Does Medicare Coverage Improve Cancer Detection and Mortality Outcomes?

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Abstract

Despite large public investments in providing Medicare insurance for adults over age 65, there is little evidence it improves health. We study a group of vulnerable older adults for whom access to health insurance could have plausible, immediate impacts on health – people with cancer. We used a regression discontinuity design to assess impacts of near-universal Medicare insurance at age 65 using population-based cancer registries and vital statistics data. At age 65, cancer detection increased by 50 per 100,000 population (8%) and cancer mortality decreased by 4.13 per 100,000 population (2%), while one-year survival after detection increased by 1%. Importantly, the effects of near-universal coverage via Medicare on cancer mortality were similar among Black patients and non-Black patients. Accordingly, while Medicare coverage improved cancer mortality among all groups, disparities by race remained.

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INTRODUCTION

Despite large public investments in providing Medicare insurance for adults over age 65, there is little evidence that it improves health. While mortality for hospitalized patients is lower for those with Medicare insurance, population-level mortality effects have been difficult to show (Card, Dobkin, & Maestas, 2009; Finkelstein & McKnight, 2008; McWilliams, Zaslavsky, Meara, & Ayanian, 2004). Some have concluded that Medicare has little impact on health, while others have pointed out the difficulty of deriving reliable empirical inferences on this question (Black, Espín-Sánchez, French, & Litvak, 2017; Polsky et al., 2009; McWilliams, Meara, Zaslavsky, & Ayanian, 2010). To address the gap in the literature on the health effects of Medicare, this paper studies the impacts of near-universal access to Medicare insurance for a specific group of people for whom access to care could have plausible, immediate impacts on health – patients with cancer.

Cancer is the second leading cause of death in the United States, and people over age 65 account for 60% of newly diagnosed cancers and 70% of all cancer deaths (Berger et al., 2006; White et al., 2014). Timely detection of certain cancers can improve treatment outcomes and reduce mortality risk (Humphrey, Helfand, Chan, & Woolf, 2002; Maciosek, Solberg, Coffield, Edwards, & Goodman, 2006; Mandelblatt et al., 2009; Moyer & U.S. Preventive Services Task Force, 2012, 2014; Nelson et al., 2009; Pignone, Saha, Hoerger, & Mandelblatt, 2002; US Preventive Services Task Force et al., 2016; Siu & U.S. Preventive Services Task Force, 2016). The Institute of Medicine noted that uninsured people with cancer experience longer delays in diagnosis and worse survival outcomes than patients with private insurance (Institute of Medicine (US) Committee on Health Insurance Status and Its Consequences, 2009). Yet, economists have questioned whether such associations represent a causal effect of insurance or confounding factors (Levy & Meltzer,

2008). Because the majority of cancer patients in the United States are older adults covered by Medicare, resolving uncertainty about the effects of public insurance is crucial for ongoing public policy discussions.

The goal of this study was to determine the impact of Medicare's nearly universal coverage at age 65 on cancer detection and mortality. As cancer detection is considered health-improving for some cancers but not others, we focused on the tumor sites with A and B grade screening recommendations from United States Preventive Services Task Force for people both below and above age 65: breast, colorectal, and lung cancer (US Preventive Services Task Force, 2018). We used the most recent 15 years of data on cancers reported to population-based cancer registries and vital statistics databases across the United States.

We found that concurrent with near-universal Medicare coverage at age 65, cancer detection increased by 50 per 100,000 population (8%) and cancer mortality decreased by 4.13 per 100,000 population (2%). One-year survival after cancer diagnosis improved by 1% after adjustment for a large set of tumor characteristics, which closely matched the mortality data. Lung cancer – the top cause of cancer death in the United States – accounted for the improvements in mortality outcomes we found at age 65. Multiple checks, including comparison with data from Canada as a placebo check, suggested the robustness of findings. Thus, our findings provide new evidence that Medicare coverage improves health outcomes for people with cancer.

Comparison with the literature

The association between insurance and cancer outcomes varies by source of insurance coverage, with some publicly insured patients faring no better than the uninsured (Ellis et al., 2018; Halpern et al., 2008; Niu, Roche, Pawlish, & Henry, 2013; Ward, Fedewa, Cokkinides, & Virgo, 2010). To

understand which of these associations represent causal effects, researchers can study insurance experiments or leverage a policy change as a natural experiment. Many such studies have focused on insurance expansions among the non-elderly, i.e., expansions of Medicaid or private insurance. While some studies found that access to insurance increased cancer screening, others found that the impact of insurance on cancer screening and detection varied by tumor site or the length of follow-up after a policy change (Han, Zang Xiong, Kramer, & Jemal, 2016; Kolstad & Kowalski, 2012; Robbins et al., 2015; Sabik & Bradley, 2016; Soni, Simon, Cawley, & Sabik, 2017). The Oregon Health Insurance Experiment, a randomized expansion of Medicaid insurance, found that insurance increased cancer screening and reduced financial strain; however, cancer detection and outcomes were not assessed (Baicker et al., 2013; Conlin, Allen, Tsui, Carlson, & Li, 2016; Finkelstein et al., 2012; White et al., 2014). Given the low incidence of cancer among the non-elderly, studies of Medicaid or private insurance expansions often avoid studying population-level mortality impacts because of limited statistical power to detect effects.

Prior research has linked Medicare to improvements in self-reported health, survival after acute care hospital visits, and measures of cardiovascular health, as well as improved access to inpatient and outpatient care (Card, Dobkin, & Maestas, 2008; Card et al., 2009; Decker, 2005; McWilliams, Meara, Zaslavsky, & Ayanian, 2009, 2013). The results of studies linking Medicare and mortality are more mixed, with population-level studies often finding no effect (Finkelstein & McKnight, 2008; Card et al., 2009; McWilliams et al., 2004; Polsky et al., 2009). Likewise, studies of the mortality effects of health insurance expansions among younger adults have found mixed effects; a randomized trial found no impact on mortality, though confidence intervals were large (Black et al., 2017; Finkelstein et al., 2012; Kronick, 2009; Sommers, Baicker, & Epstein, 2012; Woolhandler & Himmelstein, 2017).

We are aware of one study of the causal effect of Medicare coverage on cancer detection and survival outcomes among older adults. Almost all adults in the United States become automatically eligible for Medicare coverage at age 65 (Card et al., 2008). Exploiting this change as a natural experiment, Decker used data on older adults from 1980-2001 and found that access to Medicare coverage produced small increases in detection of early-stage breast cancer and post-detection survival (Decker, 2005). However, since the 1980's and 1990's changes have occurred which could alter the impact of Medicare on breast cancer detection and outcomes, such as new treatments, changes in screening guidelines, and increased uptake of mammography (De Pergola & Silvestris, 2013; Sabik & Bradley, 2016). Finally, although this study examined breast cancer, treatment data from Medicare claims suggest that effects may vary by tumor site (Huesch & Ong, 2016a, 2016b).

Studies of changes in survival after cancer detection, rather than population-level mortality in vital statistics data, may be influenced by lead or length time bias (Lakdawalla et al., 2010; Manning & Zelen, 1969). These biases can be explained as follows. First, when people are diagnosed with cancer earlier, they may appear to survive longer after detection simply due to becoming classified as a cancer patient earlier. Second, the additional cases detected might be slower-growing cancers less likely to have ultimately killed the patient in the absence of intervention. In the epidemiological literature, these biases are considered as a reason that some expansions in screening may impact detection but have no impact on population-level cancer mortality, i.e., cancer deaths ultimately averted (Ahn, Kim, & Welch, 2014; Shwartz, 1980). Therefore, changes in post-diagnosis survival for cancer patients after changes in screening and detection should be interpreted with caution (Barratt, Bell, & Jacklyn, 2018; Grubbs et al., 2013). Our study addresses the issues of lead and length time bias by adjusting for precise tumor characteristics and validating

our findings by analyzing disease-specific mortality rates on the population-level. Analyzing population-level disease-specific mortality rates is considered a best practice to address diagnosis bias in the cancer epidemiology literature (Duffy et al., 2008; Morrison, 1982).

