rest of the population, that is, the poorest 5%. The National Health Insurance Corporation (NHIC), a single insurer, manages both the NHI and the MCA programs. There are two categories of insurance in the NHI program: employee and self-employed insurance. Employees and their dependents are eligible for the employee insurance, and those who are excluded from employee insurance are eligible for self-employed insurance.[6]

[6]There are 31.4 and 17.2 million people in Korea with employee and self-employed insurance, respectively. Employee insurance applies to regular employees, but daily wage workers with less than one month of continuous employment are excluded from this category. Spouses, lineal ascendants and descendants, and siblings of employees who do not have remunerations or income are dependents of employee insurance.

The financial resources of the NHI system mainly come from insurance contributions paid by the insured and their employers. The insurance contribution amount is calculated differently by type of insurance. The contribution rate of the employee insurance, which this study investigates, is based solely upon a fixed percentage of the basic wage.[7]

It is important to note that there are three types of resources for cancer detection in Korea: public cancer screening organized by the NHIC, private opportunistic screening, and diagnostic testing. The first two are screenings for detecting cancer in the absence of symptoms, and the last is a clinically recommended procedure when relevant symptoms are present. Public cancer screening and diagnostic testing are covered by health insurance, while private opportunistic cancer screening is not.

The NHI operates the National Health Screening Program (NHSP) and the National Cancer Screening Program (NCSP). The NHIC implements a national campaign and sends letters to households to promote public health and cancer screenings. The NHSP provides a general health screening, including measurement of Body Mass Index (BMI), blood pressure, blood sugar level, and cholesterol. The NCSP provides cancer screenings. Both programs offer screenings every two years. People born in even/odd-numbered years are strongly encouraged to undertake screenings in an even/odd-numbered year, but those who missed the offer are allowed to undertake screenings in the next year.

Table 1 summarizes the NCSP. The NCSP for NHI beneficiaries started in 2002 with stomach, breast, and cervical cancer screenings (Kim et al. (2011)).[8] An upper gastrointestinal (UGI) series, which is a radiologic examination, and an Esophagogastroduodenoscopy (EGD), which is an endoscopic procedure, are used for stomach cancer screening. Screening takers are allowed to choose either of them based on their preferences. EGD, a confirmatory test, is provided to those who received cancer suspicion results from UGI. Mammography is used for breast cancer screening. The price of stomach and breast screenings were approximately $38 and $20, respectively, during the study period (Appendix Table 1). The prices of public cancer screening and diagnostic testing, both of which are covered by the NHI, are the same, and private screening is more expensive.

The NCSP offers subsidized cancer screenings. The amount of the subsidy is determined by

[7]The contribution rate was 3.40% in 2001, 3.62% in 2002, and 3.94% in 2003, respectively.

[8]The NCSP for MCA recipients began in 1999. I limit my sample to only NHI beneficiaries since MCA beneficiaries are also eligible for other social programs such as the National Basic Livelihood Security (NBLS) program.

age and insurance contribution amount. Health and cervical cancer screenings are free of charge for people satisfying the age criteria regardless of insurance contribution amount. However, free stomach, breast, and liver cancer screenings are available to those satisfying both the age and insurance contribution criteria shown in Table 1.[9] The age cutoff is 40 years old for stomach and breast cancer screenings. A 50% copayment is applied to those who satisfy the age criteria but not the insurance contribution criteria. The maximum cash incentive is \$19 (=50%×\$38) in males and \$29 (=50%×(\$38+\$20)) in females, respectively. Insurance contribution cutoffs are updated every year based on the government budget situation. During the study period, free cancer screening is available to those with around the lowest 30% of income.[10] The cutoff insurance contribution for employee type insurance was 26,180 and 24,630 Korean Won (KRW) in 2002 and 2003, respectively.

The identification strategy of this study is to compare people just below and above insurance contribution cutoffs among those who satisfy the age criteria. Specifically, the causal effect of stomach cancer screening in males can be estimated by comparing people just below and above the cutoffs. Not a single cancer screening effect can be isolated in females. For females, the combined effect of stomach and breast cancer screenings can be estimated around cutoffs.

4 Data

4.1 Data Description

The primary analysis relies on the NHI data for those with employee insurance for the years 2001-2008.[11] My empirical analysis requires data on the running variable, level of insurance contribution; indicator for take up of cancer screening; and relevant intermediate and final outcome variables explaining the effect of and behavioral responses to cancer screening.

The NHI data consists of three parts: eligibility, medical records, and screening.[12] The eligibility

[9] Liver cancer screenings were introduced in 2003. Liver cancer screening is not a mass screening because it is offered to people with chronic liver disease who account for less than 1% of the population. Moreover, the cutoff for liver cancer screening in 2003 was 16,750 Korean Won (KRW), far enough from those of stomach and breast cancer screenings.

[10] Basic salary level (without including allowance, bonuses, and incentives) around the cutoff was \$713, and annual medical expenditure is \$702 and \$774 in males and females, respectively. Therefore, the \$19 - \$29 cash incentive for cancer screening is not large.

[11] The data is longitudinal in nature but not a perfectly balanced panel because of deaths and drop outs from the NHI (i.e., becoming an MCA recipient).

[12] The insurance cutoff for free cancer screening is determined based on November of the previous year. Therefore, I match November eligibility for the years 2000-2007 to the medical records and screening data of 2001-2008.

component contains basic demographic information such as gender, age, type of insurance, and monthly insurance contribution. Mortality (without cause-of-death information) is included. Also included is individual and household labor market participation. Medical records include medical expenditure based on the International Statistical Classification of Diseases and Related Health Problems, 10th Revision (ICD-10), which allows me to measure cancer detection and treatment. Lastly, the screening data includes information from health and cancer screenings.

4.2 Study Sample

The study sample consists of those with employee-type insurance at the time of screening offer. Males who were previously diagnosed with stomach cancer are excluded from the sample, as are females who were previously diagnosed with stomach or breast cancer. Insurance contribution is the running variable. Specific-year cohort is defined as people with employee health insurance in a specific year. "Even" and "odd" mean those born in even- and odd-numbered years, respectively. For example, "2002 even cohort" refers to people who are aged 40 and over, were born in an even-numbered year, and have employee health insurance in 2002. The main sample is a stacked-up sample of the 2002 even and 2003 odd cohorts aged 40 and over. Cohorts are stacked up by standardized insurance contribution, which measures how far each individual's insurance contribution is from the cutoff (=(Insurance contribution - Cutoff)/Standard deviation).

The outcome variables are cancer detections, cancer mortality, and all-cause mortality. Cancer detections are based on ICD-10 information, which captures all cancers regardless of detection channels. One concern with using ICD-10 information is over-diagnosis.[13] To prevent misinterpretation, I restrict cancer detections to only if medical expenditure on cancer in the first year of detection is greater than 300,000KRW (≈$300).[14] Alternative definitions with different restrictions are used for the robustness check: no restriction and with non-zero medical expenditure on cancer in two or more sequential years.[15] Results are similar across definitions. Cancer detection by public cancer

[13] An anecdotal story is that doctors are likely to input the "stomach cancer" ICD-10 code even when they are still just suspicious of the cancer (i.e., a malignant-looking stomach cancer). This is because it is preferable to record a more serious disease, as doing so means more procedures can be covered by the insurance.

[14] This definition is recommended by the National Cancer Center (NCC) of Korea. According to the NCC, more than 90-95% of cancer cases meeting this definition is matched with the national cancer registry, an official record of cancer cases in Korea. Unfortunately, data from the national cancer registry is not available in this study. The $300 restriction excludes 10.8% and 15.3% of cancer cases in males and females, respectively

[15] The two sequential year restriction excludes 27.3% and 33.4% of cancer cases in males and females, respectively. The two sequential year restriction may exclude early stomach cancer cases that are not necessary for the subsequent

screening is defined as cancer detection with take up of public cancer screening either in the same or previous year[16]; otherwise it is categorized as cancer detection by other channels.[17]

The final health outcomes are cancer-related and all-cause mortalities. Cancer-related mortality is defined as death with non-zero medical expenditure on cancer in the last year of death.[18] Cancer-related mortality is potentially a more comprehensive concept than cancer-specific mortality in that cancer-specific mortality captures death where cancer is a main cause of death, while cancer-related mortality encompasses death where cancer is a comorbid condition such as suicide due to depression accompanied by cancer. All-cause mortality equals to one if an individual died for any reason, and zero otherwise. It is, of course, the most comprehensive outcome in my analysis.

4.3 Summary Statistics

Table 2 presents the descriptive statistics of the study sample. Panels A to F of Table 2 describe the general information, baseline medical expenditure, cancer screening take up, cumulative cancer incidence, and cumulative mortality. Around 10% of the population took up cancer screening within the first two years (panel C) and the cumulative screening take up within 6 years is over 50%. The cumulative stomach cancer incidence (up to 6 years) is 1.3% for males and .5% for females. In terms of mortality, the cumulative all cause mortality (up to 6 years) is 7.3% for males and 5.7% for females. The cumulative cancer mortality (also up to 6 years) is 4.7% for males and 4.3% for females.

Panels A, B, and C of Table 3 provide the results of the stomach and breast cancer screenings. Each panel consists of two sub-panels. The first sub-panel presents the statistics of the entire sample, which includes all individuals regardless of whether they get screened for cancer or not. The next sub-panel presents statistics by the cancer screening result of screening takers. Column (1) presents the total number of people in each category, and column (2) presents the number of cancer detections within two years in each category. Cancer incidence, the proportion of new cancer cases out of the total number of people, is presented in column (3). For example, the two-

chemo- or radio-therapy. Results are available by request.

[16]Cancer detected by public screening late in the previous year can be captured in next year.

[17]Cancer detections with take up of both channels are categorized as detection by public cancer screening. Public cancer screening take ups might lead to extra take up of diagnostic testing for confirmation, but not the other way around.

[18]It also must satisfy the cancer detection restriction that medical expenditure in the first year of cancer detection is greater than $300.

year incidences of stomach cancer in males and females were 0.44% (=17,447/3,948,584) and 0.19% (=8,482/4,41,1321), respectively.

Table 3 reveals four important facts about the efficiency of cancer screening. The first is that the rate of false negatives is low. As an example, the probability that a screening reports a stomach cancer-free result even though a patient has cancer is 0.23% for men and 0.06% for women.[19] The second is that the rate of false positives, the probability that a screening reports a cancer suspicion for a cancer-free patient, is high. For example, the false positive rate is 93.53% (=100-6.47%) for stomach cancer screening in males. Such a high false positive rate is not surprising given that cancer screenings tend to minimize false negatives and largely tend to ignore false positives. The third is that cancer screening detects other types of diseases in addition to cancer. For example, stomach cancer screening detects benign diseases such as gastritis, stomach ulcer, and duodenal ulcer. The fourth is that the total number of new cancer detections through public cancer screening is low. For example, public cancer screening detects 749 out of 17,447 stomach cancers in males. Stomach cancer detection by public cancer screening accounts for only 4.3% of total detections. The corresponding numbers in female stomach and breast cancers are 3.8%(=320/8,482) and 4.8%(=347/7,299), respectively.

5 Estimation Strategy

5.1 Empirical Analysis Setup

I take advantage of the insurance contribution cutoff for free cancer screening eligibility in order to estimate the effect of cancer screening. This corresponds to the intent-to-treat effect of offering free cancer screening versus charging a 50% copayment without controlling for any subsequent take up of cancer screening. I consider the following main regression equation:

$$Y_{it} = \beta \cdot \mathbf{1}(I_i > \tau) + f(I_i) + \psi + \epsilon_i \tag{1}$$

where Y_{it} is outcomes for an individual i, such as cancer mortality or all cause mortality, t years after the cancer screening offer. $\mathbf{1}(\cdot)$ is an indicator function for whether an individual's insurance

[19] In reality, the number of false negative can be smaller than the suggested statistics because new cancer cases developed after the screenings are included in these statistics.

contribution (I) is greater than or equal to the cutoff, τ, which determines eligibility for free cancer screening. $f(\cdot)$ is a flexible polynomial function of I. ψ is a cohort fixed effect and ϵ is an error term. Considering that the distribution of standardized insurance contribution is not continuous, errors are clustered by the level of the normalized insurance contribution as suggested by Lee and Card (2008). The analysis is done separately by gender as different types of cancer screenings are offered based on gender.

The idea behind the RD design is that the discontinuity measured by β measures the causal effect of cancer screening, if all other factors except cancer screening take up are smooth around the cutoff. If this assumption holds, people right above and below the cut-off can serve as proper control and treatment groups, respectively, and therefore any difference in outcomes, which is captured by β, can be attributed to eligibility for cancer screening.

5.2 Bandwidth Selection and Modeling f(Ii)

Bandwidth selection is one of the critical decisions in the RD model. Since there is no universally accepted convention for how to choose the optimal bandwidth, I try several ways that have been proposed in the literature. In my analysis, I use a bandwidth of 0.3 as well as the Imbens-Kalyanarman (IK) optimal bandwidth suggested by Imbens and Kalyanaraman (2012). My preferred bandwidth is 0.3, since it is wide enough not to be too imprecise and narrow enough to compare observations around the cutoff. Furthermore, I use a rectangular kernel and the local linear regression method suggested by Hahn, Todd, and Van der Klaauw (2001) for modeling f(Ii).

5.3 Smoothness of Predetermined Characteristics around the Cutoff

An important assumption of RD design is that individuals just below and just above the cutoff can be compared with each other. There are several reasons why this assumption might not hold. One concern might be that those slightly above the cutoff may reduce their income level in order to become eligible for free cancer screening. However, such manipulation of income reporting is extremely unlikely. First, the cutoff for the program is decided annually based on the government budget and the cutoff is not announced in advance.[20] Secondly, it is not likely for people to

[20]For example, eligibility for cancer screening in 2002 was decided by the insurance contribution of November 2001, and screening was offered starting in January 2002.

manipulate their income level in order to get such small cash incentive.

Appendix Figure 1 provides a visual illustration of the density of observations by the standard insurance contribution using the smallest bin size around the cutoff. In addition, I test for differences in observable characteristics around the cutoff. Appendix Table 2 presents estimates of the discontinuity around the cutoff for predetermined variables such as age, general screening take up, employment status, and medical expenditure. Most variables appear to be continuous around the cutoff.

5.4 Compliers, Always Takers, and Never Takers

My analysis estimates the local average treatment effect (LATE) for compliers around the cutoff. Since compliers are not randomly selected from the population, the impacts of cancer screening in this study do not necessarily represent that for the average population. Moreover, in my specific case more than 80% of the sample remain never takers during the study period.

I propose two different ways to compare the characteristics of compliers, always takers, and never takers. First, I compare compliers and always takers by restricting the sample to screening takers. Since everyone has undergone public cancer screening in the restricted sample, any difference around the cutoff is due to the compositional change of screening takers around the cutoff. In this sample, those right below the cutoff consist of always takers and compliers while those right above the cutoff are always takers. Thus, the analysis with the restricted sample allows me to compare the characteristics of compliers and always takers. Similarly, I restrict the sample to screening non-takers. This allows me to compare compliers and never takers.

Another way to compare compliers characteristics is suggested by Almond and Doyle (2011). Under the assumption that other things are equal around the cutoff, always takers and never takers are identified at just above and below the cutoff, respectively. Even though compliers are not identifiable, observable characteristics of compliers can be calculated from the sample (Abadie (2003)). To do so, I first define a binary variable F, an indicator for free cancer screening eligibility:

$$F = \begin{cases} 0 & \text{above cutoff} \\ 1 & \text{below cutoff} \end{cases}$$

Next, I also define a binary variable S, an indicator for cancer screening take up is also defined:

$$S = \begin{cases} 0 & \text{not take up of cancer screening} \\ 1 & \text{take up of cancer screening} \end{cases}$$

Lastly, I define S_F, as the value S would have if F were either 0 or 1. For example, $E(X|S_1 = 1)$ presents the mean value of screening takers in the eligible group.

To estimate complier characteristics, three conditions are required: the existence of a first stage, monotonicity and independence. First, the existence of first stage implies that the probability of cancer screening take up is higher in the eligible group than in the non-eligible group. This is empirically testable. Second, the monotonicity assumption implies that $S_1 > S_0$ for everyone with probability 1. In other words, anyone who takes cancer screening in the absence of the cash incentive would also undertakes cancer screening in the presence of the cash incentive. This is not directly testable since I do not observe S_1 and S_0, but it is reasonable to assume monotonicity in my setting. Third, independence implies that S_1 and S_0 are independent of F and the potential outcomes. This is not directly testable either, but it is plausible not only because eligibility is determined by the government ex ante but also because people are not likely to manipulate income in order to get a small cash incentive. To see this, the smoothness of the observable characteristics around the cutoff is shown in section 5.4.

Let's first consider $E(X|S_1 = 1)$. It can be written as:

$$E(X|S_1 = 1) = E(X|S_1 = 1, S_0 = 1) \cdot P(S_0 = 1|S_1 = 1) + E(X|S_1 = 1, S_0 = 0) \cdot P(S_0 = 0|S_1 = 1) \tag{2}$$

Equation (2) implies that $E(X|S_1 = 1)$ is divided by always takers and compliers components. $E(X|S_1 = 1, S_0 = 0)$ represent the characteristics of compliers I am interested in. $E(X|S_1 = 1, S_0 = 1) = E(X|S_0 = 1)$ holds by the monotonicity assumption. P(S_0=1) and P(S_1=0) can be directly measured from the sample. P(S_0=1), the proportion of always-takers, can be measured by π_A the proportion of screening takers in the non-eligible group. Similarly, the proportion of never-takers, P(S_1=0) also can be measured by π_N, the proportion of screening non-takers in the eligible group. The proportion of compliers (π_C) is 1- π_A - π_N. Therefore, $P(S_0 = 1|S_1 = 1)$ and $P(S_0 = 0|S_1 = 1)$ are $\frac{\pi_A}{\pi_C+\pi_A}$ and $\frac{\pi_C}{\pi_C+\pi_A}$, respectively.

