When Public Health Intervention Is Not Successful: Cost Sharing, Crowd-out, and Selection in Korea's National Cancer Screening Program*

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Abstract

This study investigates the impact of and behavioral responses to cost sharing in Korea's National Cancer Screening Program, which provides free stomach and breast cancer screenings to those with an income below a certain cutoff. Free cancer screening substantially increases the screening take up rate, yielding more cancer detections. However, the increase in cancer detection is quickly crowded out by cancer detection through other channels such as diagnostic testing and private cancer screening. Further, compliers are much less likely to have cancer than never takers. Crowd-out and selection help explain why the program has been unable to reduce cancer mortality.(JEL: I10, H40)

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1 Introduction

Cancers are the major cause of death in developed countries. In response to the huge disease burden, many developed countries implement public cancer screening programs. For example, Korea spends around $400 million on public cancer screening (NCC (2009)), and most European countries including the United Kingdom, Germany, and France also have such programs. Even the United States spends $194 million on a public cancer screening program, the National Breast and Cervical Cancer Early Detection Program (NBCCEDP), which provides free cancer screenings to those with an income below 250% of the federal poverty level.[1]

Public cancer screening became popular based on the results of the clinical randomized controlled trials (RCTs).[2] However, evidence on population-based cancer screening is still rare, even though the effects of such screening might differ from those provided by clinical RCTs because of behavioral responses. For example, the take-up rate in RCTs is close to 100%, which is far higher than that in the population-based setting.[3] Therefore, if population-based cancer screening unintentionally encourages specific groups of people to take up screening, the effects of the screening on these groups might differ from those in a clinical experimental setting.[4] Furthermore, because cancer screening is more popular than it was in the early days of RCTs, the availability of substitutes such as private screening and diagnostic testing has increased. Therefore, understanding these behavioral responses is important for examining the impact of public cancer screening programs.[5]

This study analyzes the impacts of and behavioral responses to cost sharing in Korea's National Cancer Screening Program (NCSP), one of the largest population-based cancer screening programs in the world. The NCSP provides subsidized stomach and breast cancer screenings for individuals aged 40 and above once every two years. Cancer screening is free to those below a designated

[1] Information is available at https://www.cdc.gov/cancer/nbccedp/ (accessed on September 2016).

[2] Mammography for breast cancer (Shapiro (1977); Moss et al. (2006)) and the fecal occult blood test (FOBT) for colorectal cancer (Mandel et al. (1993); Hardcastle et al. (1996)) 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 in medical journals.

[3] RCT study participants are not randomly chosen from the population; rather, they are those who agree to participate in the study.

[4] The take-up rates in a population-based breast cancer screening program were found to be 55.2%, 67.0%, and 73.8% in Korea, the United States, and the United Kingdom, respectively. (NCC (2009), NCI (2007), NHS (2008))

[5] Crowd-out and selection could also explain why the effects noted in experimental settings differ from those in population-based cancer screening. The compliance rate is close to 100% in the experimental setting and the crowd-out effect could be timing- and setting-specific.

insurance contribution cutoff, while a 50% copayment is charged to those above the cutoff.[6]

We use a regression discontinuity (RD) design that takes advantage of this contribution cutoff in the NCSP. This design allows us to compare people with similar characteristics, but sharply different cost sharing, and thus different public cancer screening take-up rates. Therefore, we measure the causal effect of one time free public cancer screening eligibility. Moreover, we carefully demonstrate behavioral responses to the program such as crowd-out and selection to screening. We first investigate the dynamic aspect of cancer detection through various channels by using data on all cancer detections regardless of the detection channel over five years after screening. Furthermore, we explore the characteristics and cancer mortality of those induced to take up cancer screening by the program (compliers) and compare them with 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 undergo screening, even when it is free (never takers).

The analysis allows us to draw three main conclusions. First, we find that the take-up rate of public cancer screening increases by around 10 percentage points - more than doubling - when the price of public cancer screening decreases from a 50% copayment to zero. The estimated arc elasticities of demand for public cancer screening are approximately -0.47. In addition, cost sharing reduces demand for public cancer screening without increasing the efficiency of cancer detection. In other words, cost sharing does not encourage the screening of people who are more likely to have cancer.

Second, we find that an increase in the cancer screening take-up rates results in a significantly increase in cancer detections in the short-term; however this detection hike quickly erodes over time because of a decrease in cancer detections through other channels such as private cancer screening and diagnostic testing.[7] Specifically, the initial increase in cancer detections through public cancer screening is crowded out within a year by a decrease in detections through private screening and diagnostic testing. This finding implies that public cancer screening is provided to those who would have nevertheless been tested within a year through other cancer detection channels. Conceptually, the increase in cancer detections through public cancer screening should erode completely over

[6]The insurance contribution is a fixed percentage of the basic salary of those with employee insurance. It was 3.62% and 3.94% in 2002 and 2003, respectively.

[7]The cancer screening process tests for cancer in the *absence* of symptoms in contrast to diagnostic tests, which people undergo to detect cancer in the *presence* of relevant symptoms, based on a doctor's recommendation.

time if cancer is eventually detected sometime before death (e.g., through diagnostic testing) and screening per se does not cause cancer. Therefore, time to crowd-out could be critical to the benefit of the individual if the early detection of cancer can decrease cancer mortality.

Third, we find that never takers are significantly less healthy than compliers and always takers in terms of cancer mortality. This policy-relevant finding suggests that the provision of population-based public cancer screening did not reach people more in need of screening during the study period. These behavioral responses to public cancer screening explain, at least partially, why subsidizing cancer screening is unable to make early detections of cancer or reduce cancer mortality.

Hence, the present study makes two novel contributions. The first contribution is to show that behavioral responses to public health intervention programs, such as crowd-out and selection, could be crucial to their success. The second contribution is to improve the understanding of cost sharing in the provision of preventive health services.

The remainder of this paper is organized as follows. Section 2 discusses the existing body of knowledge on the subject. Section 3 explains the background to the study. Section 4 describes the data and presents the descriptive statistics. Section 5 shows the estimation strategy. Section 6 presents the results, and Section 7 conducts an additional robustness check. Finally, Section 8 concludes the study.

2 Review of the Literature

We first study whether an increase in cancer detections though public cancer screening is crowded out (over time) by the decrease in cancer detections through other channels including diagnostic testing and private cancer screening.[8] Therefore, this study is related to the attenuation of public intervention program when alternatives are available. For example, Heckman et al. (2000) show that the impacts of job training program weakens when the control group receives substitute training and/or the compliance in the treatment group is low.

We also investigate selection to public cancer screening programs by exploring the characteristics of compliers, always takers, and never takers to address the following question: when expanding

[8]It it worth noting that the concept of crowd-out in our study is different from that in previous *crowd-out* literature which shows the manner in which a public intervention program erodes private provision. For example, Gruber and Simon (2008) provide an excellent literature review on the crowd-out in health insurance.

a public health program, which parts of the population in terms of health and socioeconomic status does the program reach. Only a few studies have explored compliers' characteristics in relation to health intervention programs. For example, Almond and Doyle (2011) and Anderson, Dobkin, and Gross (2012) investigate compliers' characteristics in the context of postpartum hospital stays and health insurance, respectively, but neither studies find significant differences between compliers, always takers, and never takers. Thus, ours is one of the few studies to identify that the characteristics of compliers have real policy relevance.

This study is also related to cost sharing in preventive health services. The benefits of cost sharing for healthcare service provision are unclear based on the findings of previous studies. Charging a non-zero price for health services could improve their effectiveness of these services by curbing unnecessary demand. However, it may also reduce necessary demand as well as treatment compliance, which could lead to worse health outcomes and higher medical expenditures in the future (Goldman, Joyce, and Zheng (2007)). Moreover, in the context of preventive healthcare, the impact of cost sharing has not been made clear. Since individuals are usually unaware of how much preventive healthcare they need, price sensitivity in preventive healthcare could be different compared with other therapeutic healthcare services. However, there is remarkably little evidence on the effects of cost sharing in preventive healthcare. One of the few exceptions is the study by Cohen and Dupas (2010), who show that the cost sharing of insecticide-treated nets (ITNs), which help prevent malaria infection, decreases demand without inducing the selection of people who are more vulnerable. Similarly, Meredith et al. (2013) show that households are highly sensitive to the price of preventive health products, such as rubber shoes for the prevention of worm infection, soap, and vitamins.

The overall effect of cost sharing can be categorized into own-price effect, cross-price effect, selection effect, and effect on health. For example, the degree to which cost sharing decreases the demand for public cancer screening can be deemed to be an own-price effect.[9] In addition, examining whether cost sharing encourages people who are more likely to have cancer to be screened or simply reduces the screening take-up rate without increasing the detection rate is referred to

[9]Newhouse et al. (1981), Manning et al. (1987), Newhouse and Group (1993), Hsu et al. (2006), and Chandra, Gruber, and McKnight (2010) show that cost sharing decreases demand for therapeutic healthcare. Evidence on preventive healthcare is relatively rare. (Newhouse and Group (1993)) find that the price elasticity of demand for preventive care is -0.17 to -0.43.

as the selection effect. A change in the price of a particular healthcare service may affect the demand for both health service and a complementary or substitutable service (other sources of cancer detection, such as private screening and diagnostic testing, discussed in the present study). This is described as the cross-price effect. For example, Chandra, Gruber, and McKnight (2010) find that the "offset effect" results in an increase in hospitalization in response to higher cost sharing for outpatient or pharmaceutical use in Medicare. Finally, the effect on health relates to whether changes in public cancer screening take-up influence health outcomes such as the early detection of cancer and mortality. Although the greater use of healthcare is not necessarily related to better health outcomes for the average population (Manning et al. (1987); Wennberg and Cooper (1996)), increased cost sharing could be associated with adverse health outcomes for the vulnerable population (Swartz (2010)).

Lastly, our study is related to the literature on population-based cancer screening take-up. For example, Kadiyala and Strumpf (2016) find that the U.S. guidelines that recommend screening for breast and colorectal screening starting at ages 40 and 50, respectively, generate discontinuous increases in screening rates that result in significant increases in early cancer detection at these ages. Bitler and Carpenter (2016) also show that state mandates for private health insurance coverage of mammography significantly increased its take-up.

3 Background to the Study

Korea provides universal health insurance coverage through its National Health Insurance (NHI) and Medical Care Assistance (MCA) programs.[10] The NHI program has two categories of insurance: employee and self-employed insurance. Altogether, 31.4 and 17.2 million people in Korea hold employee and self-employed insurance, respectively. Employee insurance, which this study investigates, applies to regular employees and household members of employees are also eligible for employee insurance.[11] Households in which no members are employed are eligible for self-employed

[10]The NHI is available to 95% of the total population, while the MCA covers the rest of the population (i.e., the poorest 5%). The National Health Insurance Corporation (NHIC), a single insurer, manages both these programs.

[11]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 remuneration or income are considered to be dependents of employees in this regard.

insurance.[12] The financial resources of the NHI system mainly come from the insurance contributions paid by the insured and their employers. The contribution rate of employee insurance was 3.62% and 3.94% of the basic wage in 2002 and 2003, respectively.

As shown in Table 1, the NHI started the NCSP in 2002 with stomach, breast, and cervical cancer screenings. In addition, the NHI operates the National Health Screening Program (NHSP) which provides general health screening including measuring Body Mass Index (BMI), blood pressure, blood sugar level, and cholesterol. Both the NHSP and the NCSP 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 can be screened the following year on request.[13]

Eligibility to the NHSP and NCSP is determined by age.[14] For example, stomach and breast cancer screening are recommended to those aged over 40.[15] The subsidy for public stomach and breast cancer screenings is determined by a person's insurance contributions.[16] Therefore, in the context of this study, free public stomach and breast cancer screenings are available to those satisfying the age and insurance contribution criteria shown in Table 1.[17]

The cutoff of insurance contribution was $26.18 and $24.63 in 2002 and 2003, respectively.[18]

[12] Although households may have multiple NHI employee insurances when more than one household member is employed, the benefits of NHIC insurance are the same.

[13] In terms of screening modality, an upper gastrointestinal (UGI) series, which is a radiologic examination, and an esophagogastroduodenoscopy (EGD), which is a confirmatory endoscopic procedure, are used for stomach cancer screening. Screening takers are allowed to choose between these two procedures based on their preferences. The EGD, a confirmatory test, is provided to those who received suspected cancer results from a UGI. Mammography is used for breast cancer screening.

[14] The age cutoff for stomach and breast cancer screening is 40. We decided not to exploit the age cutoff (40 years old) because the cancer incidence of people aged around 40 is very low. For example, the incidence of stomach cancer in men in their sixties (0.566% annually) is more than 10 times higher than that in men aged 40 (0.055% annually) in the study sample.

[15] In the United States breast cancer screening is recommended for women between the ages of 50 and 74 years, but stomach cancer screening is not (Force et al. (2009)). Stomach cancer incidence is very high in Asian men (i.e., 63.3 and 45.7 out of 100,000 in Korea and Japan, respectively) compared with that in the United States (7.5). Many studies have shown strong correlations between stomach cancer screening and stage of cancer at diagnosis as well as cancer mortality. For example, endoscopy with a shorter interval (less than three years) is significantly more likely to detect cancer at an earlier stage in Korea (Nam et al. (2012)), while detections through stomach cancer screening are significantly correlated with an earlier stage of stomach cancer at diagnosis and cancer mortality reduction in Japan (Tsubono and Hisamichi (2000); Morii et al. (2001)). Nevertheless, the net benefit of stomach cancer screening remains unclear in low incidence settings.

[16] General health screening (NHSP) and cervical cancer screenings are free for people satisfying the age criteria, regardless of their insurance contributions.

[17] Note that liver cancer screenings, which were introduced in 2003, are only offered to people with chronic liver disease. Moreover, the cutoff for liver cancer screening in 2003 was $16.75, well below the cutoffs for stomach and breast cancer screenings.

[18] Cancer screening after 2004 is not within the scope of this study. We study a sample between 2002 and 2003 in order to examine the long-term (five-year) effect of the program. Moreover, because screening take-up rates have increased substantially over time, from less than 15% in 2002 to 41.4% in 2011, crowd-out and selection patterns could differ by study period.

These cutoffs are updated every year based on the government budget. During the study period, free cancer screening was available to approximately the lowest 35% of households based on income. Since the prices of stomach and breast screenings were approximately \$38 and \$20, respectively during the study period (see Table A1), the maximum cash incentive is \$19 (=50%×\$38) for men and \$29 (=50% ×(\$38+\$20)) for women.[19]

Along with a nationwide public cancer screening advertisement campaign through the mass media to promote public health and screenings take-up, the NHI also sends a letter directly to individuals who satisfy the age criteria for the NHSP and NCSP. This letter introduces the NHSP and NCSP and provides a list of hospitals that provide screenings.[20] It also includes coupons to redeem against health and cancer screenings (free coupons for individuals below the cutoff and 50% discount coupons for those above the cutoff).

Lastly, there are three types of resources for cancer detection in Korea: public cancer screening (the NCSP), private cancer screening, and diagnostic testing. Private screening is generally more expensive than diagnostic testing and public cancer screening. The prices of public cancer screening and diagnostic testing, both covered by the NHI, are the same. In diagnostic testing, the copayment is 20%. Under the NCSP, the copayment is 50% for those above the cutoff and free for those below. Private cancer screening requires 100% out-of-pocket expenses. According to the National Cancer Center in Korea, the market shares of the NCSP and private cancer screening were 45.7% and 54.3% in 2004, respectively.[21] Given that these three procedures for detecting cancer can be offered in any private and public hospital, a core characteristic of the NCSP is it serving as a publicly incentivized cancer screening program.[22]

[19]The basic monthly salary level (excluding allowances, bonuses, and incentives) around the cutoff was \$713, while the annual medical expenditure for men and women was \$702 and \$774, respectively. Therefore, the \$19-\$29 cash incentive for cancer screening is relatively small.

[20]Public health and cancer screenings are available in most public and private hospitals. However, hospitals that specialize in gynecology and obstetrics may offer only breast and cervical cancer screenings.

[21]Information is available at $http://www.ncc.re.kr/webzine/201501/sub02.jsp$ (accessed on November 2015).

[22]Unfortunately, we cannot measure the take-up of private cancer screening and diagnostic testing because of data limitations.

4 Data

4.1 NHI Data

The primary analysis relies on NHI data during 2001-2008.[23] Our empirical analysis requires data on insurance contribution (the running variable), the take-up of cancer screening, and the relevant intermediate and final outcome variables that explain the effect of and behavioral responses to cancer screening.

NHI data are divided into three parts: eligibility, medical records, and screening.[24] The eligibility component contains basic demographic information such as gender, age, type of insurance, and monthly insurance contribution. Mortality (without cause-of-death information) and employment status are also included. Medical records include medical expenditure based on the International Statistical Classification of Diseases and Related Health Problems, 10th Revision (ICD-10), which allows us to measure cancer detection and treatment. Lastly, the screening data include information on health and cancer screenings.[25]

4.2 Study Sample

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

The main outcome variables are cancer detections, cancer mortality, and all-cause mortality.

[23] These data are longitudinal in nature but this dataset is not a perfectly balanced panel because of deaths and subjects that drop out of the NHI (i.e., become MCA recipients or emigrate).

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

[25] screening data is, of course, available only for the screening takers.

Cancer detections are based on ICD-10 information, which captures all cancers regardless of detection channel. As Du et al. (2000) point out, medical claim data provide valid information on cancer detection and treatment in the United States, and this could be even more effective in Korea, where the NHIC is the sole insurer. A concern about using ICD-10 information is not under-reporting but over-diagnosis.[26] To prevent misinterpretation from over-diagnosis, we restrict cancer detections to those that incur medical costs of greater than $300 on cancer-related treatment in the first year of detection.[27] Furthermore, we apply other cutoffs from no restriction to $500, in increments of $100. The point estimates are, of course, different; however, the crowding out and selection patterns are similar across cutoff levels.

Cancer detection by public screening is defined as detection with public cancer screening in either the same or the previous year, if not, it is considered cancer detection through other channels.[28] As a robustness check, we also define cancer detection by public screening as detection in the same year only.[29] Unfortunately, data limitations do not allow us to distinguish between private cancer screening and diagnostic testing because of data limitations. Cancer-related mortality is defined as death along with non-zero medical expenditure on cancer in the year of death. Cancer-related mortality may be a more comprehensive concept than cancer-specific mortality. The latter includes cancer as the main cause of death, while the former encompasses those situations in which cancer is a comorbid condition such as suicide due to depression accompanied by cancer. All-cause mortality is equal to one if an individual died for any reason and zero otherwise.

Table 2 presents the descriptive statistics of the study sample. Panels A to E describe the general information, baseline medical expenditure, cancer screening take-up, six-year cumulative cancer incidence, and six-year cumulative mortality. Around 10% of the population took up cancer screening within the first two years. The cumulative stomach cancer incidence (up to six years) is

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

[27] This definition is recommended by the National Cancer Center in Korea, which claims that more than 95% of cancer cases meeting this definition match the national cancer registry, an official record of cancer cases in Korea. Unfortunately, data from the national cancer registry are not available in this study. The $300 threshold excludes 10.8% and 15.3% of cancer cases defined by ICD-10 for men and women, respectively.

[28] Detections late in the previous year may be captured in the following year because of the administrative process in place. In addition, detections through both public and private channels are categorized as detection by public cancer screening because public cancer screening take-ups might lead to the additional take-up of diagnostic testing for confirmation, but not the other way around.

[29] We discuss the results of this alternative definition in Section 6.2.

1.3% for men and 0.5% for women. In terms of mortality, the cumulative all-cause mortality (up to six years) is 7.3% for men and 5.7% for women. The cumulative cancer mortality (also up to six years) is 2.6% for men and 2.4% for women.

Panels A, B, and C of Table 3 provide the results of the stomach cancer screenings for men and the stomach and breast cancer screenings for women, respectively. Each panel consists of two sub-panels. The first sub-panel presents the statistics for the entire sample, which includes all individuals regardless of whether they were screened for cancer. The second sub-panel presents the statistics for those screened. 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. Column (3) shows the cancer incidence, which is the proportion of new cancer cases in the overall group. For example, the two-year incidences of stomach cancer for men and women were 0.44% (=17,447/3,946,996) and 0.19% (=8,482/4,402,839), respectively. Columns (4) to (6) and (7) to (9) show the results for the treatment group (those at [-0.3, 0]) and the control group (those at (0, 0.3]), respectively.[30]

Table 3 shows 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 no stomach cancer result, even though a patient has cancer, is 0.18% for men and 0.06% for women.[31] The second is that the rate of false positives, the probability that a screening reports a possible cancer in a cancer-free patient, is high. For example, the false positive rate is 99.31% (=100-0.69%) for breast cancer screening in women. Such a high false positive rate is not a big surprise given that cancer screenings tend to minimize false negatives and largely ignore false positives. The third is that cancer screening detects other types of diseases in addition to cancer. For example, stomach cancer screening also detects benign diseases such as gastritis, stomach ulcers, and duodenal ulcers. The fourth is that the number of new cancer detections resulting from public cancer screening is relatively low. For example, public cancer screening detected 749 out of 17,447 stomach cancers in men during the study period. Hence, stomach cancer detection by public screening accounts for only 4.3% (=749/17,447) of total detections, even though it is offered to the entire population aged 40 and over. The corresponding numbers in stomach and breast cancers for women are 3.8%

[30] Our preferred bandwidth is 0.3. Bandwidth selection is discussed in Section 5.1.

[31] In reality, the number of false negatives may be even lower because new cancer cases that occurred after screening could be included in these statistics.

(=320/8,482) and 4.8% (=346/7,299), respectively.[32] In sum, cancer screening detects cancers as well as other diseases even though false positives and negatives are high. However, the share of cancer detections through public cancer screening is relatively small compared with other detection channels.

5 Estimation Strategy

5.1 Setup of the Empirical Analysis

We take advantage of the insurance contribution cutoff discussed earlier to estimate its causal effects of offering free cancer screening compared with charging a 50% copayment. In this regard, we consider the following main regression equation:

$$Y_{ict} = \beta \cdot \mathbf{1}(I_{ic} > \tau) + f(I_{ic}) + \psi_c + \epsilon_{ict} \tag{1}$$

where Y_{ict} denotes the outcome for individual i, cohort c, t years after the cancer screening offer. In addition, $\mathbf{1}(\cdot)$ is an indicator function showing whether an individual's insurance contribution (I) is greater than the cutoff, τ, which is normalized to zero. $f(\cdot)$ is a flexible polynomial function of I, ψ is a cohort fixed effect, and ϵ is an error term. Errors are clustered by the level of the normalized insurance contribution, as suggested by Lee and Card (2008).

We compare people just below and just above the insurance contribution cutoffs, where the subsidy for public stomach and breast cancer screening sharply changes. The idea behind the RD design is that the discontinuity measured by β quantifies the causal effect of free public cancer screening eligibility, assuming all other factors are smooth around the cutoff. If this assumption holds, people just above and below the cutoff can serve as suitable control and treatment groups, respectively. Therefore, any difference in outcomes, as captured by β, can be attributed to eligibility for free public cancer screening.

The analysis is carried out separately by gender, as different types of cancer screenings are offered on this basis. The causal effect of free public stomach cancer screening eligibility in men

[32]That cancer screening was taken up by around 10% of the population, but explains only a small percentage of total cancer detections, suggests the potential inefficiency of public cancer screening. However, it does not mean that cancer screening does not function properly. The proportion of cancer detection in the "suspected cancer" group is higher than that in the "normal" group.

can be estimated by β. However, we were not able to isolate the impact of free breast and stomach cancer screening eligibility in women because the subsidy for both screening types was offered based on a single cutoff. Instead, we estimated the combined effect around the cutoffs in women.

Bandwidth selection and modeling $f(\cdot)$ are critical decisions in the RD model. Since there is no universally accepted convention for choosing the optimal bandwidth, we adopted several of the approaches proposed in the literature. Our preferred bandwidth is 0.3, since this is wide enough not to be too imprecise and narrow enough to compare observations around the cutoff.[33] However, we also re-estimate regression (1) by using a bandwidth from 0.15 to 0.5, in increments of 0.05, as a robustness check. In addition, we use a local linear regression method with a rectangular kernel, as suggested by Hahn, Todd, and Van der Klaauw (2001), as well as quadratic and cubic functions to model $f(\cdot)$. We also estimate our main outcomes after controlling for a standard set of variables including age, residential area, employment status, company size, baseline amount of medical expenditure, and an indicator of general screening take-up.

5.2 Smoothness of the Predetermined Characteristics around the Cutoff

An important assumption of the RD design is that individuals just below and just above the cutoff can be compared. However, this assumption might not hold for several reasons. One concern is that those slightly above the cutoff may reduce their income level to become eligible for free cancer screening. However, such a manipulation of income would be extremely unlikely in this case. First, the cutoff for the program is decided annually based on the government budget and not announced in advance.[34] Second, people would be unlikely to manipulate their income levels to receive such a small cash incentive.