In summary, the impact of Medicare insurance on detection and mortality outcomes for all cancers for which timely detection is considered health-improving is not known. Given that the Medicare population is projected to increase from 54 million in 2015 to 80 million by 2030 and that the older adults served by Medicare will account for 70% of cancer patients by 2030, understanding the influence of Medicare coverage on these outcomes is warranted (Medicare Payment Advisory Commission, 2015; Smith, Smith, Hurria, Hortobagyi, & Buchholz, 2009).

METHODS

We employed a regression discontinuity research design. This design assessed the impact of near-universal Medicare coverage on cancer detection and outcomes at age 65 by comparing data from people aged 65 or slightly older with data from people slightly younger than age 65 (Imbens & Lemieux, 2008). Regression discontinuity designs have been used in numerous prior studies of the impact of Medicare insurance coverage on patient outcomes (Barcellos & Jacobson, 2015; Card et al., 2008; Finkelstein & McKnight, 2008). Additional details are provided below.

Data

We extracted data on cancer detection, post-detection outcomes, and population-level cancer mortality from multiple sources.

Cancer Detection and Post-Detection Survival

We extracted data from the Surveillance, Epidemiology and End Results (SEER) program database from 2001 through 2015, the most recent data available. SEER collects information from population-based cancer registries covering one-quarter of the United States population (SEER, 2017). These data include information on patient characteristics, characteristics of the tumor at the time of detection, and survival after cancer detection.

Our sample included all breast, colorectal, and lung cancers among people in our age range of interest. Our main specification included people aged 59-71, i.e., over 740,000 tumors diagnosed from 138 million patient-years at risk. Data on detected cancers and at-risk population were tabulated by year, SEER cancer registry, single year of age, patient gender, and patient race (Black vs. non-Black), yielding 13,650 observations in our main specification. We additionally constructed a tumor-level dataset with patient survival outcomes, and tumor characteristics at diagnosis including stage, size, and extension.

Our outcomes of interest from these data were total, early-stage, and late-stage cancer detection for breast, colorectal, and lung cancer per 100,000 population, and one-year survival after cancer diagnosis. One-year survival was analyzed because most patients in our comparison group would become eligible for Medicare within five years contingent on survival. Early-stage cancer included in situ, localized, or regional by direct extension in the SEER classification. Late-stage cancer included regional with only lymph node involved, regional with lymph nodes involved and by direct extension, regional not otherwise specified, or distant. Cancers without a stage classification were still included in the analysis of total cancers detected.

Population-level Cancer Mortality

Our additional outcomes of interest were breast, colorectal, and lung mortality per 100,000 population. We used vital statistics data over 2001-2015 compiled by the Centers for Disease Control and Prevention, and used the ICD-10 based 113 cause list to identify deaths attributed to malignant breast, colorectal, and lung cancer. Data were tabulated by location of the cancer, single year of age at death, gender, race (Black vs. non-Black), and year of death. (Tabulating by state of residence would lead some data to be masked due to low counts. The decision to not tabulate by state is not essential to our findings.) For our main specification this yielded 2,340 rows of tabulated data, representing 1.2 million cancer-related deaths over 1.5 billion patient-years at risk (Centers for Disease Control and Prevention, 2018).

Research Design

We used a regression discontinuity research design (RDD) to examine the impact of near-universal Medicare eligibility at age 65 on cancer detection and outcomes. Regression discontinuity designs are frequently used to analyze policies that cause a sudden change in an outcome of interest that cannot be easily manipulated by patients or providers. Birth weight criteria for neonatal intensive care is one example; intensive care is recommended for infants under 1500 grams. Comparing 1502-gram infants to 1498-gram infants illustrates how intensive care influences outcomes, since the 4-gram difference is not otherwise likely to materially influence outcomes (Almond, Doyle, Kowalski, & Williams, 2010). Time of day is another example, since some hospital patients lose insurance coverage precisely at midnight. Comparing data just before or after midnight identifies how patient insurance status influences hospital treatment decisions (Almond & Doyle, 2011). We exploited patient age as a source of change in insurance coverage, because Medicare coverage is

nearly universally available at age 65, but not one day before it (Decker, 2005; Barcellos & Jacobson, 2015; Card et al., 2009). The key assumption in our analysis was that outcomes would have continued along a smooth trend at age 65 in the absence of the Medicare program, but Medicare creates a break in that trend. Because smooth trends by age are accounted for in the analysis, it would not invalidate our research design if survival were to decrease with age overall.

Our research design followed previous studies that used regression-discontinuity models to estimate the impact of Medicare insurance (Barcellos & Jacobson, 2015; Card et al., 2009; Decker, 2005). The predictor of interest was an indicator variable for age 65 or older. To account for the effects of aging on cancer incidence and detection, we included a polynomial in age estimated separately for people above and below age 65. We also accounted for time trends in cancer detection using year indicator variables, accounted for variation in detection across states using state indicator variables, and controlled for patient gender and race. We clustered standard errors by single year of age (Lee & Card, 2008). Section A1 of the Appendix provides more details. Our main analyses focused on people aged 59 to 71; as described below, we expanded and narrowed this sample frame in sensitivity checks. We assessed whether findings varied by race or tumor site by stratifying the data.

The functional form used for the models varied by the outcome analyzed. We used negative binomial models to assess changes in cancer detection per population or cancer deaths per population, and used logistic models to assess changes in one-year survival after cancer detection. We then extracted the following quantities of interest as average marginal effects: change in cancers detected per 100,000 population, change in cancer deaths per 100,000 population, and changes in one-year survival after cancer detection at age 65.

Sensitivity Checks

When people are diagnosed with cancer earlier, they may appear to survive longer with cancer due to becoming classified as a cancer patient earlier. Furthermore, when additional cancer cases are detected, the additional cases may be less severe than the previously detected cases. These issues are known as lead-time bias and length bias in the cancer epidemiology literature (Lakdawalla et al., 2010; Manning & Zelen, 1969). We took two approaches to ensure that such bias did not account for the changes in cancer outcomes we measured. First, we adjusted for tumor severity at diagnosis including: precise tumor stage at diagnosis, captured using indicator variables; the largest dimension of the primary tumor at diagnosis, in millimeters; and extension of tumor away from the primary site at diagnosis, on a 0 to 99 scale. Second, we analyzed data on cancer mortality per 100,000 population from vital statistics data. Because these data track all cancers including those diagnosed at autopsy, biases related to timing of diagnosis are largely removed.

We further assessed the robustness of findings in numerous supplemental analyses. First, we assessed the sensitivity of our results to our chosen age window by re-estimating our models on a narrower sample of patients aged 62 to 68, and a broader sample of patients aged 56 to 74. Second, we used alternative approaches to modeling the smooth growth in cancer detection with age, i.e., changed the order of the polynomial used to adjust for the aging process. Third, we relaxed our modeling assumptions and reported results derived more closely from the raw data, i.e., used a local linear regression. Fourth, we conducted a variety of placebo tests that use age cut-offs other than age 65, to assess whether other ages not associated with Medicare eligibility yielded similar or stronger changes in cancer mortality. Fifth, we assessed the assumption that outcomes would

have remained smooth at age 65 in the absence of the Medicare program by using data from Canada, a country which does not have a change in public insurance coverage at age 65.

Finally, we assessed whether our findings could be plausibly driven by population-level changes in health insurance coverage at age 65 by calculating changes in insurance coverage over ages 59-71. Because the SEER and vital statistics data do not include a reliable measure of health insurance coverage, we used the Behavioral Risk Factor Surveillance System data. This analysis used data from 2011-2016, years which included a nationally representative sample of both cellular and landline telephone users.