Finally, by rearranging the components of equation (2), the mean characteristics of compliers are presented by the terms that can be calculated with the sample:

$$E(X|S_1 = 1, S_0 = 0) = \frac{\pi_C + \pi_A}{\pi_C} \cdot \Big[E(X|S = 1, F = 1) - \frac{\pi_A}{\pi_C + \pi_A} \cdot E(X|S = 1, F = 0)\Big] \quad (3)$$

6 Results

This section presents the results from equation (1). I first explore the effects of cost-sharing on screening take up and crowd out behaviors. Specifically, I present evidence of discrete changes in eligibility and a subsequent increase in cancer screening take ups. I then describe dynamic changes in cancer detections by public as well as other channels. I also explore the characteristics of compliers, always takers and never takers to explore self-selection. Lastly, I estimate the causal impacts of the increase in public cancer screening take up on mortality, and other behavioral responses.

6.1 Effect of Cost-sharing on Screening Take Up

I first illustrate that the eligibility for free cancer screening increases from 0 to 1, as shown in Figure 1. I plot the standardized insurance contribution that determines eligibility on the x-axis, and the outcomes on the y-axis. The solid lines present the fitted values from equation (1) with local linear regression using a 0.3 bandwidth and a rectangular kernel. The open circles in the figure display the means of the fitted values that are collapsed into bins containing individuals who are within 0.05 of a standardized insurance contribution. The vertical difference between two points right below and over the cutoff (vertical line) is an analog of β in equation (1).[21] Its regression analog is shown in column (1) of Table 4.

Columns (2) to (5) of Table 4 show how much eligibility for the cash incentive translates into an increase in cancer screening take up. Panels A, B, and C of Table 4 show an increase in male stomach, female stomach, and female breast cancer screening take ups. Columns (2) and (3) present the cancer screening take up in the first year with bandwidth 0.3 and IK optimal bandwidth, respectively. Columns (4) and (5) present the cumulative cancer screening take up until the second

[21] Figure 1- 15 have similar structures where the standardized insurance contribution is plotted on the x-axis, and the outcome variable on the y-axis and the open circles are the mean of the outcome in each bin.

year from the screening offer.[22] Figure 2 corresponds to column (4) of Table 4. As expected, eligible people took up public cancer screening mostly in the first year. Up to the second year, male stomach, female stomach, and female breast cancer screening take ups increased by 8.3%, 10.9%, and 10.7% points, respectively. This corresponds to an 83.6, 86.9, and 84.4 percent increase.[23]

The estimated arc-elasticities of demand is around -0.47.[24] The estimated arc elasticity is close to the elasticity of preventive health products in developing countries, such as -0.6 for chlorine, a disinfectant that prevents water-borne diseases in Zambia (Ashraf, Berry, and Shapiro (2010)), and -0.37 for ITNs for malaria prevention in Kenya (Cohen and Dupas (2010)). On the other hand, it is much bigger than the elasticity in therapeutic care in developed countries, such as -0.07 to -0.21 for ambulatory utilization in Korea (Kim, Ko, and Yang (2005)), around -0.2 for health care for the non-elderly in the US (Newhouse and Group (1993)), -0.10 for clinic visits for the elderly in the US(Chandra, Gruber, and McKnight (2010)), and -0.15 to -0.17 for the elderly in Japan (Shigeoka (2011)).

Next, I examine the impact of past public cancer screening take up on future public cancer screening take up. If past and future cancer screenings are substitutes, future public cancer screening take up would decrease. On the other hand, if they are complements, future cancer screening take ups would increase. I first check whether there is a change in eligibility for future free public cancer screening. Unless the free cancer screening offer influences future wage levels (and thus insurance contribution), the eligibility for future cancer screening should be smooth around the cutoff. Figure 3 and columns (6) and (7) of Table 4 confirm the limited change in future eligibility.[25] I find no impact on future public cancer screening take ups as shown in columns (8) and (9) of Table 4 and Figure 4.

In sum, free cancer screening increased the demand for public cancer screening dramatically and take up of previous public cancer screening does not influence future take up.

[22]Remember that people born in even/odd-numbered years are strongly encouraged to take cancer screening in an even/odd-numbered year, but those who missed the offer are allowed to take up the screening in the next year. Therefore, the offer is actually valid for two years.

[23]Percentage increase is calculated by the formula $\frac{A}{B}$, where A is a the β from equation (1), and B is the mean of predicted value at just below and above the cutoff from the local linear regression with bandwidth 0.3

[24]The arc-elasticities are calculated as $((Q_2 - Q_1)/(Q_1 + Q_2)/2)/((P_2 - P_1)/(P_1 + P_2)/2)$. Comparing the arc-elasticity in a zero price setting to those in other settings could be problematic because the denominator, $(P_2 - P_1)/(P_1 + P_2)/2$, is always 2 if P_1=0. Moreover, people treat a zero price as not only a decrease of cost but also as an extra benefit (Shampanier, Mazar, and Ariely (2007)). This must be interpreted with this caveat.

[25]The dependent variable is a summation of eligibility between years 3 and 6. Since the screening is offered every two years, it ranges between 0 and 2.

6.2 Effect on Cancer Detections: Dynamic Aspect of Cancer Detections

In this section, I study whether public cancer screening actually promotes cancer detections, and explore whether the increased cancer detections diminish over time. As mentioned before, if cancers are eventually detected before death, the initial increase in cancer detections by the cancer screening program should be crowded out over time by other channels such as diagnostic testing. Therefore, while the crowd out by private cancer screening or diagnostic testing is expected, what is important is the time it takes for the crowd out to occur. The effect of cancer screening would depend upon the difference between the timing of cancer detection by screening and that of detection without screening.[26]

Table 5, Table 6, and Table 7 present the dynamic change of cumulative stomach cancer detections in males, stomach cancer in females, and breast cancer in females, respectively. Panels A, B, and C in each table present cumulative cancer detections by public cancer screening and by other channels, and overall cumulative detections. Overall detection is the summation of detection by public cancer screening and other channels. Columns (1) to (6) show cumulative cancer detections over a six year period. Columns (7) and (8) present cumulative cancer detections between 3 and 6 years after the cancer screening offer. Figure 5 and Figure 6 are analogs of columns (2) and (7) in each table.

Table 5 and Table 6 reveal that impacts on stomach cancer detections are similar for males and females. First, stomach cancer detections by public cancer screening significantly increases by 0.045% points for males (a 30.3% increase) and 0.022% points for females (a 36.0% increase) up to the second year of the screening offer (panel A). Second, cancer detections by other channels decrease as well (i.e., crowd out). As a result, overall cancer detections in males and females increase by 0.020% points (an 8.8% change) and 0.018% points (a 4.4% change) in the first year of the screening offer, but both decrease to zero within a year (panel C). The time it takes for the crowd out to occur is no more than a year. I also find similar result from breast cancer screening (Table 7). To summary, increased cancer detections by free public cancer screening were quickly crowded out,

[26]It is worth mentioning that cancer detections (and medical expenditures) are observed only if individuals are under the NHI. It is important to address the concern of systematic sample selection by dropping out of the NHI, which could account for my finding. Therefore, whether public cancer screening had any impact on eligibility for the NHI is another relevant outcome. To check this possibility, I look at the NHI status directly. I find no statistically significant difference in the NHI status.

less than one year, by other channels including private screening and diagnostic testing.

6.3 Stage at Which Cancer is Detected

In order to be effective the screening should find the cancer at the earlier stages, but detecting cancer early does not necessarily mean detecting it at the earlier stages. If the target cancer grows slowly, for example, thyroid cancer, the difference in timing in cancer detections would not translate to detection at the earlier stages.[27] The question, then, is whether this short advance in timing of cancer detection translates into cancer detection at the earlier stage. In this section, I explore whether the difference in the timing of cancer detection I find in section 6.2 actually translated into cancer detection at the earlier stages.

The dependent variable that I use is the amount of medical expenditure in the first year of cancer detection. I believe that it is a good proxy for the stage of the cancer because it reflects the intensity of cancer treatment. Higher medical expenditures may imply a more advanced cancer stage. However, given the low incidence of cancer, the sample for which medical expenditure in the first year of cancer detection could be measured is much smaller than the initial sample,[28] and this might limit the precision of the estimates.

Figure 7 provides a graphical illustration of the level of medical expenditure in the first year of stomach and breast cancer detection during the first two years (panel A) as well as between 3 to 6 years after the screening offer (panel B). Table 8 is the regression analog. I find no evidence on stomach and breast cancer detection at the earlier stages. This suggests that cancer detection one year early did not actually translate to cancer detection at the earlier stages.

6.4 Selection to Cancer Screening

6.4.1 Selection Effect by Cost-Sharing

I examine whether cost-sharing in cancer screening changes the types of testers. To do so, I compare compliers and always takers by restricting the sample to screening takers as suggested in section 5.3.

[27] Moreover, if the target cancer is too malignant, for example, pancreatic cancer, screening could detect cancer at the earlier stage but doing so might not translate to mortality reduction because earlier intervention is less likely to be successful.

[28] Even though stomach and breast cancers are one of the most common cancers in Korea, the annual incidence for people aged 40 and over is no greater than 0.5%

Table 9, Figure 8 and Figure 9 illustrate the cancer screening results and cancer detections among screening takers. Panels A, B, and C of Figure 8 present the probabilities of having normal results, cancer suspicion results, and results for other diseases, respectively. They show that compared to always takers, compliers are more likely to have normal results (panel A), less likely to have cancer suspicion results (panel B, female stomach cancer), and less likely to have results for other diseases. Always takers are actually are more likely to have symptoms than compliers.

However, these relationships do not apply to stomach and breast cancers: I find no difference in cancer detections between compliers and always takers. This implies that the baseline health status of compliers in terms of cancer prevalence is as good as that of always takers. From a different perspective, it also implies that cost-sharing reduces the demand for cancer screening without increasing the efficiency of cancer detection.[29]

6.4.2 Characteristics of Compliers, Always Takers, and Never Takers

As mentioned above, the effects I measure stem from compliers. Since compliers are not randomly selected from the sample, understanding the characteristics of compliers, always takers, and never takers is important. Table 10 presents summary statistics of the entire sample for bandwidth [-0.3,0.3], compliers, always takers in bandwidth [0,0.3], and never takers in bandwidth [-0.3,0]. As explained in section 5.3, the characteristics of compliers can be estimated with the proportion of always takers (π_A) and never takers (π_N), as well as the average characteristics of always takers ($E(X|S=1,F=0)$), and eligible screening takers ($(X|S=1,F=1)$). The estimated proportions of compliers, always takers, and never takers are presented in panel A1, B1, and C1 of Table 10. The proportion of compliers is between 9% to 12%, and more than 80% of the sample remained never takers.

I find that never takers, those who did not undergo public cancer screenings even with a cash incentive, are significantly different from compliers and always takers. In contrast to the belief that people with higher risk are more likely to utilize medical services, never takers in cancer screening have the highest risk in terms of cancer mortality. Even though the 6-year cumulative stomach cancer detection rate is lowest among never takers (with always takers at 1.7%, compliers at 1.5%,

[29]This finding is similar to the result that cost-sharing of ITNs for malaria prevention in Sub-Saharan Africa decreases the demand without inducing a selection of people who actually need the ITNs more (Cohen and Dupas (2010)).

and never takers at 1.3%)[30], the 6-year cumulative stomach cancer mortality is highest among males in this group (with always takers at 0.24%, compliers at 0.34%, and never takers at 0.54%).[31] In female stomach and breast cancers, the 6-year cumulative cancer mortality in never takers is much greater than that in compliers and always takers.

Appendix Figure 2 illustrates that cancer screening take up is negatively correlated with health status, which in turn might also be related to cancer incidence and mortality. This finding implies that public cancer screening did not reach people who needed cancer screening the most during the study period. This potentially explains why, as described in a later section, I find no evidence of reductions in mortality.

Figure 10 illustrates another aspect of the characteristics of compliers, always takers, and never takers. Panel A compares compliers with always takers by using the sample of screening takers, and panel B compares compliers with never takers by using the sample of screening non-takers. Table 11 is its regression analog. It is important to note that panels A and B compare compliers with always takers and never takers indirectly because compliers are not identifiable. For example, I compare never-takers right below the cutoff with the combined sample of $5.6\%(= 5.1/(85.3 + 5.1))$ compliers and 94.4% never-takers right below the cutoff in male stomach cancer screening. Even though the power of the test significantly decreases, I find a significant difference in female breast cancer screening mortality between non-takers and compliers. This result confirms that non-takers have the highest breast cancer mortality.

6.5 Effect on Health Behaviors

I also explore additional behavioral responses: future health screening, medical expenditure, and intermediate health outcomes such as BMI, blood sugar, and total cholesterol. The human capital formation model provides a conceptual framework for understanding the effect of cancer screening on health behaviors and medical expenditure. It predicts that more information on health would decrease medical expenditures and time spent on health promotion since such information allows people to manage their health more efficiently (Grossman (1972)).

[30]Low detection among never-takers does not mean that cancer prevalence is lowest among never-takers. Further, never-takers are not diagnosed with cancer through public cancer screenings but through other channels or future public screening.

[31]Since I exclude previous cancer patients from the study sample, the cancer mortality that I measure is death from cancer that developed after the screening offer.

Take up of free general health screening, which is offered every two years, is shown in Figure 11 and columns (1) and (2) of Table 12. The results indicate no significant impact on general health screening take up. I also evaluate the impact on medical expenditure, as shown in Figure 12 and columns (3) to (8) of Table 12. To increase precision, I use the differences in medical expenditure from baseline medical expenditure as dependent variables. I find no significant change in medical expenditure.

6.6 Effect on Health Outcomes: Bio-markers and Mortality

First, I explore intermediate health outcomes such as the probability of being obese, blood sugar level (Diabetes Mellitus (DM) indicator), and total cholesterol level (hyperlipidemia indicator).[32] Table 13 reveals no evidence of a change in intermediate health outcomes.[33]

Finally, I explore the impact on a number of mortality measures. Figure 15 presents the average effect on cancer-, non-cancer-, and all-cause mortalities, respectively. Table 14 presents the corresponding estimates of β from equation (1). I do not find evidence of an effect on stomach and breast cancer mortalities. This is not a surprise at all given that cancer screening has a limited impact on the stage at which cancer is detected. I do not find any statistically significant changes in all-cause mortality either. Figure 16 illustrates a changing trend in mortalities over time. Even though none of the estimates is statistically significant, it presents a decreasing pattern in males and an increasing pattern in females, suggesting that 6 years could be too short to measure mortality outcomes.

6.7 False Positive

Behavioral responses to cancer screening might differ by screening result. Especially, behavioral responses for those with false positive results are of a particular interest. To see this, I implement another RD regression with the additional interaction terms of eligibility and screening result. Screening result is categorized as result of "normal","cancer detection","false positive", and "other type of diseases". Cancer detection is the case when an individual is diagnosed with cancer after

[32] I additionally have results for blood pressure, γGTP, and hemoglobin level. I find no change in these outcomes. These results are available by request.

[33] Intermediate health outcomes can be measured only for the general health screening takers. It is possible that this selection is a source of bias. Appendix Figure 3 reveals that screening takers are more likely to have better health status (upward bias). Thus, the coefficient estimates on intermediate health outcomes would be upper bound.

receiving a cancer suspicious result; otherwise it is categorized as a false positive. I construct an additional RD model in the following way:

$$Y_{it} = \beta \cdot \mathbf{1}(I_i > \tau) + \delta \cdot \mathbf{1}(I_i > \tau) \cdot \sum R_i + \eta \cdot \sum R_i + f(I_i) + \gamma X_i + \epsilon_i$$

where R is a dummy for the four types of cancer screening results. Since the cancer screening results are endogenous, results of this analysis need to be interpreted with care.

The results are presented in Table 15. Columns (1) and (2) show that males with false positive result from stomach cancer screening are more likely to take health and stomach cancer screenings in the future. Columns (6) to (8) show that females with false positive result from breast cancer screening are more likely to take stomach and breast cancer screenings in the future. I find no significant change in medical expenditure both for males and females with false positive result. It implies that false positives only induce additional clinic visits and procedures, which are covered by the public cancer screening program.

6.8 Cost Analysis

This section presents estimates of the cost-effectiveness of the program, in terms of cancer detection, from a societal perspective.[34] Panels A, B, and C of Table 16 present calculations of the cost per cancer detected for male stomach, female stomach, and breast cancer screenings. Column (1) shows the number of screenings, travel days, and lost work days per cancer detected. Column (2) indicates the corresponding unit costs.[35] Column (3) presents the total cost of each category, and column (4), the proportion of that categorys cost to the overall cost. The overall cost of each cancer screening is the sum of direct screening costs, transportation costs, and opportunity costs.

Those who were induced to screen by the program are compliers. Accordingly, the numbers and costs presented in columns (1) and (2) are determined from equation (3). These are further weighted by the proportion of compliers in 2002 and 2003.[36] Medical expenditures induced by false positives and cancer detections are not included since there are no significant impacts as shown in

[34]There is no "benefit" in terms of mortality since I do not find change in cancer- and all-cause mortality as shown in Table 14.

[35]The price of cancer screening is described in Appendix Table 1.

