The Effect of Patient Cost-sharing on Utilization, Health and Risk Protection: Evidence from Japan*

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Abstract

Cost-sharing, requiring patients to pay a share of the cost of care, is one main strategy for the government to contain health care costs. A key question is how much cost-sharing affects the demand for care, health itself, and risk protection among the elderly, the largest consumers of health services. Previous studies of cost-sharing have had difficulty separating the effect of cost-sharing on patients from the responsive behavior by medical providers and insurers. This paper overcomes that limitation by examining a sharp reduction in cost-sharing at age 70 in Japan in a regression discontinuity design. I find that reduced cost-sharing at age 70 discontinuously increases health care consumption. The corresponding price elasticity for both outpatient visits and inpatient admissions is around -0.2, comparable to prior estimates for the *non*-elderly. On the benefit side, I do not find any impact of lower cost-sharing on mortality or health despite utilization change, but I find that lower cost-sharing transforms the distribution of out-of-pocket expenditures. I then combine the expected utility framework with the quantile RD estimates and find that the welfare gain of risk reduction from lower cost-sharing is relatively small compared to the deadweight loss of program financing, suggesting that the social cost of lower cost-sharing may outweigh the social benefit.

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1 Introduction

Governments increasingly face an acute fiscal challenge of rising medical expenditures especially due to aging population and expansion of coverage. Spending growth for Medicare, the public health insurance program for the elderly in the United States, has continued unchecked in spite of a variety of government attempts to control costs.[1] As more than one third of current health spending is on the elderly, future cost control efforts can be expected to focus on seniors.[2]

One main strategy for the government to contain health care cost is cost-sharing, requiring patients to pay a share of the cost of care. However, cost-sharing has clear tradeoffs. While cost-sharing may reduce direct costs by decreasing moral hazard of health care services, it may also reduce access to beneficial and necessary health care that could mitigate future severe and costly health events. Moreover, very high levels of cost-sharing may undermine one of the primary reasons of having health insurance, which is financial protection from large out-of-pocket medical expenditure. Thus, there is a desperate need for knowledge on how cost-sharing affects utilization, health itself and risk protection, especially among the elderly, to determine the appropriate level of cost-sharing.

Credible evidence on the price sensitivity of health care consumption among the elderly is limited. For instance, individuals above age 62 were excluded from the well-known RAND Health Insurance Experiment (hereafter, RAND HIE), which randomly assigned individuals to insurance plans with different generosities. It is not clear *a priori* whether the elderly are expected to have a larger or smaller price elasticity of demand for health care services than the non-elderly. On one hand, the price elasticity for the elderly may be larger if they tend to be poorer or more credit-constrained than the non-elderly. On the other hand, it can be smaller if their health problems are more severe than those of non-elderly. An exception that studied the elderly is Chandra et al. (2010) who examined the effect of a small increase in the copayments for physician office visits and prescription drugs in a supplemental Medicare insurance policy.

Most U.S. studies, however, have difficulty separating the demand elasticities of patients from the responsive behavior by insurers and medical providers. This limitation arises because insurers prevent patients from freely choosing medical providers through managed-care, and medical providers determine which treatments to provide based on the patients' health insurance plans. Indeed, there is substantial evidence that the medical providers are reluctant to treat patients with government-funded health insurance beneficiaries due to low reimbursement rates as well as frequent delays in reimbursement.[3] If insurers and medical providers limit the patients' access to health care services, the elasticities of demand that are estimated in these studies could be biased.

By contrast, the unique setting in Japan permits isolation of the demand elasticity for health care

[1]Examples of supply-side attempts by the government to control cost are the introduction of prospective payment for hospitals and reductions in provider reimbursement rates (Cutler, 1998).

[2]The elderly are the most intensive consumers of health care. Patient over age 65 consume 36 percent of health care in the US despite representing only 13 percent of the population (Centers for Medicaid and Medicare Services 2005). Furthermore, Medicare costs are expected to comprise over a quarter of the primary federal budget by 2035, or between five and six percent of GDP (CBO, 2011). Likewise, in Japan, the elderly consume five times as many health services as non-elderly (Okamura et al, 2005). Also Japan has the most rapidly aging population in the world (Anderson and Hussey, 2000).

[3]For example, see Cunningham and O'Malley (2009) and Garthwaite (2011).

services since medical providers and insurers typically play a small, if any, role in patients' demand for health care services. Under universal health insurance coverage in Japan, there are no restrictions on patients' choices of medical providers. Also physicians' payments are based on a national fee schedule that does *not* depend on patients' insurance type. This institutional setting limits physicians' incentives to influence patient demand and prevents cost-shifting, a well-known phenomenon in the U.S. where medical providers charge private insurers higher prices to offset losses from the beneficiaries of government-funded health insurance (Cutler, 1998).

My research design exploits a sharp reduction in patient cost-sharing at age 70 in Japan in a regression discontinuity design to compare the outcomes of those just below versus those just over age 70. Due to national policy, cost-sharing for outpatient visits and inpatient admissions is as much as 60-80 percent lower at age 70 than at age 69 in Japan. This reduction is substantial, especially for inpatient admissions: out-of-pocket medical expenditures for inpatient admissions can reach as much as 25 percent of the average annual income of a 69-year-old patient among those admitted. Since turning 70 in Japan does not coincide with changes in any other confounding factors such as employment or pension receipt, I can plausibly isolate the effect of the cost-sharing on demand for health care services.

This setting also offers additional advantages over previous empirical settings. While the change in co-payment in Chandra et al. (2010) is limited to office visits and prescription drugs, in Japan cost-sharing for inpatient admissions also changes abruptly at age 70. Thus I can estimate the elasticity of inpatient admissions of the elderly as well. Also, since I have detailed information on outpatient visits, I can investigate the price sensitivity of preventive care in the outpatient setting.[4] In contrast, most existing datasets capture either outpatient visits or inpatient admissions.[5] Finally, I examine the effect of cost-sharing on exposure to out-of-pocket medical expenditure risk. While there is a large literature on the impact of cost-sharing on health care utilization and health, there is remarkably little analysis of the impact of cost-sharing on expenditure risk, which is arguably the primary purpose of health insurance (e.g., Zeckhauser, 1970).[6]

I reach three conclusions. First, I find that reduced cost-sharing at age 70 discontinuously increases health care consumption. The corresponding elasticity is modest, around -0.2 for both outpatient visits and inpatient admissions. As it turns out, the elasticity I estimate is similar to the estimates found in the RAND HIE for the non-elderly, and slightly larger than that estimates for the elderly by Chandra et al. (2010) in the US. The finding indicates that the price elasticity of the elderly is similar in magnitude to that of the non-elderly.

Looking in more detail at patterns of utilization, I also find that lower cost-sharing is associated with increase in the number of patients presenting with both serious and non-serious diagnoses. Thus, I find that demand for both more and less beneficial care is price sensitive. For example, I find large increases in outpatient visits for diagnoses that are defined as Ambulatory Care Sensitive Conditions (ACSCs), for which proper and early treatment reduce subsequent avoidable admissions.