Analyses were conducted using Stata MP, version 14.1. We used two-sided p-values and calculated 95% confidence intervals for each quantity of interest.

RESULTS

Figures 1 depicts population-level health insurance coverage rates just before and after age 65. At age 65, insurance coverage increased from 90 to 97% (6.6 percentage point increase in coverage, 95% confidence interval: 5.9 to 7.3, $p<0.001$). Figures 2 and 3 depict cancer detection rates and post-detection survival just before and after this population-level change in insurance coverage, which have two notable characteristics. First, detection of cancer increases and post-detection survival decrease with age in general, reflecting the overall aging process. Second, there are visible increases in cancer detection and post-detection survival at age 65, the age at which health insurance coverage becomes nearly universal.

Our regression discontinuity estimates identified significant improvements in cancer detection and outcomes at age 65, after adjusting for aging and other factors. The first rows of Tables 1 and 2

present results when the three tumor sites of interest were pooled together. Cancer detection increased by 50 per 100,000 population (95% CI 35 to 64 per 100,000, $p<0.001$). This represented an 8% increase in cancer detection for the 65 year-olds compared to people aged 63-64, the "untreated"' group in our analysis. Early-stage cancer detection increased by 33 per 100,000 population (95% CI 25 to 41 per 100,000 population, $p<0.001$), or 10%. Late-stage cancer detection increased by 19 per 100,000 population (95% CI 13 to 26 per 100,000 population, $p<0.001$), or 6%. One-year survival after cancer detection increased by 0.61 percentage points, or 1%, after adjusting for exact stage at detection, tumor size in millimeters, and extension at diagnosis on a 0-99 scale (95% CI 0.24 to 0.99 percentage points, $p=0.001$). Cancer mortality declined at age 65, that is, increased by less than expected in the absence of the Medicare program, by 4.13 per 100,000 population or 2% (95% CI -2.3 to -6.0, $p<0.001$).

The subsequent rows of Tables 1 and 2 present results when breast, colorectal, and lung cancer are analyzed separately, and Figure A2 in the Appendix show the unadjusted data by tumor site. The poor outcomes for lung cancer are particularly notable. At ages 63-64, patients with newly diagnosed lung cancer had a one-year survival rate of only 42%, compared to 75% and 86% for colorectal and breast cancer, respectively; only 26% of lung cancer patients were diagnosed at an early stage compared to higher rates for the other cancers; and lung cancer accounted for more deaths than breast and colorectal cancer combined. Subsequently, at age 65, detection significantly increased for all three tumor sites examined, but mortality improvements were significant only for lung cancer.

Tumor site also played an important role in determining the effects of Medicare coverage on cancer outcomes across racial groups. When examining the data by race, we found that improvements in

cancer mortality were larger for Black patients. However, this appeared to be driven by the fact that Black patients are more likely than non-Black patients to develop lung cancer (Schabath, Cress, & Muñoz-Antonia, 2016). When stratifying the data by tumor site, improvements in lung cancer mortality were similar for Black and non-Black patients. See Table 3.

The key identifying assumption of the RDD model is that cancer detection and outcomes would have remained smooth at age 65 if the onset of Medicare coverage had not occurred. Prior studies have demonstrated the plausibility of this assumption by showing a lack of significant change in retirement, educational attainment, family income, and geographic location at age 65 (Barcellos & Jacobson, 2015; Card et al., 2008). We further assessed the plausibility of this assumption using data from Canada, a country which does not have a change in public insurance coverage at age 65. As expected, cancer detection for our tumor sites of interest remained on a smooth path at age 65 in Canada, but increased in the United States concurrent with the onset of Medicare. See Figure 4.

In placebo tests, we did not find comparable changes in population-level cancer mortality at ages other than 65. See Figure 5. This evidence supports the plausibility that changes at age 65, concurrent with near-universal eligibility for Medicare, accounted for our findings. Our findings did not substantially change when we re-estimated our models on a narrower sample of patients aged 62 to 68, or a broader sample of patients aged 56 to 74; controlled for the background trends in aging using a more flexible method, or relaxed our modeling assumptions and reported results derived more closely from the raw data. See section A3 of the Appendix. These additional sensitivity analyses further supported the robustness of the findings.

To identify the effect of each 1 percentage-point increase in population-level health insurance coverage on cancer detection, we divided the estimated changes in cancer detection at age 65 by

the estimated changes in insurance coverage in a "fuzzy" regression discontinuity analysis (Imbens & Lemieux, 2008). Each percentage-point increase in population-level insurance coverage was associated with increases in total, early-stage, and late-stage cancer detection of 8 per 100,000 people (or 1%), 5 per 100,000 people (or 2%) and 3 per 100,000 people (or 1%), respectively; an increase in one-year cancer survival by 0.1 percentage points (0.1%); and a decrease in cancer mortality by 0.6 per 100,000 population per year (0.3%).

Our regression discontinuity design identified the marginal effects of Medicare at age 65, rather than the full effect of Medicare among adults aged 65+. Nonetheless, our estimates can be used to assess the number of cancer deaths averted by having the onset of Medicare occur at age 65 rather than 66. We observed a decline in mortality of 4.13 per 100,000 population at age 65. Applied to the number of people aged 65 nationally, our findings suggest 140 cancer deaths avoided in 2015, or about 1,600 cancer deaths avoided during our sample period (2001-2015) by having the onset of Medicare at 65 rather than 66.

DISCUSSION

The goal of this study was to estimate the impact of Medicare health insurance coverage at age 65 on cancer detection, post-detection cancer survival, and population-level cancer mortality over 2001-2015. We are not aware of any previous study linking insurance coverage with improvements in population-level cancer mortality. Our analysis linking Medicare with cancer detection and survival outcomes builds on a previous study of the impact of Medicare on breast cancer detection and post-detection survival which used data from 1980-2001 (Decker, 2005). We studied all tumor sites for which screening is recommended among older adults, yielding a sample of over 740,000 breast, colorectal, and lung cancer cases diagnosed among patients aged 59-71.

Insurance coverage abruptly increased from 90% to 97% at age 65, the age of eligibility for Medicare. This nearly-universal coverage increased cancer detection by 50 per 100,000, an 8% increase compared to people aged 63-64; the majority of additional cancers detected were early-stage cancer. These findings are important for population heath because prompt detection improves health for the tumor sites we study, according to systematic reviews by the United States Preventive Services Task Force (Moyer & U.S. Preventive Services Task Force, 2014; Siu & U.S. Preventive Services Task Force, 2016; US Preventive Services Task Force et al., 2016). Supplemental analyses supported the robustness of our findings.

Even though cancer survival tends to decrease with age, we find that cancer survival increased at age 65, concurrent with near-universal Medicare coverage. Our analysis adjusted for detailed tumor characteristics at diagnosis, increasing the plausibility that these data represent genuine improvements in survival at age 65 rather than diagnosis bias. We found an adjusted increase in survival of 0.61 percentage points, or 1%. In an additional robustness check, we analyzed vital statistics data. In the vital statistics data, we found that cancer mortality increased by less than expected at age 65 by 2%, matching the survival data.

To contextualize these analyses and findings, a brief explanation of diagnosis bias and how our two analytic strategies address them may be helpful. Two key diagnosis biases applicable in cancer research are lead time bias and length bias, which can be summarized as follows. First, patients whose cancer is diagnosed earlier will appear to live longer after diagnosis even if earlier detection provides no clinical benefit. Second, as detection rates rise, the additional detected cancers may be slow-progressing cancers that are less deadly. When diagnosis rates rise, these biases may result in spurious improvements in rates of post-diagnosis survival -- simply because the additional

diagnosed patients had less severe disease (Barratt et al., 2018; Manning & Zelen, 1969; Shwartz, 1980). We addressed these diagnosis biases by adjusting for severity of diagnosed cancers, and by including undiagnosed cancers, i.e., those diagnosed only at autopsy, in the analysis. By using vital statistics data to measure population-level cancer mortality rates, we employ an established approach to addressing diagnosis bias (Duffy et al., 2008; Morrison, 1982).