[36]Proportions of compliers in male stomach cancer are 6.7% and 11.6% in 2002 and 2003, respectively. Weighted average is calculated by the formula, $\frac{X_{2002} \times 6.7 + X_{2003} \times 11.6}{6.7 + 11.6}$. Corresponding figures in female stomach cancer are 9.2% and 13.3%, and in breast cancer are 8.5% and 13.6%.

columns (5) and (11) of Table 15.

I first consider the direct screening cost. Since individual level biopsy data are not available, I use the average biopsy rate in 2002 and 2003, and assume that it is constant around the cutoff.[37] Screening is often accompanied by procedures paid for out-of-pocket expenses by the patients such as conscious sedation in the case of EGD and ultrasonography to perform a biopsy of breast tissue. I assume that 30% of EGD procedures are undergone with conscious sedation. I also assume that the cost of conscious sedation and breast ultrasonography are $30 and $100, respectively.

Transportation costs are also considered. Transportation costs are based on the average transportation cost for a clinic visit computed from the Korean National Health and Nutrition Examination Survey in 2005.[38] The number of first visits is equal to the number of screenings undertaken, and I assume that those with "cancer suspicion" result from cancer screening made a follow-up visit.

Lastly, I consider the opportunity cost resulting from lost labor productivity. Since the insurance contribution is a fixed percentage of wage, foregone labor productivity can be directly calculated.[39] Since the insurance contribution is based only on base salary (not including bonuses and benefits), this leads to conservative estimates of the cost. The number of lost work days is the number of screenings undergone by employees in each sample.

The total estimated cost costs for identifying one additional case of male stomach, female stomach, and female breast cancers are $15,073, $59,590, and $63,811, respectively. Direct screening costs, transportation costs, and lost labor productivity account for 58%-66%, 20%-22%, and 13%-19% of total cost, respectively.

7 Conclusion

My paper presents empirical evidence on the impacts of and behavioral responses to cost-sharing in population-based public cancer screening. I use an RD design that takes advantage of the unique

[37] I use the average biopsy rate of the entire sample. Average biopsy rate of stomach cancer screening were 26.7% and 39.8% in 2002 and 2003, respectively. Average biopsy rate of breast cancer screening were 25.5% and 38.5% in 2002 and 2003, respectively.

[38] The average transportation costs for a round trip clinic visit are $19.31 and $15.61 for males and females, respectively, in 2005. These cost are consumer price index (CPI) adjusted. Based upon a 2005 base of 100, the CPI is 90.747 and 93.946 in 2002 and 2003, respectively.

[39] I assume that screening only takes one day. The monthly wage is divided by 23, the average number of working days in a month, to compute daily labor productivity.

experience of the NCSP in Korea, which provides free stomach and breast cancer screenings to those below the insurance contribution cutoff, while charging a 50% copayment to those above.

My results suggest that although free cancer screening substantially increases the cancer screening take up rate and the number of cancer detections, there is no evidence that the program had an impact on cancer- and all-cause mortality rate. My analysis provides two main explanations for these results. First, the initial increase in cancer detections due to the public screening program was quickly crowded out by the decrease in cancer detections through other channels, such as private screening and diagnostic testing. Second, those induced into screening by the cash incentive (compliers) were relatively healthy. These compliers' baseline cancer prevalence and cancer mortality is as high as of those who take up screening regardless of the availability of free cancer screening (always takers), implying no selection effect of cost-sharing. In addition, those who do not undergo screening regardless of the availability of free cancer screening (never takers) had the poorest health and stood to benefit the most from the screening they did not receive.

My result suggests that in order to be successful, a population-based cancer screening program should promote a sufficiently high take up rate in order to reach the people most in need of cancer screening. My study also provides implications on the additional provision of cancer screening, given that cancer screening is already popular. First, provision of cancer screening can be crowded out easily. Crowd out is more likely the more popular cancer screening is, which means better access to outside options. Second, people who are more likely to have cancer would be less likely to participate in cancer screening. Therefore, incentives for cancer screening must be well-designed in order to reach these people.

My results also imply that findings from RCTs might be quite different from that in population-based programs due to the behavioral responses to the programs. More broadly, even though the findings of this study may reflect responses that are specific to cancer screening in Korea, this analysis demonstrates that the impacts of health programs, even when they display large participation responses, crucially depend on the potential behavioral responses of the agents involved.

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Table 1: National Cancer Screening Program (NCSP)

Year	Male	Female	Age	Insurance contribution cutoff (KRW)
2002	Stomach	Stomach	40 and over	26,180
		Breast	40 and over	26,180
		Cervix	30 and over	n/c
2003	Stomach	Stomach	40 and over	24,630
		Breast	40 and over	24,630
		Cervix	30 and over	n/c

Note: This table presents cancer screenings covered by National Cancer Screening Program (NCSP) and the cutoffs for free cancer screening. Cervical cancer screening was free of charge for all. For stomach, breast and colorectal cancer were free for those with insurance contribution below the cutoff, while 50% copayment was charged those above. Liver cancer screening is offered since 2003 with a cutoff 16,750 KRW. Liver cancer screening targets on people with chronic liver disease such as liver cirrhosis, and HBV and HCV related liver diseases, explaining less than 1% of the population. Unit is KRW. \$1 $\approx$ 1,000KRW.

Table 2: Basic Statistics

	Male			Female		
	N	Mean	Std.Dev	N	Mean	Std.Dev
Panel A. General Information						
Age	4,041,275	53.9	11.2	4,460,789	56.2	12.3
Cancer Screening Eligibility	4,041,275	0.347	0.476	4,460,789	0.374	0.484
Standard insurance contribution	4,041,275	0.468	1.006	4,460,789	0.441	1.006
Employment	4,041,275	0.625	0.484	4,460,789	0.157	0.364
Panel B. Medical expenditure (Unit:1000KRW=$1)						
Total	3,641,741	709.9	1709.2	4,217,969	796.9	1524.9
Non cancer	3,641,741	643.7	1479.7	4,217,969	760.0	1395.1
Cancer	3,641,741	66.3	812.4	4,217,969	37.0	595.3
Panel C. Screening take up (Year 1-2)						
Stomach cancer screening	4,041,275	0.097	0.295	4,460,789	0.110	0.312
EGD	4,041,275	0.042	0.200	4,460,789	0.043	0.202
UGI	4,041,275	0.058	0.233	4,460,789	0.068	0.251
Breast cancer screening				4,460,789	0.114	0.317
General health screening	4,041,275	0.467	0.499	4,460,789	0.287	0.452
Panel D. Cumulative screening take up (Year 1-6)						
Stomach cancer screening	4,041,275	0.512	0.868	4,460,789	0.586	0.840
Breast cancer screening				4,460,789	0.626	0.865
General health screening	4,041,275	1.819	1.744	4,460,789	1.198	1.307
Panel E. Cumulative Cancer Incidence (up to Year 6)						
Stomach	4,021,374	0.013	0.112	4,440,967	0.005	0.074
Breast				4,440,967	0.005	0.073
Panel F. Cumulative mortality (up to Year 6)						
All-cause	4,041,275	0.073	0.261	4,460,789	0.057	0.231
Non-cancer	4,041,275	0.047	0.211	4,460,789	0.043	0.202
Cancer-related	4,041,275	0.027	0.161	4,460,789	0.014	0.117
Stomach cancer-related	4,041,275	0.005	0.071	4,460,789	0.003	0.059
Breast cancer-related				4,460,789	0.002	0.046

Note: This table shows summary statistics of study samples. N is the sample size and Std. Dev refers a standard deviation. The data covers universe Korean people with employee health insurance. Screening take up is defined as 1 for individuals took cancer screening within two-years from the offer. See text for definitions of variables. All measures are at the baseline

Table 3: Result of Public Cancer Screening

	(1)	(2)	(3)
Panel A. Male stomach cancer screening			
	Total	Cancer	Cancer incidence
Panel A1. Whole sample			
Total	3,948,584	17,447	0.44%
Screening non-takers	3,687,115	15,599	0.42%
Screening takers	261,469	1,848	0.71%
Panel A2. By screening result (among screening takers)			
Normal	123,462	317	0.26%†
Cancer suspicion	11,585	749	6.47%‡
Other stomach disease	126,422	782	0.62%
Panel B. Female stomach cancer screening			
Panel B1. Whole sample			
Total	4,411,321	8,482	0.19%
Screening non-takers	4,001,177	7,674	0.19%
Screening takers	410,144	808	0.20%
Panel B2. By screening result (among screening takers)			
Normal	228,523	150	0.07%†
Cancer suspicion	11,590	320	2.76%‡
Other stomach disease	170,031	338	0.20%
Panel C. Female breast cancer screening			
Panel C1. Whole sample			
Total	4,411,321	7,299	0.17%
Screening non-takers	3,972,497	6,325	0.16%
Screening takers	437,922	974	0.22%
Panel C2. By screening result (among screening takers)			
Normal	331,144	250	0.08%†
Cancer suspicion	39,518	347	0.88%‡
Other stomach disease	67,260	377	0.56%

Note: This table shows the results of the stomach and breast cancer screenings. Each panel consists of two sub-panels. The first sub-panel presents the statistics of the entire sample, which contains all individuals regardless if they get screened for cancer or not. The next sub-panel presents statistics by the cancer screening result of screening takers. Column (1) presents the total number of people in each category, and column (2) presents the number of cancer detections within two years in each category. Cancer incidence, the proportion of new cancer cases out of the total number of people, is presented in column (3). False negative is statistics with '†' and false positive is 1 - statistics with '‡'.

Table 4: Effect of Cost-Sharing on Cumulative Cancer Screening Take up

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependant variable	Eligibility Year 1-2	Screening take up Year 1		Screening take up Year 1-2		Eligibility Year 3-6		Screening take up Year 3-6	
Panel A. Male stomach cancer screening									
bandwidth	0.3	0.3	IK(0.14)	0.3	IK(0.12)	0.3	IK(0.09)	0.3	IK(0.12)
	1.0000**	0.0791**	0.0695**	0.0829**	0.0725**	0.0543	-0.0252*	0.0007	-0.0119*
	(0.000)	(0.0078)	(0.0106)	(0.0114)	(0.0174)	(0.064)	(0.009)	(0.011)	(0.005)
N	1,260,729	1,260,729	606,937	1,260,729	465,339	1,260,729	408,959	1,260,729	465,335
Panel B. Female stomach cancer screening									
bandwidth	0.3	0.3	IK(0.07)	0.3	IK(0.09)	0.3	IK(0.09)	0.3	IK(0.11)
	1.0000**	0.1115**	0.1711**	0.1087**	0.0919**	0.0702	-1.0550**	-0.0015	-0.0185**
	(0.000)	(0.0085)	(0.0098)	(0.0101)	(0.0182)	(0.070)	(0.010)	(0.012)	(0.003)
N	1,396,081	1,396,081	271,655	1,396,081	445,477	1,396,081	271,655	1,396,081	506,252
Panel C. Female breast cancer screening									
bandwidth	0.3	0.3	IK(0.18)	0.3	IK(0.06)	0.3	IK(0.09)	0.3	IK(0.24)
	1.0000**	0.1101**	0.1085**	0.1065**	0.1936**	0.0702	-1.0550**	-0.0021	-0.0086
	(0.000)	(0.0106)	(0.0148)	(0.0124)	(0.0110)	(0.070)	(0.010)	(0.011)	(0.008)
N	1,396,081	1,396,081	823,434	1,396,081	271,655	1,396,081	271,655	1,396,081	1,026,628

Note: Each cell represents a coefficient β from different local linear regression of equation (1). The running variable is the standardized insurance contribution. Rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution in parentheses. **, * and + indicates statistical significance at the 1, 5 and 10 percent level respectively.

Table 5: Effect on Cumulative Stomach Cancer Detection, Male

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year	Year 1	Year 1-2	Year 1-3	Year 1-4	Year 1-5	Year 1-6	Year 3-6	
Panel A. Cumulative stomach cancer detection by public screening								
Bandwidth	0.3	0.3	0.3	0.3	0.3	0.3	0.3	IK(0.35)
	0.00013	0.00045*	0.00044*	0.00052*	0.00069**	0.00051*	0.00006	0.00003
	(0.00015)	(0.00018)	(0.00017)	(0.00019)	(0.00020)	(0.00022)	(0.00010)	(0.00011)
N	1,212,427	1,212,427	1,212,427	1,212,427	1,212,427	1,212,427	1,244,400	1,458,485
Panel B. Cumulative stomach cancer detection by other channels								
Bandwidth	0.3	0.3	0.3	0.3	0.3	0.3	0.3	IK(0.39)
	0.00003	-0.00046**	-0.00068*	-0.00080*	-0.00072+	-0.00063	-0.00010	-0.00010
	(0.00004)	(0.00012)	(0.00028)	(0.00037)	(0.00040)	(0.00041)	(0.00034)	(0.00033)
N	1,212,427	1,212,427	1,212,427	1,212,427	1,212,427	1,212,427	1,244,400	1,733,954
Panel C. Overall cumulative stomach cancer detection								
Bandwidth	0.3	0.3	0.3	0.3	0.3	0.3	0.3	IK(0.37)
	0.00020	0.00004	-0.00017	-0.00019	0.00002	-0.00002	-0.00004	-0.00011
	(0.00017)	(0.00024)	(0.00039)	(0.00050)	(0.00058)	(0.00057)	(0.00037)	(0.00038)
N	1,212,427	1,234,492	1,244,400	1,249,522	1,252,297	1,254,031	1,244,400	1,559,108

Note: Dependent variables in Panels A, B, and C are cumulative stomach cancer detection by public screening, by other channels, and overall cumulative detections, respectively. Each cell represents a coefficient β from different local linear regression of equation (1). The running variable is the standardized insurance contribution. Rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution in parentheses. **, * and + indicates statistical significance at the 1, 5 and 10 percent level respectively.

Table 6: Effect on Cumulative Stomach Cancer Detection, Female

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year	Year 1	Year 1-2	Year 1-3	Year 1-4	Year 1-5	Year 1-6	Year 3-6	
Panel A. Cumulative stomach cancer detection by public screening								
Bandwidth	0.3	0.3	0.3	0.3	0.3	0.3	0.3	IK(0.25)
	0.00013**	0.00022**	0.00015	0.00022+	0.00027*	0.00028*	0.00007	0.00005
	(0.00003)	(0.00005)	(0.00009)	(0.00011)	(0.00012)	(0.00013)	(0.00010)	(0.00011)
N	1,368,472	1,368,472	1,368,472	1,368,472	1,368,472	1,368,472	1,385,151	1,018,478
Panel B. Cumulative stomach cancer detection by other channels								
Bandwidth	0.3	0.3	0.3	0.3	0.3	0.3	0.3	IK(0.18)
	0.00002	-0.00016+	-0.00024	-0.00023	-0.00005	0.00004	0.00018	0.00051**
	(0.00005)	(0.00009)	(0.00015)	(0.00017)	(0.00016)	(0.00015)	(0.00014)	(0.00010)
N	1,368,472	1,368,472	1,368,472	1,368,472	1,368,472	1,368,472	1,385,151	816,816
Panel C. Overall cumulative stomach cancer detection								
Bandwidth	0.3	0.3	0.3	0.3	0.3	0.3	0.3	IK(0.27)
	0.00018**	0.00008	-0.00007	0.00000	0.00022	0.00032+	0.00025	0.00026+
	(0.00006)	(0.00010)	(0.00019)	(0.00018)	(0.00015)	(0.00016)	(0.00015)	(0.00015)
N	1,368,472	1,380,172	1,385,151	1,387,618	1,389,023	1,389,878	1,385,151	1,332,383

Note: Dependent variables in Panels A, B, and C are cumulative stomach cancer detection by public screening, by other channels, and overall cumulative detections, respectively. Each cell represents a coefficient β from different local linear regression of equation (1). The running variable is the standardized insurance contribution. Rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution in parentheses. **, * and + indicates statistical significance at the 1, 5 and 10 percent level respectively.

Table 7: Effect on Cumulative Breast Cancer Detection, Female

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year	Year 1	Year 1-2	Year 1-3	Year 1-4	Year 1-5	Year 1-6	Year 3-6	
Panel A. Cumulative breast cancer detection by public screening								
Bandwidth	0.3	0.3	0.3	0.3	0.3	0.3	0.3	IK(0.18)
	0.00007+	0.00017**	0.00013+	0.00010	-0.00004	-0.00010	-0.00026+	-0.00035**
	(0.00004)	(0.00004)	(0.00007)	(0.00007)	(0.00013)	(0.00016)	(0.00013)	(0.00011)
N	1,368,472	1,368,472	1,368,472	1,368,472	1,368,472	1,368,472	1,385,151	816,816
Panel B. Cumulative stomach cancer detection by other channels								
Bandwidth	0.3	0.3	0.3	0.3	0.3	0.3	0.3	IK(0.24)
	0.00013+	-0.00014	-0.00018	-0.00037*	-0.00041*	-0.00047*	-0.00034	-0.00009
	(0.00007)	(0.00008)	(0.00011)	(0.00017)	(0.00020)	(0.00022)	(0.00020)	(0.00021)
N	1,368,472	1,368,472	1,368,472	1,368,472	1,368,472	1,368,472	1,385,151	1,018,478
Panel C. Overall cumulative breast cancer detection								
Bandwidth	0.3	0.3	0.3	0.3	0.3	0.3	0.3	IK(0.28)
	0.00027**	0.00008	0.00001	-0.00021	-0.00039**	-0.00051**	-0.00060**	-0.00058**
	(0.00009)	(0.00009)	(0.00012)	(0.00015)	(0.00014)	(0.00017)	(0.00018)	(0.00018)
N	1,368,472	1,380,172	1,385,151	1,387,618	1,389,023	1,389,878	1,385,151	1,332,384

Note: Dependent variables in Panels A, B, and C are cumulative breast cancer detection by public screening, by other channels, and overall cumulative detections, respectively. Each cell represents a coefficient β from different local linear regression of equation (1). The running variable is the standardized insurance contribution. Rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution in parentheses. **, * and + indicates statistical significance at the 1, 5 and 10 percent level respectively.