Figure A1 illustrates the density of observations by the standard insurance contribution using bin sizes of 0.005 and 0.05 around the cutoff. The distribution of the insurance contribution is not very smooth, especially in the small bin, reflecting that the insurance contribution, which is a fixed percentage of wages, is often rounded. Table A2 presents the t-statistics for the test for the smoothness of frequency density at the cutoff at zero and other falsified cutoffs from -0.3 to 0.5 with

[33] In addition, the optimal IK (Imbens-Kalyanaraman) bandwidths for most outcome variables range from 0.1 to 0.5.

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

different bandwidths from 0.15 to 0.5 (McCrary (2008)). The results show that none of the cutoffs is smooth, but that the cutoff at zero investigated herein has a relatively smooth density compared with the other falsified cutoffs. Moreover, stacking itself does not necessarily mean a violation of the RD assumption. This assumption could be problematic only if the factors that lead to stacking are correlated with the outcomes of interest (Urquiola and Verhoogen (2009)). Therefore, a more fundamental question is whether the predetermined characteristics that might be related to the outcome variables are smooth around the cutoff.

We test for differences in the observable characteristics around the cutoff. Table A3 presents the estimates of the discontinuity around the cutoff for predetermined variables such as age, employment status, residential area, company size, general screening take-up, and medical expenditure on cancer and non-cancer diseases. We find that most variables seem to be continuous around the cutoff, with a few exceptions such as age in men and company size. However, the difference in age and company size are not statistically significant in the other specifications and bandwidths, as shown in Panels A and D of Figure A2 and Figure A3. Moreover, the coefficient estimates for the baseline observable characteristics from a placebo test with falsified cutoffs are not located at the tail of the distribution, as shown in Figure A4 and Figure A5, implying that the few differences in baseline characteristics are not systematic. Lastly, the results from the regression including the control variables are almost identical to those from the regression without them.[35] As a result, we can confirm that our results are not driven by differences in the baseline characteristics.

5.3 Compliers, Always Takers, and Never Takers

The effects of the free public cancer screening eligibility we measure are driven by the people induced to take up public cancer screening by the cash incentive (compliers). Since compliers are not randomly selected from the population, the impact of cancer screening does not necessarily represent that for the average population. Moreover, in our specific case, more than 80% of the sample remain never takers during the study period.

We propose two ways of comparing the characteristics of compliers, always takers, and never takers. First, we compare compliers with always takers by restricting the sample to screening takers only. Since everyone has undergone public cancer screening in the restricted sample, any difference

[35] We discuss our findings including the control variables in Section 7.1.

around the cutoff is due to the compositional change of screening takers around this point. In this sample, those just below the cutoff consist of always takers and compliers, while those just above are always takers. Thus, using the analysis with the restricted sample allows us to compare the characteristics of compliers and always takers. Similarly, we restrict the sample to those that did not undergo screening (screening non-takers), which allows us to compare compliers with never takers.

Another way in which to compare compliers' characteristics is suggested by Almond and Doyle (2011) that we follow closely. 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, the observable characteristics of compliers can be calculated from the sample (Abadie (2003)). To do so, we first define a binary variable F, an indicator of free public cancer screening eligibility:

$$F = \begin{cases} 0 & \text{not eligible: above the cutoff} \\ 1 & \text{eligible: below the cutoff} \end{cases}$$

Next, we define a binary variable S, an indicator for public cancer screening take-up:

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

Lastly, we 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.

Further, three conditions are required to estimate compliers' characteristics: the existence of the first stage, monotonicity, and independence. First, the existence of the first stage implies that the probability of cancer screening take-up is higher in the eligible group than it is in the non-eligible group. This is empirically testable, and we find a significant increase in screening take-up. Second, the monotonicity assumption implies that $S_1 > S_0$ for everyone with a probability of 1. In other words, people that undertake cancer screening in the absence of the cash incentive would also do so in the presence of one. This is not directly testable since we do not observe S_1 and S_0, but it is reasonable to assume monotonicity in our 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 because income manipulation is unlikely in this context, as discussed in Section 5.2.

Let us first consider $E(X|S_1 = 1)$, which 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. $E(X|S_1 = 1, S_0 = 0)$ represents the characteristics of compliers. $E(X|S_1 = 1, S_0 = 1) = E(X|S_0 = 1)$ holds from 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 thus measured by π_A the proportion of screening takers in the non-eligible group. Similarly, the proportion of never takers, P(S_1=0) can also 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:

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

6 Results

In this section, we first present evidence of discrete changes in eligibility and a subsequent increase in cancer screening take-ups in Section 6.1. We then describe the crowd-out of cancer detections by looking at dynamic changes in cancer detections through public screening and other channels in Section 6.2. We explore selection to the program by looking at the characteristics of compliers, always takers, and never takers in Section 6.3. We examine whether the advance in timing of cancer detection translates into mortality reduction in Section 6.4. Lastly, Section 6.5 looks at the impacts on other outcomes such as health and cancer screening take-ups as well as medical expenditure.

6.1 Effect of Cost-Sharing on Screening Take-up

Panel A of Figure 1 illustrates that eligibility for free cancer screening increases from 0 to 1.[36] We plot the standardized insurance contribution that determines eligibility on the x-axis and the outcomes on the y-axis. The solid lines represent the fitted values from equation (1) using a local linear regression with a bandwidth of 0.3 and a rectangular kernel. The shaded areas are 95% confidence intervals. The open circles in the figure indicate the means of the fitted values, which are collapsed into bins of individuals who are within 0.05 of a standardized insurance contribution. The vertical difference between the two points just below and above the cutoff (vertical line) is an analog of β in equation (1).[37] Its regression analog is shown in Column (1) of Table 4. Years 1-2, the first and second years after the screening offer, represent the time during which the cancer screening offer was valid.[38]

Columns (3) to (9) of Table 4 show the degree to which eligibility for free public cancer screening translates into an increase in public cancer screening take-up. The coefficients in each cell in Panels A, B, and C represent the cumulative difference in stomach cancer screening take-ups for men and stomach and breast cancer screening take-ups for women around the cutoff, respectively. As expected, the difference in cumulative public cancer screening take-up increases mostly in Years 1-2 and remains similar thereafter, reflecting the limited change in future free cancer screening eligibility and take-ups shown in Columns (2) and (9), respectively.[39] In sum, eligibility for free public cancer screening induces an increase in public cancer screening take-up in relevant years (Years 1-2), but neither promotes nor discourages future public cancer screening take-ups (Years 3-6).

Column (4) corresponds to Panel B of Figure 1. Screening take-ups increased by 8.3, 10.9, and 10.7 percentage points, respectively, corresponding to increases of 155%(=8.29/5.34), 163%(=10.87/6.65), and 157%(=10.65/6.77). The estimated arc elasticities of demand for public cancer screening are

[36] As explained in Section 3, eligibility to free cancer screening is determined mechanically by the level of insurance contribution.

[37] Figure 1−Figure 3 have similar structures where the standardized insurance contribution is plotted on the x-axis and the outcome variable on the y-axis, with the open circles indicating the mean of the outcome in each bin.

[38] Years 1-2 correspond to 2002-2003 for the 2002 even cohort and 2003-2004 for the 2003 odd cohort.

[39] Recall that people born in even-/odd-numbered years are encouraged to take cancer screening in an even-/odd-numbered year, but those who missed the offer can be screened in the following year on request. Therefore, the offer is actually valid for two years.

approximately -0.47.[40] The estimated arc elasticity is close to the elasticity of preventive health products in other countries,[41] but it is significantly greater than the elasticity of therapeutic care.[42]

Next, we examine the impact of past public cancer screening on future take-up. If past and future cancer screenings are substitutes (complements), the latter will decrease (increase). We find these are neither substitutes nor complements. There is no significant change in eligibility for future free public cancer screening (Column (2)),[43] and there is little, if any, change in future public cancer screening take-up, as shown in Column (9) of Table 4 and Panel B of Figure A6. In summary, free cancer screening dramatically increases demand for such screening, while screening take-up does not influence future take-up.

6.2 Dynamic Aspect of Cancer Detections: Crowd-out

Here, we study whether an increase in public cancer screening actually promotes cancer detection and explore whether increased cancer detections diminish over time. As mentioned earlier, if cancers are eventually detected before death, the initial increase in cancer detections driven by the cancer screening program should be completely crowded out by other channels over time. Therefore, while crowd-out by private cancer screening or diagnostic testing is somewhat expected, it remains important to ascertain how long it takes for this crowd-out to occur.[44] The effect of cancer screening depends on the difference between the timing of cancer detection by screening and that of detection without screening.

[40] 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 with 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 tend to treat a zero price not only as a decrease in cost but also as an extra benefit (Shampanier, Mazar, and Ariely (2007)). This results must thus be interpreted with this caveat in mind.

[41] For example, -0.17 to -0.43 for preventive health care in the United States (Newhouse and Group (1993)), -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))

[42] For example, -0.07 to -0.21 for ambulatory utilization in Korea (Kim, Ko, and Yang (2005)), around -0.2 for healthcare for the non-elderly in the United States (Newhouse and Group (1993)), -0.10 for clinic visits for the elderly in the United States (Chandra, Gruber, and McKnight (2010)), and -0.15 to -0.17 for the elderly in Japan (Shigeoka (2014)).

[43] Unless the free cancer screening offer influences future wage levels (and thus the insurance contribution), eligibility for future cancer screening should be smooth around the cutoff. The dependent variable in Column (2) is a summation of eligibility between Years 3 and 6 when cancer screenings were offered every two years. Therefore, it would be 0, 1, or 2.

[44] Cancer detections (and medical expenditures) are observed only if individuals fall under the NHI. It is important to address the concern of systematic sample selection resulting from people dropping out of the NHI, which could account for our finding. Therefore, whether public cancer screening affected eligibility for the NHI is another relevant outcome. To check this possibility, we considered the non-death dropouts of the NHI directly, but found no statistically significant difference (see Table A8 in the Appendix).

Panels A, B, and C of Table 5 represent the dynamic changes in cumulative stomach cancer detections for men and stomach and breast cancer detections for women, respectively. Each panel consists of three sub-panels showing cancer detections by public screening and by other channels, and overall detections (the sum of detections by public screening and by other channels), respectively. Columns (1) to (6) show cumulative cancer detections over a six-year period. Column (7) represents cumulative cancer detections between three and six years after the cancer screening offer. Figure 2 and Figure A7 are analogs of Columns (2) and (7), respectively.

Panels A and B show that the impacts on stomach cancer detections are similar for men and women. First, stomach cancer detections by public cancer screening significantly increase by 0.045 percentage points for men (a 35% increase) and 0.022 percentage points for women (a 37% increase) up to the second year of the screening offer (Column (2)). However, detections by other channels decrease over the same period. As a result, overall cancer detections in men and women increase by 0.020 percentage points (an 8.8% change) and 0.018 percentage points (a 4.4% change) in the first year of the screening offer, but both decrease to zero within a year. In other words, the crowd-out occurs within a year.

The breast cancer screening results shown in Panel C are striking. As in the case of stomach cancer, the increase in breast cancer detection is crowded out within a year, but the crowd-out rate is even greater than the initial increase (more than 200%), as shown in Columns (5) and (6). Panel C of Figure A7 supports this finding. A potential explanation for this result is that because the majority of people receive normal or benign results from their cancer screenings, the take-up of future cancer screening reduces. We confirm the decrease in breast cancer screening take-ups for those with normal or benign results in Column (8) of Table A7. Moreover, this may explain the positive coefficient of six-year breast cancer mortality although the results are not statistically significant.[45]

To test the robustness of these crowd-out patterns, we estimate the results by using an alternative definition, namely detection from public cancer screening in the same year as discussed in Section 4.2. Based on this alternative definition, the crowd-out pattern is similar to that for the original definition; however, the coefficients of the alternative definition are smaller.[46]

[45] We address mortality outcomes further in Section 6.4.

[46] Figure A19 and Figure A20 show the coefficient estimates for Years 1-2 and Years 3-6 with various specifications and bandwidths under the original definition, respectively. Figure A21 and Figure A22 illustrate the coefficient

There are two possible reasons to explain that the overall increase of cancer detection would erode over time. The first is that the treatment group took diagnostic testing or private cancer screening less and the second is that the control group took diagnostic testing or private cancer screening more. We think that the latter is the more likely the channel that explains this erosion. A potential explanation is that compliers who have cancer in the control group (i.e., those with cancer in the control group but who decided not to take public cancer screening due to cost sharing) detect cancer through diagnostic testing or private cancer screening within a year because symptoms related with cancer surface early. Another explanation is that compliers in the control group with symptoms related to cancer opted for diagnostic testing instead of public screening because the co-payment is lower for diagnostic testing (50% in NCSP for the control group while 20% for the diagnostic testing).[47]

The question then is whether a small improvement in the timing of cancer detection translates into the detection of earlier-stage cancers.[48] If a cancer grows slowly, such as thyroid cancer, the difference in timing between cancer detection may not translate into earlier detection. We do not observe cancer stage at diagnosis because of data limitations. Instead, we use the amount of medical expenditure covered by public health insurance in the first year of cancer detection as a proxy.[49] Figure A8 illustrates 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 three to six years after the screening offer (Panel B). Table A4 is the regression analog. We find no evidence of stomach and breast cancer detection in its earlier stages, suggesting that cancer detection one year early does not translate into cancer detection in its earlier stages. This finding also leads us to expect a limited change in cancer mortality.

In summary, the increased cancer detections found through the free public cancer screening program were quickly crowded out, in less than one year, by other channels including private

estimates under the alternative definition.

[47] In order to take diagnostic testing, patients should have related symptoms that indicates cancer screening.

[48] Indeed, many studies show that diagnosis stage is a key predictor of mortality (e.g., McPhail et al. (2015)).

[49] This measure could a good proxy for cancer stage at diagnosis because it reflects the intensity of cancer treatment, particularly in our setting. First, given the universal coverage of health insurance in Korea, giving up cancer treatment in the first year of detection is unlikely. Second, the medical expenditures covered by public health insurance only include basic standard treatment. Lastly, our sample consists of household members with employee insurance, a group that is extremely unlikely to give up basic cancer treatment. Actually, previous research shows that cancer stage at diagnosis is strongly correlated with the cost of cancer treatment both in the United States and in Korea (Brown et al. (2002); Shin et al. (2012). In terms of stomach and breast cancer in Korea, the treatment cost for advanced cancer is 1.7 and 2.4 times larger than that for localized cancer, respectively (Shin et al. (2012)).

screening and diagnostic testing. Moreover, the crowd-out rate could rise above 100%. In addition, we find suggestive evidence that the improvement in the timing of cancer detection did not translate into the detection of early-stage cancers.

6.3 Selection to Cancer Screening

6.3.1 Selection Effect by Cost-Sharing

We now examine the impact of cost sharing by comparing compliers with always takers within a subsample of screening takers only. In this sample, those above the cutoff are always takers only, while those below the cutoff are always takers and compliers. Any difference around the cutoff is driven by the change in sample composition. Table 6 illustrates the cancer screening results and cancer detections among screening takers. Figure A9 and Figure A10 are its analog. Columns (1) to (3) present the probabilities of having a normal result, a suspected cancer result, and results for other diseases, respectively. Panels A, B, and C of Figure A9 are its analog. These results show that compared with always takers, compliers are more likely to have normal results (Panel A), less likely to have suspected cancer results (Panel B, stomach cancer for women), and less likely to have results for other diseases (Panel C). However, we find no evidence of selection on the detection of stomach and breast cancers: we find no difference in cancer detections between compliers and always takers as shown in Column (4) of Table 6 as well as Figure A10. This finding 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 demand for cancer screening without increasing the efficiency of cancer detection.

6.3.2 Characteristics of Compliers, Always Takers, and Never Takers

Since compliers are not randomly selected from the sample, understanding the characteristics of compliers, always takers, and never takers is important. In this regard, Table 7 presents the summary statistics for the entire sample for the bandwidth [-0.3, 0.3], compliers, always takers for the bandwidth (0, 0.3], and never takers for the bandwidth [-0.3, 0]. As explained in Section 5.3, we can estimate the characteristics of compliers by using 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 ($E(X|S=1,F=1)$). The estimated proportions of compliers, always takers, and never takers are presented in Panels A1, B1, and C1 of Table 7. The proportion of compliers is between 9% and 12%, while more than 80% of the sample remain never takers.

In addition, we find that never takers are significantly different from compliers and always takers.[50] In contrast to the belief that people at higher risk are more likely to utilize medical services, never takers in cancer screening have the highest risk in terms of cancer mortality. Surprisingly, although the six-year cumulative stomach cancer detection rate is the lowest among never takers (1.3%) compared with always takers at 1.7% and compliers at 1.5%,[51] the six-year cumulative stomach cancer mortality is the highest among men in this group (0.54%) compared with always takers at 0.24% and compliers at 0.34%.[52] Similarly, in stomach and breast cancers in women, the six-year cumulative cancer mortality rate in never takers is much greater than that in compliers and always takers.

We also find supporting evidence that never takers are less healthy than the other two groups. Figure A11 illustrates that cancer screening take-up is negatively correlated with health status, which in turn might also be related to cancer incidence and mortality.[53] People with a normal BMI, a fasting glucose level under 100, and a cholesterol level under 200 are more likely to participate in cancer screenings.[54]

Figure A12 illustrates another aspect of the characteristics of compliers, always takers, and never takers. Panel A compares compliers with always takers by using the restricted sample of screening takers, while Panel B compares compliers with never takers by using the restricted sample of screening non-takers. Table A5 is its regression analog. Panels A and B compare compliers with

[50] We compare the cancer and general screening take-up rates (Year 1-6), cancer detection (within six years from the screening), six year cancer mortality, and all-cause mortality. To estimate average cancer and general screening take-up rate in Year 1-6, we assume that the one-time eligibility for public cancer screening does not affect future cancer screening take-up rate, which is shown in Section 6.2. Similarly, for cancer detection and mortalities, we assume that stomach and breast cancers will be detected sometime within six years; additionally cancer screening per se does not cause cancer.

[51] Low detection among never takers does not mean that cancer prevalence is lowest among this group of the population. Further, never takers are not diagnosed with cancer through public cancer screenings but rather through other channels or future public screening.

[52] Since we exclude previous cancer patients from the study sample, the measured cancer mortality is death from cancer that developed after the screening offer.

[53] The sample used in Figure A11 includes those who participated in the first round of health screening (Years 1−2: 2002−2003 for the even cohort and 2003−2004 for the odd cohort). The x-axis shows the results from the first round of health screening and the y-axis the probability of screening take-up in the second round (Years 3−4).

[54] The normal range of the BMI is between 18.5 and 25. A normal fasting blood sugar level is under 110 and diabetes mellitus is diagnosed if it is greater than 120. A normal total cholesterol level is under 200 and hyperlipidemia is diagnosed if it is over 240.

always takers and never takers indirectly as described in Section 5.3. For example, we compare never takers just below the cutoff with the combined sample of compliers and never takers right below the cutoff in stomach cancer screening for men.[55] Although the power of the test significantly decreases, we find suggestive evidence that female breast cancer mortality is higher in never takers than compliers.

In summary, these findings imply that public cancer screening did not reach the people who needed cancer screening the most during the study period. This selection effect, along with the crowd-out discussed earlier, explains, at least partially, the limited evidence of the early-stage detection of cancer and of reductions in mortality.

6.4 Effect on Mortality

Table 8 and Figure 3 present the average effects on cancer, non-cancer, and all-cause mortalities. These results show no evidence of a change in stomach and breast cancer mortalities.[56] This finding is no surprise since we find no evidence of early detection. The size of the standard errors is small enough to capture the relatively small effect of a 50% subsidy for cancer screening. For example, the mean of six-year stomach cancer mortality in men is 0.52% with a standard error of 0.00034, which is able to capture any change in mortality greater than 12.3% (=0.00034×1.96/0.0052). The corresponding numbers in stomach and breast cancer for women are 7.9% (=0.00015×1.96/0.0037) and 10.2% (=0.00012×1.96/0.0023), respectively. Indeed, this study has been able to capture even smaller changes in cancer mortality than other RCT studies of cancer screening.[57]

The outstanding question is the degree to which public stomach and breast cancer screenings would reduce cancer mortality in the ideal situation (i.e., with a very low level of crowd-out and selection). While it is likely that large-scale cancer screening programs targeting cancers whose growth speed is neither too fast nor slow increase early detection and decrease cancer mortality in the ideal situation, predicting this reduction in reality is complicated because the effectiveness of

[55]The sample below the cut off consists of 5.6% (= 5.1/(85.3 + 5.1)) for compliers and 94.4% (=85.3/(85.3 + 5.1)) for never takers.

[56]Some coefficient estimates are even positive, although not statistically significant, in the sensitivity analysis, as shown in Figure A27.

[57]Cancer mortality reductions from RCT studies of mammography for breast cancer (Shapiro (1977); Moss et al. (2006)), the fecal occult blood test (FOBT) for colorectal cancer (Mandel et al. (1993); Hardcastle et al. (1996)), the PSA test for prostate cancer (Schröder et al. (2009)), low dose computed tomography (CT) for lung cancer (Gross (2011)), and sigmoidoscopy for colon cancer (Atkin et al. (2010)), and colonoscopy for colorectal cancer (Zauber et al. (2012)) are 24−30%, 15−33%, 20%, 20%, 43%, and 53%, respectively.

such programs depends on variables that change over time and place such as cancer prevalence, time to crowd-out, and accessibility to treatment.[58] Nevertheless, it is clear that these behavioral responses are major challenges to the success of public cancer screening and explain the program failure, at least partially.

6.5 Effect on Future Screening Take-up and Medical Expenditure

First, providing public cancer screening might have a spillover effect onto the NHSP, the public general health screening take-up. The take-up of free general health screening, which is also offered every two years to all individuals aged over 40 regardless of insurance contribution level, is shown in Figure A13 and Column (1) of Table A6. Here, we find no evidence that the take-up of general screening would decrease in the future as a result of the provision of public cancer screening.

Second, we evaluate the impact on medical expenditure, as shown in Figure A14 and Columns (2) to (4) of Table A6. To increase precision, we use the difference between medical expenditure and baseline medical expenditure as the dependent variable. Cancer screening would change peoples' medical expenditure if they altered the way in which they used medical services as a result of the screening. The detection of non-cancer diseases could be one of the main channels in this regard, but we find no significant change in medical expenditure.

We also consider that changes in future screening take-up and medical expenditure might differ according to different screening results. Here, the behavioral responses of false positive result recipients are of particular interest. To examine these responses, we run another RD regression with the additional interaction terms of eligibility and screening result. Screening result is categorized as "normal","cancer detection","false positive", and "other types of diseases". Here, cancer detection refers to the case in which an individual is diagnosed with cancer after receiving a suspected cancer result and a false positive result otherwise. We construct our additional RD model in the following way:

[58]For this reason, the results presented by RCT studies are often mixed. For example, one RCT study in the United States found no reduction in prostate cancer mortality (Andriole et al. (2009)), while a European study found a 20% reduction (Schröder et al. (2009)). Similarly, a number of authors have shown that breast cancer screening is effective at reducing mortality (Shapiro (1977); Moss et al. (2006)), while other studies have found no impact (Miller et al. (2000)). Likewise, some studies report a very strong correlation between the frequency of stomach cancer screening and cancer stage at diagnosis (Nam et al. (2012)), while others find no impact (Riecken et al. (2002)).

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

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

The results are presented in Table A7. Columns (1) and (2) show that men who receive a false positive result from a stomach cancer screening are more likely to take health and stomach cancer screenings in the future. Columns (6) to (8) show that women who receive a false positive result from a breast cancer screening are also more likely to take future stomach and breast cancer screenings. However, we find no significant change in the medical expenditures of either men or women who receive a false positive result as shown in Columns (3) to (5) for men and (9) to (11) for women. This finding implies that false positives only induce additional clinic visits and procedures, which are covered by the public cancer screening program in any case.

7 Robustness Check

7.1 Other Specifications

First, we examine the sensitivity of our results to the choice of bandwidth and higher-order specifications of $f(\cdot)$. To do so, we estimate equation (1) for our main outcomes of interest at multiple bandwidths, from 0.15 to 0.5, in increments of 0.05, as well as using the first-, second-, and third-order specifications of $f(\cdot)$. We present coefficient estimates at the 95% confidence interval with 24 different specifications for all the outcomes of interest in Figure A15 to Figure A27.