The reductions in mortality we found were accounted for by reductions in lung cancer mortality. Reducing lung cancer mortality is crucial for population health because lung cancer is the leading cause of cancer death in the United States, accounting for more deaths than breast and colorectal cancer combined (Cronin et al., 2018). Medicare could plausibly reduce lung cancer mortality by providing access to lung cancer screening via CT scan, and access to costly treatments that improve survival (Herbst, Morgensztern, & Boshoff, 2018). In contrast to studies of data from 2001 and earlier, we did not detect an increase in survival after diagnosis with breast cancer at age 65 (Decker, 2005). This may reflect the 39% decline in the breast cancer death rate over 1989 to 2015, which occurred alongside increases in use of mammography (Cronin et al., 2018). Regardless, the increases in detection of breast and colorectal cancer we measure at age 65 could have improved health outcomes other than survival for breast or colorectal cancer patients (Siu & U.S. Preventive Services Task Force, 2016; US Preventive Services Task Force et al., 2016).

Importantly, the effects of near-universal coverage via Medicare on cancer mortality were similar among Black patients and non-Black patients. Accordingly, while Medicare coverage improved cancer mortality among all groups, disparities by race remained. Black patients have higher rates of late cancer detection and poorer survival outcomes than other racial groups (Virnig, Baxter,

Habermann, Feldman, & Bradley, 2009). Therefore, efforts to further address disparities in cancer outcomes by race should be further explored.

Key strengths of our study included validation of results using vital statistics data, use of recent data from an era of rapid advances in cancer treatment, and a large sample size resulting in high statistical power. A study of traditional Medicare claims data merged with SEER data from 2004-2007 compared patients diagnosed at ages 64 and 65-66 and detected no change in survival at age 65, in contrast to our findings (Huesch & Ong, 2016a). That study provided crucial insight on treatment. Yet, the study's power to analyze lung cancer survival is likely smaller than our study, given that the sample of lung cancer patients was 50 times smaller than that of our study (5,000 vs. 280,000 lung cancer patients). Additionally, using a wider age band to adjust for existing trends in survival by age may be important to detect a survival effect of the size we find (1%), given that cancer survival decreases by about 1% per year of age in our age range of interest.

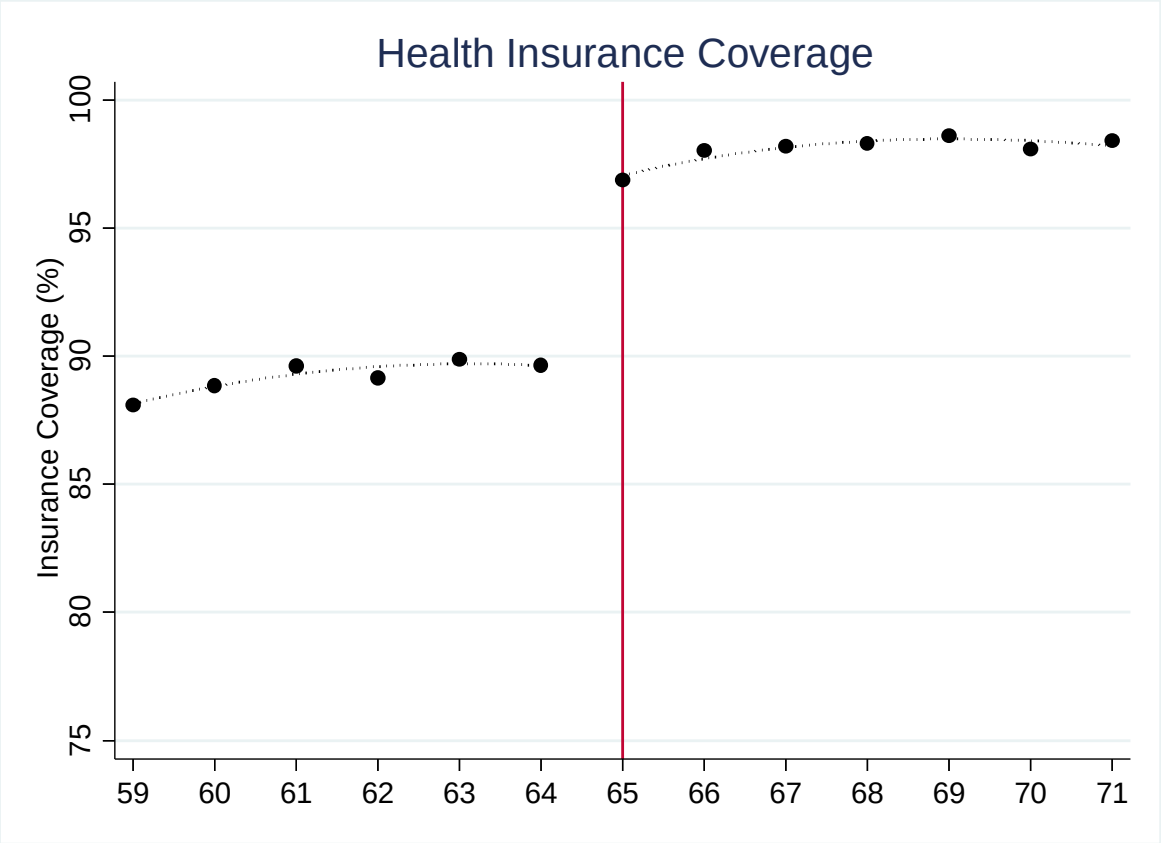
Our findings inform ongoing policy discussions about Medicare and the benefits of access to public insurance. Changes to the Medicare eligibility age have been repeatedly proposed. Informing this policy proposal, our findings suggest that setting Medicare eligibility age at 65 rather than 66 avoided about 1,600 deaths from cancer at age 65 during our sample period (2001-2015). Our regression discontinuity design only captures marginal changes at age 65, but given that deaths at age 65 account for only 4% of cancer deaths among adults age 65 and older, the total number of cancer deaths prevented by Medicare is likely to be much larger.

Our study had limitations. First, insurance coverage is not well-measured among cancer patients in the SEER data. To address this limitation, we used an additional data source to present contextual information about the increase in coverage at age 65. Second, changes in rates are

subject to population dynamics. However, our population denominator is updated annually by single year of age, state, gender, and racial group. Our analysis therefore accounts for any changes in migration or mortality by age, including differential migration or mortality by race or gender. Finally, ours is an observational study and we cannot rule out the possibility that changes other than onset of Medicare at age 65 account for our findings.