Table 8: Effect on Early Detection

	(1)	(2)	(3)	(4)	(5)	(6)
Year	Cancer detected within 2 year			Cancer detected after 3-6 year		
Gender	Male	Female	Female	Male	Female	Female
Cancer	Stomach	Stomach	Breast	Stomach	Stomach	Breast
Bandwidth	0.3	0.3	0.3	0.3	0.3	0.3
	40.8	169.7	-220.3	-84.0	374.4	-29.9
	(182.5)	(436.1)	(310.6)	(166.7)	(342.2)	(364.5)
N	5,237	2,373	2,163	10,595	4,785	4,562

Note: The dependent variable is the amount of medical expenditure at the first year of cancer detection. Each cell represents a coefficient β from different local linear regression of equation (1). The running variable is the standardized insurance contribution. Rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution in parentheses. **, * and + indicates statistical significance at the 1, 5 and 10 percent level respectively.

Table 9: Selection Effect by Cost-Sharing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Male stomach cancer								
Dependent variable	Stomach cancer screening result						Cancer detection	
	Normal		Cancer suspicion		Other disease			
Bandwidth	0.3	IK(0.29)	0.3	IK(0.56)	0.3	IK(0.33)	0.3	IK(0.24)
	0.06878**	0.06883**	0.00123	0.00296	-0.07001**	-0.06214**	0.00024	0.00048
	(0.01132)	(0.01134)	(0.00315)	(0.00247)	(0.01103)	(0.01034)	(0.00030)	(0.00031)
N	97,186	97,185	97,186	162,648	97,186	110,433	130,413	111,160
Panel B. Female stomach cancer								
Dependent variable	Stomach cancer screening result						Cancer detection	
	Normal		Cancer suspicion		Other disease			
Bandwidth	0.3	IK(0.31)	0.3	IK(0.64)	0.3	IK(0.33)	0.3	IK(0.16)
	0.05642**	0.05642**	-0.00598**	-0.00692**	-0.05044**	-0.04710**	0.00012	0.00016
	(0.00704)	(0.00704)	(0.00089)	(0.00094)	(0.00731)	(0.00762)	(0.00021)	(0.00025)
N	162,907	162,907	162,907	289,627	162,907	186,289	185,371	95,666
Panel C. Female Breast cancer								
Dependent variable	Breast cancer screening result						Cancer detection	
	Normal		Cancer suspicion		Other disease			
Bandwidth	0.3	IK(0.13)	0.3	IK(0.28)	0.3	IK(0.16)	0.3	IK(0.15)
	0.03899**	0.03467*	-0.00025	-0.00023	-0.03874**	-0.03519**	0.00006	0.00051
	(0.00825)	(0.01300)	(0.00113)	(0.00113)	(0.00759)	(0.00896)	(0.00026)	(0.00029)
N	162,979	56,439	162,979	153,127	162,979	86,649	186,922	95,985

Note: The sample is restricted to screening takers. Each cell represents a coefficient β from different local linear regression of equation (1). The running variable is the standardized insurance contribution. Rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution in parentheses. **, * and + indicates statistical significance at the 1, 5 and 10 percent level respectively.

Table 10: Characteristics of Compliers, Always Takers and Never Takers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Male, stomach cancer screening	Total	Compliers	Always Takers	Never Takers	(2)=(3)	t-stat (2)=(4)	(3)=(4)
Panel A1. Proportion	1.000	0.096	0.051	0.853			
Panel A2. Public screening take-ups							
stomach cancer (Year 1-2)	0.103	1.000	1.000	0.000			
stomach cancer (Year 1-6)	0.542	2.042	2.090	0.363	8.8	2038.7	304.0
general health (Year 1-2)	0.568	1.106	1.134	0.457	10.0	698.4	224.8
general health (Year 1-6)	1.713	2.561	2.811	1.455	35.6	303.1	104.3
Panel A3. Mortality							
Cumulative stomach cancer detection (6 year)	0.0130	0.0167	0.0146	0.0125	3.0	28.8	2.9
Cumulative stomach cancer mortality (6 year)	0.0051	0.0034	0.0024	0.0054	3.5	21.2	10.1
Cumulative all-cause mortality (6 year)	0.0727	0.0493	0.0332	0.0760	15.4	77.4	38.9
Panel B. Female, stomach cancer screening	Total	Compliers	Always Takers	Never Takers	(2)=(3)	T-stat (2)=(4)	(3)=(4)
Panel B1. Proportion	1.000	0.118	0.066	0.816			
Panel B2. Public screening take-ups							
stomach cancer (Year 1-2)	0.133	1.000	1.000	0.000			
stomach cancer (Year 1-6)	0.657	2.085	2.042	0.438	10.7	2009.9	384.8
general health (Year 1-2)	0.352	1.073	0.965	0.291	64.8	1075.1	363.5
general health (Year 1-6)	1.235	2.544	2.380	1.107	33.6	837.7	245.0
Panel B3. Mortality							
Cumulative stomach cancer detection (6 year)	0.0052	0.0049	0.0046	0.0050	1.0	0.7	1.1
Cumulative stomach cancer mortality (6 year)	0.0034	0.0011	0.0006	0.0037	3.7	34.5	20.9
Cumulative all-cause mortality (6 year)	0.0525	0.0140	0.0113	0.0569	5.2	148.4	75.8
Panel C. Female, breast cancer screening	Total	Compliers	Always Takers	Never Takers	(2)=(3)	T-stat (2)=(4)	(3)=(4)
Panel C1. Proportion	1.000	0.118	0.067	0.815			
Panel C2. Public screening take-ups							
breast cancer (Year 1-2)	0.136	1.020	1.010	0.000			
breast cancer (Year 1-6)	0.690	2.119	2.109	0.468	2.6	1952.6	390.2
general health (Year 1-2)	0.352	1.076	0.967	0.289	61.7	1094.4	351.7
general health (Year 1-6)	1.235	2.546	2.397	1.103	29.9	846.0	245.4
Panel C3. Mortality							
Cumulative breast cancer detection (6 year)	0.0052	0.0057	0.0064	0.0051	1.8	6.3	3.1
Cumulative breast cancer mortality (6 year)	0.0022	0.0001	0.0002	0.0026	1.4	40.0	19.2
Cumulative all-cause mortality (6 year)	0.0525	0.0140	0.0123	0.0571	3.8	148.8	81.2

Note: This table presents the mean characteristics of the entire sample for bandwidth [-0.3,0.3] (Column 1), compliers (Column 2), always takers in bandwidth [0,0.3] (Column 3), and never takers in bandwidth [-0.3,0] (Column 4). The mean characteristics of compliers are estimated from Equation (3). Columns 5 to 7 present t-statistics from two sample t-test comparing compliers and always takers, compliers and never takers, and always takers and never takers, respectively.

Table 11: Comparing Compliers with Always Takers and Never Takers

Dependent Variable : 6-Year Cumulative Cancer Mortality

	(1)	(2)	(3)	(4)
Panel A. Male stomach cancer				
Sample	Screening takers		Screening non-takers	
	Compliers vs. Always takers		Compliers vs. Never takers	
Bandwidth	0.3	IK(0.46)	0.3	IK(0.30)
	0.00070	0.00093+	-0.00053	-0.00059
	(0.00058)	(0.00052)	(0.00035)	(0.00035)
N	130,413	198,231	1,130,316	1,156,970
Panel B. Female stomach cancer				
Sample	Screening takers		Screening non-takers	
	Compliers vs. Always takers		Compliers vs. Never takers	
Bandwidth	0.3	IK(0.31)	0.3	IK(0.32)
	0.00027	0.00027	0.00022	0.00034
	(0.00023)	(0.00023)	(0.00018)	(0.00021)
N	185,371	185,371	1,210,710	1,321,841
Panel C. Female breast cancer				
Sample	Screening takers		Screening non-takers	
	Compliers vs. Always takers		Compliers vs. Never takers	
Bandwidth	0.3	IK(0.36)	0.3	IK(0.33)
	0.00014	-0.00007	0.00029+	0.00040*
	(0.00025)	(0.00020)	(0.00015)	(0.00015)
N	186,922	227,356	1,209,159	1,385,665

Note: The dependent variable is 6-Year cumulative cancer mortality. I restrict sample to screening takers in Columns (1) and (2), and screening non-takers in Columns (3) and (4). Each cell represents a coefficient β from different local linear regression of equation (1). The running variable is the standardized insurance contribution. Rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution in parentheses. **, * and + indicates statistical significance at the 1, 5 and 10 percent level respectively.

Table 12: Effect on Other Behavioral Responses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Male								
Dependent variable	Health screening				Medical expenditure ($)			
	Year 3-6		Year 1-2		Year 3-5		Year 1-5	
Bandwidth	0.3	IK (0.15)	0.3	IK(0.24)	0.3	IK(0.25)	0.3	IK(0.25)
	-0.0410+	-0.0593+	-1.1	0.6	2.1	2.9	11.9	14.0
	(0.021)	(0.033)	(12.5)	(13.9)	(27.8)	(33.2)	(34.3)	(41.1)
N	1,260,729	667,548	970,661	820,817	905,003	765,586	841,751	711,935
Panel B. Female								
Dependent variable	Health screening				Medical expenditure ($)			
	round 2 & 3		Year 1-2		Year 3-5		Year 1-5	
Bandwidth	0.3	IK (0.18)	0.3	IK(0.50)	0.3	IK(0.28)	0.3	IK(0.50)
	-0.0131	-0.0184	12.9	13.5+	-18.0	-13.8	-8.5	-11.7
	(0.013)	(0.015)	(8.8)	(7.2)	(20.9)	(20.7)	(27.6)	(26.4)
N	1,396,081	823,434	1,219,294	2,008,286	1,164,312	1,120,102	1,123,043	1,850,072

Note: Each cell represents a coefficient β from different local linear regression of equation (1). The running variable is the standardized insurance contribution. Rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution in parentheses. **, * and + indicates statistical significance at the 1, 5 and 10 percent level respectively.

Table 13: Effect on Intermediate Health Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Male								
Dependent variable	Blood sugar		BMI		Obesity		Cholesterol	
	R2	R3	R2	R3	R2	R3	R2	R3
Bandwidth	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
	0.0858	0.4815	0.0089	0.0131	-0.0033	-0.0021	-0.2125	-0.2866
	(0.229)	(0.364)	(0.011)	(0.010)	(0.002)	(0.002)	(0.326)	(0.415)
N	385,222	340,704	384,997	340,497	384,997	398,406	384,736	339,665
Panel B. Female								
Dependent variable	Blood sugar		BMI		Obesity		Cholesterol	
	R2	R3	R2	R3	R2	R3	R2	R3
Bandwidth	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
	0.7122**	0.0908	0.0297**	0.0328**	0.0088**	-0.0017	-0.9765**	-0.3523
	(0.231)	(0.198)	(0.009)	(0.007)	(0.002)	(0.002)	(0.338)	(0.425)
N	273,933	268,214	273,675	267,961	273,675	353,559	273,417	267,015

Note: Each cell represents a coefficient β from different local linear regression of equation (1). The running variable is the standardized insurance contribution. Rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution in parentheses. **, * and + indicates statistical significance at the 1, 5 and 10 percent level respectively.

Table 14: Effect on Cumulative Mortality (6 Year)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Male										
Dependant variable	Stomach cancer mortality		All-cancer mortality		Non-cancer mortality		All-cause mortality			
Bandwidth	0.3	IK(0.32)	0.3	IK(0.44)	0.3	IK(0.31)	0.3	IK(0.27)		
	-0.00062+	-0.00052	-0.00147+	-0.00086	-0.00202	-0.00167	-0.00349	-0.00336		
	(0.00034)	(0.00035)	(0.00078)	(0.00073)	(0.00155)	(0.00156)	(0.00210)	(0.00216)		
N	1,260,729	1,441,721	1,260,729	1,931,589	1,260,729	1,373,890	1,260,729	1,218,000		
Panel B. Female										
Dependant variable	Stomach cancer mortality		Breast cancer mortality		All-cancer mortality		Non-cancer mortality		All-cause mortality	
Bandwidth	0.3	IK(0.25)	0.3	IK(0.28)	0.3	IK(0.32)	0.3	IK(0.24)	0.3	IK(0.33)
	-0.00011	-0.00007	0.00001	0.00003	-0.00014	0.00004	0.00079	0.00088	0.00065	0.00176
	(0.00015)	(0.00017)	(0.00012)	(0.00012)	(0.00042)	(0.00037)	(0.00101)	(0.00104)	(0.00126)	(0.00112)
N	1,396,081	1,026,628	1,396,081	1,343,027	1,396,081	1,524,119	1,396,081	1,026,628	1,396,081	1,178,589

Note: Each cell represents a coefficient β from different local linear regression of equation (1). The running variable is the standardized insurance contribution. Rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution in parentheses. **, * and + indicates statistical significance at the 1, 5 and 10 percent level respectively.

Table 15: Behavioral Responses by Cancer Screening Result

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Gender	Male					Female					
Dependant variable	Future screening take-ups		Medical Expenditure			Future screening take-ups			Medical Expenditure		
	Health	Stomach ca	Year 1-2	Year 3-5	Year 1-5	Health	Stomach ca	Breast ca	Year 1-2	Year 3-5	Year 1-5
Eligibility	-0.0825**	-0.0464**	4.0	-12.9	1.1	-0.0770**	-0.0696**	-0.0688**	20.2*	-25.7	-10.4
	(0.020)	(0.010)	(13.0)	(27.8)	(35.3)	(0.010)	(0.011)	(0.011)	(9.7)	(21.9)	(28.9)
Eligibility * Stomach_Normal	0.0260*	-0.0258	16.7	20.4	27.6	-0.0358	-0.0129+	0.0102	6.9	-24.3	-32.0
	(0.012)	(0.020)	(24.8)	(53.2)	(64.9)	(0.024)	(0.007)	(0.009)	(27.2)	(60.9)	(83.4)
Eligibility * Stomach_Cancer	0.1344	0.0038	761.5	58.0	377.0	-0.0026	-0.0390	-0.0885	588.7	944.5	603.2
	(0.093)	(0.100)	(812.3)	(934.5)	(1546.1)	(0.154)	(0.093)	(0.168)	(761.9)	(1365.2)	(1806.1)
Eligibility * Stomach_False(+)	0.0786**	0.0591*	52.3	403.4	367.6	0.0053	0.0185	0.0350	-70.3	169.5	113.1
	(0.023)	(0.022)	(131.1)	(251.7)	(377.1)	(0.044)	(0.037)	(0.039)	(70.8)	(132.7)	(171.5)
Eligibility * Stomach_Other	0.0399**	-0.0290+	-38.2	-79.8	-129.9	-0.0311	-0.0202**	0.0127	-31.6	-51.1	-87.8
	(0.012)	(0.017)	(24.0)	(65.5)	(80.8)	(0.026)	(0.007)	(0.011)	(23.4)	(55.6)	(72.2)
Eligibility * Breast_Normal						-0.0694**	-0.0230	-0.0801**	53.8*	138.8**	192.9**
						(0.019)	(0.021)	(0.026)	(23.1)	(39.6)	(55.8)
Eligibility * Breast_Cancer						0.1759	0.0994	0.0887	-1106.1	-1638.4	-1378.2
						(0.169)	(0.181)	(0.165)	(1864.6)	(974.2)	(1555.7)
Eligibility * Breast_False(+)						0.0009	0.1047*	0.1326*	210.9	481.1	651.2
						(0.070)	(0.049)	(0.052)	(192.9)	(518.8)	(622.8)
Eligibility * Breast_Other						-0.0600**	-0.0089	-0.0620**	31.3	231.5**	253.1**
						(0.018)	(0.019)	(0.022)	(21.2)	(36.8)	(50.8)
Constant	0.9711**	0.3727**	342.2**	1,492.6**	1,785.8**	0.7282**	0.4343**	0.4561**	287.3**	1,414.7**	1,681.3**
	(0.012)	(0.009)	(12.710)	(26.096)	(32.255)	(0.008)	(0.011)	(0.010)	(8.2)	(17.5)	(25.0)
N	1,260,729	1,260,729	970,661	905,003	841,751	1,396,081	1,396,081	1,396,081	1,219,294	1,164,312	1,123,043

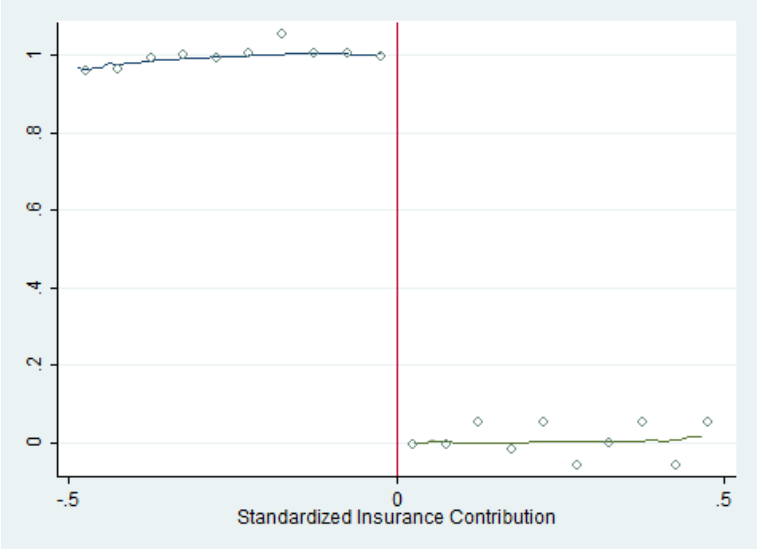
Note: The running variable is the standardized insurance contribution. Rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution in parentheses. **, * and + indicates statistical significance at the 1, 5 and 10 percent level respectively. N is number of observations