[4] Outpatient visits are visits to a clinic or hospital without being admitted. It is common for individuals to visit hospitals for outpatient care rather than clinics (similar to physicians' office visits in the U.S.) in Japan.

[5] In fact, the Agency for Healthcare Research and Quality (AHRQ) has recognized the need to develop a methodology for studying preventive care in an outpatient setting by using inpatient data to identify admissions that should not occur in the presence of sufficient preventive care (AHRQ, 2011). This issue is more discussed in section 4.

[6] See Chandra et al. (2008) for an excellent summary of the past literature on cost-sharing and utilization.

Second, on the benefit side, I do not find statistically significant improvements in health at age 70 at least in the short run. Both mortality, and self reported physical and mental health are unchanged despite utilization changes, implying that patient cost-sharing can reduce health care utilization without adversely affecting health.

Finally, I find that lower cost-sharing at age 70 yield reductions in out-of-pocket expenditures since lower cost-sharing overwhelms the increase in utilization. I then compute the gain in risk premiums through increased generosity in health insurance at age 70 by combining the expected utility framework with the quantile RD estimates. Although somewhat speculative, my estimates suggest that the welfare gain of risk protection from lower cost-sharing is small for most, suggesting that the social cost of lower cost-sharing may outweigh the social benefit. Taken together, this study shows that increased cost-sharing may be achieved without decreasing the total welfare.

This paper is related to an influential literature that examines Medicare eligibility at age 65 in a similar RD framework as this paper. Card et al. (2009) and Chay et al. (2010) show that Medicare eligibility has a modest positive effect on the health of those above age 65. However, these studies cannot definitely address whether these health improvements are the result of health insurance provision *per se* (extensive margin) or changes in health insurance generosity (intensive margin). This issue arises because turning age 65 in the US entails a number of coincident changes: transitions from private to public health insurance, increases in multiple coverage due to supplementary coverage (e.g., Medigap), and fewer gatekeeper restrictions due to the change from managed care to fee-for-services. Indeed, Card et al. (2009) conclude that it is not clear whether reductions in mortality are due to health insurance provision or generosity. In a companion paper, Card et al. (2008) show that both supply-side incentives and shifts in insurance characteristics play an important role for the utilization of health care services. In contrast, the change at age 70 only reflects increases in benefit generosity in my case.

The rest of the paper is organized as follows. Section 2 briefly describes the institutional background. Section 3 describes the data, and presents the identification strategy. Section 4 shows the main results on utilization. Section 5 turns to the analysis on benefit, and examines the health outcomes as well as risk reduction. Section 6 carries out simple cost-benefit analysis and section 7 concludes.

2 Background

This section describes the universal health insurance system in Japan, focusing on the differences in patient cost-sharing between the elderly and non-elderly.[7]

2.1 Institutional Setting

For this study, there are two important features of Japanese medical system that arguably permits isolation of the patient demand for health care services from responsive behavior by insurers and medical providers: universal coverage and the uniform national fee schedule. First, under universal coverage, patients in Japan have unrestricted choices of medical providers unlike in the U.S where managed-care

[7] Japan achieved universal health insurance coverage in 1961. See Kondo and Shigeoka (2012) for more details about the effect of the introduction of universal health insurance on utilization and supply-side responses.

often restricts the set of the providers at which beneficiaries can receive treatment. For example, it is common for individuals to visit hospitals for outpatient care rather than clinics (similar to physicians' office visits in the U.S.) in Japan. Patients have direct access to specialist care without going through a gatekeeper or referral system. There is also no limit on the number of visits a patient can have.[8] Patients may go either hospitals or clinics for outpatient visits and go to hospitals for admissions, unlike in the U.S., where those who lack insurance use hospitals as primary care.

Second and perhaps more importantly, all medical providers are reimbursed by the national fee schedule, which is uniformly applied to all patients regardless of patients' insurance type and age. Since patients' insurance type and age do not affect reimbursements, physicians have few incentives to influence patients' demand.[9] For example, from physicians' perspective, there are few reasons to delay surgeries until age 70 because reimbursements do not differ by age of patients. The uniform fee schedule also implies that there is little room for cost-shifting, a well-known behavior of medical providers in the U.S. where they charge private insurers higher prices to compensate for losses from beneficiaries of public health insurance (Cutler, 1998).[10]

2.2 Changes in Cost-sharing at Age 70

Unlike a normal health insurance plan that has three basic components (a deductible, a coinsurance rate, and a stop-loss), there is no deductible in Japan.[11] A patient pays coinsurance which is the percentage of medical costs for which beneficiary is responsible. Since inpatient admissions are more expensive than outpatient visits, coinsurance rate of inpatient admissions tends to be set lower than that of outpatient visits in Japan. The insurer pays the remaining fraction of expenses until the beneficiary meets the stop-loss (also known as the maximum out-of-pocket), and the insurer pays all expenses above the stop-loss.

The elderly become eligible for lower cost-sharing on the first day of the next month after they turn 70.[12] They receive a notice from the government that indicates that they are eligible for Elderly Health Insurance and a new insurance card, which they can present at medical institutions to receive the discount. Elderly Health Insurance is also provided to bedridden people between the ages of 65 and

[8] As a result, Japan has the highest per-capita number of physician visits among all OECD countries; physician consultations (number per capita per year) is 13.2 in Japan, which is more than three times larger than 3.9 in the U.S. (OECD, 2011).

[9] The national schedule is usually revised biennially by the Ministry of Health, Labor and Welfare through negotiation with the Central Social Insurance Medical Council, which includes representatives of the public, payers, and providers. See Ikegami (1991) and Ikegami and Campbell (1995) on details.

[10] Japan introduced prospective payment for hospitals since 2003 for only acute diseases, but the reimbursement does not differ by the insurance type or age of the patients. See Shigeoka and Fushimi (2011).

[11] A deductible is lump-sum amount of spending that beneficiary must pay before the insurers cover any expenses. Typically coinsurance is applied for medical costs above the deductible in the US.

[12] Japan introduced free care for the elderly over age 70 in January 1973. However, this policy substantially increased the utilization of health care services and medical expenditures. In fact, the medical expenditures rose by 55 percent in just one year, from 429 billion Yen in 1973 to 665 billion Yen in 1974. In February 1983, the Japanese government passed the Act on Assurance of Medical Care for Elderly People, which imposed cost-sharing on those over 70 starting after the 10 years of generous policy. Even after its introduction, there has been still a large discrepancy in cost-sharing between those just above and below age 70. Due to data availability, this study focuses on the period after the implementation of the cost-sharing for the elderly.

70.