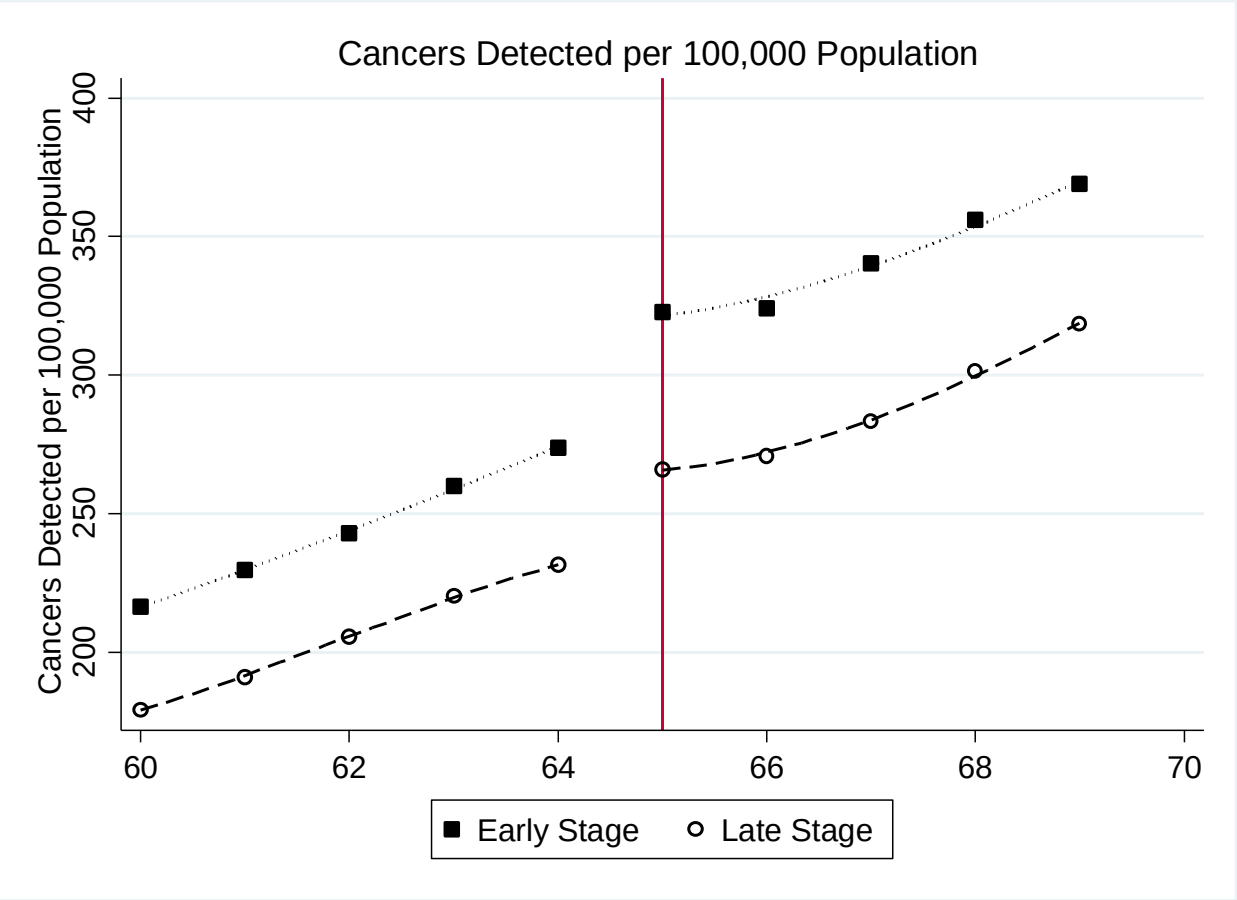
In conclusion, access to Medicare insurance was associated with a significant increase in detection of breast, colorectal, and lung cancer and a decline in mortality from lung cancer, the leading cause of cancer death in the United States. These estimates provide new evidence of Medicare's impact on health outcomes for vulnerable older adults in need of medical care.

Figure 1. Health insurance coverage just above and below age 65



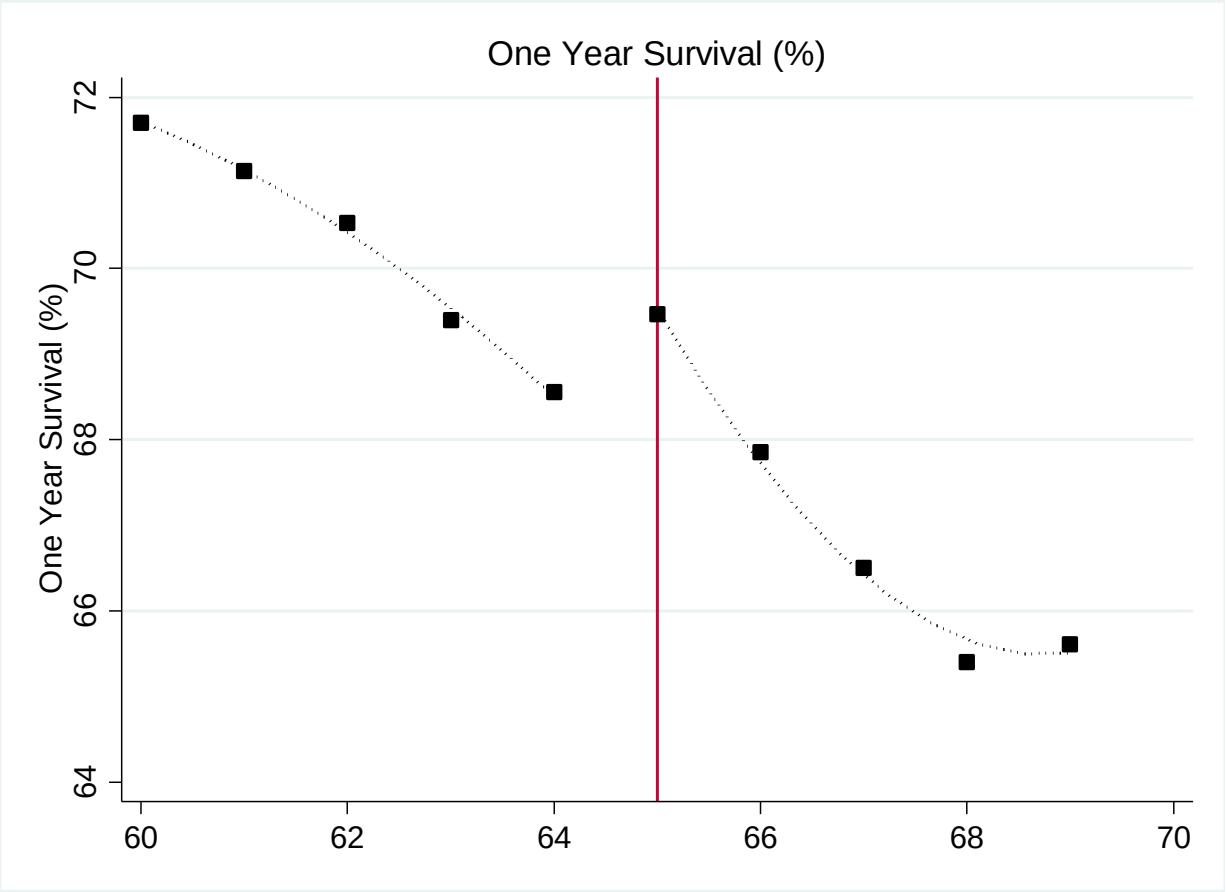
These graphs show trends in population-level health insurance coverage just above and below age 65, the age of near-universal health insurance coverage via Medicare. The x-axis is age and the y-axis is the percentage of people with health insurance coverage. The dotted lines are quadratic regression lines, estimated separately below vs. above age 65.

Figure 2. Cancer detection among patients just above and below age 65, by stage



This graph shows trends in early- and late-stage detection for cancers with recommended screening just above and below age 65, the age of near-universal health insurance coverage via Medicare. The x-axis is age at diagnosis; and the y-axis is cancers detected per 100,000 population. The dotted lines are quadratic regression lines, estimated separately below vs. above age 65.

Figure 3: One-year cancer survival among patients just above and below age 65



This graph shows trends in one-year survival for cancers with recommended screening just above and below age 65, the age of near-universal health insurance coverage via Medicare. The x-axis is age at diagnosis; and the y-axis is one-year survival after cancer diagnosis. The dotted lines are quadratic regression lines, estimated separately below vs. above age 65.