Four main findings are worthy of note. First, the coefficients are consistent, with a few exceptions at very small bandwidths with a cubic specification. Second, the coefficients with the other bandwidths are located in the 95% confidence interval of the estimate with a bandwidth of 0.3. Third, for the most part, the coefficient estimates based on the linear specification of $f(\cdot)$ are also located in the 95% confidence interval for the second- and third-order specifications. These findings imply that our estimates are not too sensitive to bandwidth selection or the functional form of $f(\cdot)$. Lastly, the variances of the higher-order specifications are larger, which supports using a linear specification. We also run this sensitivity analysis by including in the regression control variables

such as age, type of insurance, and an indicator of general screening take-up. The results, not shown here, are similar to the original specification.

7.2 Differential Dropout from the NHI

Another relevant outcome is whether cancer screening eligibility leads to people dropping out of the NHI. The main causes of dropout are death, becoming an MCA recipient, and emigration. It is important to consider whether the difference in dropout rates around the cutoff may explain our results. We thus explored the probability of non-death dropout from the NHIC and found no systematic change in the dropout rate, as shown in Table A8.

8 Discussion and Conclusion

This study presented and discussed behavioral responses to the subsidization of the public cancer screening program in Korea in terms of crowd-out and selection. We found that public cancer screening, when offered for free substantially increases the cancer screening take-up rate and cancer detection, compared to that with a 50% copayment. The arc price elasticity of demand for public cancer screening is high (-0.47). This figure is much larger than that for therapeutic medical services in Korea, Japan, and the United States, but similar to the elasticities of other preventive health services measured in both developed and developing countries.

However, the initial increase in cancer detection is quickly crowded out by a decrease in cancer detection through other channels such as diagnostic testing and private screening. Furthermore, never takers are significantly less healthy than compliers and always takers in terms of cancer mortality. These behavioral responses explain, at least partially, why the subsidy program was unable to make early detections of cancer incidence or reduce cancer mortality.

Our crowd-out findings are in line with the study by Heckman et al. (2000), who also show that the effects of public intervention programs are attenuated if substitutions are available for the control group. Moreover, results on selection echo the study by Kline and Walters (2015), who present a selection pattern wherein children less likely to enroll in the Head Start program would experience larger test score gains. In terms of external validity, most public intervention programs, unless they are mandatory, may have a similar selection problem, but the degree of selection may

vary across the settings. For example, our estimation is based on the first two years of the public cancer screening program where only about 10% of the eligible population participated. Therefore, the selection patterns (average characteristics of compliers, always-takers, and never-takers) in our study are not necessarily similar to those in the higher take-up settings.

There are some limitations to our study. The study has data limitation that some important variables are measured by adopting proxies. For example, we do not directly measure the take-up of private cancer screening and diagnostic testing. Moreover, cancer detection information is taken from medical claim data and not from the cancer registry; therefore, the results should be interpreted with caution.

A better understanding of crowd-out and selection in this area would allow policymakers to design optimal cancer screening policies. The early detection of cancer is crucial for the success of public cancer screening intervention programs. The speed at which cancer detections through the public cancer screening programs are crowded out by other channels determines early detection. Therefore, public cancer screening is less likely to be effective when such a screening program is already popular, as the time for crowding out is shorter. For instance, while public cancer screening in the United States could be crowded out quickly, this phenomenon is less likely to be observed in developing countries. In addition, people who are susceptible to cancer are less likely to participate in cancer screening. Therefore, the incentive design for cancer screening must be improved to reach this high-risk target population.

Broadly, although the findings of this study specifically reflected the behavioral responses to the NCSP in Korea, this analysis still provides a number of implications for other health and social programs. In particular, we demonstrated that the impact of public health and social programs, even those that already benefit from high participation rates, crucially depends on the potential behavioral responses of the parties involved.

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Table 1: History of the NHSP and NCSP

Year	Men	Women	Age cutoff	Monthly insurance contribution cutoff ($)
2002	Health (NHSP)	Health (NHSP)	40	n/c
	Stomach	Stomach	40	26.18
		Breast	40	26.18
		Cervix	30	n/c
2003	Health (NHSP)	Health (NHSP)	40	n/c
	Stomach	Stomach	40	24.63
	Liver	Liver	40	16.75
		Breast	40	24.63
		Cervix	30	n/c
2004	Health (NHSP)	Health (NHSP)	40	n/c
	Stomach	Stomach	40	25.26
	Colon	Colon	50	23.15
	Liver	Liver	40	25.26
		Breast	40	23.15
		Cervix	30	n/c
2005	Health (NHSP)	Health (NHSP)	40	n/c
	Stomach	Stomach	40	35.00
	Colon	Colon	50	35.00
	Liver	Liver	40	35.00
		Breast	40	35.00
		Cervix	30	n/c
2006	Health (NHSP)	Health (NHSP)	40	n/c
	Stomach	Stomach	40	50.00
	Colon	Colon	50	50.00
	Liver	Liver	40	50.00
		Breast	40	50.00
		Cervix	30	n/c
2007	Health (NHSP)	Health (NHSP)	40	n/c
	Stomach	Stomach	40	52.00
	Colon	Colon	50	52.00
	Liver	Liver	40	52.00
		Breast	40	52.00
		Cervix	30	n/c

Note: This table presents the types of screening options covered by the NHI. The age cutoffs determine an individual's eligibility to the public screening program and the monthly insurance contribution cutoffs determine the level of subsidy. Stomach, breast, and colorectal cancer screening was free for those below the designated monthly insurance contribution cutoff, while a 50% copayment was charged to those above. NHSP and cervical cancer screening are offered free regardless of monthly insurance contribution level. Liver cancer screening has been offered since 2003 with a cutoff of $16.75, which is far below the cutoff for other screenings. Liver cancer screening targets the less than 1% of the population with chronic liver disease such as liver cirrhosis and HBV- and HCV-related liver diseases. The insurance contribution is a fixed percentage of the basic salary of those with employee insurance, and it was 3.62% and 3.94% of the salary in 2002 and 2003, respectively. Unit is 1 USD $\approx$ 1,000 KRW.

Table 2: Basic Statistics

	Men			Women		
	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 status	4,041,275	0.625	0.484	4,460,789	0.157	0.364
Residential Area (Urban)	3,984,201	0.931	0.254	4,398,654	0.929	0.257
Company size (Number of employees)	4,041,275	2243	7773	4,460,789	2309	7638
Panel B. Medical expenditure (Unit:1 USD)						
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 (Years 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. Six-year cumulative cancer incidence						
Stomach	4,021,374	0.013	0.112	4,440,967	0.005	0.074
Breast				4,440,967	0.005	0.073
Panel E. Six-year cumulative mortality						
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 the summary statistics of the study samples. N is the sample size and Std. Dev refers a standard deviation. The data cover all Korean people with employee health insurance. Screening take-up is defined as one for individuals that undertook cancer screening within two years of the offer. Company size is measured by number of employees. See Section 4.2 for the definitions of the variables. All measures are at the baseline: 2002 for the even cohort and 2003 for the odd cohort.

Table 3: Results of Public Cancer Screening

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Whole sample			The treatment group Sample at [-0.3, 0]			The control group Sample at (0, 0.3]		
Panel A. Stomach cancer, men	Total	Cancer	Proportion	Total	Cancer	Proportion	Total	Cancer	Proportion
Panel A1. Whole sample									
Total	3,946,996	17,447	0.44%	668,891	3,045	0.46%	560,053	2,502	0.45%
Screening non-takers	3,558,289	15,599	0.44%	568,479	2,460	0.43%	530,786	2,354	0.44%
Screening takers	388,707	1,848	0.48%	100,412	585	0.58%	29,267	148	0.51%
Panel A2. Screening result									
Normal	173,334	317	0.18%†	46,284	101	0.22%†	12,365	19	0.15%†
Cancer suspicion	17,895	749	4.19%‡	4,197	229	5.46%‡	1,142	70	6.13%‡
Other stomach disease	197,476	782	0.40%	49,931	255	0.51%	15,760	59	0.37%
Panel B. Stomach cancer, women									
Panel B1. Whole sample									
Total	4,402,839	8,482	0.19%	777,758	1,377	0.18%	599,899	1,138	0.19%
Screening non-takers	3,914,727	7,674	0.20%	631,733	1,147	0.18%	559,852	1,069	0.19%
Screening takers	488,112	808	0.17%	145,025	230	0.16%	40,047	69	0.17%
Panel B2. Screening result									
Normal	270,469	150	0.06%†	103,475	50	0.05%†	20,651	6	0.03%†
Cancer suspicion	13,458	320	2.38%‡	4,873	85	1.74%‡	1,193	30	2.51%‡
Other stomach disease	204,184	338	0.17%	76,724	95	0.12%	18,203	33	0.18%
Panel C. Breast cancer, women									
Panel C1. Whole sample									
Total	4,404,022	7,299	0.17%	777,828	1,307	0.17%	600,113	924	0.15%
Screening non-takers	3,898,340	6,348	0.16%	631,966	1,032	0.16%	559,413	839	0.15%
Screening takers	505,682	951	0.19%	145,862	275	0.19%	40,700	85	0.21%
Panel C2. Screening result									
Normal	370,726	228	0.06%†	110,429	81	0.07%†	29,994	15	0.05%†
Cancer suspicion	50,229	346	0.69%‡	13,588	91	0.67%‡	3,900	37	0.95%‡
Other breast disease	84,727	377	0.44%	21,845	103	0.47%	6,806	33	0.48%

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 of whether they were screened for cancer. The second sub-panel presents the cancer screening results for screening takers. Columns (1), (4), and (7) present the total number of people in each category, and columns (2), (5), and (8) present 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 columns (3), (6), and (9). Therefore, a false negative is represented by '†' and a false positive by '‡' (1 - statistics with '‡').

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable	Eligibility		Cumulative public cancer screening take-up						
Year	Years 1-2	Years 3-6	Year 1	Years 1-2	Years 1-3	Years 1-4	Years 1-5	Years 1-6	Years 3-6
Panel A. Stomach cancer screening, men									
Discontinuity at the cutoff	1.000**	0.054	0.0791**	0.0829**	0.0839**	0.0859**	0.0834**	0.0833**	0.001
	(0.000)	(0.064)	(0.008)	(0.011)	(0.016)	(0.014)	(0.017)	(0.018)	(0.011)
Mean at (0,0.3]	0.000	0.701	0.0348	0.0534	0.1608	0.2180	0.4103	0.4570	0.385
N	1,260,729	1,260,729	1,260,729	1,260,729	1,260,729	1,260,729	1,260,729	1,260,729	1,260,729
Panel B. Stomach cancer screening, women									
Discontinuity at the cutoff	1.000**	0.070	0.1115**	0.1087**	0.1085**	0.1076**	0.1088**	0.1066**	-0.002
	(0.000)	(0.070)	(0.009)	(0.010)	(0.013)	(0.013)	(0.015)	(0.015)	(0.012)
Mean at (0,0.3]	0.0000	0.6821	0.0574	0.0665	0.2186	0.2547	0.5144	0.5512	0.478
N	1,396,081	1,396,081	1,396,081	1,396,081	1,396,081	1,396,081	1,396,081	1,396,081	1,396,081
Panel C. Breast cancer screening, women									
Discontinuity at the cutoff	1.000**	0.070	0.1102**	0.1065**	0.1065**	0.1052**	0.1065**	0.1040**	-0.002
	(0.000)	(0.070)	(0.011)	(0.012)	(0.015)	(0.015)	(0.016)	(0.016)	(0.011)
Mean at (0,0.3]	0.0000	0.6821	0.0574	0.0677	0.2296	0.2686	0.5421	0.5813	0.506
N	1,396,081	1,396,081	1,396,081	1,396,081	1,396,081	1,396,081	1,396,081	1,396,081	1,396,081

Note: Each cell represents the coefficient β from a different local linear regression of equation (1) with a bandwidth of 0.3. Years 1-2 represent the first and second years after the screening offer. The running variable is the standardized insurance contribution. A rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution are reported in parentheses. **, * and + indicate statistical significance at the 1%, 5% and 10% level respectively. The sensitivity analysis results for Columns (1), (2), (4), and (9) are shown in Figure A15, Figure A16, Figure A17, and Figure A18, respectively.

Table 5: Effect on Cumulative Cancer Detection

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Year	Year 1	Years 1-2	Years 1-3	Years 1-4	Years 1-5	Years 1-6	Years 3-6
Panel A. Cumulative stomach cancer detection in men							
Panel A1. By public screening							
Discontinuity at the cutoff	0.00013	0.00045*	0.00044*	0.00052*	0.00069**	0.00051*	0.00006
	(0.00015)	(0.00018)	(0.00017)	(0.00019)	(0.00020)	(0.00022)	(0.00010)
Mean at (0,0.3]	0.0012	0.0013	0.0017	0.0022	0.0030	0.0037	0.0023
N	1,212,427	1,212,427	1,212,427	1,212,427	1,212,427	1,212,427	1,244,400
Panel A2. By other channels							
Discontinuity at the cutoff	0.00003	-0.00046**	-0.00068*	-0.00080*	-0.00072+	-0.00063	-0.00010
	(0.00004)	(0.00012)	(0.00028)	(0.00037)	(0.00040)	(0.00041)	(0.00034)
Mean at (0,0.3]	0.0009	0.0029	0.0047	0.0064	0.0078	0.0092	0.0063
N	1,212,427	1,212,427	1,212,427	1,212,427	1,212,427	1,212,427	1,244,400
Panel A3. Overall detection							
Discontinuity at the cutoff	0.00020	0.00004	-0.00017	-0.00019	0.00002	-0.00002	-0.00004
	(0.00017)	(0.00024)	(0.00039)	(0.00050)	(0.00058)	(0.00057)	(0.00037)
Mean at (0,0.3]	0.0023	0.0044	0.0066	0.0087	0.0109	0.0130	0.0086
N	1,212,427	1,234,492	1,244,400	1,249,522	1,252,297	1,254,031	1,244,400
Panel B. Cumulative stomach cancer detection in women							
Panel B1. By public screening							
Discontinuity at the cutoff	0.00013**	0.00022**	0.00015	0.00022+	0.00027*	0.00028*	0.00007
	(0.00003)	(0.00005)	(0.00009)	(0.00011)	(0.00012)	(0.00013)	(0.00010)
Mean at (0,0.3]	0.0005	0.0006	0.0008	0.0010	0.0012	0.0015	0.0009
N	1,368,472	1,368,472	1,368,472	1,368,472	1,368,472	1,368,472	1,385,151
Panel B2. By other channels							
Discontinuity at the cutoff	0.00002	-0.00016+	-0.00024	-0.00023	-0.00005	0.00004	0.00018
	(0.00005)	(0.00009)	(0.00015)	(0.00017)	(0.00016)	(0.00015)	(0.00014)
Mean at (0,0.3]	0.0003	0.0012	0.0021	0.0027	0.0033	0.0039	0.0027
N	1,368,472	1,368,472	1,368,472	1,368,472	1,368,472	1,368,472	1,385,151
Panel B3. Overall detection							
Discontinuity at the cutoff	0.00018**	0.00008	-0.00007	0.00000	0.00022	0.00032+	0.00025
	(0.00006)	(0.00010)	(0.00019)	(0.00018)	(0.00015)	(0.00016)	(0.00015)
Mean at (0,0.3]	0.0010	0.0019	0.0029	0.0038	0.0047	0.0055	0.0037
N	1,368,472	1,380,172	1,385,151	1,387,618	1,389,023	1,389,878	1,385,151
Panel C. Cumulative breast cancer detection in women							
Panel C1. By public screening							
Discontinuity at the cutoff	0.00007+	0.00017**	0.00013+	0.00010	-0.00004	-0.00010	-0.00026+
	(0.00004)	(0.00004)	(0.00007)	(0.00007)	(0.00013)	(0.00016)	(0.00013)
Mean at (0,0.3]	0.00005	0.00015	0.00031	0.00055	0.00086	0.00121	0.00106
N	1,368,472	1,368,472	1,368,472	1,368,472	1,368,472	1,368,472	1,385,151
Panel C2. By other channels							
Discontinuity at the cutoff	0.00013+	-0.00014	-0.00018	-0.00037*	-0.00041*	-0.00047*	-0.00034
	(0.00007)	(0.00008)	(0.00011)	(0.00017)	(0.00020)	(0.00022)	(0.00020)
Mean at (0,0.3]	0.00061	0.00136	0.00203	0.00266	0.00326	0.00384	0.00249
N	1,368,472	1,368,472	1,368,472	1,368,472	1,368,472	1,368,472	1,385,151
Panel C3. Overall detection							
Discontinuity at the cutoff	0.00027**	0.00008	0.00001	-0.00021	-0.00039**	-0.00051**	-0.00060**
	(0.00009)	(0.00009)	(0.00012)	(0.00015)	(0.00014)	(0.00017)	(0.00018)
Mean at (0,0.3]	0.00069	0.00154	0.00236	0.00323	0.00415	0.00508	0.00355
N	1,368,472	1,380,172	1,385,151	1,387,618	1,389,023	1,389,878	1,385,151

Note: The dependent variables in Panels A, B, and C are cumulative stomach cancer detections in men and stomach and breast cancer detections in women, respectively. Each panel consists of three sub-panels showing cancer detections by public screening and by other channels, and overall detections, respectively. Each cell represents the coefficient β from a different local linear regression of equation (1) with a bandwidth of 0.3. The running variable is the standardized insurance contribution. A rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution are reported in parentheses. **, * and + indicate statistical significance at the 1%, 5% and 10% levels, respectively. The sensitivity analysis results for Columns (2) and (7) are shown in Figure A19 and Figure A20, respectively. The corresponding sensitivity analysis results with alternative definition of cancer detection are shown in Figure A21 and Figure A22, respectively.

Table 6: Selection Effect by Cost Sharing

	(1)	(2)	(3)	(4)
Panel A. Stomach cancer, men				
Dependent variable	Cancer screening result			Cancer detection
	Normal	Cancer suspicion	Other disease	
Discontinuity at the cutoff	0.06878**	0.00123	-0.07001**	0.00024
	(0.01132)	(0.00315)	(0.01103)	(0.00030)
Mean at (0, 0.3]	0.2916	0.0277	0.3598	0.0050
N	97,186	97,186	97,186	130,413
Panel B. Stomach cancer, women				
Dependent variable	Cancer screening result			Cancer detection
	Normal	Cancer suspicion	Other disease	
Discontinuity at the cutoff	0.05642**	-0.00598**	-0.05044**	0.00012
	(0.00704)	(0.00089)	(0.00731)	(0.00021)
Mean at (0, 0.3]	0.4478	0.0272	0.3952	0.0017
N	162,907	162,907	162,907	185,371
Panel C. Breast cancer, women				
Dependent variable	Cancer screening result			Cancer detection
	Normal	Cancer suspicion	Other disease	
Discontinuity at the cutoff	0.03899**	-0.00025	-0.03874**	0.00006
	(0.00825)	(0.00113)	(0.00759)	(0.00026)
Mean at (0, 0.3]	0.4338	0.0025	0.1523	0.0013
N	162,979	162,979	162,979	186,922

Note: The sample consists of screening takers only. The dependent variables are cancer screening result and cancer detection in the two years of the screening offer. Each cell represents the coefficient β from a different local linear regression of equation (1) with a bandwidth of 0.3. The running variable is the standardized insurance contribution. A rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution are reported in parentheses. **, * and + indicates statistical significance at the 1%, 5% and 10% levels, respectively. The sensitivity analysis results are shown in Figure A23 and Figure A24, respectively.

Table 7: Characteristics of Compliers, Always Takers, and Never Takers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Stomach cancer screening, men	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 (Years 1-2)	0.103	1.000	1.000	0.000			
Stomach cancer (Years 1-6)	0.542	2.042	2.090	0.363	8.8	2038.7	304.0
General health (Years 1-2)	0.568	1.106	1.134	0.457	10.0	698.4	224.8
General health (Years 1-6)	1.713	2.561	2.811	1.455	35.6	303.1	104.3
Panel A3. Mortality							
Cumulative stomach cancer detection (six year)	0.0130	0.0167	0.0146	0.0125	3.0	28.8	2.9
Cumulative stomach cancer mortality (six year)	0.0051	0.0034	0.0024	0.0054	3.5	21.2	10.1
Cumulative all-cause mortality (six year)	0.0727	0.0493	0.0332	0.0760	15.4	77.4	38.9
Panel B. Stomach cancer screening, women	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 (Years 1-2)	0.133	1.000	1.000	0.000			
Stomach cancer (Years 1-6)	0.657	2.085	2.042	0.438	10.7	2009.9	384.8
General health (Years 1-2)	0.352	1.073	0.965	0.291	64.8	1075.1	363.5
General health (Years 1-6)	1.235	2.544	2.380	1.107	33.6	837.7	245.0
Panel B3. Mortality							
Cumulative stomach cancer detection (six year)	0.0052	0.0049	0.0046	0.0050	1.0	0.7	1.1
Cumulative stomach cancer mortality (six year)	0.0034	0.0011	0.0006	0.0037	3.7	34.5	20.9
Cumulative all-cause mortality (six year)	0.0525	0.0140	0.0113	0.0569	5.2	148.4	75.8
Panel C. Breast cancer screening, women	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 (Years 1-2)	0.136	1.020	1.010	0.000			
Breast cancer (Years 1-6)	0.690	2.119	2.109	0.468	2.6	1952.6	390.2
General health (Years 1-2)	0.352	1.076	0.967	0.289	61.7	1094.4	351.7
General health (Years 1-6)	1.235	2.546	2.397	1.103	29.9	846.0	245.4
Panel C3. Mortality							
Cumulative breast cancer detection (six year)	0.0052	0.0057	0.0064	0.0051	1.8	6.3	3.1
Cumulative breast cancer mortality (six year)	0.0022	0.0001	0.0002	0.0026	1.4	40.0	19.2
Cumulative all-cause mortality (six 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)) and 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 the t-statistics from the two-sample t-test comparing compliers with always takers, compliers with never takers, and always takers with never takers, respectively.

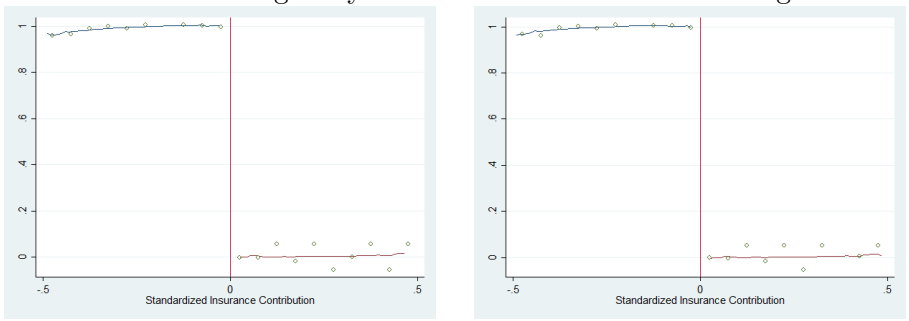
Table 8: Effect on Cumulative Mortality (Six Years)

	(1)	(2)	(3)	(4)	(5)
Panel A. Men					
Dependent variable	Stomach cancer mortality	All-cancer mortality	Non-cancer mortality	All-cause mortality	
Discontinuity at the cutoff	-0.00062+	-0.00147+	-0.00202	-0.00349	
	(0.00034)	(0.00078)	(0.00155)	(0.00210)	
Mean at (0, 0.3]	0.0052	0.0274	0.0471	0.0745	
N	1,260,729	1,260,729	1,260,729	1,260,729	
Panel B. Women					
Dependent variable	Stomach cancer mortality	Breast cancer mortality	All-cancer mortality	Non-cancer mortality	All-cause mortality
Discontinuity at the cutoff	-0.00011	0.00001	-0.00014	0.00079	0.00065
	(0.00015)	(0.00012)	(0.00042)	(0.00101)	(0.00126)
Mean at (0, 0.3]	0.0037	0.0023	0.0140	0.0432	0.0572
N	1,396,081	1,396,081	1,396,081	1,396,081	1,396,081

Note: The dependent variables are six-year cumulative cancer, non-cancer, and all-cause mortality. Each cell represents the coefficient β from a different local linear regression of equation (1) with a bandwidth of 0.3. The running variable is the standardized insurance contribution. A rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution are reported in parentheses. **, * and + indicate statistical significance at the 1%, 5% and 10% levels, respectively. The sensitivity analysis results are shown in Figure A27.