Table 1 displays the cost-sharing formulas for those below and above age 70 for outpatient visits and inpatient admissions separately for each survey year of the Patient Survey, which I describe in detail in the data section. For those below age 70, the coinsurance rate is determined by the type of health insurance, employment status (retired or not), and whether the person is a (former) employee or is a dependent. There are two types of health insurance for those below age 70; employment-based health insurance covers the employees of firms that satisfy certain requirements and employees' dependents. National Health Insurance (hereafter, NHI) is a residential-based system that provides coverage to everyone else, mainly including the employees of small firms, self-employed workers, the unemployed, and the retired.

Employment-based health insurance had a lower coinsurance rate than NHI until 2003, when both were equalized to a common coinsurance rate of 30 percent for both outpatient visits and inpatient admissions. At the age of 70, people switch to Elderly Health Insurance and in principle face the same cost-sharing.[13] Note that on the other hand, physicians' reimbursements are based on a national fee schedule that does not depend on patients' insurance type or age.

Figure 1 illustrates the amount of out-of-pocket expenditures with respect to total monthly medical expenditures for year 2008 as an example based on the formula in Table 1. Unlike in the US, in Japan, the stop-loss is set monthly rather than annually.[14] The horizontal axis is total monthly medical expenditures, and the vertical axis shows the corresponding monthly out-of-pocket medical expenditures. Since the stop-loss differs for outpatient visits and inpatient admissions for those over age 70, I show separate lines for outpatient visits and inpatient admissions. For those below 70, there is no distinction between these two services in 2008. Figure 1 shows that the price schedule of out-of-pocket medical expenditures for those above 70 always lies below that of those below age 70.

Unfortunately, the actual out-of-pocket expenditure information among the general population is only available for year 2007, and this data does not distinguish outpatient visits and inpatient admissions. However, I have individual level insurance claim data for outpatient visits and inpatient admissions respectively, which is the monthly summary of medical expenditures claimed for insurance reimbursement to medical institutions (called the Survey of Medical Care Activities in Public Health Insurance). Since a portion of this monthly total medical expenditure is paid as patient cost-sharing according to the formula in Table 1, I can compute the average out-of-pocket medical expenditures at each age for each survey year of the Patient Survey.

Table 2 summarizes the actual monthly out-of-pocket expenditures of the average 69-year-old, and the counterfactual monthly out-of-pocket medical expenditures for a 70-year-old. For those age 70-year-old, since observed out-of-pocket medical expenditure already reflects the change in cost-sharing (i.e. out-of-pocket medical expenditures are endogenous), I compute their counterfactual out-of-pocket

[13]In fact, high income earners above age 70 are charged higher coinsurance rate (20 percent instead of 10 percent) since October 2002. The bar for high income level is set quite high, so that a limited number of patients is in this category (7 percent according to Ikegami et al. 2011). Since income is not collected in the Survey of Medical Care Activities in Public Health Insurance, which I use to derive the monthly out-of-pocket expenditures, I compute the monthly out-of-pocket expenditures for a normal family. See Appendix A1 for detail.

[14]This is purely administrative reason; reimbursements to the medical institutions are conventionally paid monthly in Japan and thus stop-loss is set monthly.

expenditures by applying the cost-sharing rules of Elderly Health Insurance to the utilization of the average 69-year-old. See Appendix A1 for details on these derivations. Note here that I do not exploit the year-to-year variation in cost-sharing, and rather pool all the survey rounds to increase the statistical power, and to smooth out cohort-size effect.[15] The overall out-of-pocket medical expenditure conditional on using medical institutions in Table 2 is the weighted average of the out-of-pocket medical expenditure across all survey years, using the population of 69-year-old in each survey year as weights.

Table 2 reveals a couple of interesting facts. First, out-of-pocket medical expenditures, especially from inpatient admissions, can pose a substantial financial burden on the near elderly (those just below age 70). Since the average annual income for 69-year-old is 1,822 thousand Yen (or roughly 18,220 US dollars), out-of-pocket medical expenditures for inpatient admissions can reach as much as 25 percent of an average person's total annual income for those admitted.[16] On the other hand, once the patient turns 70, the counterfactual ratio of medical expenditures to the average income is reduced to as small as 8.2 percent.[17]

It is also important to note that stop-loss plays a role in reducing the out-of-pocket medical expenditures for those *below* 70, especially for inpatient admissions. In the absence of stop-loss, the gap between above and below 70 would be even larger. Since coinsurance rate is much higher for those below age 70 than those over 70 (30 percent vs. 10 percent), the stop-loss kicks in at a much lower total amount, which is jointly paid by the patient and the insurers, for those below 70 (267 thousands Yen) than those above 70 (444 thousand Yen = 44.4/0.1). Indeed, column (4) in Table 2 shows that while only 0.1 percent of outpatient visit claims for 69-year-old reach the stop-loss, 14.6 percent of inpatient admissions reach the stop-loss conditional on the use of the medical institutions. Interestingly, no 70-year-old patients reach the stop-loss for inpatient admissions in my data, since their coinsurance rate is set particularly low, as seen in column (5) in Table 2. I explore the effect of cost-sharing on out-of-pocket medical expenditures in detail in Section 5.

3 Data and Identification

I use one of the most comprehensive sources of health-related datasets ever assembled on Japan. Here I summarize the most important datasets in the study; further details can be found in the Data Appendix. My main outcomes are health care utilization on the cost-side, and health outcomes, and out-of-pocket expenditures on the benefit-side.

[15] Due to the smaller sample size, the estimates from separate years are noisier and do not have any consistent pattern. Also I need to view these results with caution since fluctuation in cohort-size due to such as Spain Flu and World War I may affect the estimates in this RD framework since I use counts rather than rate in most of the specifications. These results are available from the author.

[16] One thousands Yen is roughly $10 US dollars. Author's calculation from the Comprehensive Survey of Living Conditions (38.0*12)/1,822 = .25

[17] Author's calculation from the Comprehensive Survey of Living Conditions (12.4*12)/1,822 = .082

3.1 Data

The dataset for health care utilization is the Patient Survey, a nationally representative repeated cross-section that collects administrative data from both hospitals and clinics.[18] Since the survey is conducted every three years, I have individual patient level data for nine rounds of surveys between 1984 and 2008. One of the biggest advantages of this survey relative to usual hospital discharge data is that the Patient Survey includes information for outpatient visits as well. In contrast, most existing datasets capture either outpatient visits or inpatient admissions. In fact, the Agency for Healthcare Research and Quality (AHRQ) has recognized the need to develop a methodology for studying preventive care in an outpatient setting by using inpatient data to identify admissions that should not occur in the presence of sufficient preventive care (AHRQ, 2011).[19] In my case, I can look at changes in the number of patients for beneficial and preventive care in the outpatient setting.[20] The disadvantage of this data is that, as in the case for most of the discharge data, it only includes limited individual demographics such as gender, and place of living (no education or income).