Table 1: Impact of Medicare on detection of cancers with recommended screening, in total and by tumor site

	Cancers detected per 100,000 population per year		**Early-stage cancers detected per 100,000 population per year**		**Late-stage cancers detected per 100,000 population per year**	
	Age 63-64	**RD at 65**	**Age 63-64**	**RD at 65**	**Age 63-64**	**RD at 65**
Total	507	50***	267	33***	226	19***
		(35 to 64)		(25 to 41)		(13 to 26)
		[P<0.001]		[P<0.001]		[P<0.001]
By tumor site						
Breast	243	26***	179	17***	60	9***
		(20 to 32)		(14 to 20)		(5 to 13)
		[P<0.001]		[P<0.001]		[P<0.001]
Colon and Rectum	82	16***	44	10***	36	7***
		(11 to 22)		(7 to 14)		(4 to 9)
		[P<0.001]		[P<0.001]		[P<0.001]
Lung and Bronchus	182	11***	45	6***	129	4***
		(5 to 16)		(3 to 8)		(2 to 7)
		[P<0.001]		[P<0.001]		[P<0.001]

NOTE: *p<0.1, **p<0.05, ***p<0.01

This table shows the results of regression discontinuity analyses of cancer detection at age 65, the age of near-universal eligibility for Medicare health insurance. Entries in odd-numbered columns are values of the outcome for people age 63-64 years-old. Entries in even-numbered columns are estimated regression discontinuities at age 65 after adjusting for background trends in aging and over time, time-invariant confounders by state, and patient gender and race. Standard errors are clustered by single year of age. Rows indicate findings from models stratified by tumor site. 95% confidence intervals are in parentheses and p-values are in brackets.

Table 2: Impact of Medicare on survival outcomes, in total and by tumor site

	Cancer mortality per 100,000 population (CDC data)		One-year survival after cancer diagnosis (%) (SEER data)			
	Age 63-64	**RD at 65**	**Age 63-64**	**RD at 65**	**RD at 65 adjusting for stage at diagnosis**	**RD at 65 adjusting for tumor stage, size, and extension at diagnosis**
Total	208.3	-4.13***	68.98	1.46***	0.87***	0.61**
		(-2.27 to -5.98)		(1.04 to 1.89)	(0.47 to 1.27)	(0.24 to 0.99)
		[P<0.001]		[P<0.001]	[P<0.001]	[P=0.001]
By tumor site						
Breast	31.73	0.17	86.31	1.39	0.15	0.17
		(-0.47 to 0.80)		(-0.23 to 0.52)	(-1.44 to 4.51)	(-0.11 to 0.44)
		[P=0.601]		[P=0.461]	[P=0.312]	[P=0.228]
Colon and Rectum	37.07	0.48	75.74	1.31***	0.77*	0.95**
		(-0.39 to 1.36)		(0.54 to 2.09)	(-0.07 to 1.62)	(0.04 to 1.86)
		[P=0.281]		[P<0.001]	[P=0.072]	[P=0.041]
Lung and Bronchus	139.51	-4.26***	42.45	3.25***	1.92***	1.02**
		(-5.66 to -2.85)		(2.20 to 4.31)	(0.96 to 2.88)	(0.12 to 1.92)
		[P<0.001]		[P<0.001]	[P<0.001]	[P=0.026]

NOTE: *p<0.1, **p<0.05, ***p<0.01

This table shows the results of regression discontinuity analyses of post-diagnosis cancer survival and population-level cancer mortality at age 65. Entries in columns marked "Age 63-64" are values of the outcome for people age 63-64 years-old. Entries in columns marked "RD at 65" are estimated regression discontinuities at age 65 after adjusting for background trends in aging and over time, time-invariant confounders by state, and patient gender and race; standard errors are clustered by single year of age, plus the additional controls listed in the column header. Rows indicate findings from models stratified by tumor site. 95% confidence intervals are in parentheses and p-values are in brackets.

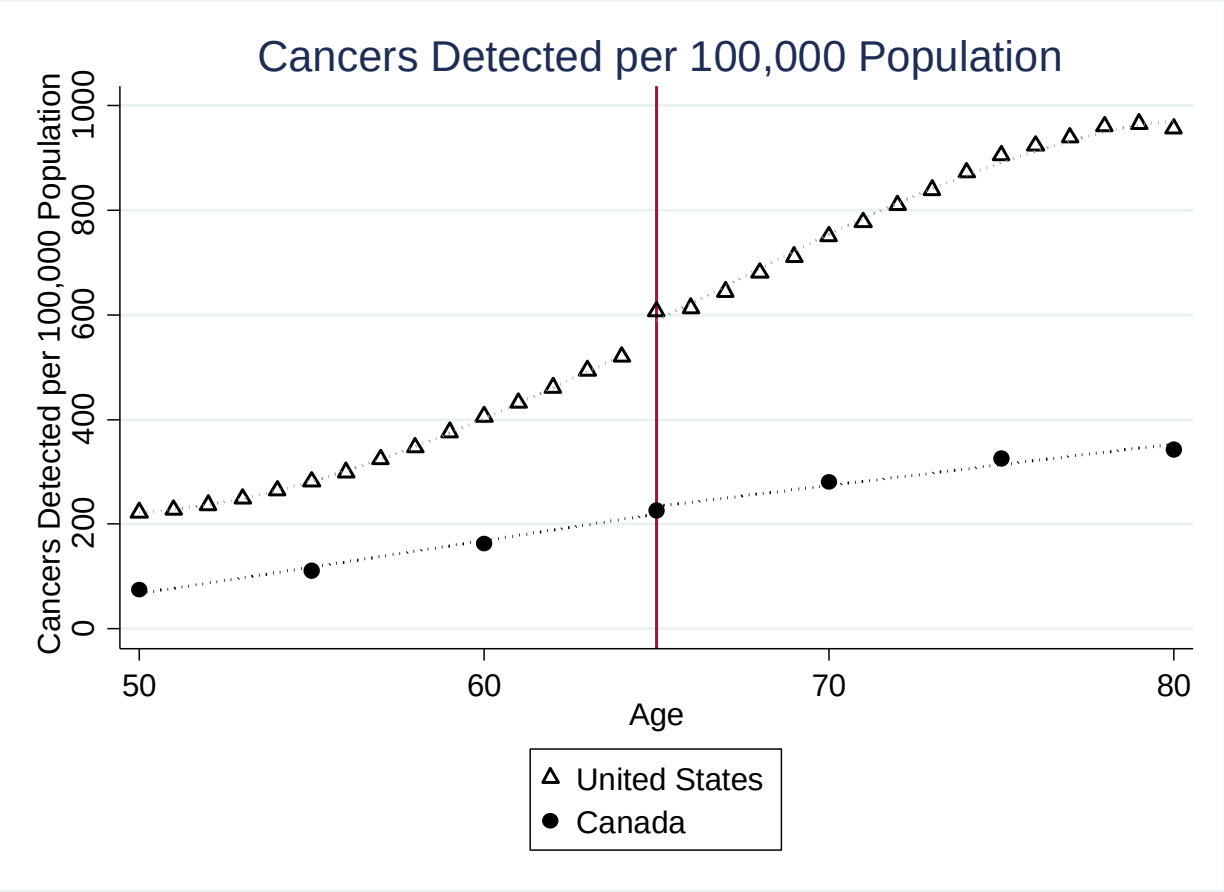
Table 3: Impact of Medicare on mortality outcomes for cancers with recommended screening, by patient race and tumor site

	Deaths attributable to cancer per 100,000 population		**Deaths attributable to lung cancer per 100,000 population**	
	Age 63-64	**RD at 65**	**Age 63-64**	**RD at 65**
Black	270	-8.33***	167	-4.07***
		(-11.43 to -5.24)		(-7.29 to -0.86)
		[P<0.001]		[P=0.013]
Non-Black	201	-1.59	136	-3.51***
		(-3.87 to 0.69)		(-4.69 to -2.33)
		[P=0.171]		[P<0.001]
Tumor site	All considered in this study (Breast, colorectal, or lung)		Lung cancer only	