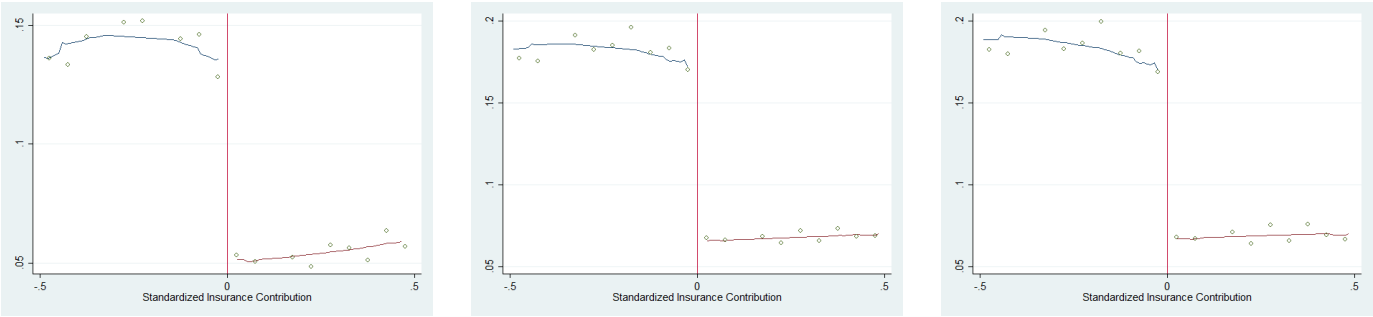
Figure 1: Eligibility for and Take-up of Public Cancer Screening

Panel A. Eligibility for Free Public Cancer Screening



Men Women

Panel B. Effect of Cost-Sharing on Cumulative Public Cancer Screening Take-up, Years 1-2



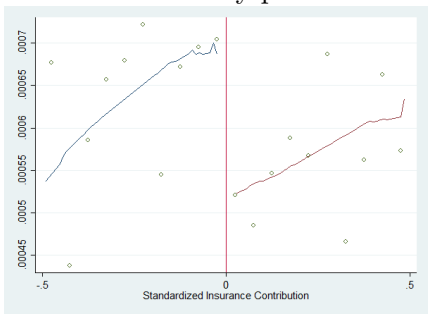
Stomach cancer, Men Stomach cancer, Women Breast cancer, Women

Note: The dependent variables in Panels A and B are eligibility for free public cancer screening and cancer screening take-ups, respectively. The running variable is the standardized insurance contribution. The open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are the fitted values from a local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. This is estimated separately on each side of the cutoff. The sensitivity analysis results are shown in Figure A15 and Figure A17, respectively.

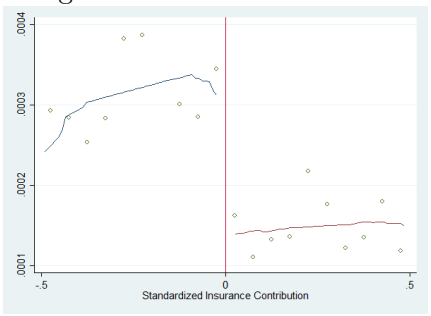
Figure 2: Effect on Cumulative Cancer Detections, Years 1-2

Panel A. Cancer detection by public cancer screening

Stomach cancer, Men

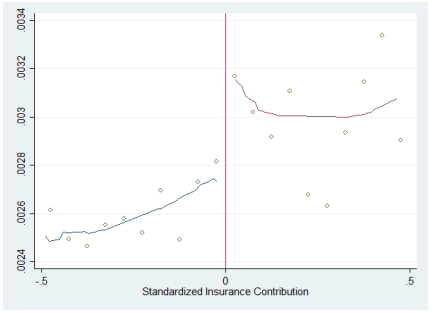


Stomach cancer, Women



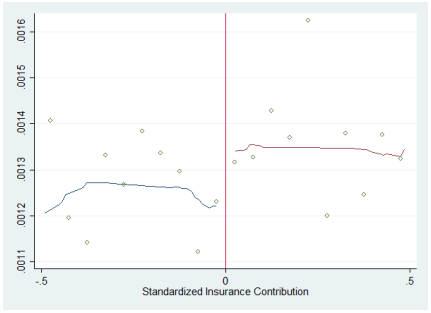
Breast cancer, Women

Panel B. Cancer detection by other channels



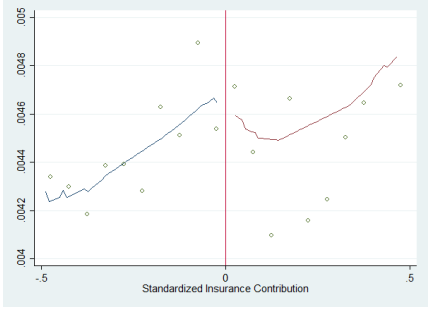
Stomach cancer, Men

Stomach cancer, Women

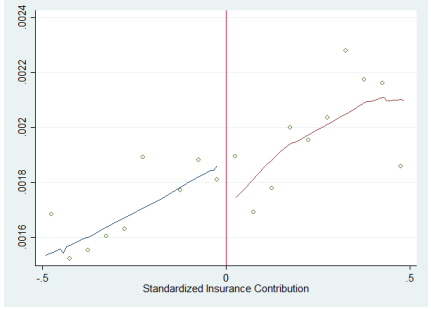


Breast cancer, Women

Panel C. Total cancer detection



Stomach cancer, Men



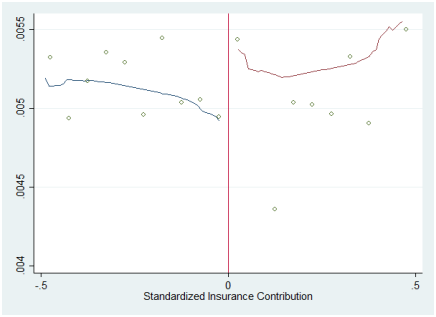
Stomach cancer, Women

Breast cancer, Women

Note: The dependent variables in Panels A, B, and C are two-year cumulative cancer detections by public cancer screening, by other channels, and overall cancer detections, respectively. The running variable is the standardized insurance contribution. The open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are the fitted values from a local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. This is estimated separately on each side of the cutoff. The sensitivity analysis results are shown in Figure A19. The corresponding results according to the alternative cancer detection definition are shown in Figure A21.

Figure 3: Effect on Six-year Cumulative Mortality

Panel A. Men



Stomach cancer mortality

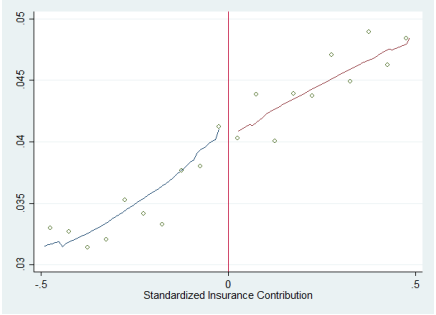
Non-cancer mortality

All-cause mortality

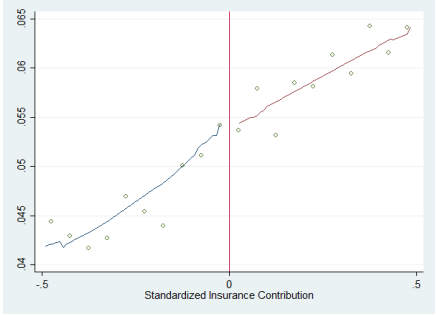
Panel B. Women

Stomach cancer mortality

Breast cancer mortality



Non-cancer mortality



All-cause mortality

Note: The dependent variables in Panels A and B are six-year cumulative cancer, non-cancer and all-cause mortalities in men and women, respectively. The running variable is the standardized insurance contribution. The open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are fitted values from a local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. This is estimated separately on each side of the cutoff. The shaded regions are 95% confidence intervals. The sensitivity results are shown in Figure A27.

A Appendix Tables and Figures

Table A1: The Price of Cancer Screening

Unit($)

	Year	2002	2003	2004
	Administration 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 A2: McCrary test

		Bandwidth							
		0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5
Panel A. Men									
	0	**-48.4**	**-53.5**	**-49.0**	**-71.8**	**-72.9**	**-69.7**	**-73.0**	**-72.8**
	-0.1	64.7	63.6	65.1	65.0	47.6	45.0	49.0	36.6
	-0.2	**149.9**	**137.7**	134.5	141.3	101.2	105.6	111.5	93.7
	-0.3	**310.2**	**304.4**	**300.8**	**281.8**	300.0	281.9	262.7	260.8
Cutoff	0.1	-129.0	-137.0	-130.9	-132.1	-137.2	-149.9	-151.5	-150.6
	0.2	**-186.4**	**-189.4**	-185.0	-182.5	-192.8	-192.5	-202.5	-196.2
	0.3	**-140.6**	**-142.3**	**-136.1**	**-144.8**	-138.6	-144.9	-142.2	-136.0
	0.4	**-280.6**	**-280.0**	**-273.9**	**-282.0**	**-275.4**	**-269.4**	-258.0	-270.5
	0.5	**-250.5**	**-256.1**	**-249.7**	**-242.0**	**-246.8**	**-257.8**	**-240.5**	**-237.1**
Panel B. Women									
	0	**-134.1**	-130.2	**-136.5**	**-149.9**	**-147.7**	**-144.6**	**-158.1**	**-162.6**
	-0.1	-8.6	-4.8	-16.1	-11.3	-33.1	-38.0	-43.5	-49.8
	-0.2	**85.8**	**84.6**	76.9	60.0	54.6	60.8	44.4	30.5
	-0.3	**287.1**	**280.6**	**271.6**	**265.1**	253.0	234.8	241.6	230.1
Cutoff	0.1	-219.0	-216.0	-221.2	-228.3	-227.3	-228.3	-230.8	-240.2
	0.2	**-260.9**	**-261.9**	-268.7	-264.5	-269.7	-268.5	-271.1	-279.5
	0.3	**-217.1**	**-210.2**	**-216.1**	**-211.4**	-215.0	-201.3	-221.8	-213.7
	0.4	**-201.2**	**-190.9**	**-195.6**	**-186.6**	**-182.0**	**-185.3**	-206.1	-186.3
	0.5	**-327.0**	**-326.5**	**-331.2**	**-328.3**	**-319.7**	**-306.3**	**-290.2**	**-314.2**

Note: This table presents the t-statistics for a test for the smoothness of frequency density at the cutoff of zero and other falsified cutoffs from -0.3 to 0.5 with different bandwidths from 0.15 to 0.5 (McCrary (2008)). If there is a manipulation at the original cutoff at zero, falsification tests which includes the original cutoff could be problematic. Bolded cells are those without inclusion of the original cutoff.

Table A3: Smoothness around the Cutoff

Dependent variables	(1) Age	(2) Residential Area (Urban)	(3) Employment status	(4) Company Size	(5) Medical Expenditure ($)	(6) General health screening
Bandwidth	0.3	0.3	0.3	0.3	0.3	0.3
Panel A. Men						
Discontinuity at the cutoff	-0.45**	0.002	0.019	-161.3**	-3.8	-0.018
	(0.21)	(0.002)	(0.019)	(53.1)	(7.0)	(0.021)
N	1,260,729	1,244,826	1,260,729	1,260,729	1,126,402	1,260,729
Panel B. Women						
Discontinuity at the cutoff	-0.30	0.003	0.004	-200.2**	0.245	0.053**
	(0.18)	(0.003)	(0.025)	(69.8)	(8.1)	(0.015)
N	1,396,081	1,377,965	1,396,081	1,396,081	1,318,282	1,396,081

Note: Company size is measured by number of employees. Each cell represents the coefficient β from a different local linear regression of equation (1) with a bandwidth of 0.3. The running variable is the standardized insurance contribution. A rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution are reported in parentheses. **, * and + indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table A4: Effect on Medical Expenditure in the First Year of Cancer Detection (Early Detection)

	(1)	(2)	(3)	(4)	(5)	(6)
Year	Cancer detected within two years			Cancer detected after three to six years		
Gender	Men	Women	Women	Men	Women	Women
Cancer	Stomach	Stomach	Breast	Stomach	Stomach	Breast
Discontinuity at the cutoff	40.8	169.7	-220.3	-84.0	374.4	-29.9
	(182.5)	(436.1)	(310.6)	(166.7)	(342.2)	(364.5)
Mean at (0, 0.3]	5480.7	5174.6	5802.5	6061.3	5658.1	6348.4
N	5,237	2,373	2,163	10,595	4,785	4,562

Note: The dependent variable is the medical expenditure in the first year of cancer detection, which is a proxy for detection stage. Each cell represents the coefficient β from a different local linear regression of equation (1) with a bandwidth of 0.3. The running variable is the standardized insurance contribution. A rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution are reported in parentheses. **, * and + indicate statistical significance at the 1%, 5% and 10% levels, respectively. The sensitivity results are shown in Figure A25.

Table A5: Comparison of Compliers with Always Takers and Never Takers

	(1)	(2)
Dependent Variable	Six-Year Cumulative Cancer Mortality	
Panel A. Stomach cancer, men		
	Among takers	Among non-takers
	Compliers vs. Always takers	Compliers vs. Never takers
Discontinuity at the cutoff	0.00070	-0.00053
	(0.00058)	(0.00035)
Mean at (0, 0.3]	0.0024	0.0053
N	130,413	1,130,316
Panel B. Stomach cancer, women		
	Among takers	Among non-takers
	Compliers vs. Always takers	Compliers vs. Never takers
Discontinuity at the cutoff	0.00027	0.00022
	(0.00023)	(0.00018)
Mean at (0, 0.3]	0.0006	0.0039
N	185,371	1,210,710
Panel C. Breast cancer, women		
	Among takers	Among non-takers
	Compliers vs. Always takers	Compliers vs. Never takers
Discontinuity at the cutoff	0.00014	0.00029+
	(0.00025)	(0.00015)
Mean at (0, 0.3]	0.0003	0.0025
N	186,922	1,209,159

Note: The dependent variable is six-year cumulative cancer mortality. We restrict the sample to screening takers in Column (1) and screening non-takers in Column (2). Column (1) compares compliers with always takers and Column (2) compares compliers with never takers. Each cell represents the coefficient β from a different local linear regression of equation (1) with a bandwidth of 0.3. The running variable is the standardized are reported insurance contribution. A rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution in parentheses. **, * and + indicate statistical significance at the 1%, 5% and 10% percent level?, respectively. The sensitivity results are shown in Figure A26.

Table A6: Effect on Other Behavioral Responses

	(1)	(2)	(3)	(4)
	Health screening take-up	Medical expenditure ($)		
	Years 3-6	Years 1-2	Years 3-5	Years 1-5
Panel A. Men				
Discontinuity at the cutoff	-0.0410+	-1.1	2.1	11.9
	(0.021)	(12.5)	(27.8)	(34.3)
Mean at (0, 0.3]	0.955	381.8	1623.9	1957.6
N	1,260,729	970,661	905,003	841,751
Panel B. Women				
Discontinuity at the cutoff	-0.0131	12.9	-18.0	-8.5
	(0.013)	(8.8)	(20.9)	(27.6)
Mean at (0, 0.3]	0.773	315.7	1521.3	1812.3
N	1,396,081	1,219,294	1,164,312	1,123,043

Note: The dependent variables are future health screening take-up and medical expenditure. Each cell represents the coefficient β from a different local linear regression of equation (1) with a bandwidth of 0.3. The running variable is the standardized insurance contribution. A rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution are reported in parentheses. **, * and + indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table A7: Behavioral Responses by Cancer Screening Result

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Gender	Men					Women					
Dependent variable	Future screening take-ups		Medical Expenditure			Future screening take-ups			Medical Expenditure		
	Health	Stomach ca Cancer	Years 1-2	Years 3-5	Years 1-5	Health	Stomach ca Cancer	Breast ca Cancer	Years 1-2	Years 3-5	Years 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 dependent variables are future screening take-ups and medical expenditure. The running variable is the standardized insurance contribution. A rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution in parentheses. **, * and + indicate statistical significance at the 1%, 5% and 10% levels, respectively.

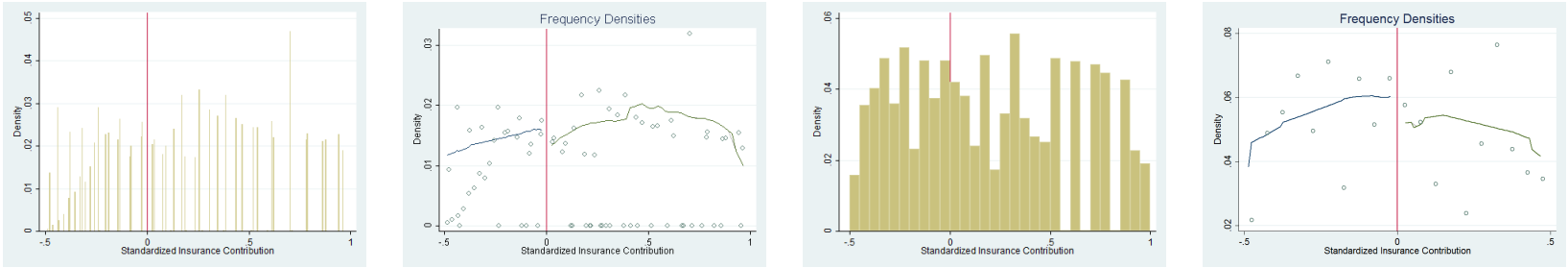
Table A8: Drop out from NHIC

	(1)	(2)	(3)	(4)	(5)	(6)
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6
Panel A. Men						
Discontinuity at the cutoff	0.00034	0.00025	0.00083	0.00058	0.00094	0.00049
	(0.00044)	(0.00049)	(0.00068)	(0.00091)	(0.00068)	(0.00125)
Mean at (0, 0.3]	0.007	0.010	0.013	0.016	0.016	0.451
N	1,260,729	1,260,729	1,260,729	1,260,729	1,260,729	1,260,729
Panel B. Women						
Discontinuity at the cutoff	0.00018	-0.00069+	-0.00021	-0.00036	-0.00045	-0.00140
	(0.00030)	(0.00036)	(0.00028)	(0.00045)	(0.00031)	(0.00135)
Mean at (0, 0.3]	0.008	0.012	0.017	0.021	0.022	0.463
N	1,396,081	1,396,081	1,396,081	1,396,081	1,396,081	1,396,081

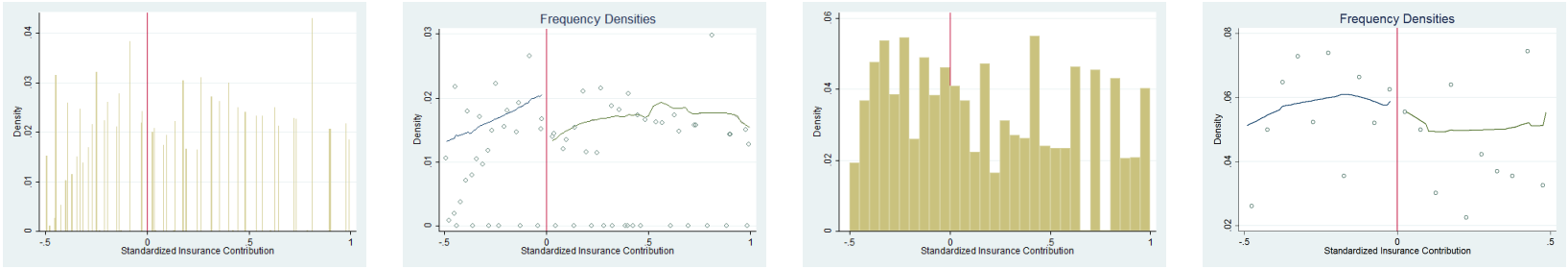
Note: Each cell represents the coefficient β from a different local linear regression of equation (1). The running variable is the standardized insurance contribution. A rectangular kernel is used. Robust standard errors clustered at standardized insurance contribution are reported in parentheses. **,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

Figure A1: Density of Insurance Contribution

Panel A. Histogram, Men



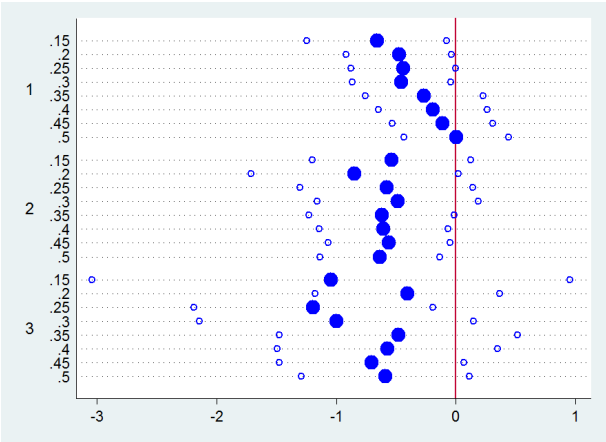
Panel B. Histogram, Women



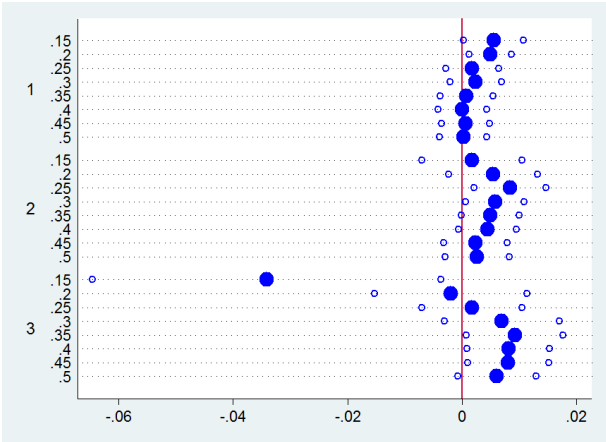
Note: Bin size 0.005 and 0.05 are used.

Figure A2: Covariate Balance, Men

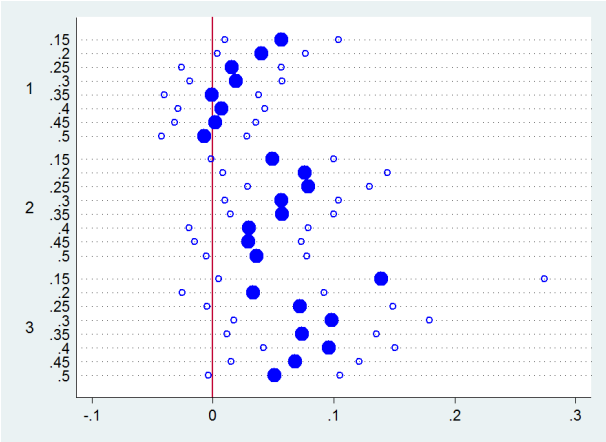
Panel A. Age



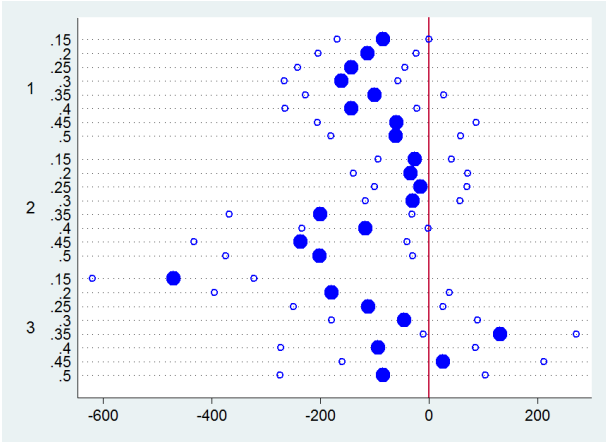
Panel B. Urban



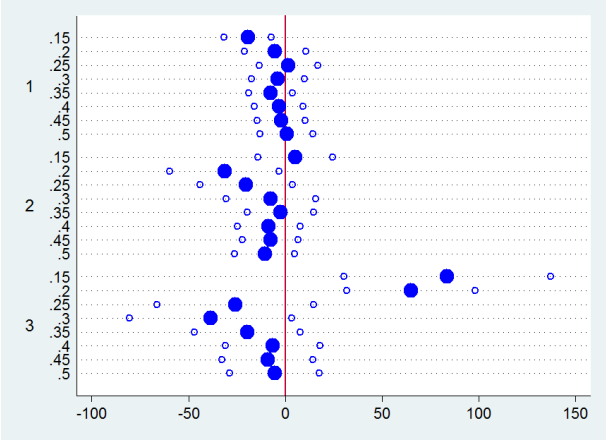
Panel C. Employment status



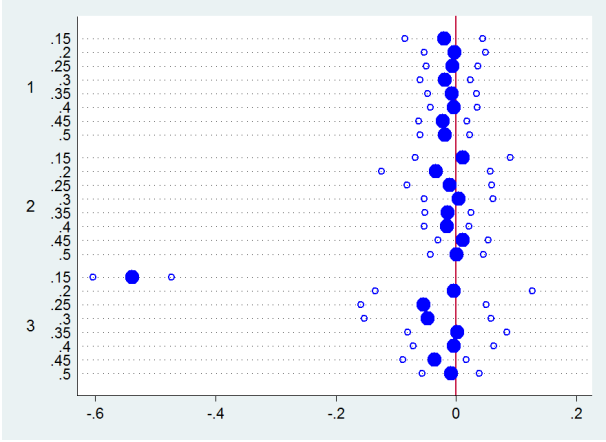
Panel D. Company size



Panel E. Medical expenditure



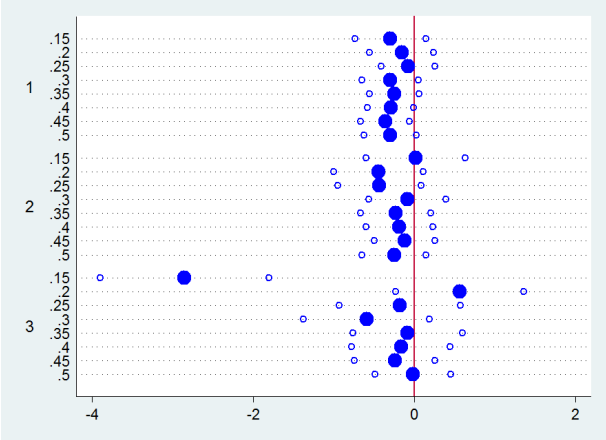
Panel F. General health screening take-up



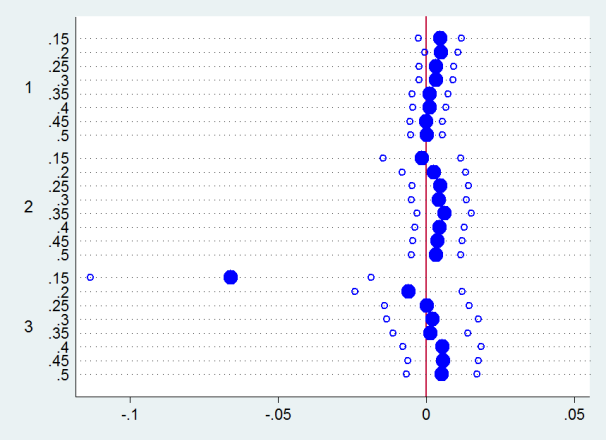
Note: The dependent variables are baseline characteristics such as age, residential area, employment status, size of the company (number of employees), medical expenditure, and health screening take-up. Each figure displays estimates of β from local linear, quadratic, and cubic regressions at different bandwidths in increments of 0.05 from 0.15 to 0.5. Degree of $f(\cdot)$ and the size of bandwidth are on the y-axis. Coefficient estimate and the lower and upper 95% confidence bounds are on the x-axis. The center solid circle represents the coefficient estimate and the open circles indicate the lower and upper 95% confidence bounds.