Table 16: Cost for cancer detection

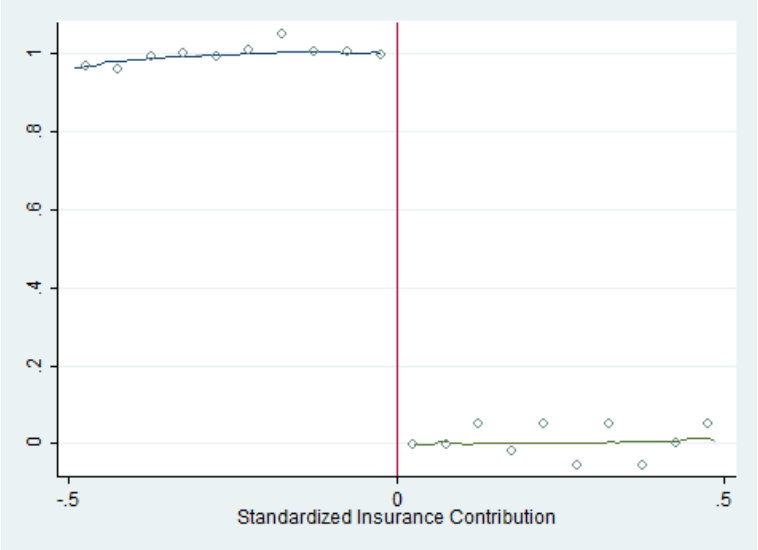
	(1)	(2)	(3)	(4)
Panel A. Male, Stomach cancer	N	Unit cost ($)	Total cost ($)	Proportion
Panel A1. Direct screening cost				
Administration	180.0	3.8	679	0.05
UGI	117.0	33.8	3,959	0.26
EGD	63.0	33.9	2,137	0.14
Biopsy	63.2	22.9	1,448	0.10
Conscious sedation	18.9	30.0	567	0.04
Subtotal			8,790	0.58
Panel A2. Transportation cost				
1st visit	180.0	17.9	3,225	0.21
Follow-up visit	8.0	17.9	143	0.01
Subtotal			3,367	0.22
Panel A3. Opportunity cost				
Loss of labor productivity	94.0	31.0	2,916	0.19
Total			15,073	1.00
Panel B. Female, Stomach cancer				
Panel B1. Direct screening cost				
Administration	808.9	3.8	3,049	0.05
UGI	547.9	33.8	18,541	0.31
EGD	261.1	33.9	8,855	0.15
Biopsy	295.9	22.9	6,778	0.11
Conscious sedation	78.3	30.0	2,349	0.04
Subtotal			39,573	0.66
Panel B2. Transportation cost				
1st visit	808.9	14.5	11,714	0.20
Follow-up visit	18.5	14.5	268	0.00
Subtotal			11,982	0.20
Panel B3. Opportunity cost				
Loss of labor productivity	259.2	31.0	8,035	0.13
Total			59,590	1.00
Panel C. Female, Breast cancer				
Panel C1. Direct screening cost				
Administration	646.0	3.8	2,435	0.04
Mammography	646.0	16.2	10,457	0.16
Biopsy	228.0	27.6	6,297	0.10
Ultrasonography	228.0	100.0	22,796	0.36
Subtotal			41,985	0.66
Panel C2. Transportation cost				
1st visit	832.7	14.5	12,058	0.19
Follow-up visit	60.0	14.5	869	0.01
Subtotal			12,927	0.20
Panel C3. Opportunity cost				
Loss of labor productivity	287.0	31.0	8,898	0.14
Total			63,811	1.00

Figure 1: Eligibility for Free Public Cancer Screening

Panel A. Eligibility in males



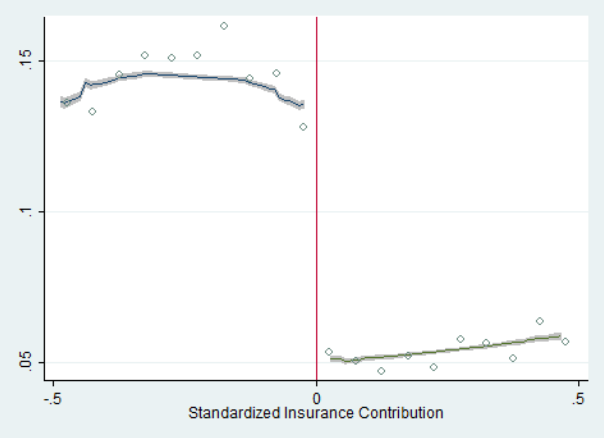
Panel B. Eligibility in females



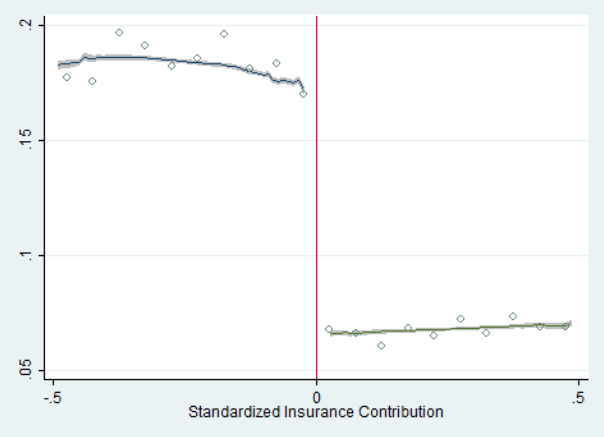
Note: The dependent variables in Panels A and B are eligibility for free public cancer screening in males and females, respectively. The running variable is the standardized insurance contribution. Open circles plot the mean of the dependent variable within 0.05 point bins. Y-axis is based on residuals from a regression (1) with a standard set of control variables. The solid lines are fitted values from local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. It is estimated separately on each side of the cutoff. The shaded regions are 95 percent confidence intervals. Dependant variable is an indicator for eligibility.

Figure 2: Effect of Cost-Sharing on Cumulative Public Cancer Screening Take up, up to 2 years

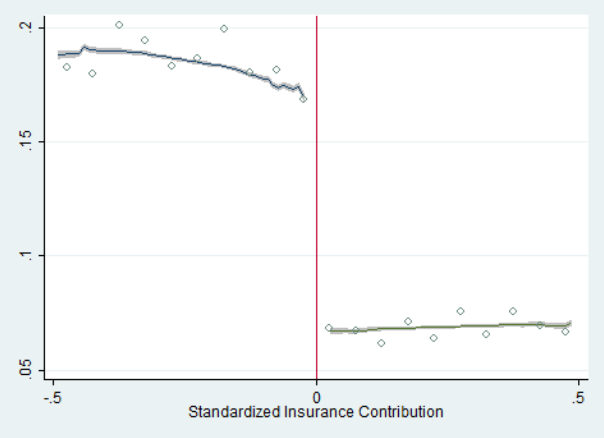
Panel A. Stomach cancer take up, Male



Panel B. Stomach cancer take up, Female



Panel C. Breast cancer take up, Female



Note: The dependent variables in Panels A, B, and C are male stomach, female stomach, and female breast cancer take ups, respectively. The running variable is the standardized insurance contribution. Open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are fitted values from local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. It is estimated separately on each side of the cutoff. The shaded regions are 95 percent confidence intervals.

Figure 3: Effect on Future Eligibility for Free Public Cancer Screening, 3 to 6 Years after Screening Offer

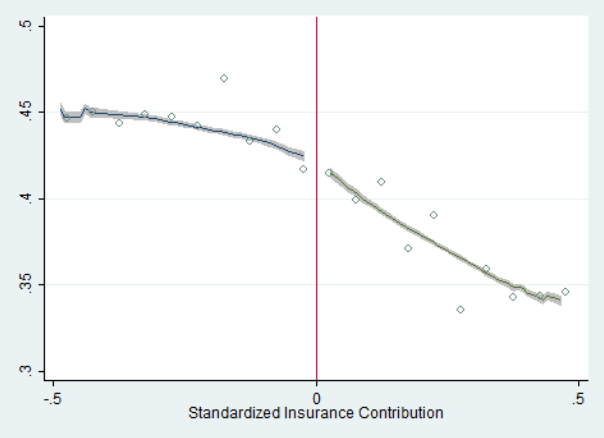
Panel A. Future eligibility in males

Panel B. Future eligibility in females

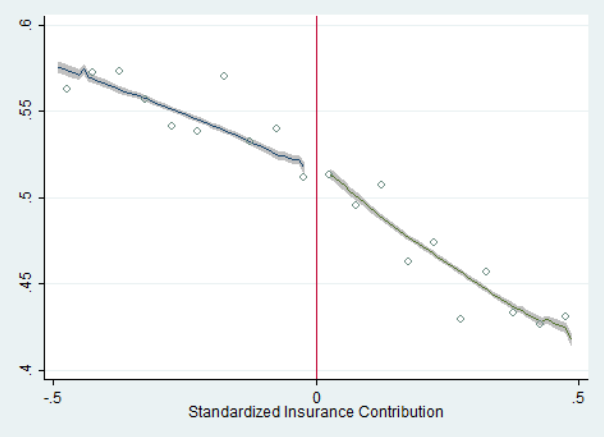
Note: The dependent variables in Panels A and B are future eligibility for free public cancer screening in males and females, respectively. The running variable is the standardized insurance contribution. Open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are fitted values from local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. It is estimated separately on each side of the cutoff. Y-axis is based on residuals from a regression (1) with a standard set of control variables. The shaded regions are 95 percent confidence intervals. Dependant variable is an indicator for eligibility.

Figure 4: Effect on Future Cancer Screening Take up, 3 to 6 Years after Screening Offer

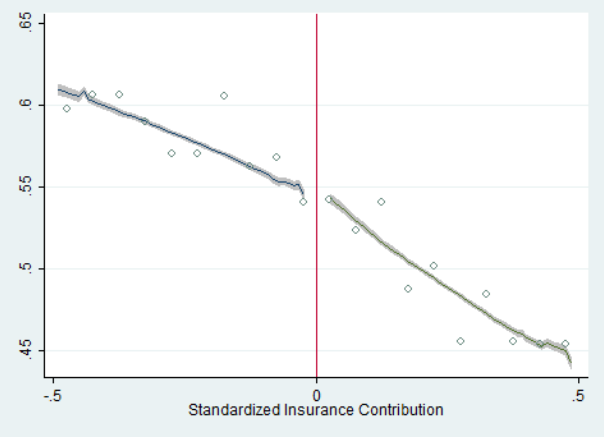
Panel A. Future stomach cancer take up, Male



Panel B. Future stomach cancer take up, Female



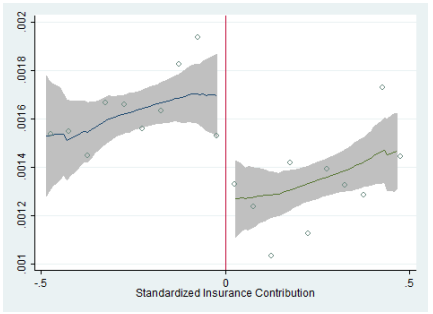
Panel C. Future breast cancer take up, Female



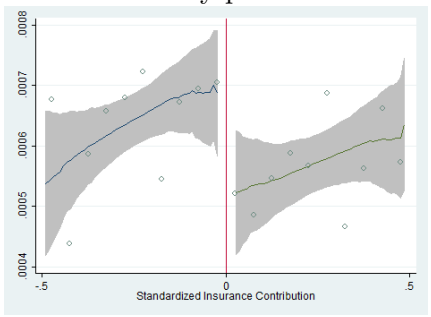
Note: The dependent variables in Panels A, B, and C are future male stomach, female stomach, and female breast cancer take ups, respectively. The running variable is the standardized insurance contribution. Open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are fitted values from local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. It is estimated separately on each side of the cutoff. The shaded regions are 95 percent confidence intervals.

Figure 5: Effect on Cumulative Cancer Detections, up to 2 years

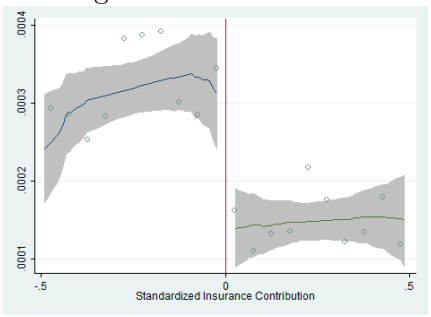
Panel A. Cancer detection by public mass cancer screening



Stomach cancer, Male

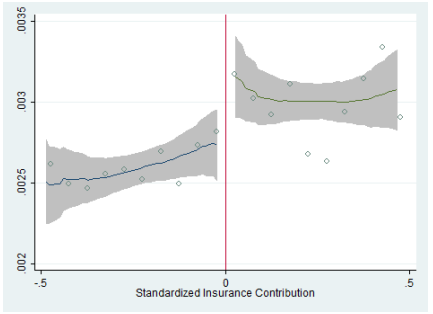


Stomach cancer, Female

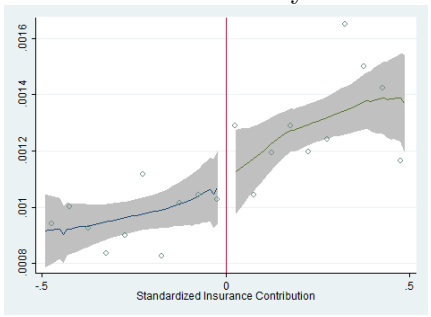


Breast cancer, Female

Panel B. Cancer detection by other channels



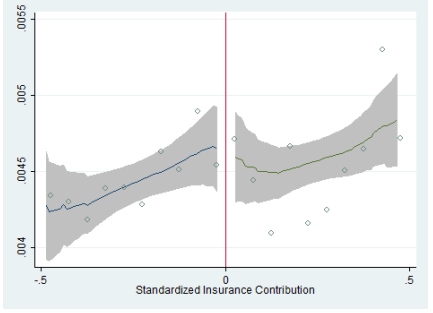
Stomach cancer, Male



Stomach cancer, Female

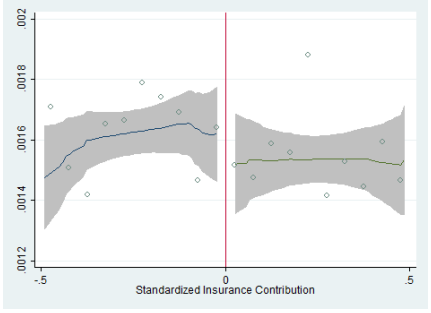
Breast cancer, Female

Panel C. Total cancer detection



Stomach cancer, Male

Stomach cancer, Female

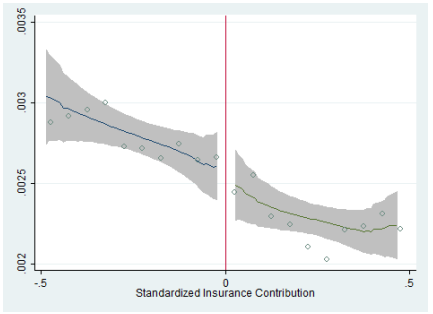


Breast cancer, Female

Note: The dependent variables in Panels A, B, and C are 2-year cumulative cancer detections by public cancer screening, by other channels, and overall cancer detections, respectively. The running variable is the standardized insurance contribution. Open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are fitted values from local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. It is estimated separately on each side of the cutoff. The shaded regions are 95 percent confidence intervals.