The Patient Survey consists of two types of data: outpatient data and discharge data. I use the former to examine outpatient visits and the latter for inpatient admissions. The outpatient data is collected during one day in the middle of October of the survey year and provides information on all patients who had outpatient visits to the surveyed hospitals and clinics during the survey day.[21] This data includes patients' exact date of birth and the survey date, which is equivalent to the exact date of the visits. The discharge data contain the records of all patients who were discharged from surveyed hospitals and clinics in September of the survey year. The discharge data report the exact dates of birth, admission, surgery, and discharge, which enable me to compute age at admission.[22] Hospital and clinic information are obtained from the Survey of Medical Institutions and merged with Patient Survey.

As health outcomes, I examine both mortality and morbidity. I examine mortality since it is one of the few objective, well-measured health outcomes and is also often easily available, and comparable across different countries. I use the universe of death records between 1984-2008, which report the exact dates of birth, death, place of death, and cause of death using International Classification of Diseases (ICD) Ninth or Ten. The main advantage of the death records is that they cover all deaths

[18] See Bhattacharya et al. (1996) for an example of a study that uses the Patient Survey.

[19] The interaction between outpatient visits and inpatient admissions may be crucial since Chandra et al. (2010) find evidence of offset effects; copayment increases reduce outpatient visits but increase subsequent hospitalizations. Offset effects are not observed in the RAND HIE. I cannot really answer whether I see the offset effects because coinsurance rate for both outpatient visits and inpatient admissions change at age 70, making it harder to examine the interaction of two services.

[20] Another advantage of the Patient Survey, which is unique to Japan's medical system, is that it has information on patients in both hospitals and clinics. In Japan, hospitals are defined as medical institutions with 20 or more beds, and clinics are defined as medical institutions with no more than 19 beds. Unlike in the U.S., direct outpatient visits to hospitals are common practice in Japan since there are no restrictions on the patients' choice of medical providers. Therefore, the government aims at having clinics provide primary care and hospitals serve more serious cases to increase the total efficiency of the health care system. However, the reduction in cost-sharing at age 70 may increase the flow of outpatient visits to hospitals for non-serious reasons. This possibility is investigated briefly in section 4.1.

[21] Since outpatient visits are collected on only one day, the survey is susceptible to external factors such as weather. Therefore it is important to include the survey year fixed effects in the specification to account for this common shock within years. This short survey period is another reason why I do not exploit the year-to-year variation in cost-sharing in this paper.

[22] I describe these dates in chorological order for simplicity, but each unit of data is per discharge.

that occur in Japan, unlike hospital discharge records, which only report deaths that occur in the hospital.[23] I complement the mortality results by examining other morbidity related measures in the Comprehensive Survey of Living Conditions (CSLC), which is survey of a stratified random sample of Japanese population conducted every three years between 1986 and 2007. The survey asks questions about insurance coverage, self-reported physical and mental health, stress levels, and so forth. Age is reported in month in this dataset. Descriptive statistics for Patient Survey (outpatient data and discharge data respectively) and CSLC are reported in the Appendix Table A.

3.2 Identification Strategy

My identification strategy is very similar to studies from the U.S. that use a regression discontinuity design to examine the effect of turning 65 (Card et al. 2004, 2008, 2009; Chay et al. 2011). However, in Japan, the change at age 70 only reflects increases in benefit generosity rather than combined effect of receiving health insurance coverage and change in benefit generosity, and turning age 70 in Japan does not coincide with changes in any other confounding factors such as employment or pension receipt as shown later.

Even though the idea behind the identification strategy is the same, for clarity, I write two regression equations, one for the CSLC and the other for the Patient Survey and mortality data. The difference comes from the nature of the datasets; while I see all the individuals in former dataset, I only observe those who are present in medical institutions or deceased in the latter two datasets.

My basic estimation equation for CSLC is a standard RD model as follows:

$$Y_{iat} = f(a) + Post70_{iat}\beta + \gamma X_{iat} + \varepsilon_{iat} \tag{1}$$

where Y_{iat} is a measure of morbidity or out-of-pocket medical expenditure (only in 2007) for individual i at age a in survey year t, $f(a)$ is a smooth function of age, X_{iat} is a set of individual covariates, and ε_{iat} is an unobserved error component. $Post70_{iat}$ is a dummy that takes on the value of one if individual i is over age 70. My parameter of interest is the coefficient β. All coefficients on Post70 and their standard errors have been multiplied by 100 unless otherwise specified, so they can be interpreted as percentage changes. Other controls include a set of dummies for gender, marital status, region, birth month, and survey year. I use a quadratic in age fully interacted with the post dummies as a baseline specification, and run several robustness checks by limiting the sample to narrower age window (ages 67-73), and adding cubic terms in age. To account for common characteristics within the same age cells, the standard errors are clustered at the age in month, following Lee and Card (2008).

Unlike the CSLC, a unique feature of the Patient Survey and mortality data is that I only observe those who are present in the medical institutions or deceased. My approach to deal with this issue is to assume that the underlying population at risk for outpatient visits, inpatient admissions and deaths

[23] A rare exception is hospital discharge records in California used in Card et al. (2008, 2009) that tracks mortality within one year of discharge. To my knowledge, data that tracks post-discharge mortality does not exist in Japan.

trends smoothly with age.[24] Since I pool several years of surveys, this assumption seems plausible.[25] Therefore, I use the log of counts as the dependent variable for these datasets and modify the regression equation as follows[26]:

$$\log(Y_{at}) = f(a) + Post70_{at}\ \beta + \mu_{at} \tag{2}$$

where Y_{at} is counts of patients or deaths at age a in year t.[27]

There is one remaining empirical issue in estimating equation (2) using the Patient Survey. As seen in Appendix Figure A, there is substantial seasonality and heaping in the reported birthdays of patients observed in the Patient Survey. First, heaping on the first day of the month is observed, which is likely due to reporting.[28] Second, there are many more births in the first quarter than in the other three quarters throughout the sample period. Some argue that this observation is due to farmers timing births for winter, when there is less work, but the evidence on this observation is little (Kawaguchi 2011).

Whatever the reason, heaping and seasonality in birthdays pose a challenge for estimating equation (2) since the Patient Survey is only conducted in one day in October for outpatient visits, and one month in September for inpatients admissions.[29] To account for heaping within the month, I collapse the data into age in months. Since people become eligible for Elderly Health Insurance at the beginning of the next month after their 70th birthday, this approach allows me to code age in months and the post age-70 dummy using the dates of birth and dates of visits without error.[30] To account for the seasonality in birth distribution, I include the birth month fixed effects in addition to survey year fixed effects in all specifications (see e.g., Barreca et al. 2010; Carneiro et al. 2010). Thus the cell is the birth month for each age for each survey year. There are 120 observations (12 month of birth months for each year times 10 years of age 65-75 windows) per survey round, and there are 9 rounds of surveys, and thus there are 1,080 cells in the estimation for outpatient visits.