Figure A3: Covariate Balance, Women

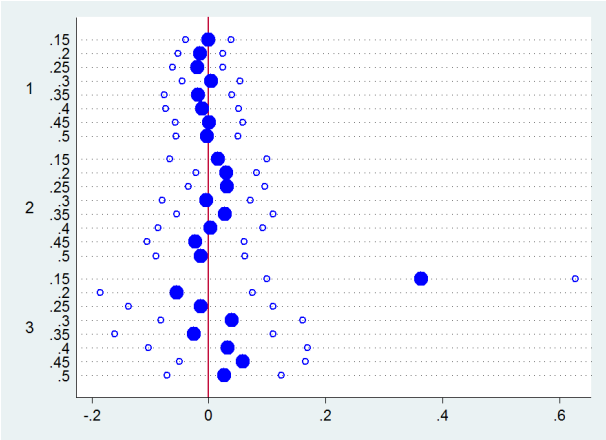
Panel A. Age



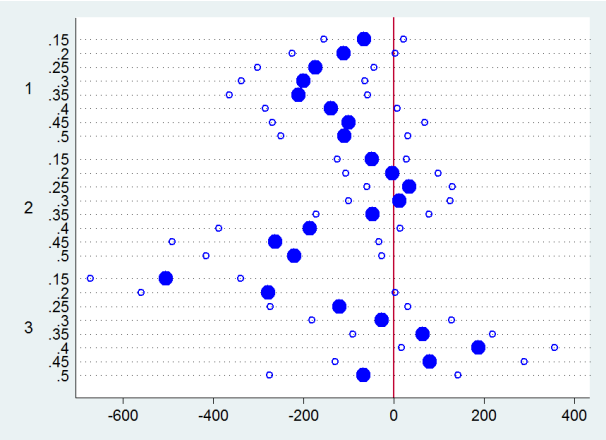
Panel B. Urban



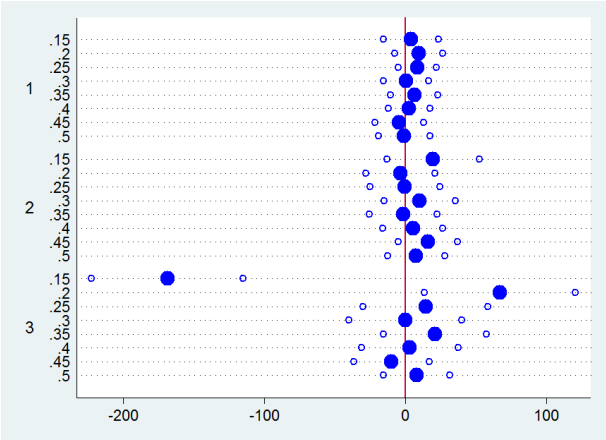
Panel C. Employment status



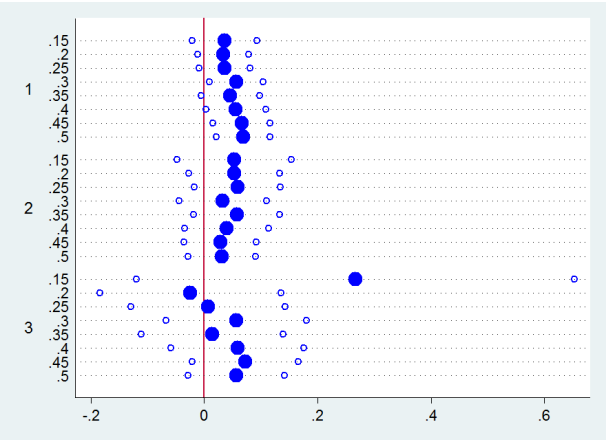
Panel D. Company size



Panel E. Medical expenditure



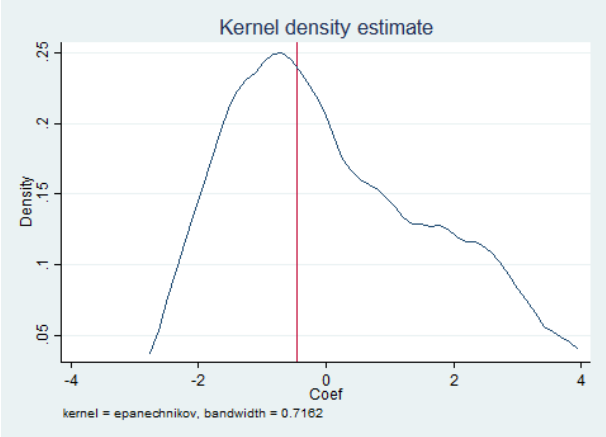
Panel F. General health screening take-up



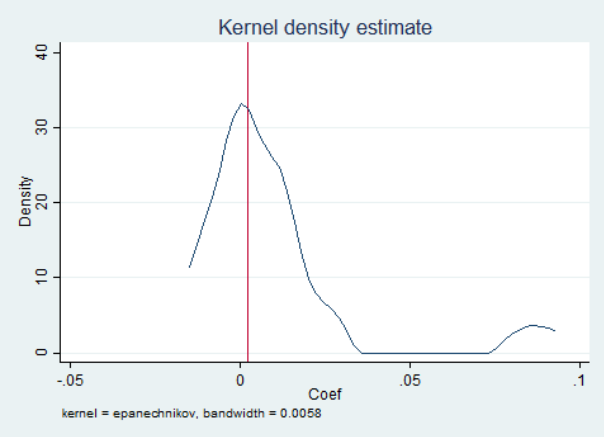
Note: The dependent variables are baseline characteristics such as age, residential area, employment status, size of the company (number of employees), medical expenditure, and health screening take-up. Each figure displays estimates of β from local linear, quadratic, and cubic regressions at different bandwidths in increments of 0.05 from 0.15 to 0.5. Degree of $f(\cdot)$ and the size of bandwidth are on the y-axis. Coefficient estimate and the lower and upper 95% confidence bounds are on the x-axis. The center solid circle represents the coefficient estimate and the open circles indicate the lower and upper 95% confidence bounds.

Figure A4: The Falsification Test for Covariate Balance, Men

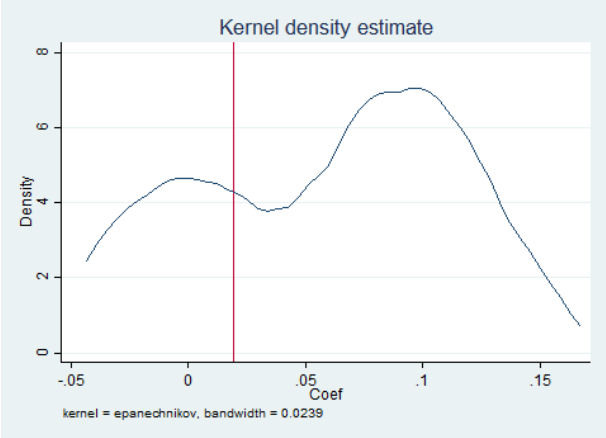
Panel A. Age



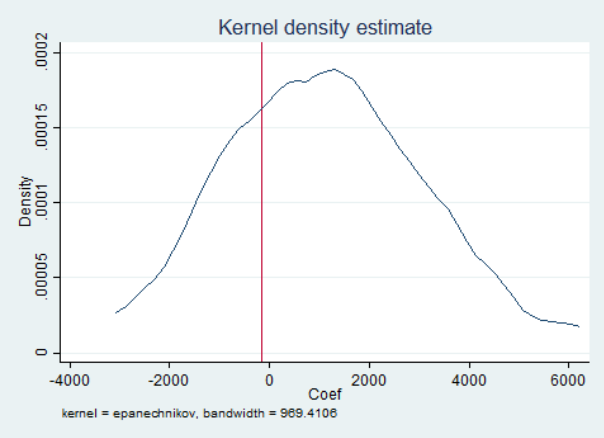
Panel B. Urban



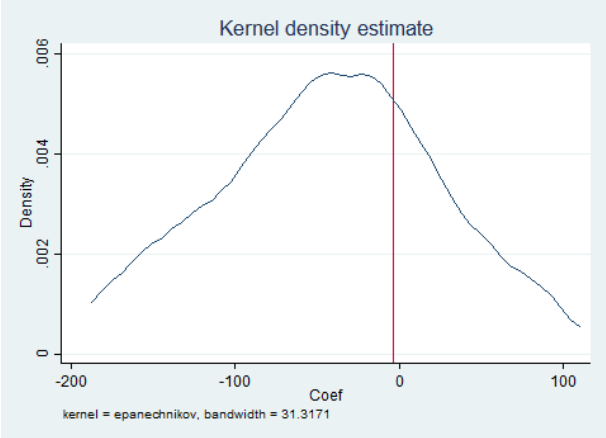
Panel C. Employment status



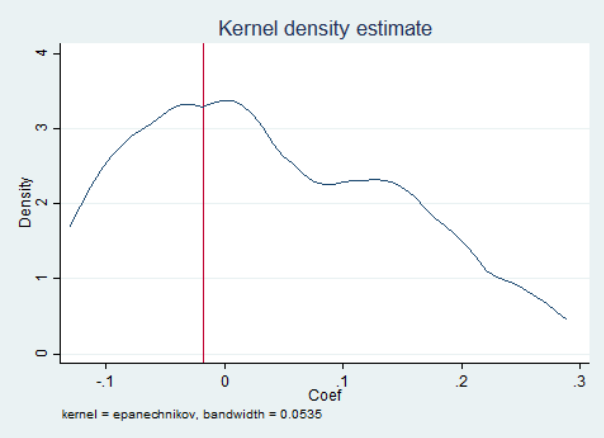
Panel D. Company size



Panel E. Medical expenditure



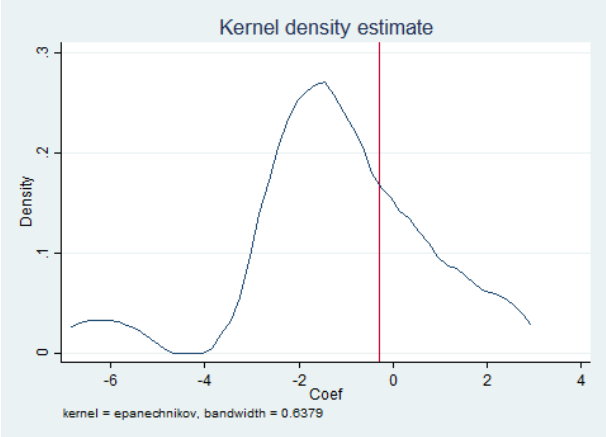
Panel F. General health screening take-up



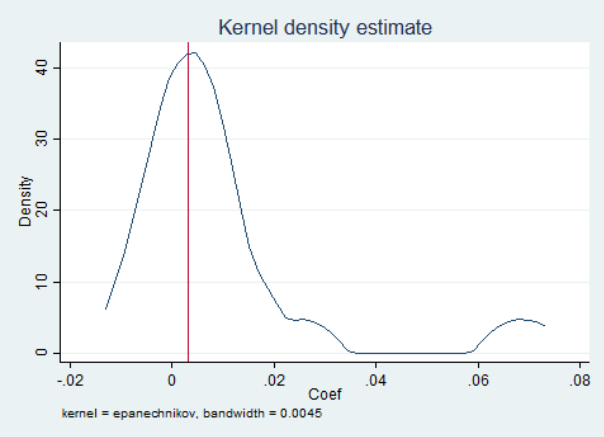
Note: The dependent variables are baseline characteristics such as age, residential area, employment status, size of the company (number of employees), medical expenditure, and health screening take-up. Each figure displays the distribution of the estimates of β from a local linear regression with a bandwidth of 0.3 at the falsified cutoffs from [-0.4, -0.3) and (0.3, 0.7], in increments of 0.05. The vertical line shows the actual coefficient estimate from the regression estimated with the true cutoff.

Figure A5: The Falsification Test for Covariate Balance, Women

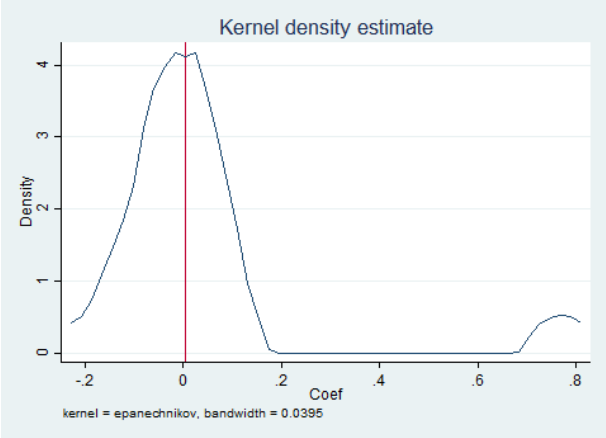
Panel A. Age



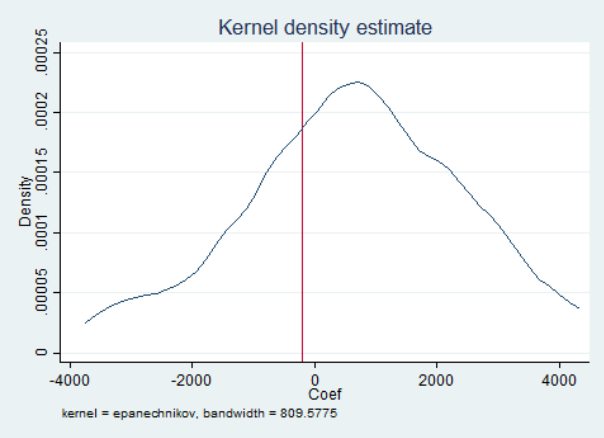
Panel B. Urban



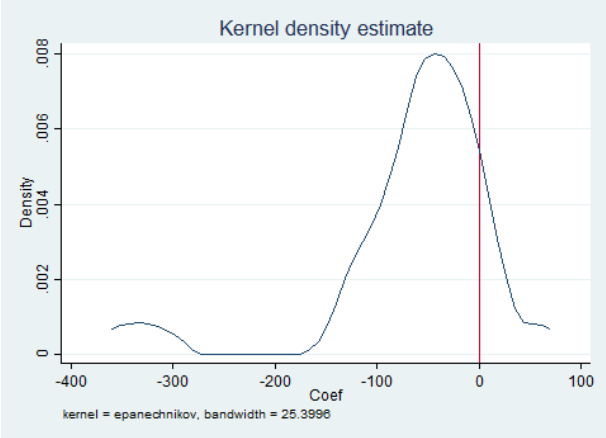
Panel C. Employment status



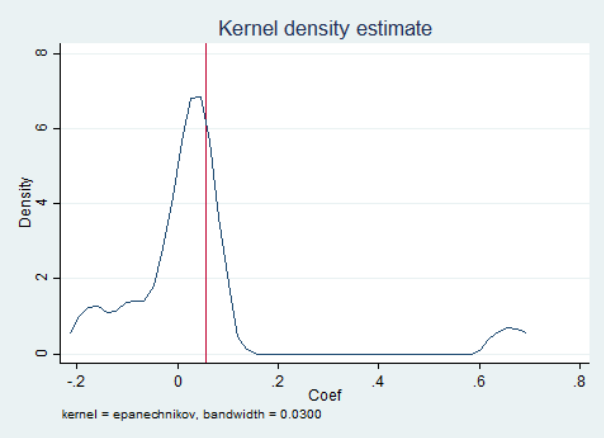
Panel D. Company Size



Panel E. Medical expenditure



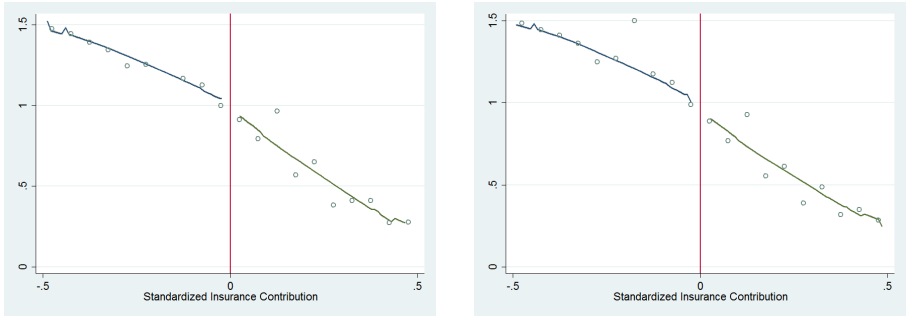
Panel F. General health screening take-up



Note: The dependent variables are baseline characteristics such as age, residential area, employment status, size of the company (number of employees), medical expenditure, and health screening take-up. Each figure displays the distribution of the estimates of β from a local linear regression with a bandwidth of 0.3 at the falsified cutoffs from [-0.4, -0.3) and (0.3, 0.7], in increments of 0.05. The vertical line shows the actual coefficient estimate from the regression estimated with the true cutoff.

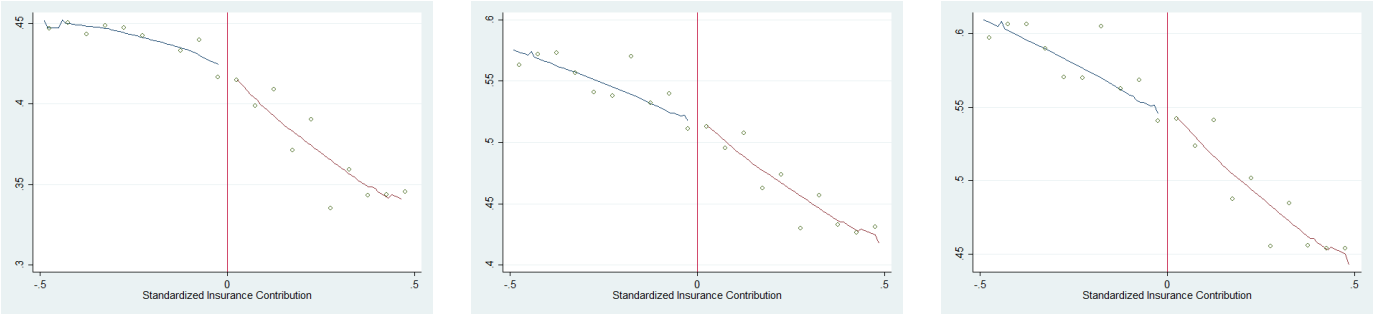
Figure A6: Future Eligibility for and Take-up of Public Cancer Screening, Years 3-6

Panel A. Future eligibility for free public cancer screening, Years 3-6



Men Women

Panel B. Future cancer screening take-ups, Years 3-6

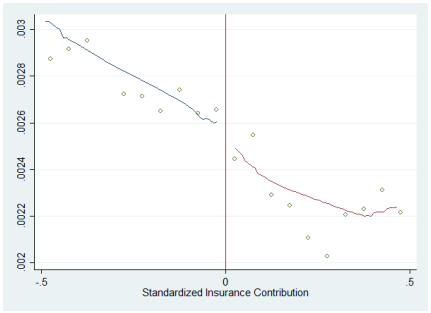


Stomach cancer, Men Stomach cancer, Women Breast cancer, Women

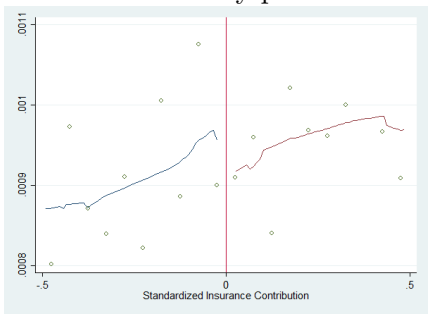
Note: The dependent variables in Panels A and B are future eligibility for free public cancer screening and cancer screening take-ups in Years 3-6, respectively. The running variable is the standardized insurance contribution. The open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are the fitted values from a local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. This 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. Dependent variable is an indicator for eligibility.

Figure A7: Effect on Future Cancer Detections during Years 3-6

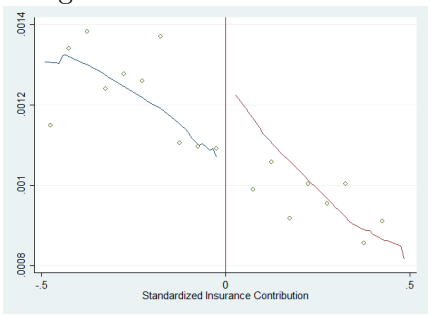
Panel A. Cancer detection by public cancer screening



Stomach cancer, Men



Stomach cancer, Women



Breast cancer, Women

Panel B. Cancer detection by other channels

Stomach cancer, Men

Stomach cancer, Women

Breast cancer, Women

Panel C. Overall cancer detection

Stomach cancer, Men

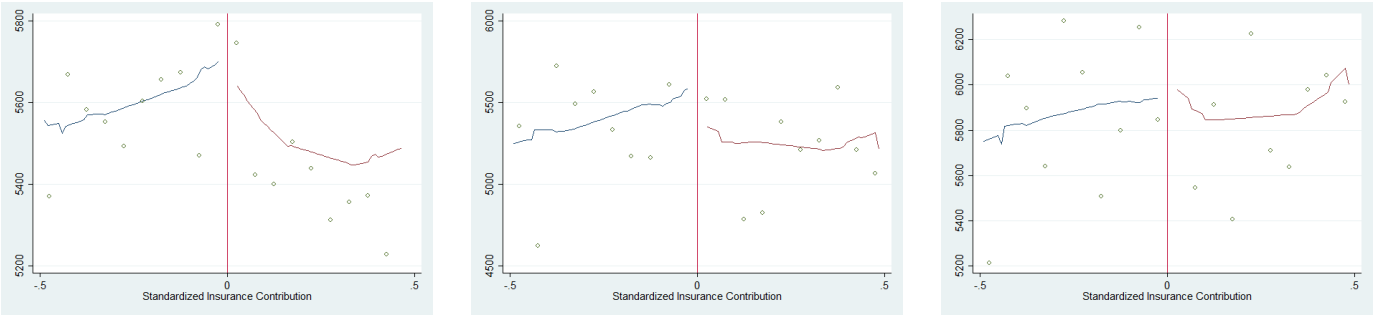
Stomach cancer, Women

Breast cancer, Women

Note: The dependent variables in Panels A, B, and C are cumulative cancer detections between years three and six by public cancer screening, by other channels, and overall cancer detections, respectively. The running variable is the standardized insurance contribution. The open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are the fitted values from a local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. This is estimated separately on each side of the cutoff.