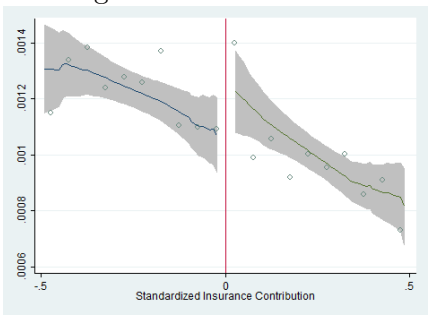
Figure 6: Effect on Future Cancer Detections, 3 to 6 Years after Screening Offer

Panel A. Cancer detection by public mass cancer screening



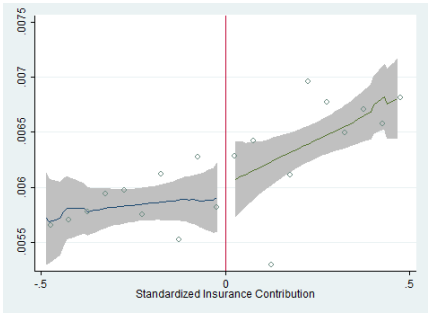
Stomach cancer, Male

Stomach cancer, Female

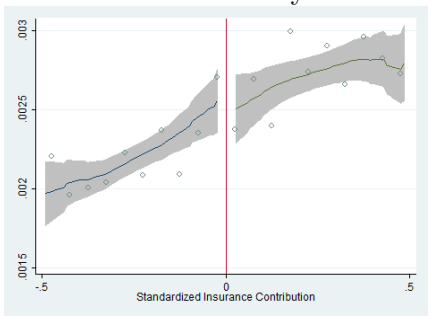


Breast cancer, Female

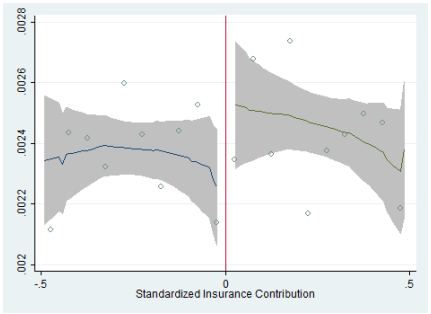
Panel B. Cancer detection by other channels



Stomach cancer, Male

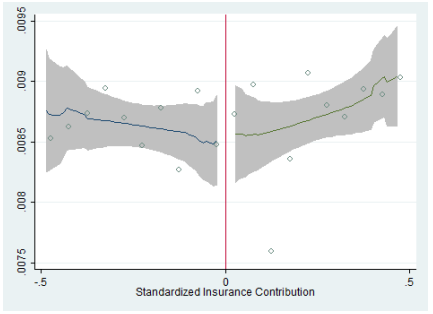


Stomach cancer, Female

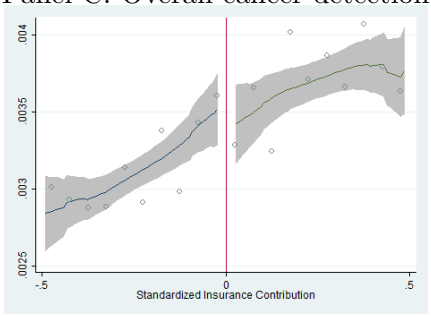


Breast cancer, Female

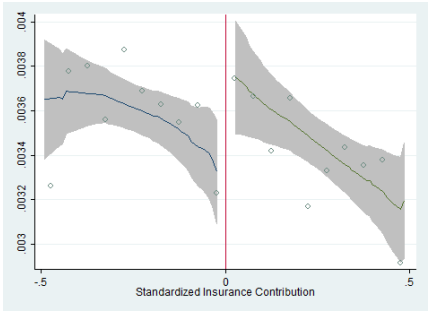
Panel C. Overall cancer detection



Stomach cancer, Male



Stomach cancer, Female

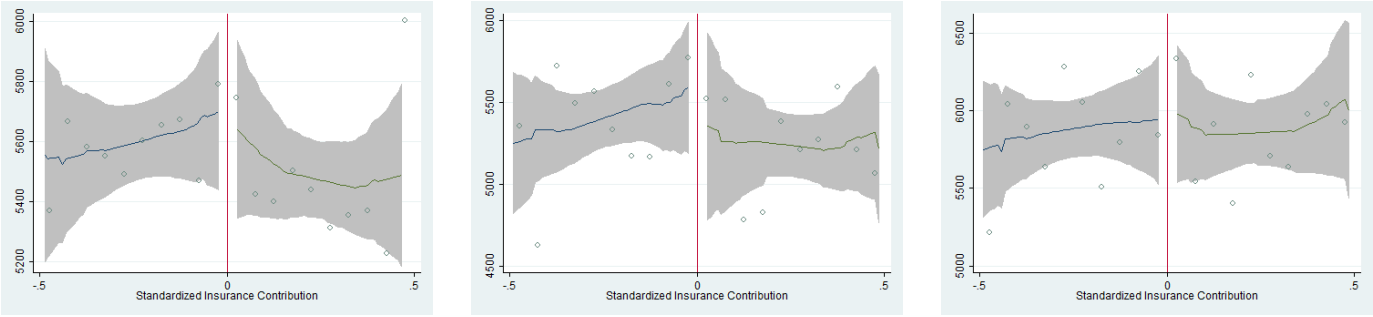


Breast cancer, Female

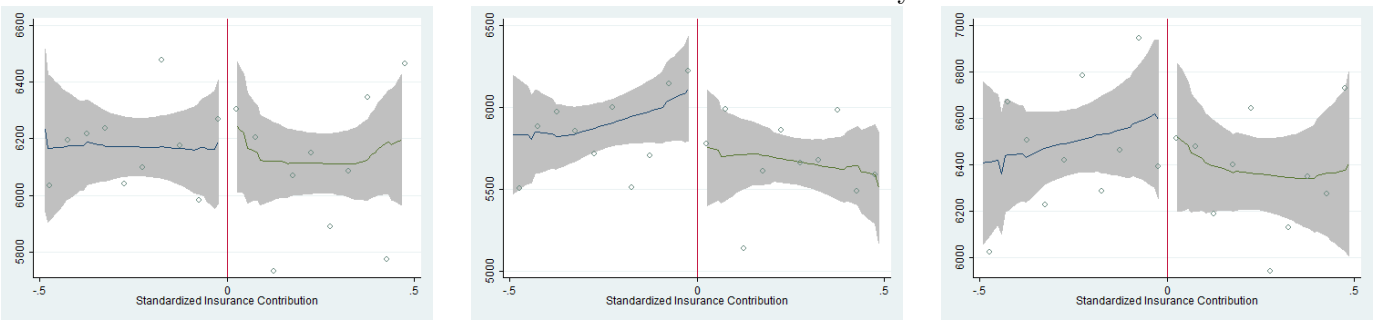
Note: The dependent variables in Panels A, B, and C are cumulative cancer detections between year 3 and 6 by public cancer screening, by other channels, and overall cancer detections, respectively. The running variable is the standardized insurance contribution. Open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are fitted values from local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. It is estimated separately on each side of the cutoff. The shaded regions are 95 percent confidence intervals.

Figure 7: Effect on Medical Expenditure in the First Year of Cancer Detection (Early Detection)

Panel A. Cancer detected within 2 years



Panel B. Cancer detected after 3 to 6 years

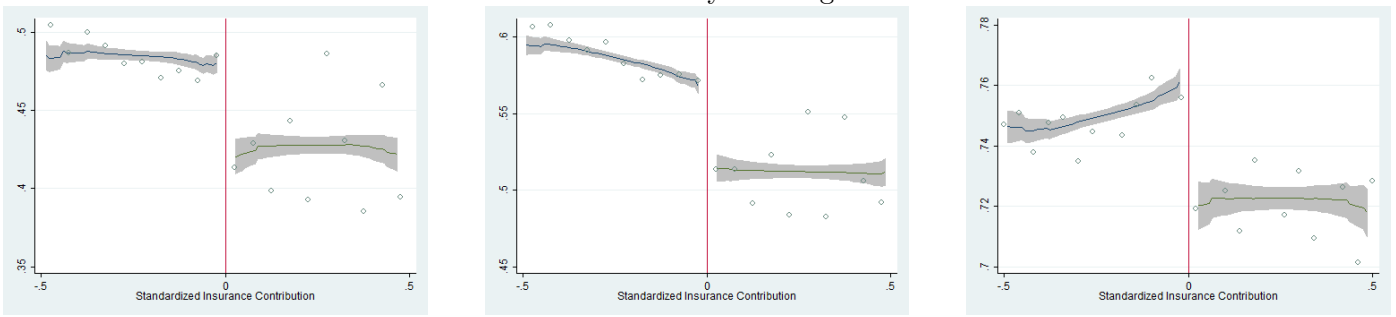


Stomach cancer, Male | Stomach cancer, Female | Breast cancer, Female

Note: The dependent variable in Panels A and B are the medical expenditure in the first year of cancer detection in year 1-2 and 3-6, respectively. The running variable is the standardized insurance contribution. Open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are fitted values from local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. It is estimated separately on each side of the cutoff. The shaded regions are 95 percent confidence intervals.

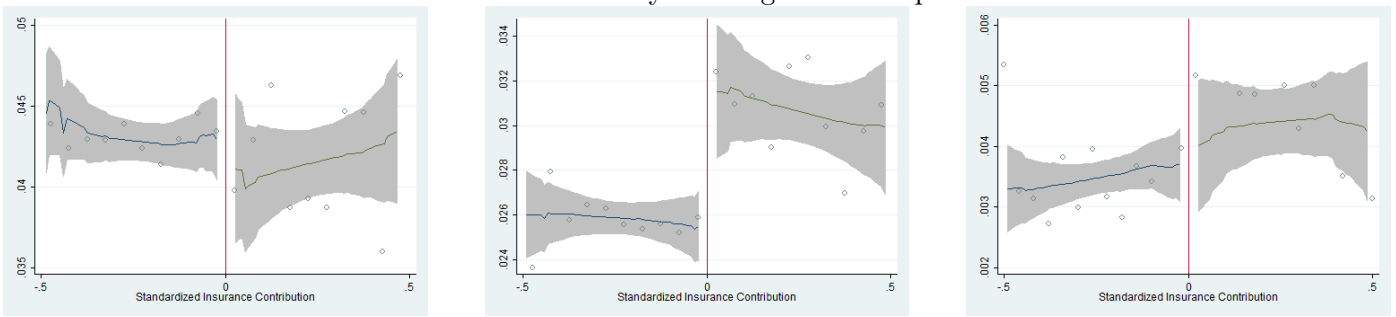
Figure 8: Selection Effect by Cost-sharing (Screening Results): Among Screening-takers

Panel A. Probability of being normal



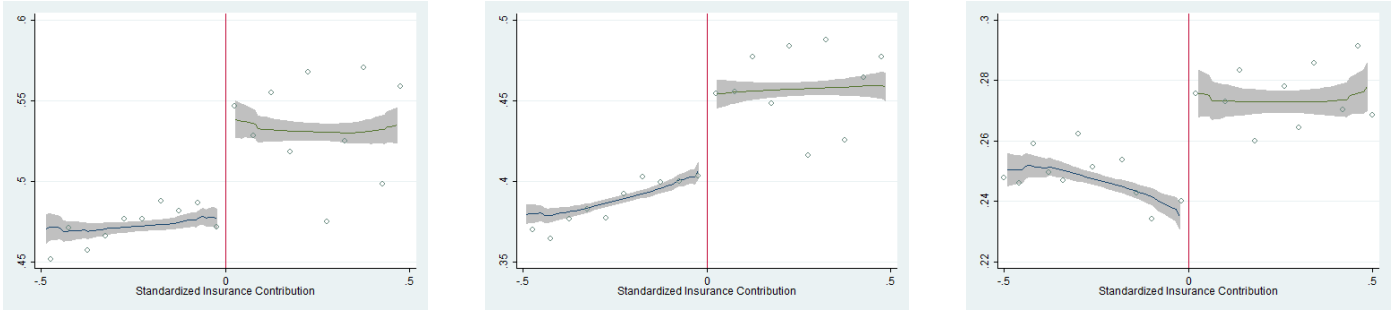
Stomach cancer, Male | Stomach cancer, Female | Breast cancer, Female

Panel B. Probability of being cancer suspicion



Stomach cancer, Male | Stomach cancer, Female | Breast cancer, Female

Panel C. Probability of detecting other disease

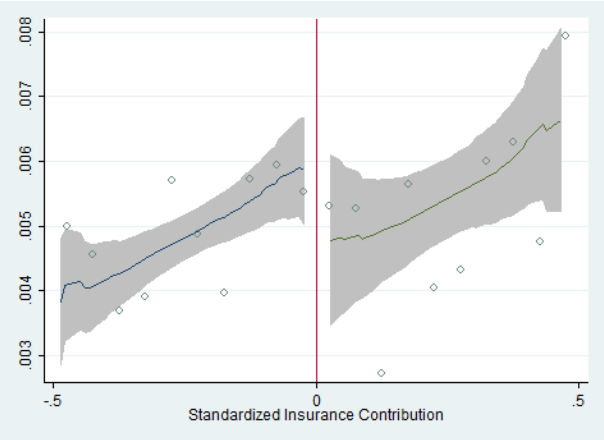


Stomach cancer, Male | Stomach cancer, Female | Breast cancer, Female

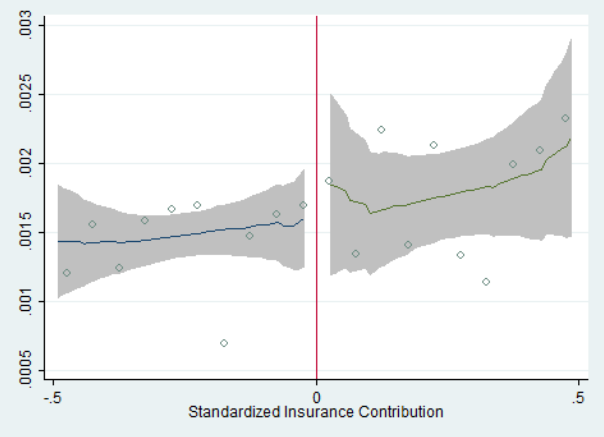
Note: The sample is restricted to screening takers. Dependent variables in Panels A, B, and C are probability of being normal, being cancer suspicion, and detecting other disease, respectively. The running variable is the standardized insurance contribution. Open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are fitted values from local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. It is estimated separately on each side of the cutoff. The shaded regions are 95 percent confidence intervals.

Figure 9: Selection Effect by Cost-sharing (Cancer Detection): Among Screening-takers

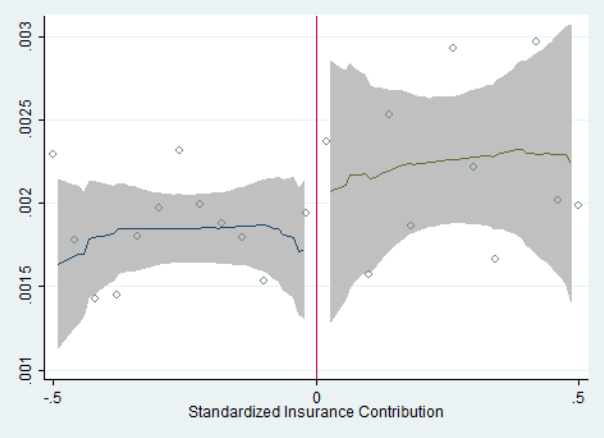
Panel A. Stomach cancer detection, Male



Panel B. Stomach cancer detection, Female



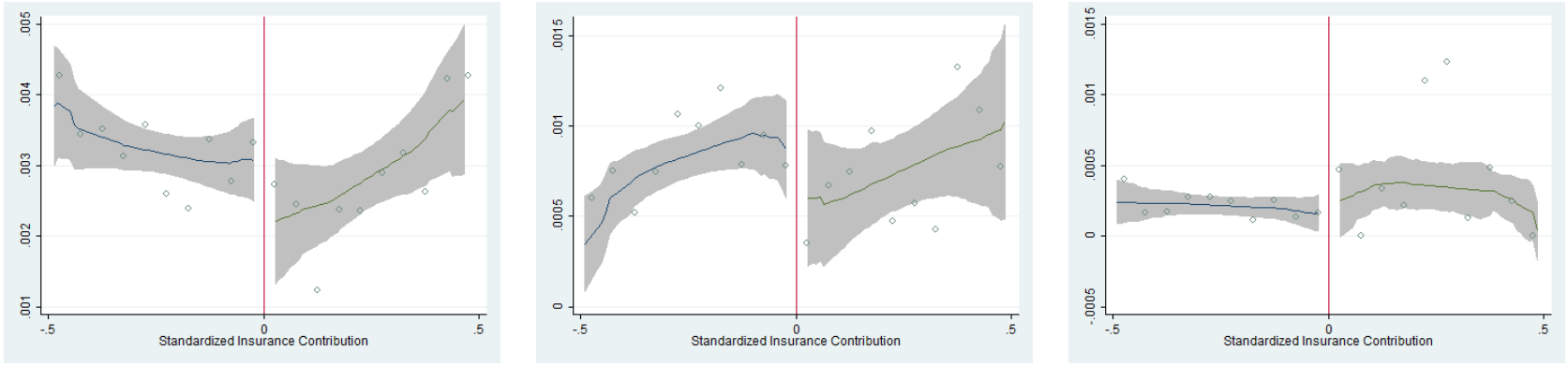
Panel C. Breast cancer detection, Female



Note: The sample is restricted to screening takers. Dependent variables in Panels A, B, and C are male stomach, female stomach, and female breast cancer detections, respectively. The running variable is the standardized insurance contribution. Open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are fitted values from local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. It is estimated separately on each side of the cutoff. The shaded regions are 95 percent confidence intervals.