I also tried two different approaches to account for heaping and seasonality. One approach is to collapse the data into age in quarters, and convert the counts into rates, since I have population data by quarter of birth from the population censuses, which are conducted every five years. The disadvantage of this approach is that the interpolation of population may introduce additional noise in the estimates. In fact, the estimates from this approach tend to be smaller than the main approach due probably to measurement error in the population estimates. Another approach is to include 365 day-of-birth fixed

[24] Card et al. (2004) formally show that under the assumption that the underlying population counts varies smoothly, the estimated discontinuities in log admission counts can be attributed to a corresponding discontinuity in the log of the probability of admission.

[25] Note that I am using 9 rounds of Patient Survey. Thus, the people in a given age group in my samples are actually drawn from 9 different age cohorts, smoothing any differences in cohort size.

[26] See Carpenter and Dobkins (2010), and Card et al. (2009) which use the log counts of deaths as outcomes in a similar RD design.

[27] Equation (2) implies that this RD framework is conceptually different from the typical RD design which relies on assumptions of imprecise control over the running variable (i.e., age in this case), and hence the smoothness of the density of the running variable to identify treatment effects (Lee, 2008). Here, it is precisely the discontinuity in the density of age at age 70 that I am attributing to an effect of lower cost-sharing on utilization (see e.g., Lee and McCrary 2009; Card et al. 2004, 2008).

[28] For example, individuals (or their designated respondents) who do not know their exact birthday may report the first day of their birth month. Other heaps occur at multiples of five and ten days and at the end of the month.

[29] If the data covers the entire year, seasonality is more likely to be smoothed out.

[30] I assign a person who reaches his 70th birthday in October of the survey year to the age 69 and 11 months.

effects as well as year-of-birth fixed effects into the equation in (2) to account for the seasonality and cohort-size effects, and use age in days at the time of outpatients visit or inpatient admissions as the running variables (Gans and Leigh 2009; Barreca et al. 2010). The disadvantage of this approach is that when I divide the sample into finer subsamples (e.g., by diagnoses), there are many birthdays without any observations, which may cause noise in the running variable. The approach of using age in months does not suffer from this problem much since I usually observe at least one observation in each month cell. The results using this alternative approach yield similar results as the main approach as long as there are not many "zero" cells in the data. Since both alternative approaches face different disadvantages, I prefer to take an approach I first described. Some of the results using age in days as running variable are shown in an Appendix Table.[31]

The discharge data pose a slightly more complicated problem. Unlike the outpatient data, the admission day can be any day of the year, as long as they are discharged in September. To avoid including patients with unusually long hospitals stays, I limit the sample to those admitted within three months from discharge in September (July, August, and September) in the survey year. This approach is reasonable since 90 percent of admissions in my data are concentrated within these three months. Since there are 1,080 cells for each admission month, there are a total of 3,240 observations in the estimation of inpatient admissions.[32] In the result sections, I show that the estimates are robust to using different windows from the discharge date.

For the mortality data, I estimate the same equation as (2), replacing Y_{at} as death counts, and using age in days as the running variable.[33] I suffer less from the seasonality of birth issues when using annual mortality census data, since deaths occur throughout the year, and pooling many years of data smoothes out the cohort size.[34] The main drawback of using death records is that I only observe exact date of the death, not exact date of admission as in the hospital discharge data. Note that this may attenuate the estimates since people who died immediately after their 70th birthday may not be eligible for Elderly Health Insurance at the time of admission even though I consider them as treated.

Importantly, the age RD design is distinct from the standard RD design because the assignment to treatment is essentially inevitable, i.e. all individuals will eventually age into the program.[35] As Lee and Lemieux (2010) point out, there are two issues specific to the age RD design. One is that, because treatment is inevitable, individuals may fully anticipate the change in the regime and, therefore, may behave in certain ways before treatment is turned on. This issue is particularly relevant for the analysis of utilization measures since there is a possibility that people may delay some expensive medical procedures until they reach 70, which may accentuate the size of the discontinuity.[36] However, in the RD setting I

[31] Other results from different approaches to handle the heaping and seasonality in the dataset are available from author.

[32] The cell for discharge is the month of birth, month of admission, and survey year. The estimation include the birth month fixed effects, admission month fixed effects as well as survey year fixed effects.

[33] In fact, since people become eligible for Elderly Health Insurance at the beginning of the next month in which their 70th birthday falls, I use the distance in days from exact day of death to the day of being eligible for Elderly Health Insurance as running variable in mortality analysis.

[34] Interestingly, I observe the same pattern in the mortality data as in the Patient Survey that births are more concentrated in the first quarter of birth, and also on the first day of the month.

[35] A few examples of "age" RD are: Card et al. (2008, 2009), Anderson et al. (2010), Carpenter and Dobkin (2009), and Lee and McCrary (2009).

[36] It is not always the case that anticipation accentuates the magnitude of the discontinuity; it can also mute the discon-

can visually examine whether the discontinuity is accentuated or not since if the increase is transitory rather than permanent, I should observe tendency after age 70 to revert to the previous level as well as drop-off just below the age 70.

Second, even if there is an effect on the outcome, if the effect is not immediate, it will not generally generate a discontinuity. This issue is particularly relevant for the analysis of health outcomes. For example, lower cost-sharing at age 70 induces individuals to receive preventive care that has long-run, but not short-run, effects on mortality. In this case, I will not find any discontinuity at age 70 even though there is a long-run effect. It is infeasible to estimate long-run effects because individuals age into treatment.

The underlying assumption of typical RD model still applies to age RD design; in this case, the assumption is that the expected outcomes below and above age 70 are continuous at age 70 (Hahn et al. 1999). Continuity requires that all other factors that might affect the outcome of interest trend smoothly at age 70. My empirical setting is potentially better than those using Medicare edibility of age 65 in the US, since age 70 in Japan does not coincide with changes in any other confounding factors such as employment or pension receipt.[37] A simple test for the potential impact of discontinuities in confounding variables is fitting the same models like (1) for confounding variables and testing for discontinuities at age 70 (Lee and Lemieux, 2010).

Figure 4 displays the actual and fitted age profiles of employment for the 1986-2007 pooled CSLC sample (age measured in months). These profiles all trend relatively smoothly through age 70 for both genders.[38] Row (1) in Table 4 confirms that there is no jump in employment at age 70. In the remaining rows in Table 4, I also investigate the age profiles of marriage, and income related variable in the CSLC, but none of these outcomes show any discontinuities at age 70. These results lead me to conclude that employment, family structure, and family income vary relatively smoothly at age 70, and are unlikely to confound the impact of cost-sharing at age 70.

3.3 Elasticity under Non-Linearity and Catch-up Effects

Before showing the results, I discuss the potential bias in the estimation of the elasticity. There are two issues that may potentially bias my estimates on elasticity: non-linearity in the budget set and the catch-up effect. To illustrate the direction of potential bias, it is convenient to write the elasticity ϵ

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tinuity. For example, simple life-cycle theories without liquidity constraints suggest that the age profile of consumption will exhibit no discontinuity at age 67, when Social Security benefits start payment in the US.