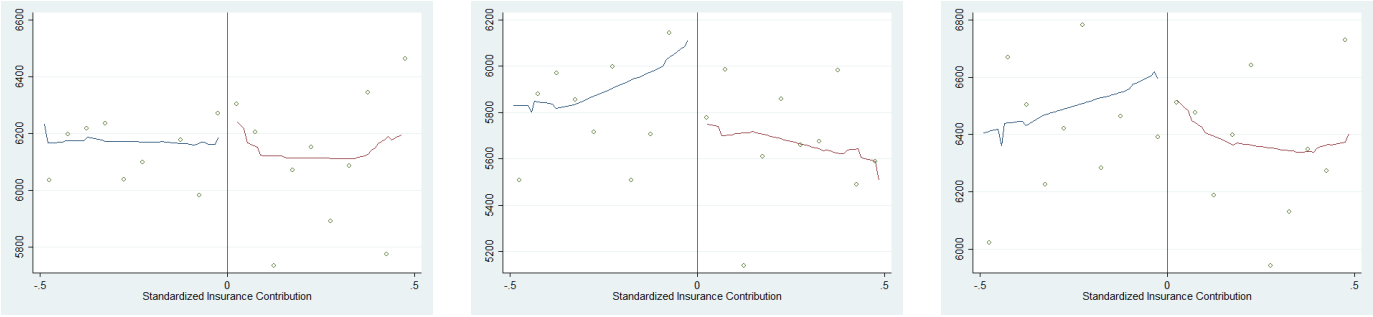
Figure A8: Effect on Medical Expenditure in the First Year of Cancer Detection (Early Detection)

Panel A. Cancer detected within two years



Stomach cancer, Men | Stomach cancer, Women | Breast cancer, Women

Panel B. Cancer detected after three to six years

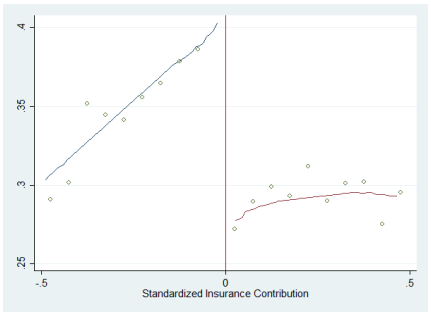


Stomach cancer, Men | Stomach cancer, Women | Breast cancer, Women

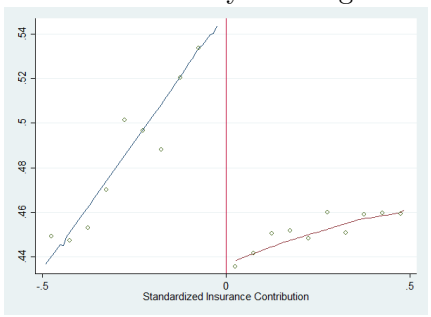
Note: The dependent variables in Panels A and B are the medical expenditures in the first year of cancer detection in Year 1-2 and 3-6, respectively. The running variable is the standardized insurance contribution. The open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are fitted values from a local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. This is estimated separately on each side of the cutoff. The shaded regions are 95% confidence intervals. The sensitivity results are shown in Figure A25.

Figure A9: Selection Effect by Cost sharing: Screening Results Among Screening-takers

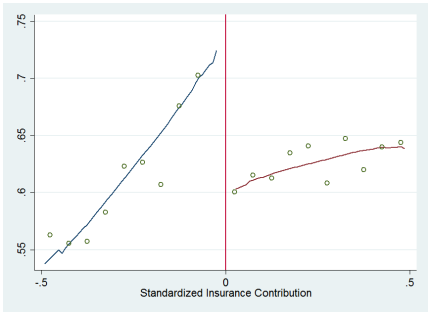
Panel A. Probability of being normal



Stomach cancer, Men



Stomach cancer, Women

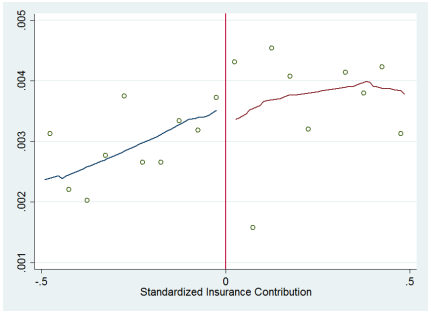


Breast cancer, Women

Panel B. Probability of being cancer suspicion

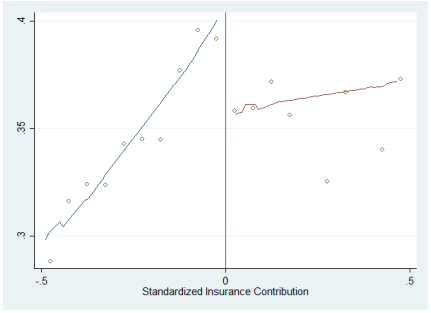
Stomach cancer, Men

Stomach cancer, Women



Breast cancer, Women

Panel C. Probability of detecting other disease



Stomach cancer, Men

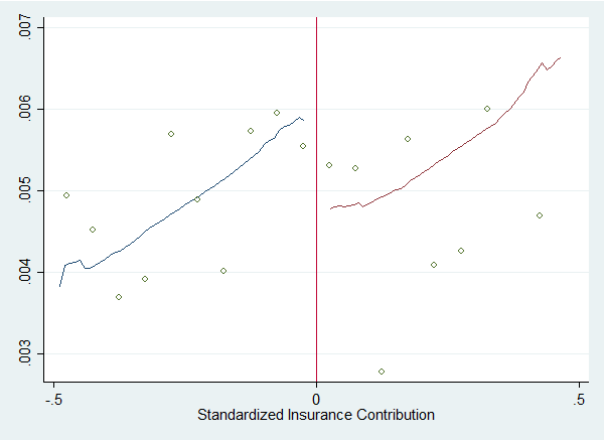
Stomach cancer, Women

Breast cancer, Women

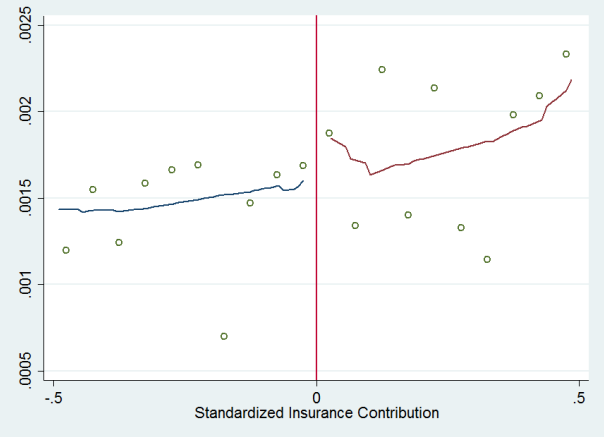
Note: The sample is restricted to screening takers. The dependent variables in Panels A, B, and C are probability of being normal, being cancer suspicion, and detecting other disease, respectively. The running variable is the standardized insurance contribution. The open circles plot the mean of the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

Figure A10: Selection Effect by Cost sharing: Cancer Detection among Screening-takers

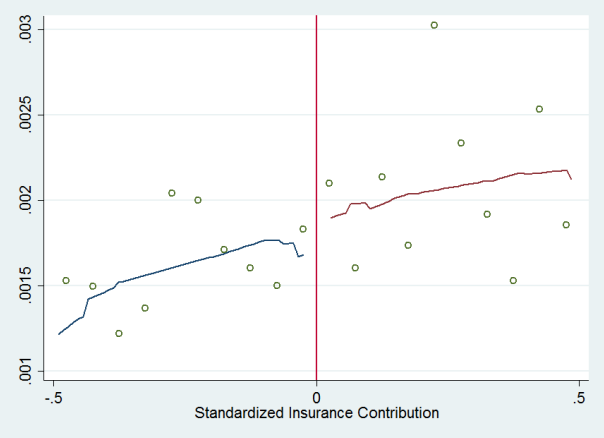
Panel A. Stomach cancer detection, Men



Panel B. Stomach cancer detection, Women



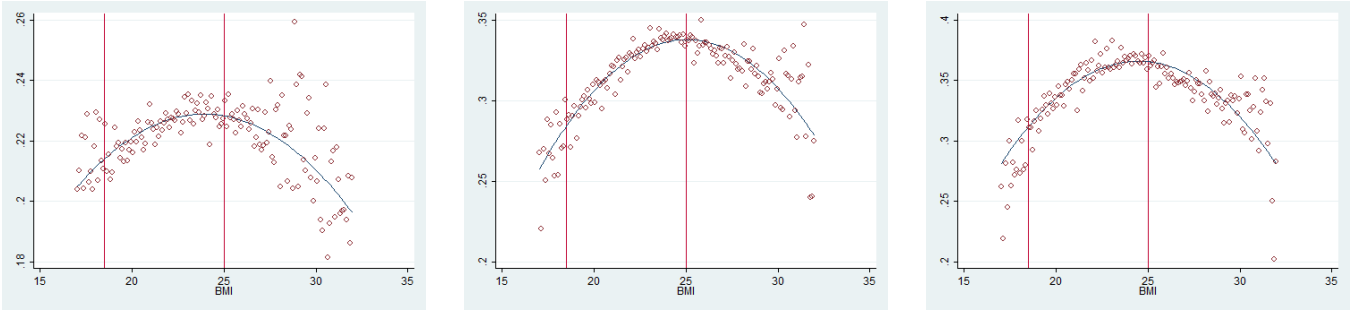
Panel C. Breast cancer detection, Women



Note: The sample is restricted to screening takers. The dependent variables in Panels A, B, and C are stomach cancer detection in Men, and stomach and breast cancer detections in women, respectively. The running variable is the standardized insurance contribution. The open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are the fitted values from local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. This is estimated separately on each side of the cutoff.

Figure A11: Probability of Cancer Screening Take-up by Health Status

Panel A. BMI

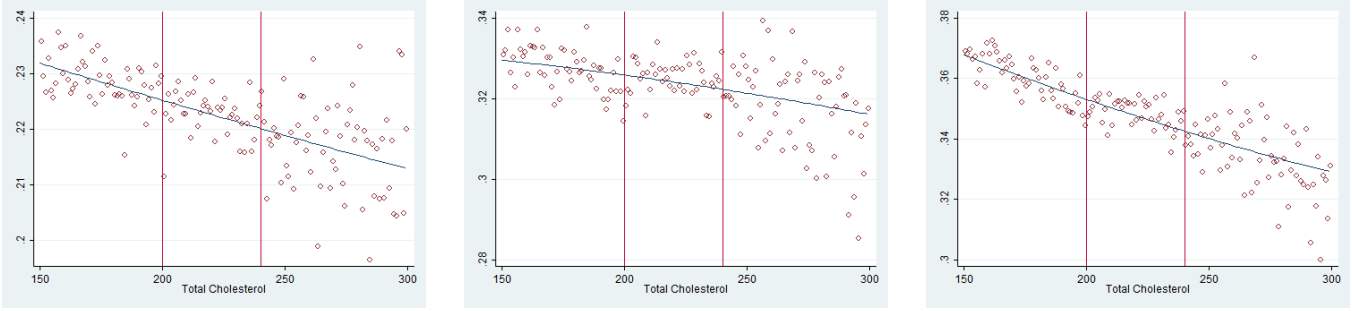


Stomach cancer, Men | Stomach cancer, Women | Breast cancer, Women

Panel B. Blood sugar level

Stomach cancer, Men | Stomach cancer, Women | Breast cancer, Women

Panel C. Total Cholesterol



Stomach cancer, Men | Stomach cancer, Women | Breast cancer, Women

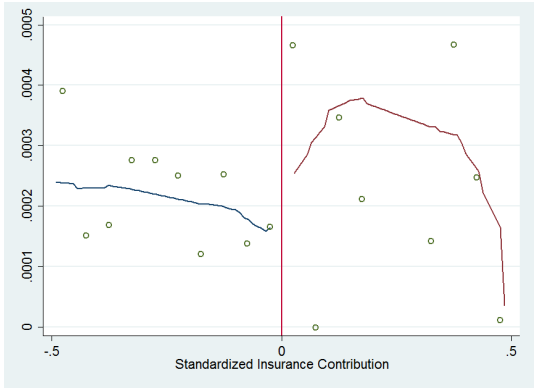
Note: Each figure shows a probability of a cancer screening take-up in the second round by the BMI, blood sugar and cholesterol level measured at the first round. The normal range of the BMI is between 18.5 and 25. A normal blood sugar level is under 110, and diabetes mellitus (DM) is diagnosed if it is greater than 120. A normal total cholesterol level is under 200, and hyperlipidemia is diagnosed if it is over 240.

Figure A12: Six-Year Cumulative Cancer Mortality: A Comparison of Compliers, Always takers, and Never takers

Panel A. Compliers vs. Always takers: Screening takers only sample

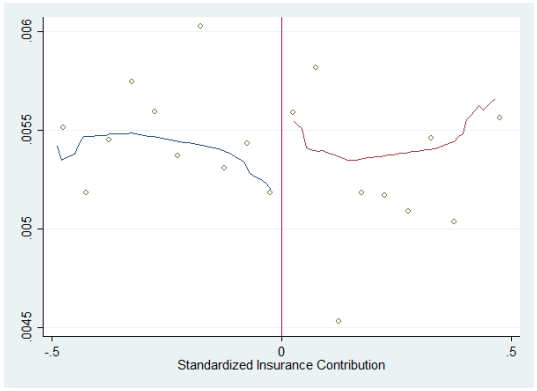
Men, Stomach cancer

Female, Stomach cancer



Women, Breast cancer

Panel B. Never takers vs. Compliers: Screening non-takers only sample



Men, Stomach cancer

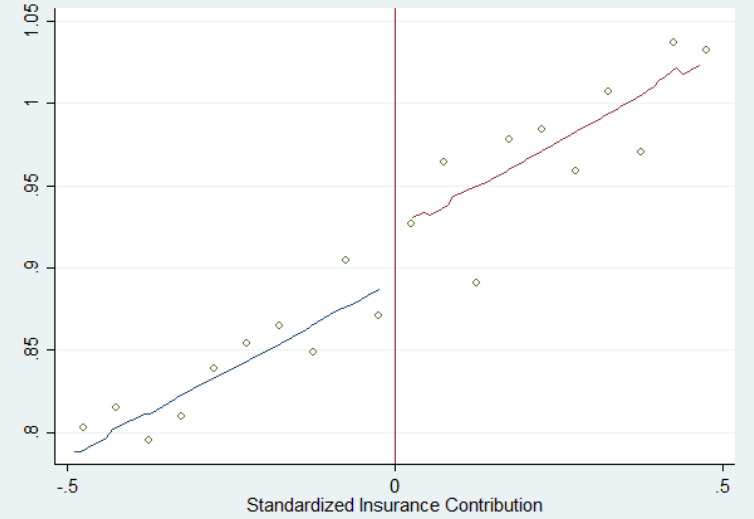
Women, Stomach cancer

Women, Breast cancer

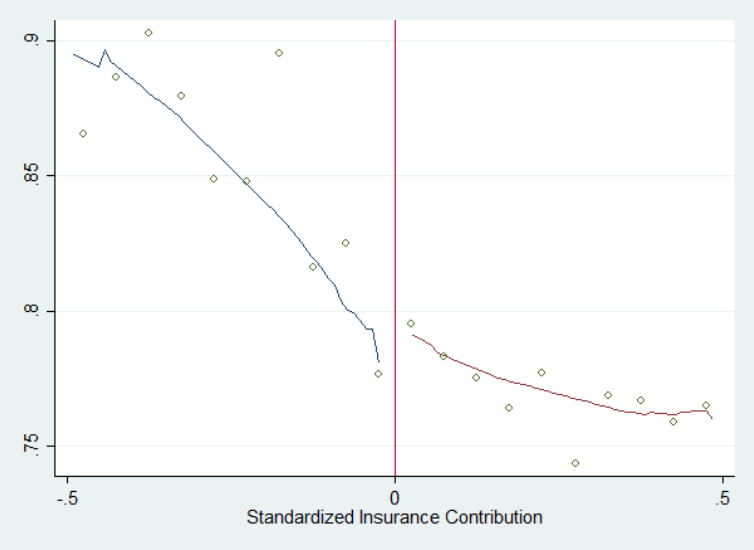
Note: The samples in Panels A and B are restricted to screening takers and screening non-takers, respectively. The dependent variable is six-year cumulative cancer mortality. The running variable is the standardized insurance contribution. The open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are fitted values from a local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. This is estimated separately on each side of the cutoff. The shaded regions are 95% confidence intervals. The sensitivity results are shown in Figure A26.

Figure A13: Effect on Future General Health Screening Take-ups, Years 3-6

Panel A. Men



Panel B. Women



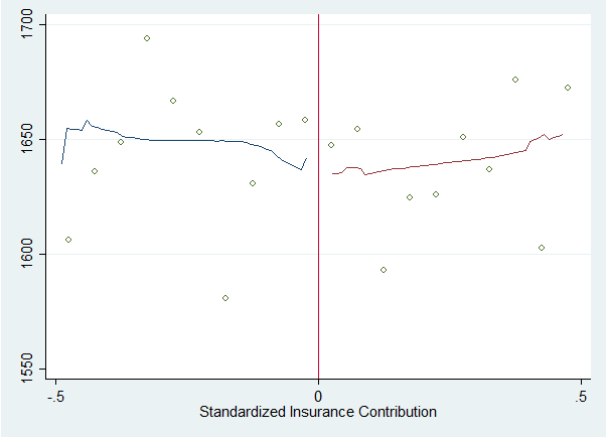
Note: The dependent variables in Panels A and B are the number of general health screening take-ups in Years 3-5 in men and women, respectively. The running variable is the standardized insurance contribution. The open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are the fitted values from a local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. This is estimated separately on each side of the cutoff.

Figure A14: Effect on Medical Expenditure

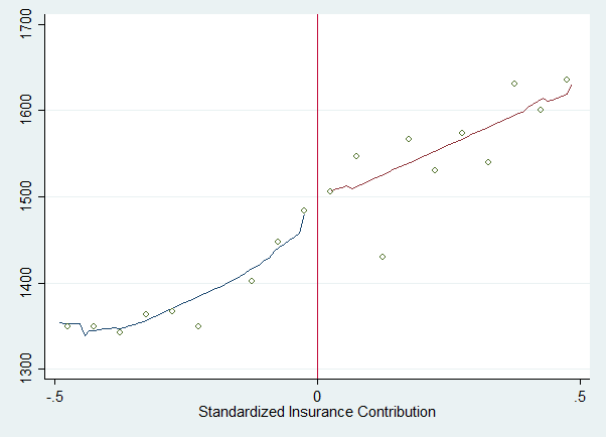
Panel A. In Years 1-2, Men

Panel B. In Years 1-2, Women

Panel C. In Years 3-5, Men



Panel D. In Years 3-5, Women

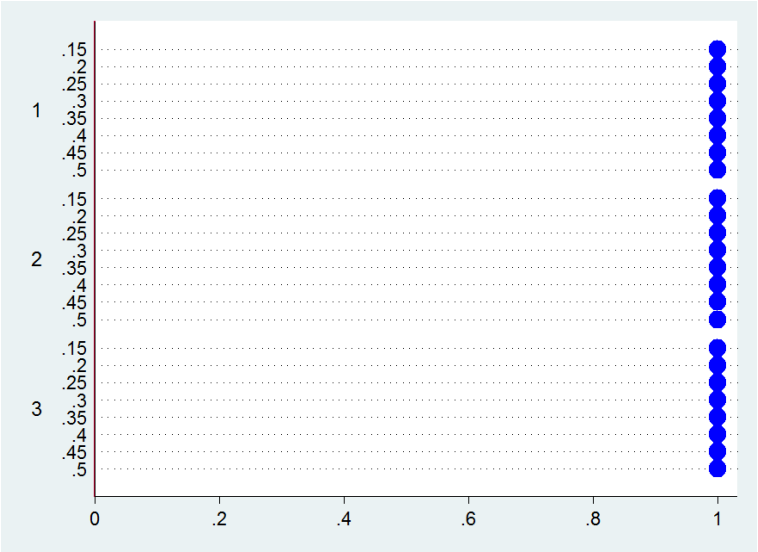


Note: The dependent variables in Panels A and B are medical expenditure in Years 1-2 for men and women, respectively. The dependent variables in Panels C and D are medical expenditure in Years 3-5 for men and women, respectively. The running variable is the standardized insurance contribution. The open circles plot the mean of the dependent variable within 0.05 point bins. The solid lines are the fitted values from a local linear regression of the dependent variable using a rectangular kernel with a bandwidth of 0.3 points. This is estimated separately on each side of the cutoff.

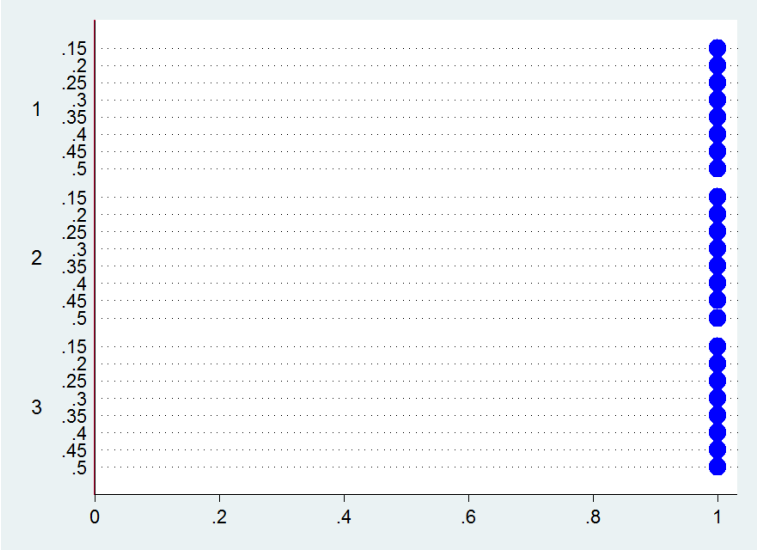
B Sensitivity Analysis

Figure A15: Eligibility for Free Public Cancer Screening

Panel A. Eligibility in men



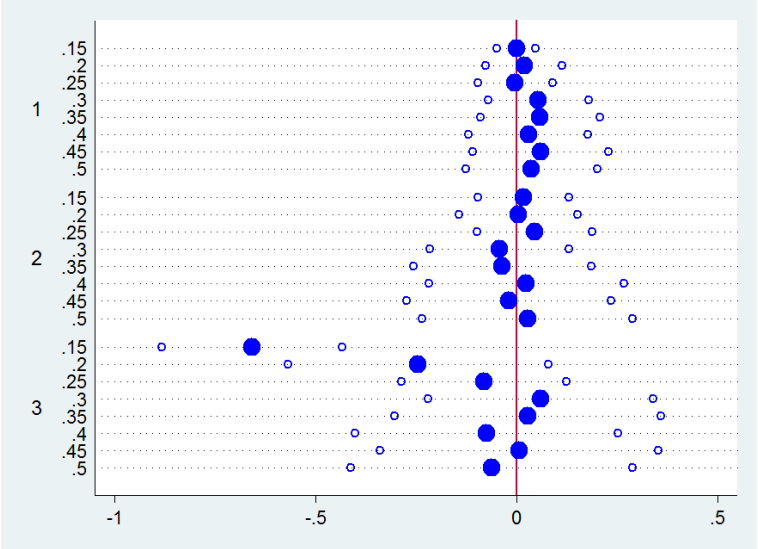
Panel B. Eligibility in women



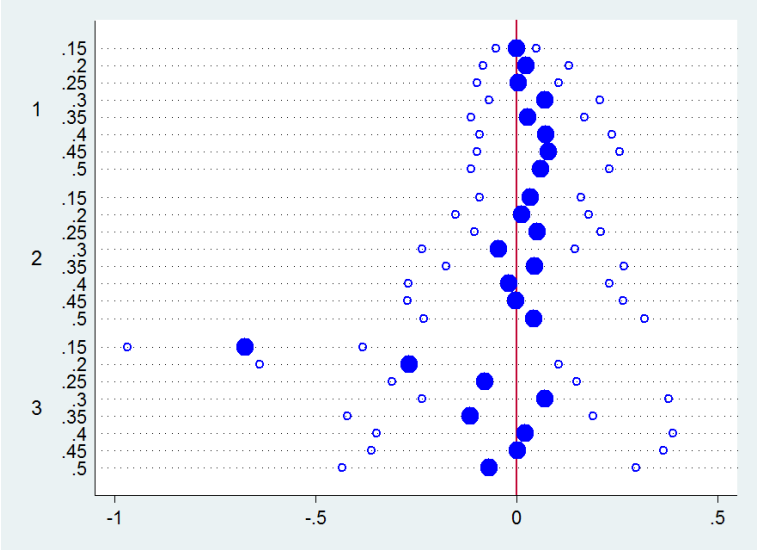
Note: The dependent variables in Panels A and B are eligibility for free public cancer screening in men and women, respectively. Each figure displays estimates of β from local linear, quadratic, and cubic regressions at different bandwidths in increments of 0.05 from 0.15 to 0.5. Degree of $f(\cdot)$ and the size of bandwidth are on the y-axis. Coefficient estimate and the lower and upper 95% confidence bounds are on the x-axis. The solid circle represents the coefficient estimate.