NOTE: *p<0.1, **p<0.05, ***p<0.01

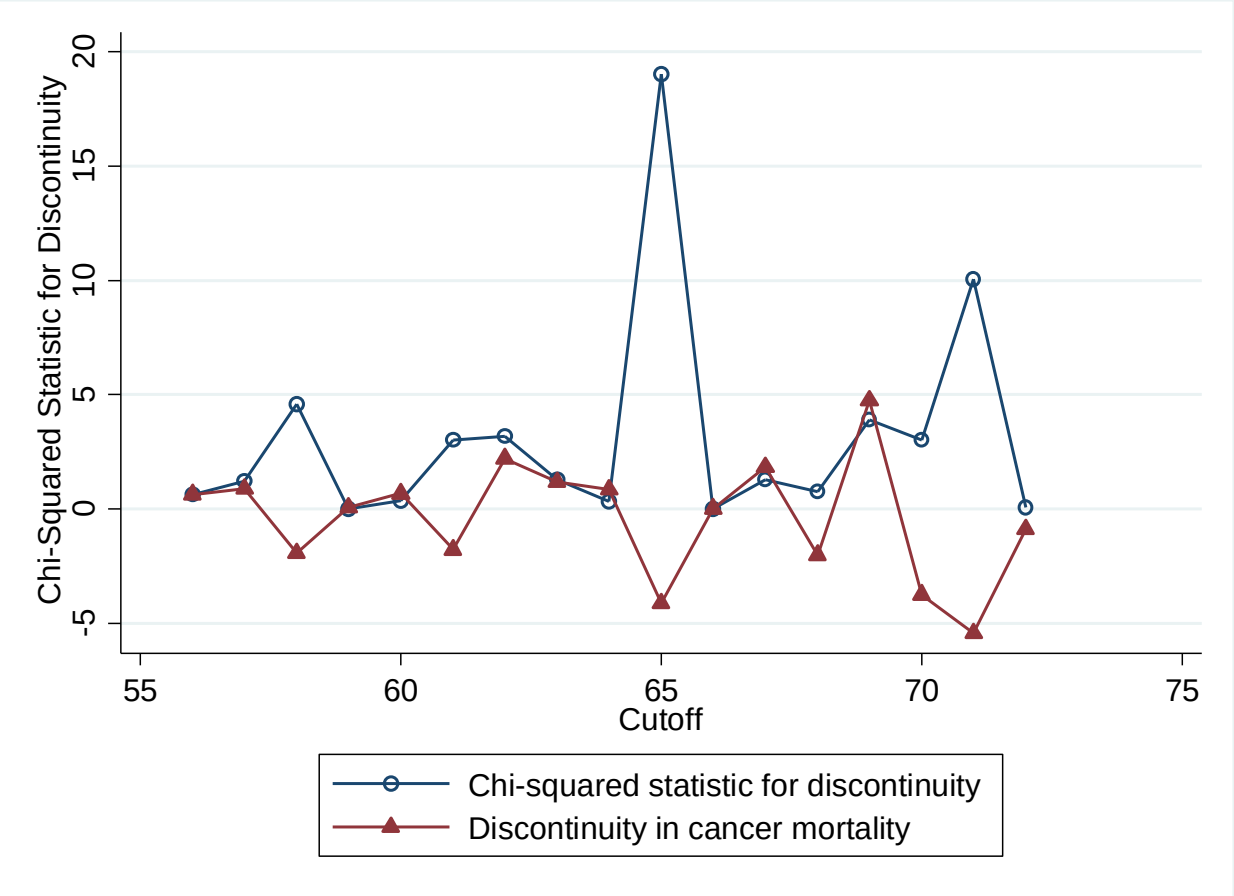
Entries in odd-numbered columns are values of the outcome for people age 63-64 years-old. Entries in even-numbered columns are estimated regression discontinuities at age 65 after adjusting for background trends in aging and over time, time-invariant confounders by state, and patient gender. Standard errors are clustered by single year of age. 95% confidence intervals are in parentheses and p-values are in brackets.

Figure 4: Cancer detection among patients just above and below age 65 in 2001-2015, in the United States vs. Canada



This figure shows no discontinuity in cancer detection for our tumor sites and years of interest at age 65 in Canada, supporting the plausibility that changes at age 65 aside from the Medicare program are unlikely to account for our results. The basis of this placebo test is that 65 is the age of near-universal health insurance coverage via Medicare in the United States, but not in Canada. The x-axis is age at diagnosis; and the y-axis is cancers detected per 100,000 population. The dotted lines are quadratic regression lines, estimated separately below vs. above age 65.

Figure 5: Findings from chi-square statistics for discontinuity in population-level cancer mortality, at age 65 and other ages



This figure shows that the largest and most statistically significant discontinuity in cancer mortality per 100,000 population, within the bandwidth we analyze, is at age 65 as expected. The chi-squared statistic plotted tests the significance of the discontinuity found when different ages were used as the cutoff in our main regression discontinuity analysis.

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Appendix:

Section A1: Description of the analysis

Our analytic strategy exploited the increases in Medicare health insurance coverage at age 65.(Barcellos & Jacobson, 2015; Card et al., 2008; Finkelstein & McKnight, 2008; McWilliams et al., 2009, 2013) We restricted the data to a small window around the Medicare eligibility threshold (age 65) to compare outcomes for the "young elderly" just over age 65 vs. the "near elderly" just under age 65. To select the size of this window, we used the *rdbwselect* Stata command, which identifies the bandwidth with the best mean squared error for a given application and data set.(Calonico, Cattaneo, & Titiunik, 2014b) This procedure yields an optimal bandwidth of 6 years in our application. We subsequently assessed the robustness of our findings to changes in this bandwidth.

To estimate the size of the discontinuities in cancer detection and survival at age 65, we employed standard methods for analysis of a regression discontinuity analysis.(Imbens & Lemieux, 2008; Lee & Lemieux, 2010) In our main analysis, we estimated the following model for people of age *a*, gender *g*, and race *r*, living in state *s* in year *t*:

$$Y_{agrst} \sim f(\delta_0 + \delta_1(a \geq 65) + \delta_1(a \geq 65)p(a) + \delta_2(a \leq 65)p(a) + X\beta + \gamma_t + \varphi_s)$$

Y_{agrst} indicates the outcomes analyzed, such as cancers detected or cancer mortality per 100,000 population, or one-year survival after cancer detection. $(a \geq 65)$ indicates age groups who have reached the age cutoff for Medicare (that is, strictly over age 64). This model adjusts for patient gender and race (covariates in vector X), as well as year and state fixed-effects (γ_t and φ_s). The effects of age are allowed to vary above vs. below the cutoff using a polynomial of age centered at age 65 ($p(a)$). Our main specification uses a quadratic function but we present results which use linear and third-order polynomial specifications in robustness checks. In secondary analyses, we stratified models of cancer detection and survival by race and by location of the cancer.

When people are diagnosed with cancer earlier, they may appear to survive longer simply due to becoming classified as a cancer patient earlier in their disease. We took two main approaches to ensure that our results capture genuine improvements in survival rather than this type of bias. First, we added to our standard controls the most detailed information available in the SEER data to adjust for tumor characteristics at diagnosis. These characteristics included exact tumor stage (1 through 6) at diagnosis, captured using indicator variables; the largest dimension of the primary tumor at diagnosis in millimeters; and extension of tumor away from the primary site at diagnosis, coded on a 0 to 99 scale. Second, we analyzed population-level mortality data from the Centers for Disease Control and Prevention, which capture the universe of cancer deaths including those diagnosed at autopsy.