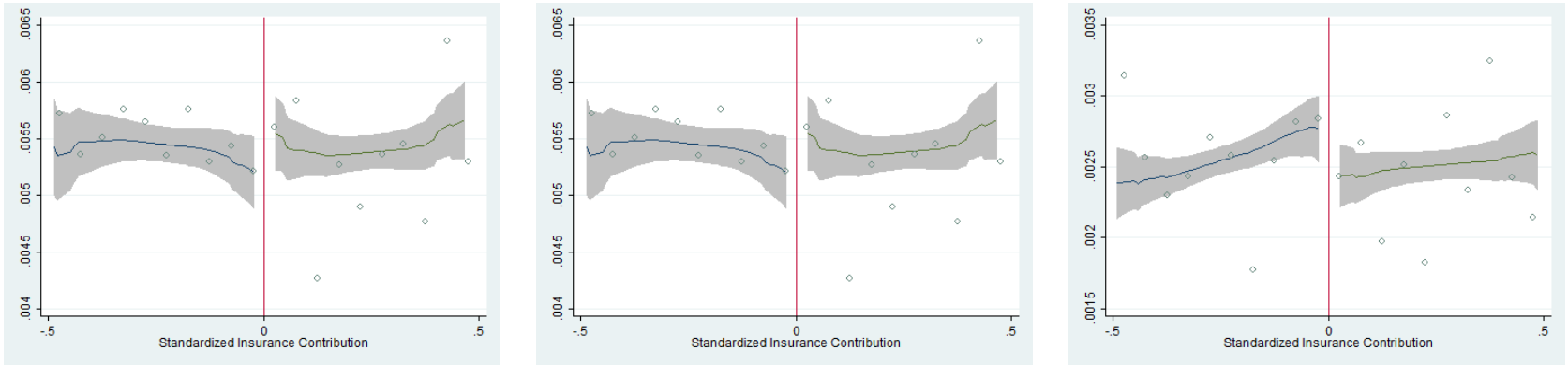
Figure 10: Compliers vs. Always takers vs. Never takers: 6-Year Cumulative Cancer Mortality

Panel A. Compliers vs. Always takers, Among screening takers



Male, Stomach cancer | Female, Stomach cancer | Female, Breast cancer

Panel B. Never takers vs. Compliers, Among screening non-takers



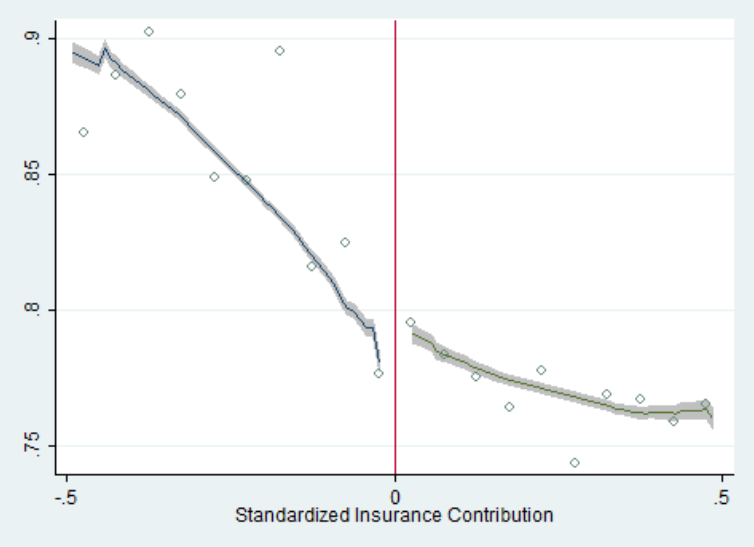
Male, Stomach cancer | Female, Stomach cancer | Female, Breast cancer

Note: The samples in Panel A and B are restricted to screening takers and screening non-takers, respectively. Dependent variable is 6-year cumulative cancer mortality. The running variable is the standardized insurance contribution. Open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are fitted values from local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. It is estimated separately on each side of the cutoff. The shaded regions are 95 percent confidence intervals.

Figure 11: Effect on Future General Health Screening Take ups

Panel A. Male

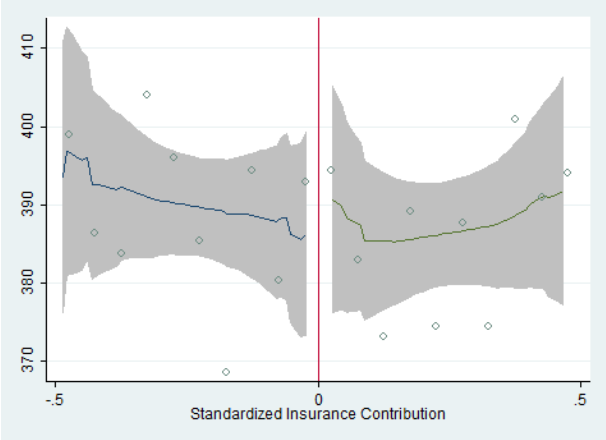
Panel B. Female



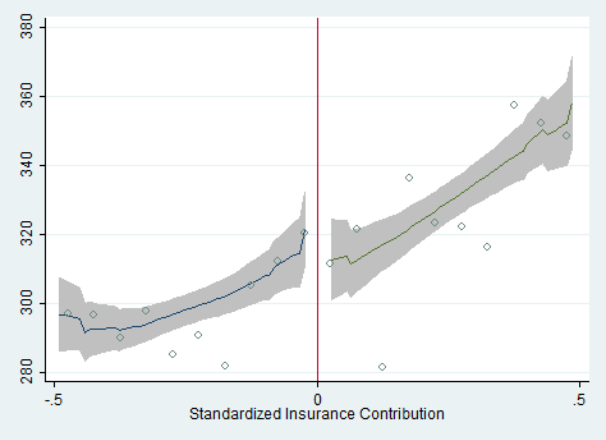
Note: The dependent variables in Panels A and B are the number of general health screening take ups in year 3-5 in males and females, respectively. The running variable is the standardized insurance contribution. Open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are fitted values from local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. It estimated separately on each side of the cutoff. The shaded regions are 95 percent confidence intervals.

Figure 12: Effect on Medical Expenditure

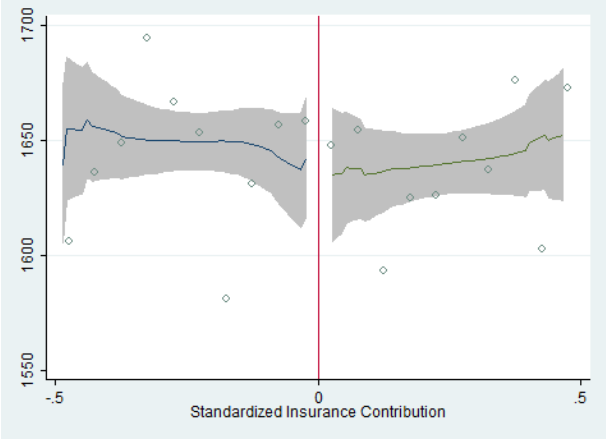
Panel A. In year 1-2, Male



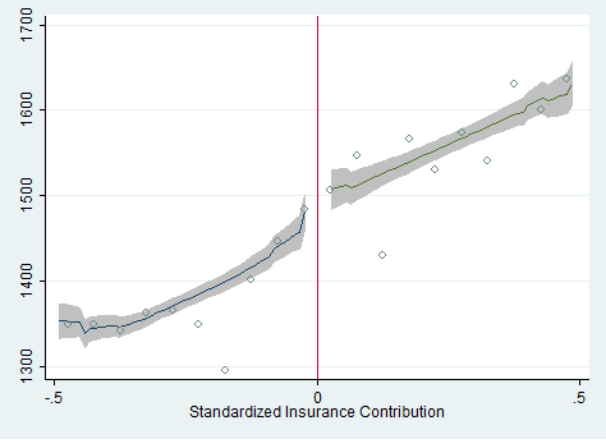
Panel B. In year 1-2, Female



Panel C. In year 3-5, Male



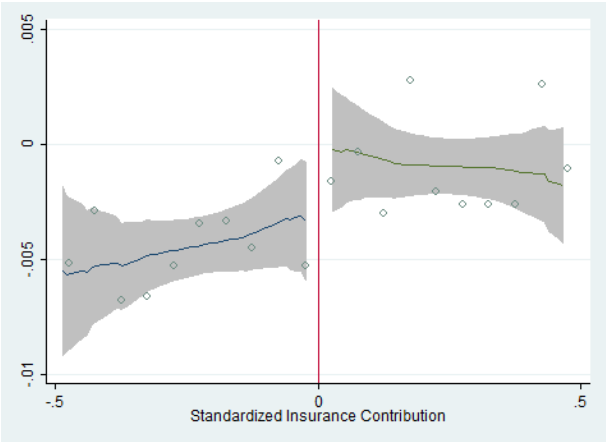
Panel D. In year 3-5, Female



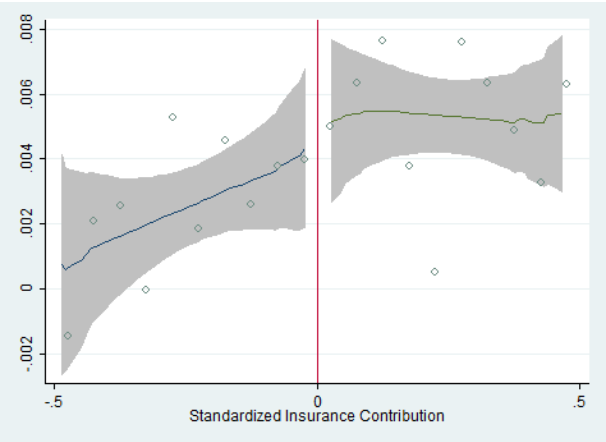
Note: The dependent variables in Panels A and B are medical expenditure in year 1-2 for males and females, respectively. The dependent variables in Panels C and D are medical expenditure in year 3-5 for males and females, respectively. The running variable is the standardized insurance contribution. Open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are fitted values from local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. It estimated separately on each side of the cutoff. The shaded regions are 95 percent confidence intervals.

Figure 13: Effect on Intermediate Health Outcomes, Male

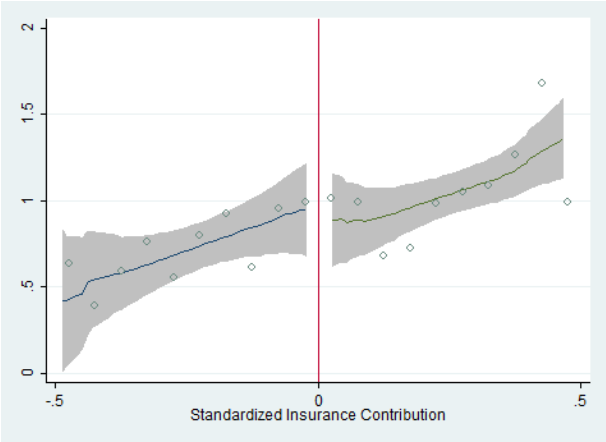
Panel A. Obesity, Round 2



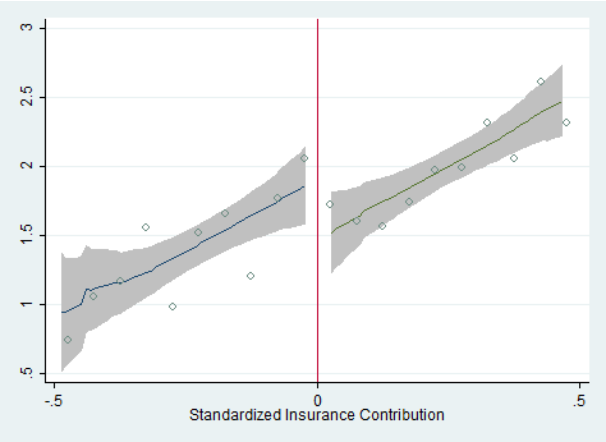
Panel B. Obesity, Round 3



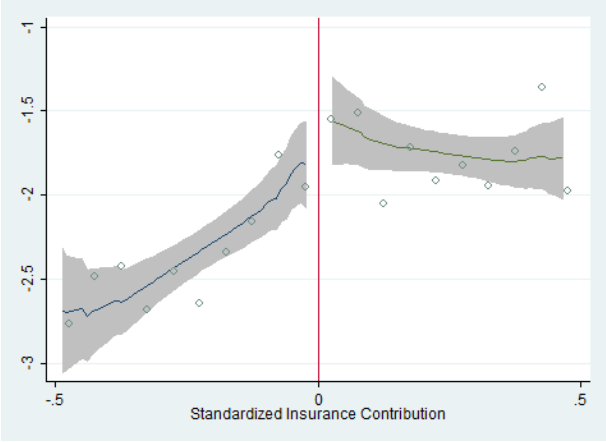
Panel C. Blood Sugar, Round 2



Panel D. Blood Sugar, Round 3



Panel E. Cholesterol level, Round 2

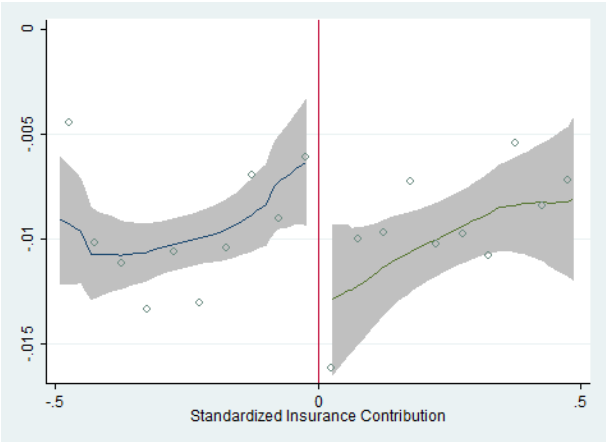


Panel F. Cholesterol level, Round 3

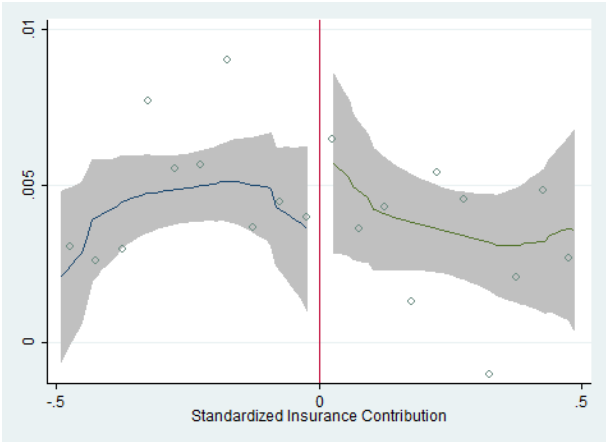
Note: The dependent variables are probability of being obese (BMI≥25), blood sugar level, and cholesterol level, respectively, in males. The running variable is the standardized insurance contribution. Open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are fitted values from local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. It estimated separately on each side of the cutoff. The shaded regions are 95 percent confidence intervals.

Figure 14: Effect on Intermediate Health Outcomes, Female

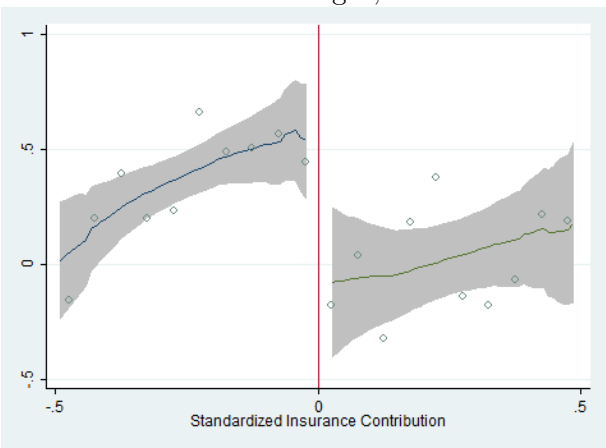
Panel A. Obesity, Round 2



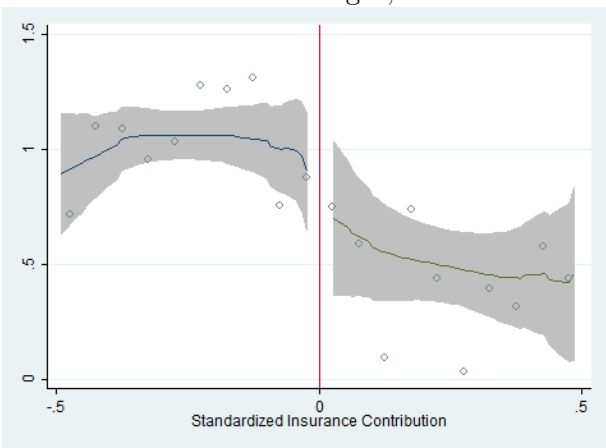
Panel B. Obesity, Round 3



Panel C. Blood Sugar, Round 2

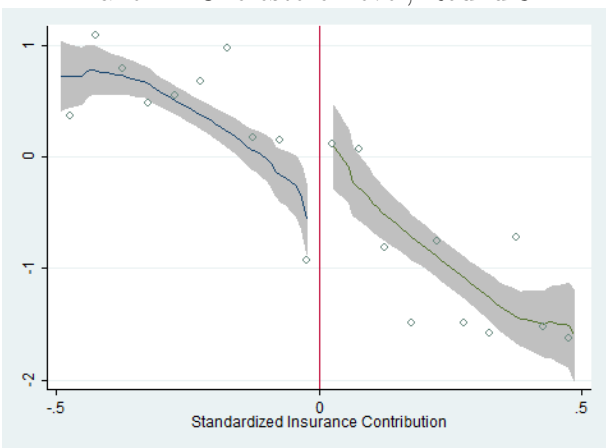


Panel D. Blood Sugar, Round 3



Panel E. Cholesterol level, Round 2

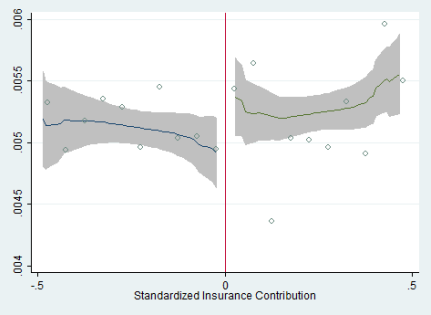
Panel F. Cholesterol level, Round 3



Note: The dependent variables are probability of being obese (BMI≥25), blood sugar level, and cholesterol level, respectively, in females. The running variable is the standardized insurance contribution. Open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are fitted values from local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. It estimated separately on each side of the cutoff. The shaded regions are 95 percent confidence intervals.