Figure A16: Effect on Future Eligibility for Free Public Cancer Screening, Years 3-6

Panel A. Future eligibility in men



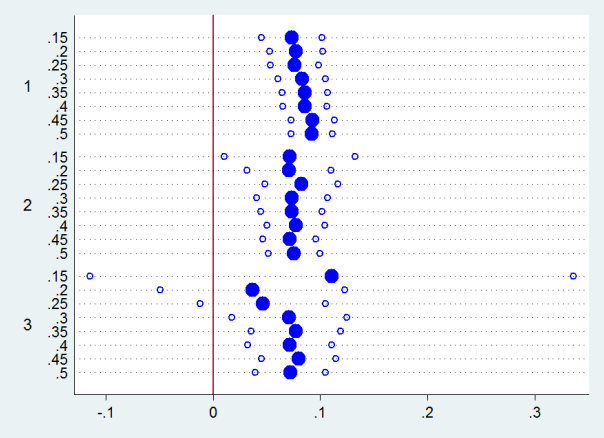
Panel B. Future eligibility in women



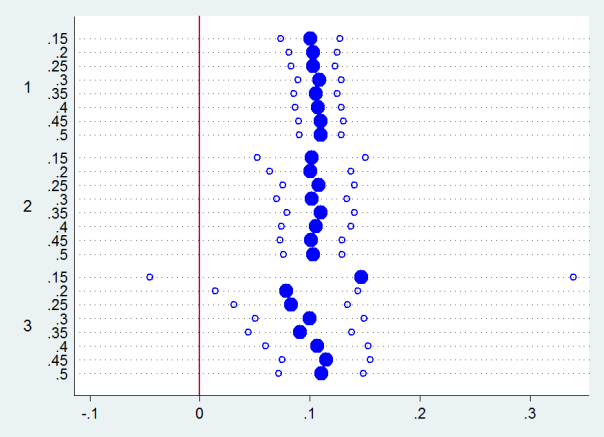
Note: The dependent variables in Panels A and B are future eligibility for free public cancer screening in men and women, respectively. Each figure displays estimates of β from local linear, quadratic, and cubic regressions at different bandwidths in increments of 0.05 from 0.15 to 0.5. Degree of $f(\cdot)$ and the size of bandwidth are on the y-axis. Coefficient estimate and the lower and upper 95% confidence bounds are on the x-axis. The center solid circle represents the coefficient estimate and the open circles indicate the lower and upper 95% confidence bounds.

Figure A17: Effect of Cost Sharing on Cumulative Public Cancer Screening Take-up, Years 1-2

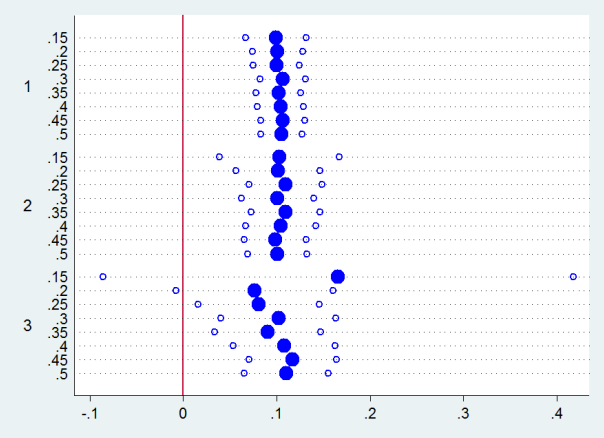
Panel A. Stomach cancer take-up, Men



Panel B. Stomach cancer take-up, Women



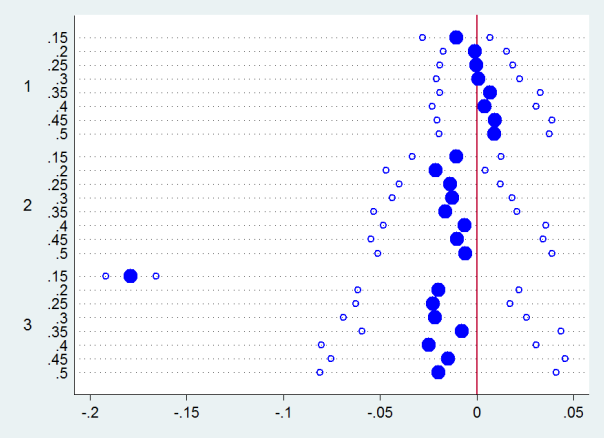
Panel C. Breast cancer take-up, Women



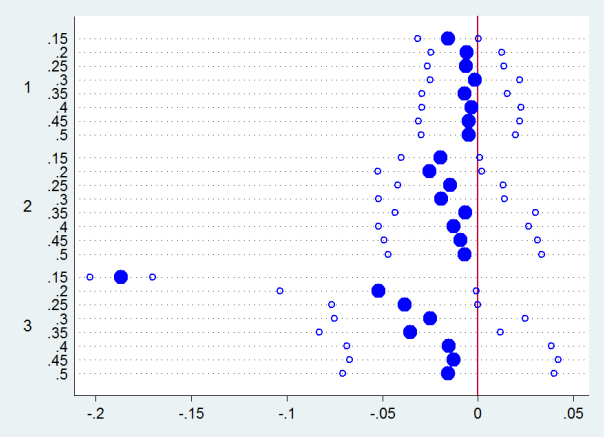
Note: The dependent variables in Panels A, B, and C are male stomach, female stomach, and female breast cancer take-ups, respectively. Each figure displays estimates of β from local linear, quadratic, and cubic regressions at different bandwidths in increments of 0.05 from 0.15 to 0.5. Degree of $f(\cdot)$ and the size of bandwidth are on the y-axis. Coefficient estimate and the lower and upper 95% confidence bounds are on the x-axis. The center solid circle represents the coefficient estimate and the open circles indicate the lower and upper 95% confidence bounds.

Figure A18: Effect on Future Cancer Screening Take-up, Years 3-6

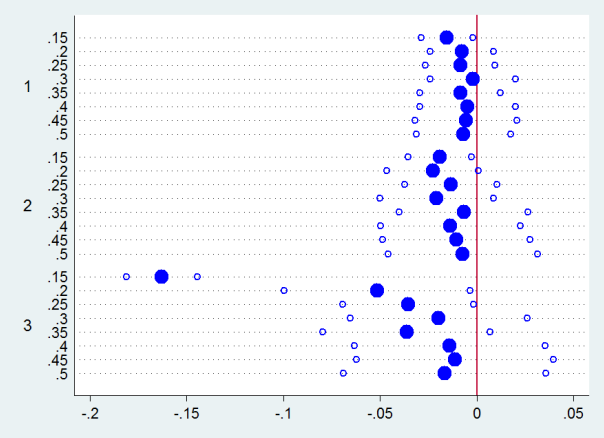
Panel A. Future stomach cancer take-up, Men



Panel B. Future stomach cancer take-up, Women



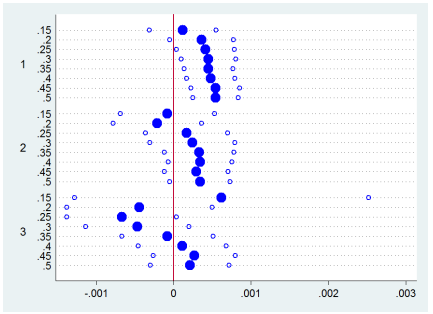
Panel C. Future breast cancer take-up, Women



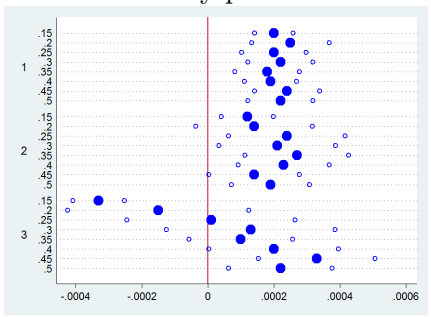
Note: The dependent variables in Panels A, B, and C are future male stomach, female stomach, and female breast cancer take-ups, respectively. Each figure displays estimates of β from local linear, quadratic, and cubic regressions at different bandwidths in increments of 0.05 from 0.15 to 0.5. Degree of $f(\cdot)$ and the size of bandwidth are on the y-axis. Coefficient estimate and the lower and upper 95% confidence bounds are on the x-axis. The center solid circle represents the coefficient estimate and the open circles indicate the lower and upper 95% confidence bounds.

Figure A19: Effect on Cumulative Cancer Detections, Years 1-2

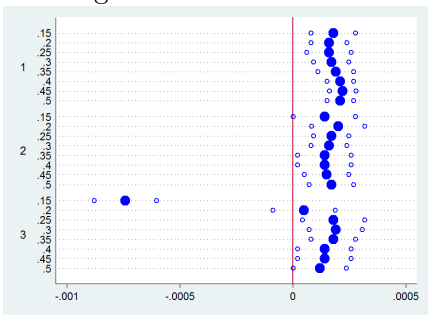
Panel A. Cancer detection by public mass cancer screening



Stomach cancer, Men

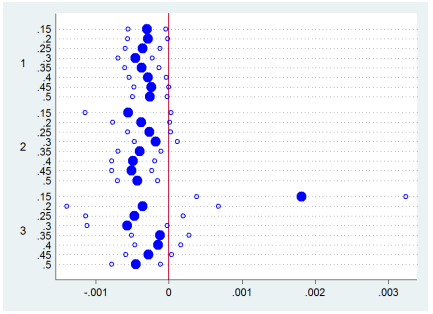


Stomach cancer, Women

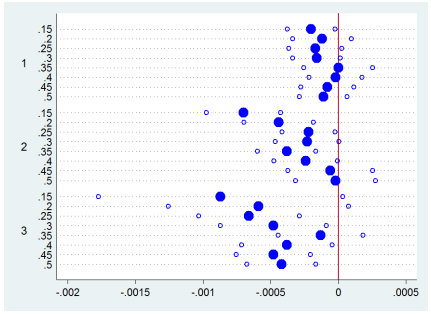


Breast cancer, Women

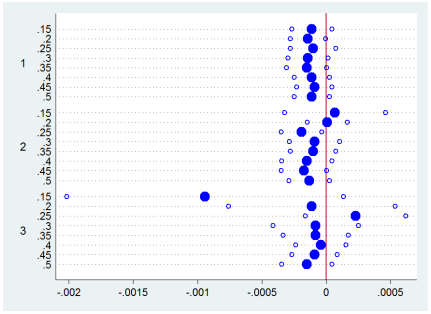
Panel B. Cancer detection by other channels



Stomach cancer, Men

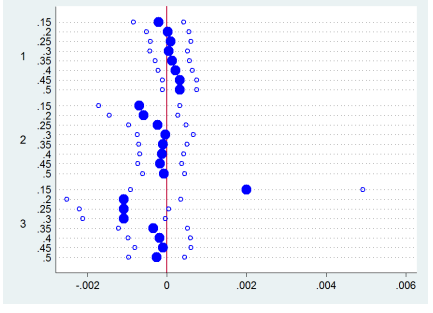


Stomach cancer, Women

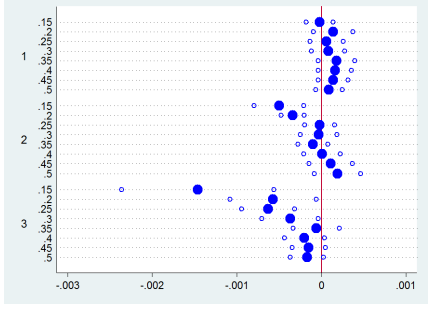


Breast cancer, Women

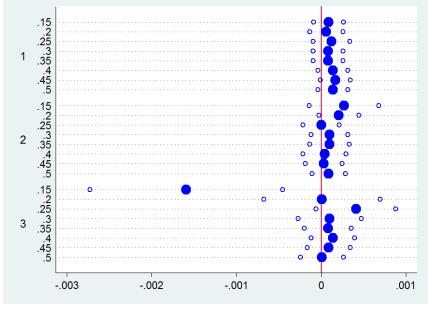
Panel C. Total cancer detection



Stomach cancer, Men



Stomach cancer, Women

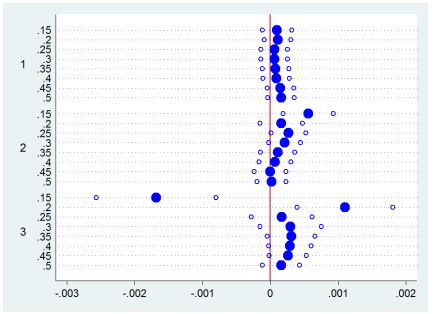


Breast cancer, Women

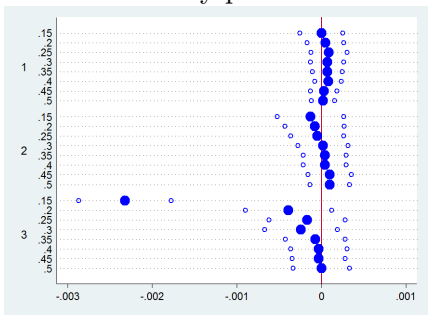
Note: The dependent variables in Panels A, B, and C are two-year cumulative cancer detections by public cancer screening, by other channels, and overall cancer detections, respectively. Each figure displays estimates of β from local linear, quadratic, and cubic regressions at different bandwidths in increments of 0.05 from 0.15 to 0.5. Degree of $f(\cdot)$ and the size of bandwidth are on the y-axis. Coefficient estimate and the lower and upper 95% confidence bounds are on the x-axis. The center solid circle represents the coefficient estimate and the open circles indicate the lower and upper 95% confidence bounds.

Figure A20: Effect on Future Cancer Detections, Years 3-6

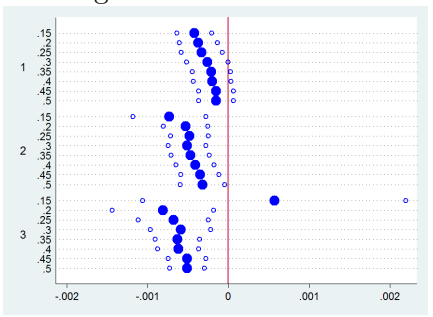
Panel A. Cancer detection by public mass cancer screening



Stomach cancer, Men

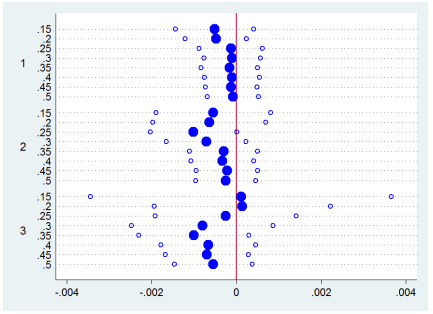


Stomach cancer, Women

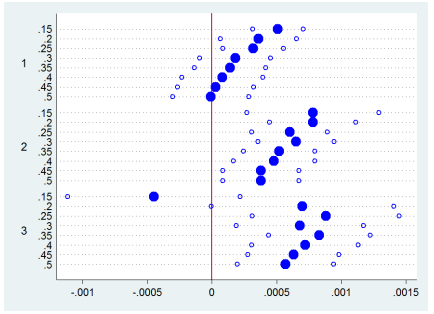


Breast cancer, Women

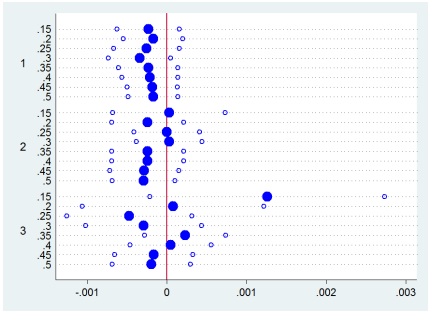
Panel B. Cancer detection by other channels



Stomach cancer, Men

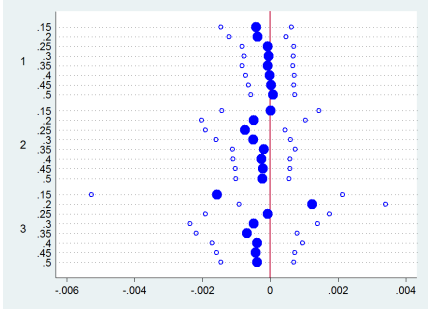


Stomach cancer, Women

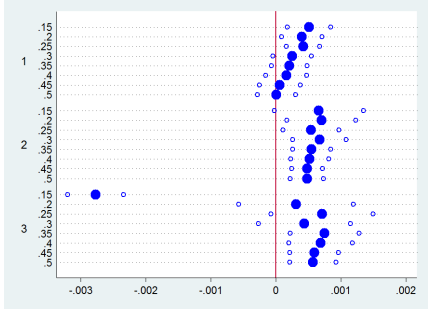


Breast cancer, Women

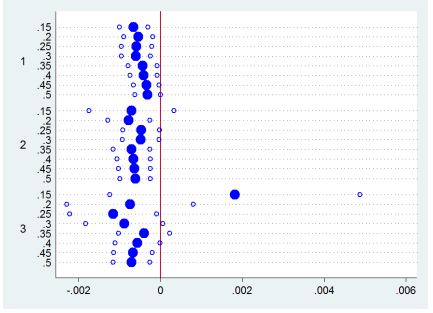
Panel C. Overall cancer detection



Stomach cancer, Men



Stomach cancer, Women

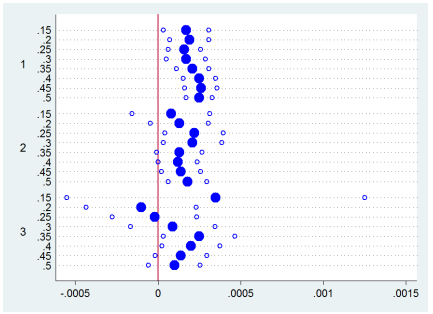


Breast cancer, Women

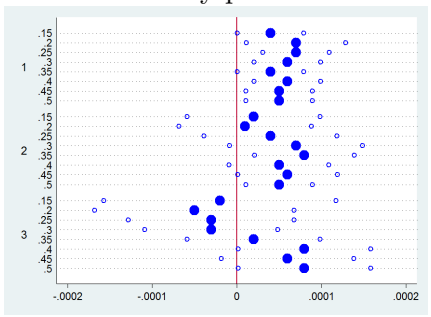
Note: The dependent variables in Panels A, B, and C are cumulative cancer detections between Years 3 and 6 by public cancer screening, by other channels, and overall cancer detections, respectively. Each figure displays estimates of β from local linear, quadratic, and cubic regressions at different bandwidths in increments of 0.05 from 0.15 to 0.5. Degree of $f(\cdot)$ and the size of bandwidth are on the y-axis. Coefficient estimate and the lower and upper 95% confidence bounds are on the x-axis. The center solid circle represents the coefficient estimate and the open circles indicate the lower and upper 95% confidence bounds.

Figure A21: Effect on Cumulative Cancer Detections, Years 1-2, Alternative Definition

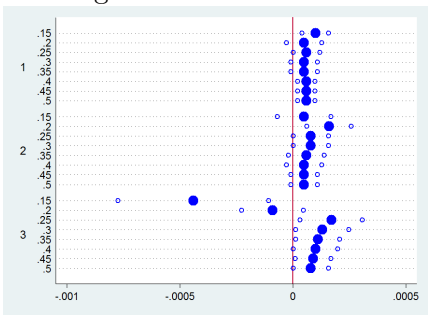
Panel A. Cancer detection by public mass cancer screening



Stomach cancer, Men

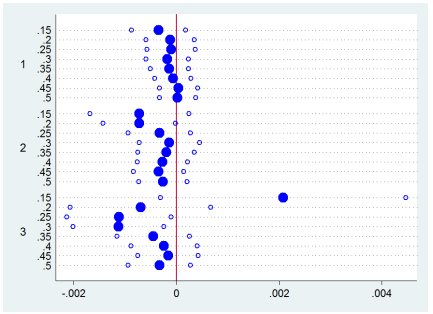


Stomach cancer, Women

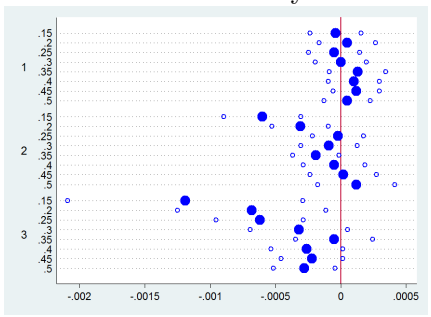


Breast cancer, Women

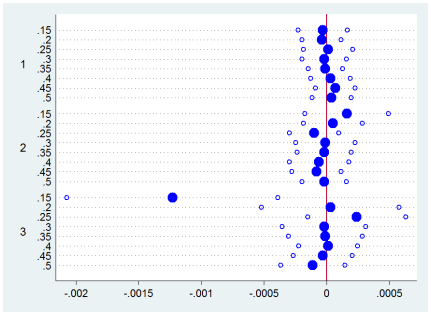
Panel B. Cancer detection by other channels



Stomach cancer, Men

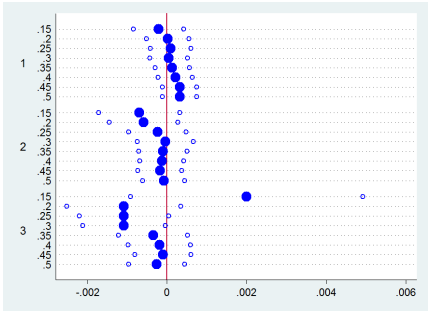


Stomach cancer, Women

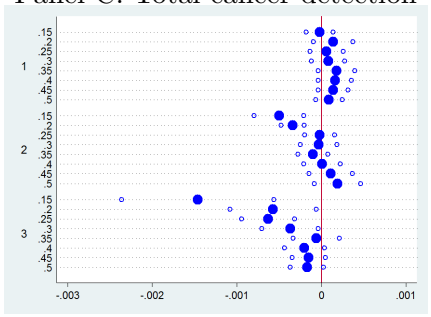


Breast cancer, Women

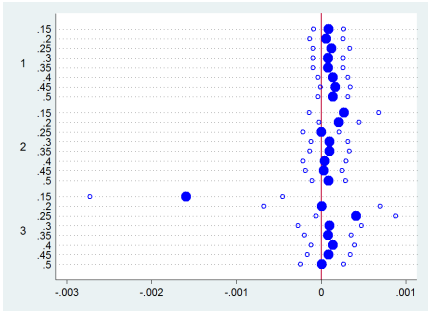
Panel C. Total cancer detection



Stomach cancer, Men



Stomach cancer, Women

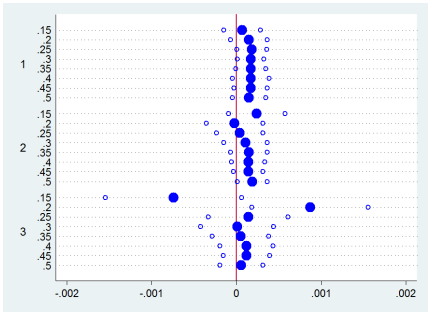


Breast cancer, Women

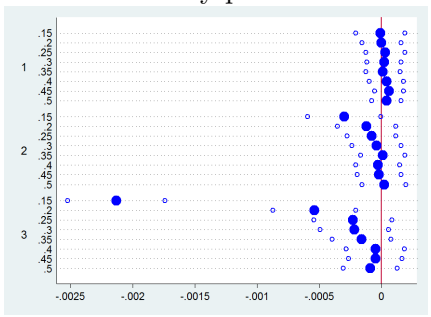
Note: The dependent variables in Panels A, B, and C are two-year cumulative cancer detections by public cancer screening, by other channels, and overall cancer detections, respectively. Each figure displays estimates of β from local linear, quadratic, and cubic regressions at different bandwidths in increments of 0.05 from 0.15 to 0.5. Degree of $f(\cdot)$ and the size of bandwidth are on the y-axis. Coefficient estimate and the lower and upper 95% confidence bounds are on the x-axis. The center solid circle represents the coefficient estimate and the open circles indicate the lower and upper 95% confidence bounds.