[37] Even though Card et al. (2008, 2009) shows no discontinuity in employment at age 65, as Dong (2010) points out, there is an obvious difference in *slopes* above and below age 65 in the age profiles of employment. In this case, treatment effects based on standard RD estimators may be weakly identified.

[38] The mandatory retirement age in Japan used to be 60 and has gradually shifted to 65 since 2003. Pension receipt starts either 60 or 65 years of age depending on the type of job. In fact, I find that there is a sharp drop in employment at 60, and a large increase in fraction of people receiving pensions at both age 60 and 65 (not shown). Also long-term care (LTC) health insurance was introduced in Japan in 2000, but age at 70 is not used to determine the edibility for LTC. Indeed, I do not see any change at age 70 in probability of receiving LTC as shown in Table 4.

simply:

$$\begin{aligned}\epsilon &= \frac{\log(Q\_above70) - \log(Q\_below70)}{\log(P\_above70) - \log(P\_below70)} \\ &= \frac{RD\ estimates\ at\ Age\ 70}{\log(P\_above70) - \log(P\_below70)}.\end{aligned} \tag{3}$$

First is the catch-up effect or intertemporal substitution. As I mentioned earlier, individuals may anticipate the lower cost-sharing once turning 70 and, therefore they may delay some expensive medical procedures until they reach 70, which may accentuate the size of the discontinuity. This may cause $Q\_above70$ to be larger and $Q\_below70$ to be smaller, and therefore may bias the estimates of the elasticity upward. Fortunately, I can to some extent visually examine whether the discontinuity is magnified by looking at the dip just below 70 and surge just above 70.

Second, the non-linearity imposed by the cap on out-of-pocket medical expenditures and deductibles is classic but important challenge in estimating elasticities that dates back to the RAND HIE (Keeler et al., 1977; Ellis, 1986; Keeler and Rolph, 1988).[39] The problem is that although many medical expenditures are caused by unpredictable illnesses, economically rational individuals can anticipate some spending and can take advantage of varying prices by spending more during periods when the price is low (Aron-Dine et.al., 2012). In the extreme case, for those whose monthly medical expenditures are already above or are expected to exceed the stop-loss, the effective price, the shadow price of consuming additional medical services, is near zero. The size of the difference between "true" and nominal out-of-pocket price depends on the probability that the individual will subsequently exceed the stop-loss. Indeed, under fairly restrictive assumptions, it can be shown that the effective price before the stop-loss has satisfied is the simple form $(1-x)P$, where P is nominal price, and x is the probability of exceeding the stop-loss (Keeler and Rolph 1988). Since those below age 70 are more likely to reach the stop-loss, the true $P\_below70$ may be smaller than that of the nominal price, thus the bias incurred from using the observed price is downward.

These two issues are less relevant for outpatient visits, since I will show later that there does not appear to be a catch-up effect, and reaching the stop-loss is very unlikely since outpatient visits are not costly. The more relevant case is inpatient admissions. I will show later that overall age trend does not seem to display any catch-up effects, but close inspection of inpatient admissions with elective surgery shows some drop-off just below age 70, and a sudden surge just over age 70. Though not far from perfect, to partially account for the catch-up effect, I run a "donut-hole" RD by excluding a few observations around the threshold.[40] The caveat of this methodology is that there is no clear economic or statistical consensus on the optimal size of the donut and excluding observations near the threshold undermines the virtue of the RD design, that is, comparing outcomes just below and above the threshold. Nonetheless, this donut-hole RD may show whether my RD estimates are sensitive to the catch-up effects.

Accounting for non-linearity associated with stop-loss is much harder, since to fully understand the

[39] See also Kowalski (2011) that discusses challenges of estimating the demand elasticity under non-linear budget set. My case is simpler than her case since there is no deductible.

[40] This approach was initially proposed by Barreca et al. (2011) to account for pronounced heaping in the observations around the threshold in RD framework. See also Bharadwaj and Neilson (2011) for an example of the donut-hole RD.

size of the difference between true and nominal price, I may need data on episodes of illness rather than monthly aggregated data. I argue that the effect of the stop-loss on over-utilization is probably much smaller in my case rather than RAND HIE because the stop-loss is set by monthly in Japan rather than annually like the RAND HIE and most health insurances in the U.S. To the extent that illnesses are unpredictable, this shorter interval may make it harder for people to time and overuse the medical services.[41] Furthermore, even under an annual stop-loss, Keeler and Rolph (1988) empirically shows that people in the RAND HIE respond myopically to stop-loss, i.e., people do not appear to change the timing of medical purchases to reduce costs.[42] Nonetheless, to partially account for this effect, I simply apply formula of $(1 - x_t)P_t$ for those whose out-of-pocket medical expenditures are more than median in each survey year t since this problem is most relevant for consumers who are close to reaching the stop-loss. Since the probability of reaching the stop-loss is not high even for the inpatient admissions (14 percent for those admitted, and 2 percent for non-conditional population), the nominal price (38.0 thousand Yen) for those just below age 70 is not so different from the "true" price (35.3 thousand Yen). Therefore, the bias coming from the non-linearity associated with stop-loss may be negligible in this case.

4 Utilization Results

In this section, I examine the effect of changes in cost-sharing on utilization. I use the pooled 1984-2008 Patient Survey for people between ages 65 and 75. I examine outpatient visits and inpatient admissions, respectively.

4.1 Outpatients Visits

I use the pooled outpatient data to examine changes in the number and characteristics of outpatient visits at 70. As I mentioned earlier, I collapse counts of patients by age in months, and include birth month fixed effects as well as survey year fixed effects to account for heaping and seasonality in birthdays. Therefore for most of the graphs shown in this section, the plotted average is residual from a regression of the log outcome on birth month fixed effects and survey year fixed effects.

Figure 3A shows the actual and fitted age profiles of outpatient visits based on the pooled outpatient data. The markers in the figure represent actual averages of the log number of outpatient visits (by age in months). The lines represent fitted regressions from models with a quadratic age profile fully interacted with a dummy for age 70 or older. Overall outpatient visits steadily increase prior to age 70, and then jump sharply at age 70. Also, the increase appears to be permanent rather than transitory, with no tendency after age 70 to revert to the previous level, which might occur if the jump in outpatient visits only represents catching up on deferred visits.

[41] Keeler et al. (1977) and Ellis (1986) formally show that the more time left in the accounting period, the more the effective price falls.

[42] Aron-Dine et.al. (2012) also show that while there is some forward-looking aspects in health care utilization, individuals' behavior is much closer to the full myopia (individuals respond only to the spot price) than forward looking behavior (individuals respond only to the future price).