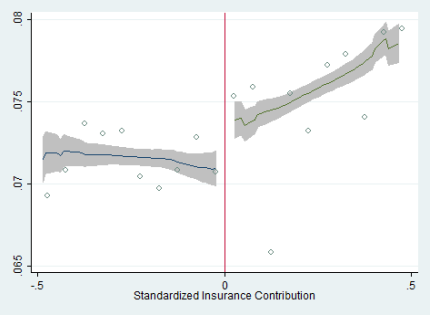
Figure 15: Effect on 6 year Cumulative Mortality

Panel A. Male



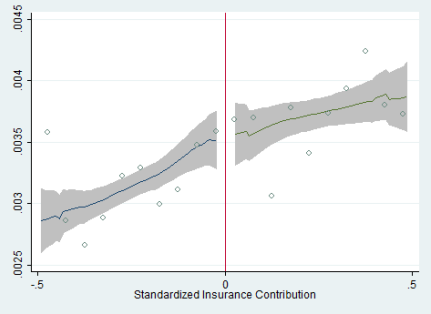
Stomach cancer mortality

Non-cancer mortality

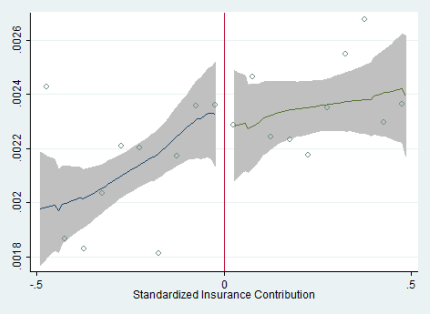


All-cause mortality

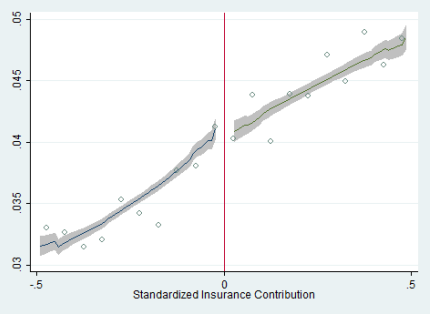
Panel B. Female



Stomach cancer mortality



Breast cancer mortality



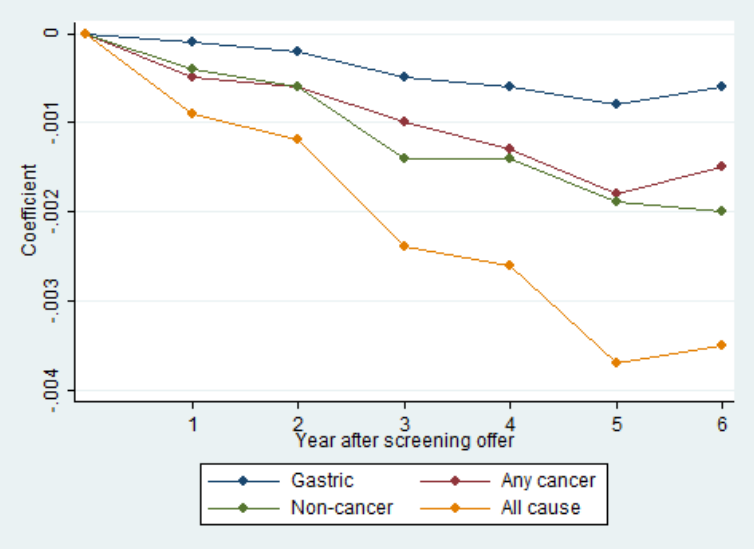
Non-cancer mortality

All-cause mortality

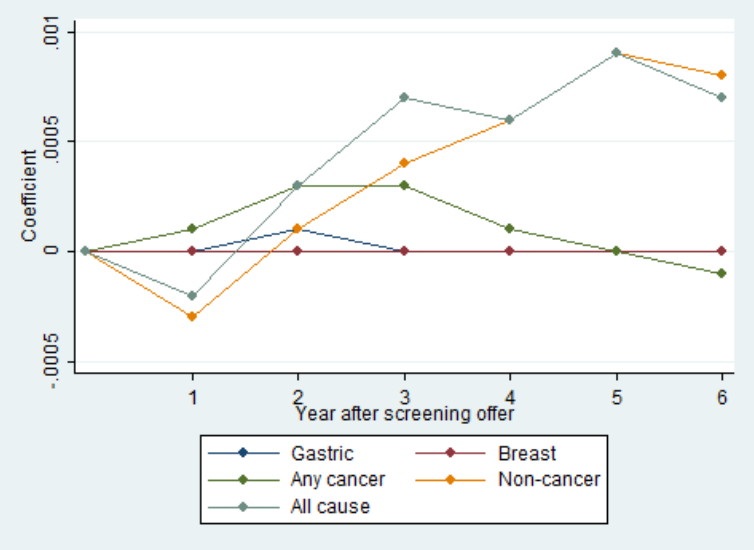
Note: The dependent variables in Panels A and B are 6-year cumulative cancer, non-cancer and all-cause mortalities in males and females, respectively. The running variable is the standardized insurance contribution. Open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are fitted values from local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. It estimated separately on each side of the cutoff. The shaded regions are 95 percent confidence intervals.

Figure 16: Effect on Mortality (trend)

Panel A. Stomach cancer, Male



Panel B. Stomach cancer, Female



Note: This figure illustrates a changing trend mortalities over time. Each dot represents a coefficient β from different local linear regression of equation (1). None of the estimates is statistically significant.

8 Appendix

8.1 Appendix Tables and Figures

Table 1: The Price of Cancer Screening

Unit($)

	Year	2002	2003	2004
	Administrarion cost	3.70	3.81	4.16
Stomach cancer screening	UGI	33.34	34.13	34.88
	EGD	33.30	34.28	35.20
	Biopsy	20.73	24.16	24.81
Breast cancer screening	Mammography	12.50	18.31	18.76
	Biopsy	24.02	29.70	30.50

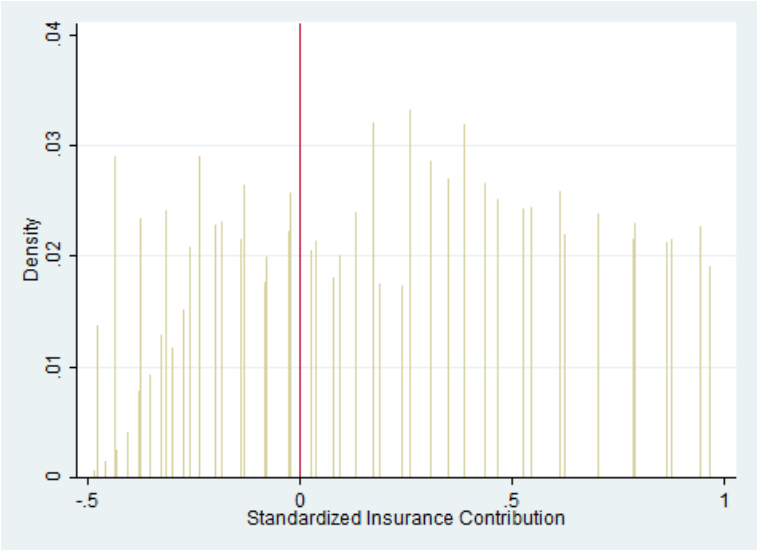
Table 2: Smoothness around Cutoff

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A. Male	Age		Employment status		Grenal health screening (R1)		Height (Cm)		Obesity (Round 1)		BMI (Round 1)	
Bandwidth	0.3	IK(0.25)	0.3	IK(0.25)	0.3	IK (0.23)	0.3	IK(0.11)	0.3	IK(0.13)	0.3	IK(0.11)
	-0.4545*	-0.3793	0.0191	0.0157	0.0007	0.0093	-0.0232	0.0486	0.0012	0.0143**	-0.0344	0.0635*
	(0.211)	(0.238)	(0.019)	(0.021)	(0.012)	(0.015)	(0.084)	(0.126)	(0.007)	(0.002)	(0.048)	(0.020)
N	1,260,729	935,784	1,260,729	1,066,081	1,260,729	935,785	527,997	195,261	527,725	195,154	527,725	195,152
Panel B. Female	Age		Employment status		Grenal health screening (R1)		Height (Cm)		Obesity (Round 1)		BMI (Round 1)	
Bandwidth	0.3	IK(0.25)	0.3	IK(0.25)	0.3	IK (0.09)	0.3	IK(0.15)	0.3	IK(0.12)	0.3	IK(0.12)
	-0.2994	-0.0799	0.0042	-0.0188	0.0534**	0.0329	-0.0903+	-0.0280	0.0096*	0.0056	0.0605*	0.0354+
	(0.180)	(0.170)	(0.025)	(0.022)	(0.015)	(0.024)	(0.044)	(0.064)	(0.004)	(0.004)	(0.027)	(0.016)
N	1,396,081	1,178,589	1,396,081	1,178,589	1,396,081	445,477	408,967	206,229	408,623	137,755	408,623	137,755

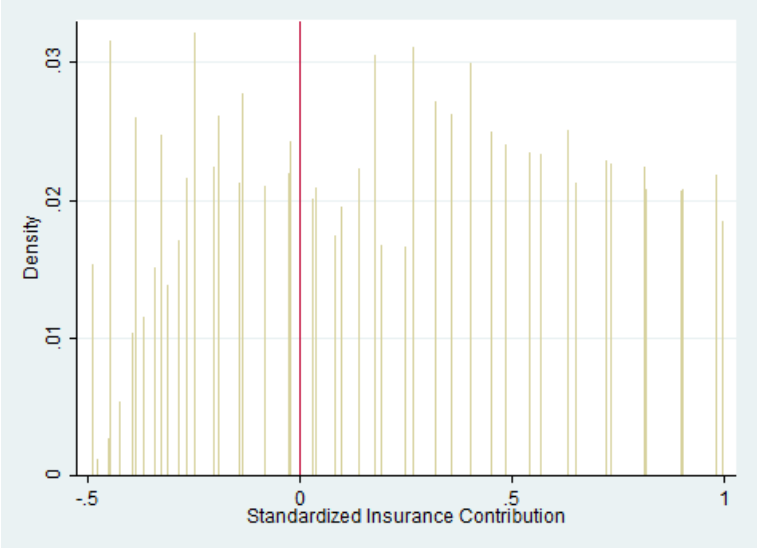
Note: Each cell represents a coefficient β from different local linear regression of equation (1). The running variable is the standardized insurance contribution. Rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution in parentheses. **, * and + indicates statistical significance at the 1, 5 and 10 percent level respectively.

Figure 1: Density of Insurance Contribution

Panel A. Histogram, Male



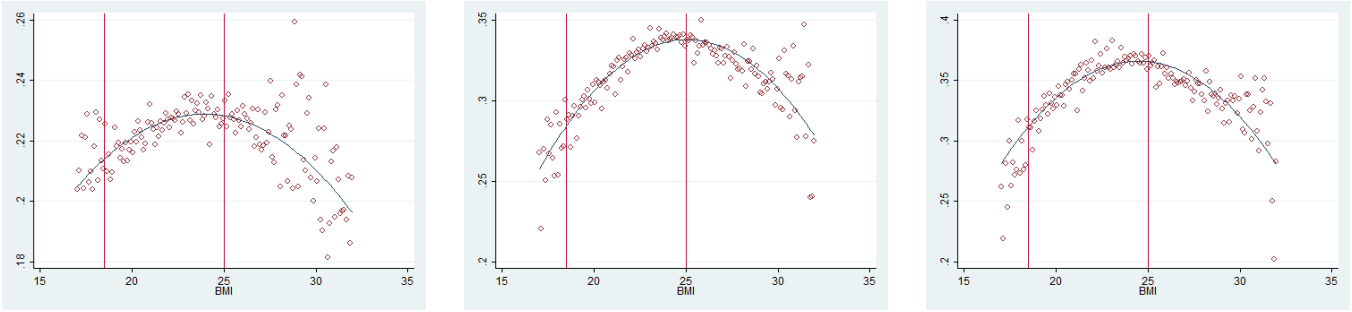
Panel B. Histogram, Female



Note: In each panel histogram with smallest bin size and 0.05 are presented

Figure 2: Probability of Cancer Screening Take up by Health Status

Panel A. BMI

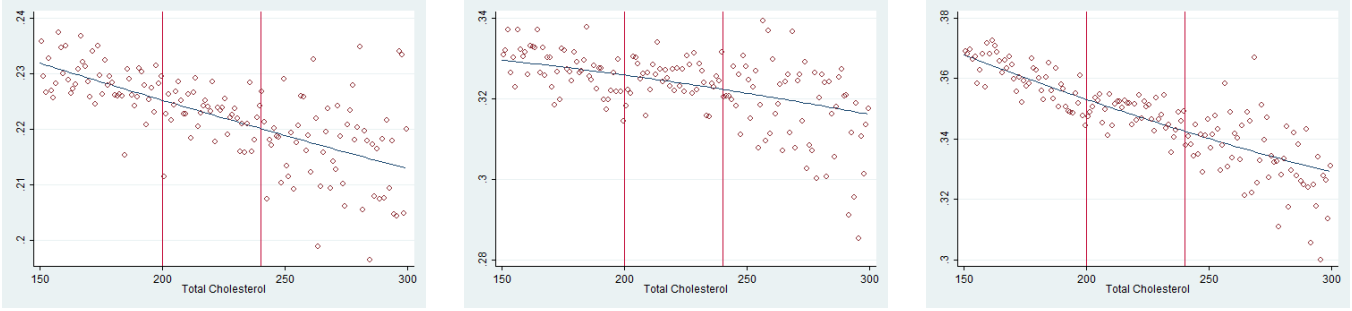


Stomach cancer, Male | Stomach cancer, Female | Breast cancer, Female

Panel B. Blood sugar level

Stomach cancer, Male | Stomach cancer, Female | Breast cancer, Female

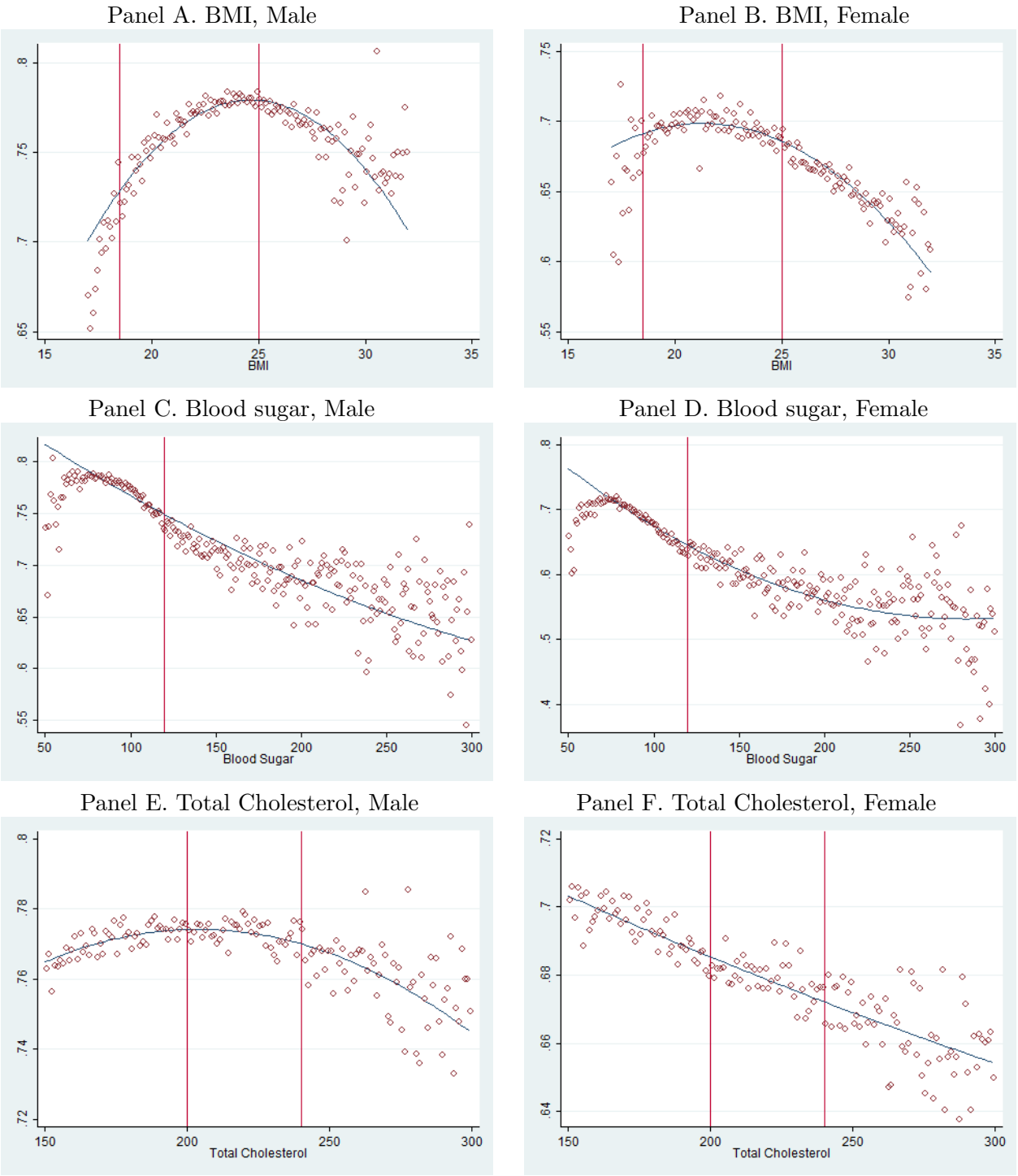
Panel C. Total Cholesterol



Stomach cancer, Male | Stomach cancer, Female | Breast cancer, Female

Note: Each figure shows probability of general screening take up in the second round by BMI, blood sugar and cholesterol level in the first round. Normal range of BMI is between 18.5 and 25. Normal level of blood sugar is under 110, and DM is diagnosed if it is greater than 120. Normal level of total cholesterol is under 200, and hyperlipidemia is diagnosed if it is over 240.

Figure 3: Probability of General Health Screening Take up by Health Status



Note: Each figure shows probability of general health screening take up in the second round by BMI, blood sugar and cholesterol level in the first round. Normal range of BMI is between 18.5 and 25. Normal level of blood sugar is under 110, and DM is diagnosed if it is greater than 120. Normal level of total cholesterol is under 200, and hyperlipidemia is diagnosed if it is over 240.