Figure A22: Effect on Future Cancer Detections, Years 3-6, Alternative Definition

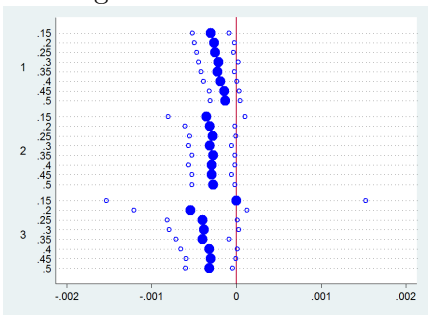
Panel A. Cancer detection by public mass cancer screening



Stomach cancer, Men

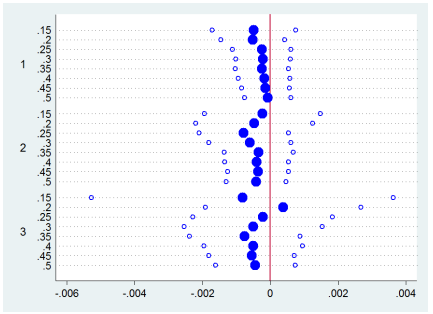


Stomach cancer, Women

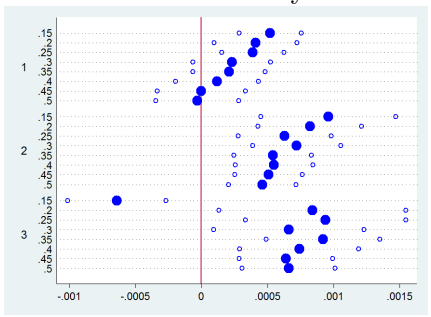


Breast cancer, Women

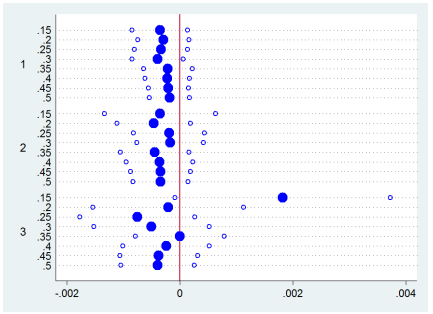
Panel B. Cancer detection by other channels



Stomach cancer, Men

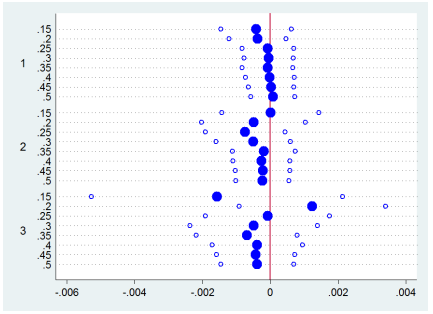


Stomach cancer, Women

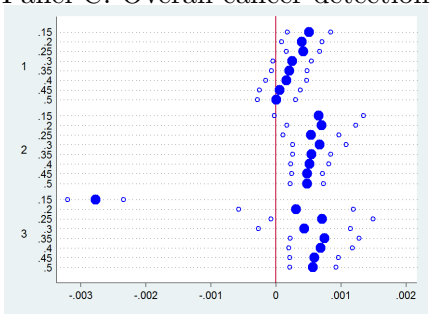


Breast cancer, Women

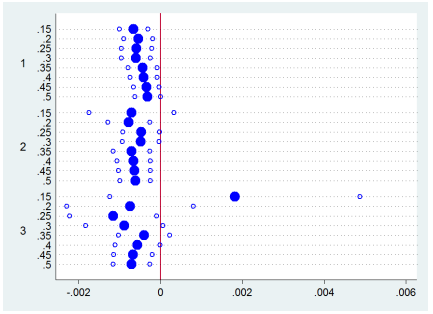
Panel C. Overall cancer detection



Stomach cancer, Men



Stomach cancer, Women

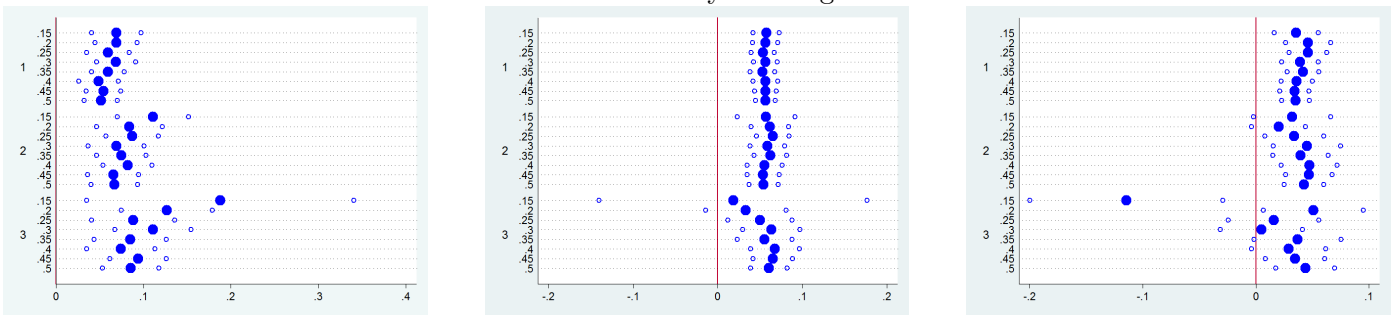


Breast cancer, Women

Note: The dependent variables in Panels A, B, and C are cumulative cancer detections between Years 3 and 6 by public cancer screening, by other channels, and overall cancer detections, respectively. Each figure displays estimates of β from local linear, quadratic, and cubic regressions at different bandwidths in increments of 0.05 from 0.15 to 0.5. Degree of $f(\cdot)$ and the size of bandwidth are on the y-axis. Coefficient estimate and the lower and upper 95% confidence bounds are on the x-axis. The center solid circle represents the coefficient estimate and the open circles indicate the lower and upper 95% confidence bounds.

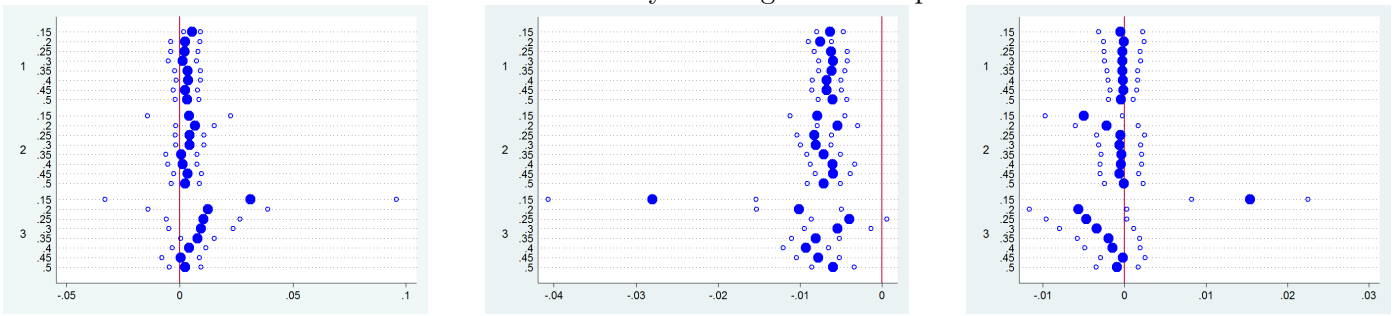
Figure A23: Selection Effect by Cost Sharing: Screening Results among Screening-takers

Panel A. Probability of being normal



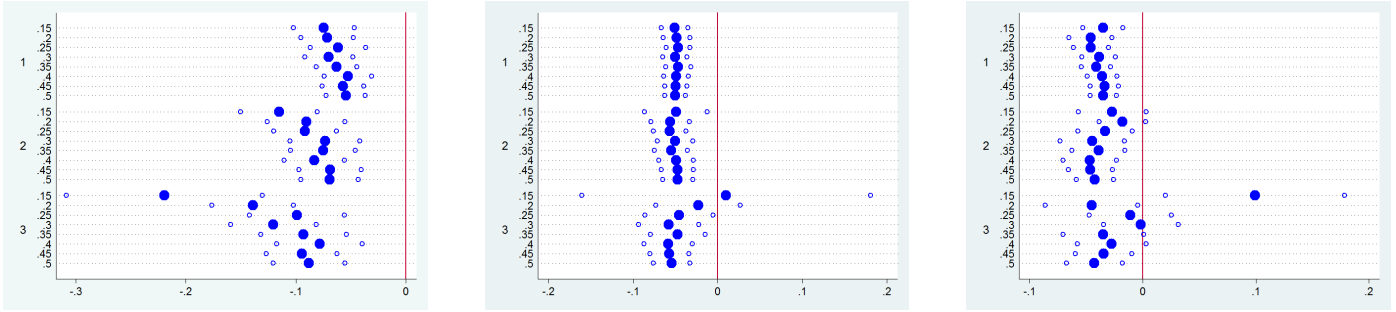
Stomach cancer, Men | Stomach cancer, Women | Breast cancer, Women

Panel B. Probability of being cancer suspicion



Stomach cancer, Men | Stomach cancer, Women | Breast cancer, Women

Panel C. Probability of detecting other disease

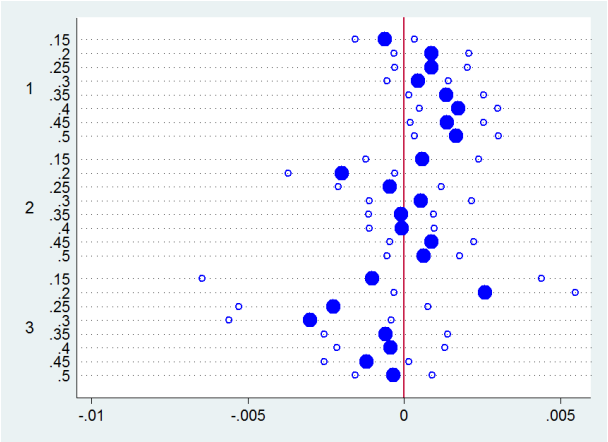


Stomach cancer, Men | Stomach cancer, Women | Breast cancer, Women

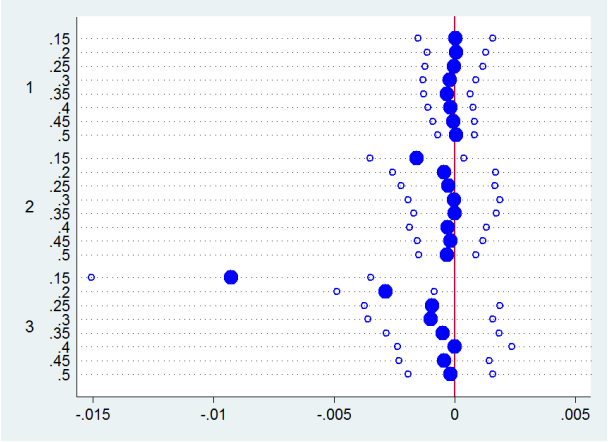
Note: The sample is restricted to screening takers. Dependent variables in Panels A, B, and C are probability of being normal, being cancer suspicion, and detecting other disease, respectively. Each figure displays estimates of β from local linear, quadratic, and cubic regressions at different bandwidths in increments of 0.05 from 0.15 to 0.5. Degree of $f(\cdot)$ and the size of bandwidth are on the y-axis. Coefficient estimate and the lower and upper 95% confidence bounds are on the x-axis. The center solid circle represents the coefficient estimate and the open circles indicate the lower and upper 95% confidence bounds.

Figure A24: Selection Effect by Cost Sharing: Cancer Detection among Screening-takers

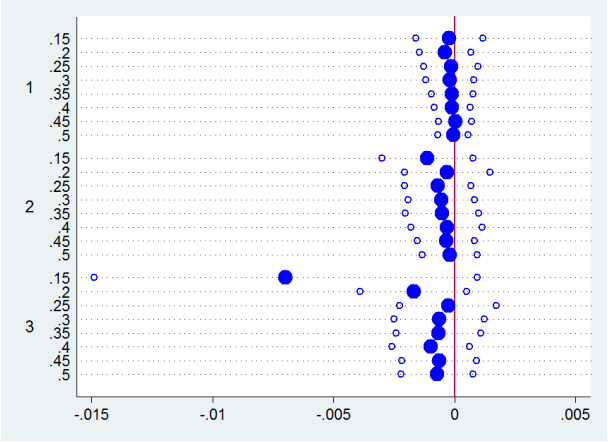
Panel A. Stomach cancer detection, Men



Panel B. Stomach cancer detection, Women



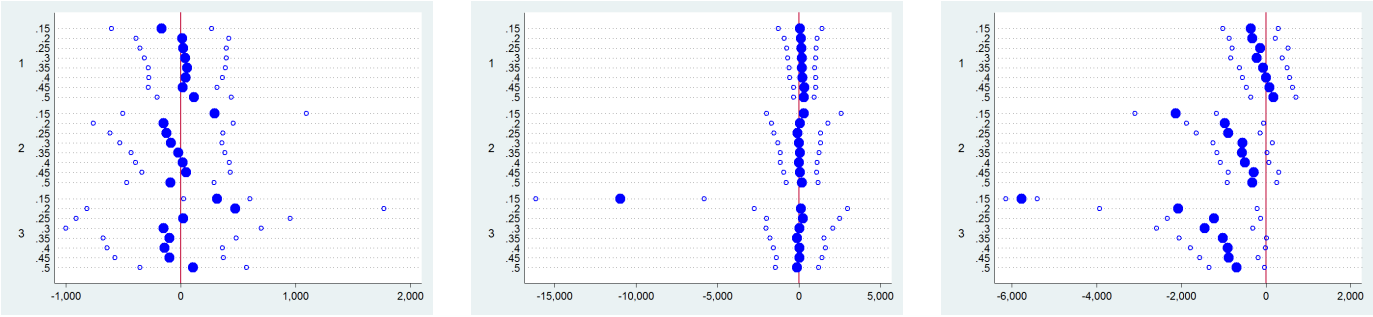
Panel C. Breast cancer detection, Women



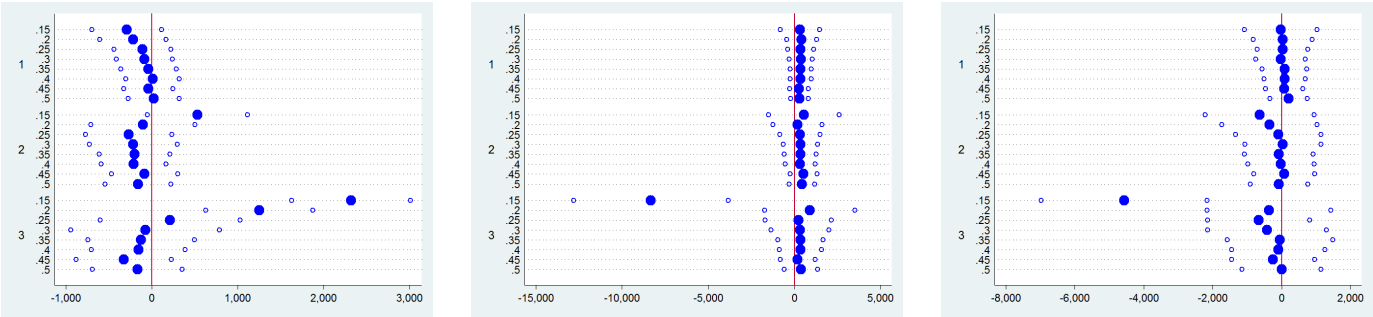
Note: The sample is restricted to screening takers. Dependent variables in Panels A, B, and C are stomach cancer detection in men, and stomach and breast cancer detections in women, respectively. Each figure displays estimates of β from local linear, quadratic, and cubic regressions at different bandwidths in increments of 0.05 from 0.15 to 0.5. Degree of $f(\cdot)$ and the size of bandwidth are on the y-axis. Coefficient estimate and the lower and upper 95% confidence bounds are on the x-axis. The center solid circle represents the coefficient estimate and the open circles indicate the lower and upper 95% confidence bounds.

Figure A25: Effect on Medical Expenditure in the First Year of Cancer Detection (Early Detection)

Panel A. Cancer detected within two years



Panel B. Cancer detected after three to six years

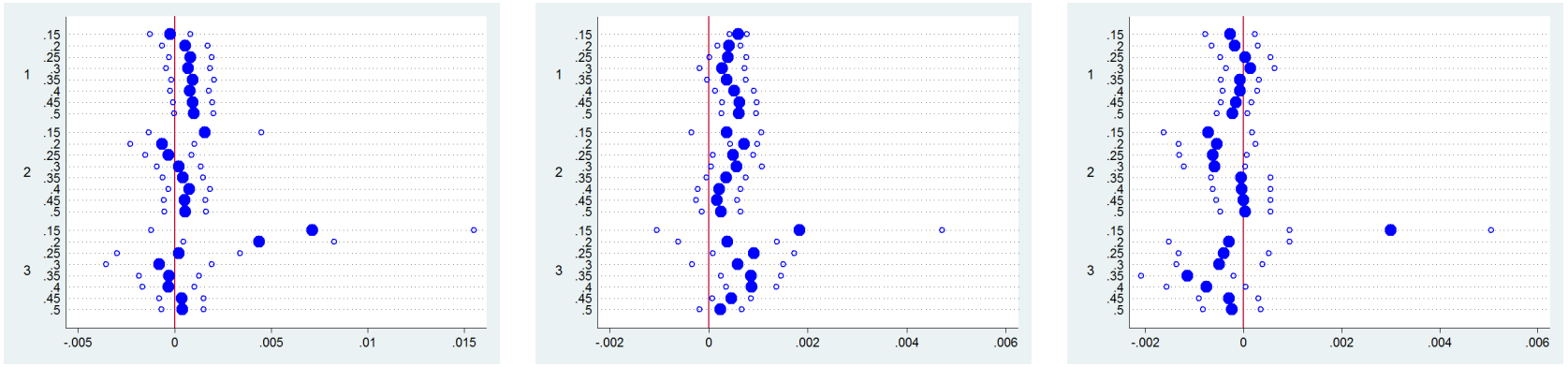


Stomach cancer, Men | Stomach cancer, Women | Breast cancer, Women

Note: The dependent variable in Panels A and B are the medical expenditure in the first year of cancer detection in Years 1-2 and 3-6, respectively. Each figure displays estimates of β from local linear, quadratic, and cubic regressions at different bandwidths in increments of 0.05 from 0.15 to 0.5. Degree of $f(\cdot)$ and the size of bandwidth are on the y-axis. Coefficient estimate and the lower and upper 95% confidence bounds are on the x-axis. The center solid circle represents the coefficient estimate and the open circles indicate the lower and upper 95% confidence bounds.

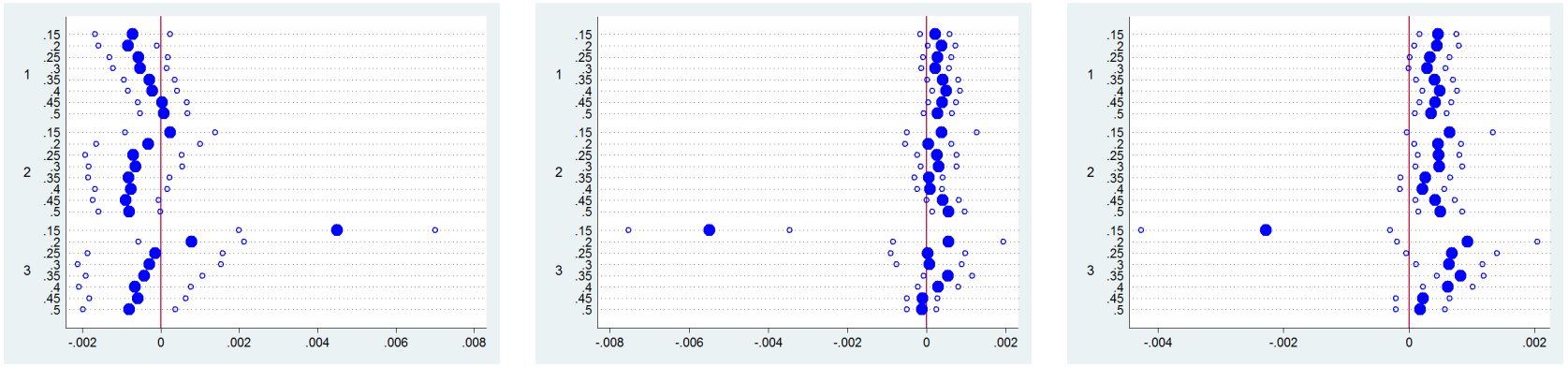
Figure A26: Compliers vs. Always takers vs. Never takers: Six-Year Cumulative Cancer Mortality

Panel A. Compliers vs. Always takers



Stomach cancer, Men | Stomach cancer, Women | Breast cancer, Women

Panel B. Never takers vs. Compliers

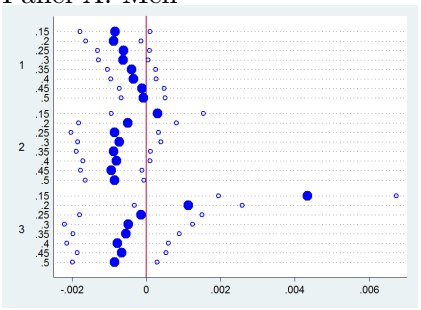


Stomach cancer, Men | Stomach cancer, Women | Breast cancer, Women

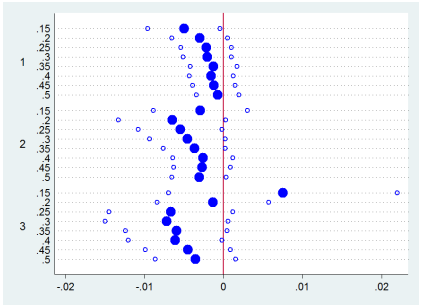
Note: The samples in Panel A and B are restricted to screening takers and screening non-takers, respectively. Dependent variable is six-year cumulative cancer mortality. Each figure displays estimates of β from local linear, quadratic, and cubic regressions at different bandwidths in increments of 0.05 from 0.15 to 0.5. Degree of $f(\cdot)$ and the size of bandwidth are on the y-axis. Coefficient estimate and the lower and upper 95% confidence bounds are on the x-axis. The center solid circle represents the coefficient estimate and the open circles indicate the lower and upper 95% confidence bounds.

Figure A27: Effect on Six-year Cumulative Mortality

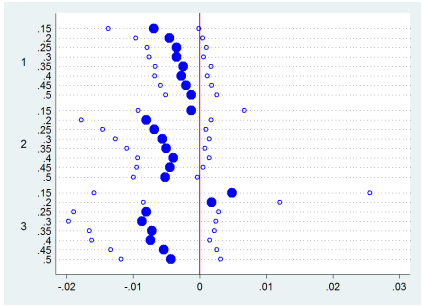
Panel A. Men



Stomach cancer mortality

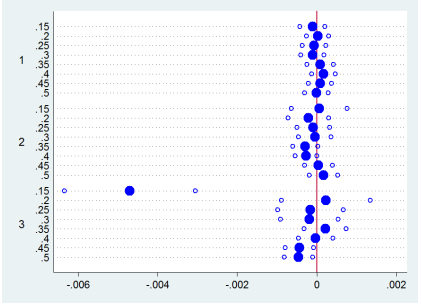


Non-cancer mortality

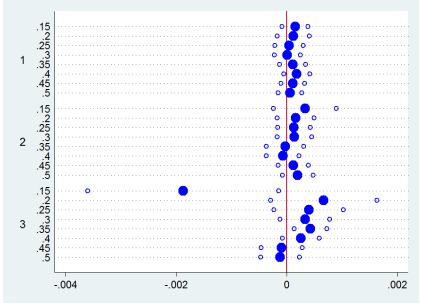


All-cause mortality

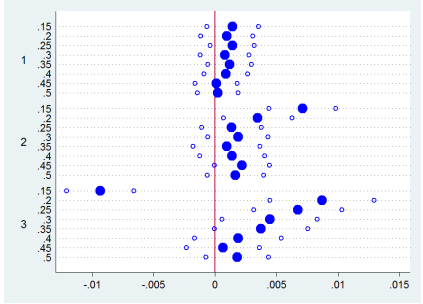
Panel B. Women



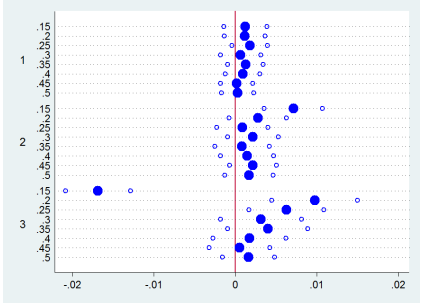
Stomach cancer mortality



Breast cancer mortality



Non-cancer mortality



All-cause mortality

Note: The dependent variables in Panels A and B are six-year cumulative cancer, non-cancer and all-cause mortalities in men and women, respectively. Each figure displays estimates of β from local linear, quadratic, and cubic regressions at different bandwidths in increments of 0.05 from 0.15 to 0.5. Degree of $f(\cdot)$ and the size of bandwidth are on the y-axis. Coefficient estimate and the lower and upper 95% confidence bounds are on the x-axis. The center solid circle represents the coefficient estimate and the open circles indicate the lower and upper 95% confidence bounds.