Table 4 presents the summary of the estimated discontinuity for outpatient visits. All the estimates in the Table 4 come from the preferred model, which uses a quadratic in age, fully interacted with dummy for age 70 or older. The first entry in first column shows that the jump in Figure 3A corresponds to a 10.3 percent increase.

The implied elasticity of the outpatient visits is -0.17 =(10.3/((log(1.0)-log(4.0))/100), where the denominator is the log difference in price between age 69 and age 70 from the first row in Table 2.[43] This estimated elasticity is similar to the estimates found in the RAND HIE for the non-elderly (roughly -0.2), and slightly larger than that estimates for the elderly (-0.07 to -0.10) by Chandra et al. (2010). The finding indicates that the price elasticity of outpatient visits for the elderly is similar in magnitude to that of the non-elderly. Since I do not visually observe catch-up effects, and the stop-loss is rarely reached, the bias on the estimating elasticity of outpatient visits seems minimal.

Another way to look at more frequent access to outpatient care is to examine the change in the interval since the last outpatient visits. A shorter interval indicates a higher frequency of outpatient visits.[44] As much as 94 percent of patients are repeated visit patients (i.e., visits for the same underlying health conditions *and* the same hospitals or clinics as last time) rather than first-time visit patients as shown in the summary statistics in Appendix Table A. The Patient Survey asks the exact day of the last outpatient visits for these repeated patients. Figure 3B plots the age profile of days from the last outpatient visit for repeated patients. Consistent with the increase in outpatient visits, the duration from the last visit steadily decreases prior to age 70, and then drops sharply at age 70 by roughly one day.[45]

So far, I find compelling evidence that people use more outpatient care once they turn 70. Next, I investigate whether the increase in outpatient visits solely reflects moral hazard or increases in beneficial care. To investigate this question, I divide the sample into various dimensions in the remaining rows in Table 3. In Panel B, I divide outpatient visits by first visit or a repeated visit. Interestingly, the results indicate not only repeated visits but also first visits increase by more than 10 percent. Since repeated visits accounts for 94 percent of all outpatient visits, the increase in first visits is small in magnitude relative to total outpatient visits. But the increase in new visits raises the possibility that those newly receiving the outpatient care may avoid outpatient care due to cost reasons before turning age 70.[46]

For repeated visits, Panel C in Table 3 shows that most of the increases in the repeated outpatient visits are concentrated within a short interval from the last visits. In fact, most of the increase is concentrated among those who receive their last outpatient care within 7 days.[47] In Panel D, I divide

[43] Note that the price in the denominator I used is the average price rather than the marginal price. Thus the elasticity estimated is with respect to the average price. However, the marginal price and the average price may not differ much. For example, as for 2008, the log marginal price difference would be log(0.1)-log(0.3) without stop-loss, while what I used here as log average price difference is log(1.0)-log(4.0) for outpatient visits and log(12.4)-log(38.0) for inpatient admissions.

[44] For this question, the Patient Survey first asks whether the outpatient visit is new or repeated. For repeated patients, then it reports the exact day of the last visit.

[45] Additionally, I can use the age at the time of the last visit as a running variable to investigate whether the last outpatient visit also jumps at age 70. I find that last outpatient visits also increase discontinuously at age 70 (not shown).

[46] Appendix Figure B shows the age profiles for first time and repeated outpatient visits, respectively. The age profiles of first time visits show a very interesting trend; the number of first time visits steadily decreases prior to age 70, reflecting the trend of deteriorating health as people get older, and then jumps sharply at age 70. The age profiles of repeated visits are very similar to that of total outpatient visits, since most of total outpatient visits are repeated visits.

[47] Average days from last outpatient visits among ages 65-75 are 13.6 days.

outpatient visits by institutions. The increase in outpatient visits is concentrated at clinics rather than at hospitals. Since people have much easier access to small clinics than large hospitals, this result indicates that these outpatient visits are more discretionary and less serious. In Panel E, I stratify the sample by the presence of a referral. Since most referrals to hospitals are provided at clinics, an increase in non-referral outpatient visits is consistent with the increase in outpatient visits at clinics.

Most of the findings so far suggest that those who visit medical institutions for outpatient reasons once they turn age 70 are less seriously ill than those who visit at age 69. Finally, I investigate the size of discontinuity at age 70 by type of diagnoses. A key advantage of the Patient Survey is that I can break down outpatient visits by diagnoses. Appendix Table B lists the top 10 diagnoses by three digit ICD 9 codes, which account for roughly half (45 percent) of all outpatient visits. By far the most frequent diagnosis is hypertension, which accounts for nearly 16 percent of all outpatient visits. Untreated high blood pressure can be an important risk factor for the elderly, and thus proper treatment may prevent subsequent hospitalization or even death from conditions such as heart failure, cerebrovascular disease or stroke, and heart attacks (Pierdomenico et al., 2009). Panel F in Table 3 first presents the results for the top 5 outpatient diagnoses: essential hypertension, spondylosis, diabetes, osteoarthrosis, and cataracts. Even though most of the large increases come from relatively elective diagnoses such as two degenerative joint diseases (spondylosis and osteoarthrosis), I also find an 8 percent statistically significant increase for essential hypertension visits.

The results on hypertension raise the possibility that increases in outpatient visits may include useful preventive treatments. Figure 4 displays the age profile of outpatient visits for commonly examined diagnoses: heart disease, cerebrovascular disease, and respiratory disease (see e.g., Chay et al., 2010). While I do not find a statistically significant jump in visits for heart disease in Panel A, Panel B and C show that there is sharp increase in the number of outpatient visits for cerebrovascular disease and respiratory disease, which may cause serious problems without proper preventive treatments.

I also look at the diagnoses defined as the Prevention Quality Indicators (PQI), which are measures of potentially avoidable hospitalizations for Ambulatory Care Sensitive Conditions (ACSCs) developed by Agency for Healthcare Research and Quality (Appendix Table C for the list of PQI). This measure is intended to study preventive care in an outpatient setting using inpatient data to identify admissions that should not occur in the presence of sufficient preventive care. Since I *do* have outpatient datasets, I can directly look at changes in the number of patients for these beneficial and preventive care. Panel D in Figure 6 shows that there is a large jump at age 70 for ACSCs diagnoses.

The remaining rows in Panel F in Table 4 confirm these patterns in the figures. In sum, I find that demand for both more and less beneficial care is price sensitive. While most of the largest increase can be found for diagnoses that may not be life-threatening but treating probably enhance the quality of life, such as diseases of genitourinary system, skin, and musculoskeletal system, I also find an increase in potentially more serious diagnoses; I find increases in outpatient visits for cerebrovascular disease, respiratory disease, and ACSCs of 15.2, 14.3, and 8.2 percents respectively. All the estimates mentioned here are statistically significant at 1 percent level.[48]

[48] I also investigate each PQI measure separately, but due to smaller sample sizes, I could not obtain precise estimates for most PQIs. The two exceptions are Chronic Obstructive Pulmonary Disease (COPD; PQI5), a progressive disease that makes it hard to breathe, and hypertension (PQI7). The increase for patients with COPD is 17.2 percent (t-stat=2.10)

Appendix Table D summarizes the results of alternative specifications that use age in days as the running variable with birthday fixed effects, and yield quantitatively similar results for most of the outcomes.[49] As a falsification test, I also run the same estimation at other ages (each single age of 66-74) that should not have any discontinuity, and did not find any statistically significant change in other ages (not shown). This result is not surprising since I do not see any visible discontinuity in other ages in either Figure 3 or Figure 4.