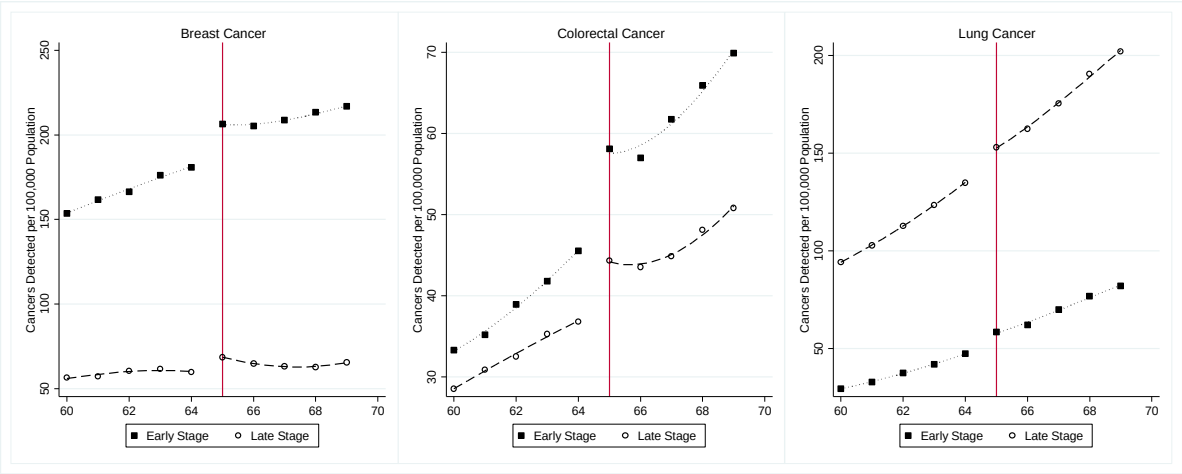
The functional form of the models used varied by the outcome analyzed. We used negative binomial models to assess changes in cancer detection per population or cancer deaths per population, and used logit models to assess changes in one-year survival after cancer detection. From these models, we used average marginal effects to extract the quantities of interest: changes

in cancers detected per 100,000 population, changes in cancer deaths per 100,000 population, and changes in one-year survival after cancer detection at age 65.

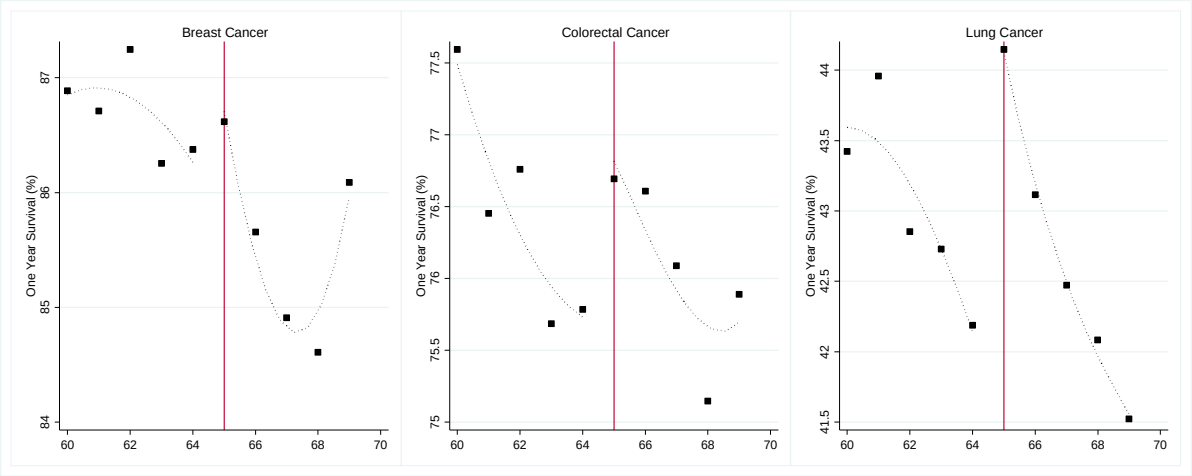
In an additional robustness check, we estimated all models using a local-linear regression implemented with the *rdrobust* Stata command.(Calonico et al., 2014b) These models used a triangle kernel which places higher weight on observations with closer distance to the threshold. For these models, we report the robust bias-corrected standard errors recommended in Calonico et al.(Calonico, Cattaneo, & Titiunik, 2014a)

Section A2: Detection and outcomes for cancers with recommended screening just above and below age 65, by location of the cancer

A. Cancers detected



B. One-year survival



These graphs shows the number of cancers detected and one-year survival for breast, colorectal, and lung cancer just above and below age 65, the age of near-universal eligibility for Medicare health insurance. In each graph, the x-axis is age at diagnosis; the y-axis is the percent of cancers detected at an early stage. The dotted lines are quadratic regression lines, estimated separately below vs. above age 65.

Section A3: Sensitivity analyses

	Total cancer detection per 100,000 population per year	Early-stage cancer detection per 100,000 population per year	Late-stage cancer detection per 100,000 population per year	One-year cancer survival (%), after full adjustment for tumor characteristics	Cancer deaths per 100,000 population
Main specification	50*** (36 to 64) [*P*<0.001]	33*** (25 to 41) [*P*<0.001]	19*** (13 to 26) [*P*<0.001]	0.52** (0.12 to 0.93) [*P*=0.001]	-4.127*** (-2.27 to 5.98) [*P*<0.001]
Larger bandwidth (9 years)	45*** (29 to 62) [*P*<0.001]	29*** (20 to 39) [*P*<0.001]	16*** (7 to 24) [*P*<0.001]	0.20* (0 to 0.4) [*P*=0.001]	-1.05 (-3.43 to -1.32) [*P*=0.385]
Smaller bandwidth (3 years)	59*** (54 to 64) [*P*<0.001]	35*** (32 to 38) [*P*<0.001]	30*** (29 to 31) [*P*<0.001]	0.38*** (0.16 to 0.6) [*P*<0.001]	-2.90*** (-3.49 to -2.30) [*P*<0.001]
Higher-order polynomial in age (3rd order)	47*** (38 to 57) [*P*<0.001]	28*** (22 to 33) [*P*<0.001]	25*** (19 to 31) [*P*<0.001]	-0.13 (-0.62 to 0.35) [*P*=0.992]	-4.20** (-0.56 to 7.83) [*P*=0.024]
Lower-order polynomial in age (linear)	36*** (21 to 51) [*P*<0.001]	25*** (16 to 33) [*P*<0.001]	11*** (4 to 19) [*P*=0.003]	0.29*** (0.07 to 0.51) [*P*=0.008]	-0.40 (-4.38 to 3.58) [*P*=0.842]
Local linear regression model	28** (2 to 53) [*P*=0.033]	27*** (8 to 46) [*P*=0.006]	-0 (-2 to 2) [*P*=0.973]	0.96*** (0.37 to 1.55) [*P*=0.002]	-4.50 (-21.97 to 12.96) [*P*=0.613]

NOTE: *p<0.1, **p<0.05, ***p<0.01

This table shows changes in cancer detection and outcomes at age 65 under various model specifications. The first row includes findings from the main specification, which used bandwidth of 6 and adjusts for trends in age using a quadratic expression; the main specification also uses a parametric regression. In the subsequent rows, we change the bandwidth to 3 and 9; and adjust for aging effects using a linear trends, a third-order polynomial, or a less-parametric local linear regression specification with a triangular kernel. All models aside from the less-parametric local linear regression adjust for year and state effects and patient gender and race, and cluster standard errors by single year of age. The cancer survival models additionally adjust for tumor stage (1 through 6), the largest dimension of the primary tumor in millimeters, and extension of tumor away from the primary site (coded 0-99) at detection. 95% confidence intervals are in parentheses.