4.2 Inpatient Admissions

Before starting the analysis of the inpatient admissions, I need to mention one potential threat to interpreting the results for impatient admissions. Since a sharp change in cost-sharing in inpatient admissions coincides with that of outpatient visits, it may be difficult to separate whether the change in inpatient admissions for a certain condition is the result of lower inpatient cost-sharing *per se* or complementarity or substitution with increased outpatient visits. For example, effective outpatient treatments may replace avoidable impatient admissions. However, since I do not see a discontinuity with time lag, it is more likely that the jump I observe is the reflection of the lower cost-sharing rather than any complementarity.

Figure 5 shows the actual and fitted age profiles of inpatient admissions based on my 1984-2008 pooled discharge data. The plotted average is the residual from a regression of the log outcome on birth month, admission month and survey year fixed effects. Overall inpatient admission steadily increases prior to age 70, and then jumps sharply at age 70. The increase appears to be permanent in this case as well as outpatient visits, with no tendency after age 70 to return to the pre age 70 level.

Table 5 presents the summary of the estimated discontinuity for inpatient admissions. All the estimates in this Table 5 come from the preferred model, which includes a quadratic in age, fully interacted with a dummy for being age 70 or older. The first entry in Table 5 shows that the jump in overall inpatient admissions in Figure 5 corresponds to an 8.2 percent increase. Appendix Figure C1 shows that the result is not an artifact of how I limit the sample from the discharge date; the results are pretty robust to the length of windows from the discharge date. Note that more than 90 percent of inpatient admissions occurred within three months from discharges.

The implied elasticity of the inpatient admissions is -0.17 (= 8.2/((log(12.4)-log(38.0))/100), where the denominator is the log difference in price between age 69 and age 70 from the second row in Table 2. As I discussed earlier, there is a potential bias in estimating elasticity especially due to the catch-up effect. To account for the catch-up effect, I run a "donut-hole" RD by excluding a few months of observations around the threshold. Since there is no guide as to the size of the donut-hole statistically or economically, I experiment with zero month to six months.[50] However, removing six months from

and for all hypertension is 8.5 percent (t-stat=3.54).

[49] I choose outcomes that do not have "zero" cells for any age in days in Appendix Table D. It is a convention to add one or small positive value before taking log for those "zero" cells, but the "zero" cells introduces the noises and hence attenuate the estimates. In fact the estimates obtained by using age in days as running variables start to deviates from those of age in months as the number of "zero" cells increases.

[50] It is not clear what magnitude of delay is fathomable/medically low cost for patients. It may vary substantially by the severity of the conditions and type of diagnosis.

both side of age 70 may be too drastic since it means that I am essentially comparing those aged 69.5 and 70.5, so there is one year age gap between those above and below threshold. Appendix Figure C2 shows that the estimates get smaller and the standard errors get larger as the "hole" is expanded. But as long as the removal of the data is within three months of 70, the estimates are statistically significant at 5 percent level. Taking the conservative RD estimate from the three-month donut-hole RD, the lower bound of the implied elasticity is -0.15 (= 7.2/((log(12.4)-log(38.0))/100), not so different from the "naive" elasticity.

Next, I examine the characteristics of inpatient admissions in the remaining rows in Table 5. First, I divide the sample by whether patients received surgery in Panel B. Interestingly, I find that the increase in admissions for people who receive surgery is larger than the overall growth in admissions (10.8 percent versus an overall increase of 8.2 percent) while estimates from non-surgery admissions are smaller in magnitude (5.4 percent) and marginally statistically significant. Indeed, close inspection of the age profile of patients with surgery in Figure 6A reveals a drop-off just prior to 70, coupled with a temporary surge shortly after 70. This pattern suggests that some people who are close to 70 delay surgery until they become eligible for Elderly Health Insurance to reduce the out-of-pocket expenditures.

This finding raises two possibilities for physicians' and patients' role in the demand for health care services. First, it may imply that physicians may consider the financial effects of treatments on patient since there are no financial incentives for physicians to delay surgeries until age 70 because reimbursements do not differ by patient age. Or alternatively, it may raise the possibility that patients play a more active role in determining their treatments. Hai and Rizzo (2009) indeed point out that recent organizational changes (e.g., alternative sources of medical information such as the internet, health care report cards, and direct-to-consumer advertising of pharmaceuticals) may have fostered patient-initiated requests for specific treatments.

In Panel C, I further investigate the discontinuities across types of surgeries. Unfortunately, this information is only collected in the most recent four survey years (1999, 2002, 2005, and 2008), and the categorization is quite coarse. Therefore, it is difficult to obtain the precise estimates. Nonetheless, the estimates indicate that the open-stomach surgery and intraocular lens implantation, which has substantial overlap with admissions for cataracts (clouding of the lens of the eye), show statistically significant jumps at age 70.[51] Appendix Figure D displays the age profile of inpatient admissions for these two procedures. Similar to the overall age profiles for inpatient admissions with surgery (Figure 6A), I find a drop-off just prior to 70, coupled with a temporary surge shortly after 70 for both procedures. These results are plausible since one hand these procedures are easily deferred, and on the other, they are relatively expensive but routine interventions that are thought to have a beneficial effect on quality of life (Card et al. 2008).

Appendix Table B lists the top 10 diagnoses in three digit ICD 9 codes, which account for 29 percent of all inpatient admissions. Panel D in Table 5 first presents the results for top 5 inpatient admission diagnoses: cataracts, angina pectoris, occlusion of cerebral arteries, diabetes, and stomach cancer. The leading diagnosis is cataracts, and I find as much as 22 percent increase in the number of inpatient

[51] Unlike Card et al. (2008), I do not find a statistically significant increase in musculoskeletal surgery, which includes joint replacements for hips and knees.

admissions for cataracts. This result is consistent with the increase in surgeries for intraocular lens implantation. As expected, I do not find an increase of inpatient admissions for chronic diseases such as diabetes or stomach cancer. Surprisingly though, I find a 14 percent statistically significant increase in occlusion of cerebral arteries, which without proper treatment may lead to one of the three most common causes of death in Japan: cerebrovascular disease (or stroke).[52]

Figure 7 displays the age profile of inpatient admissions for the same set of broad diagnoses as outpatient visits. The graphs in Panel A and B show that there is a sharp increase in the number of inpatient admissions for heart disease and cerebrovascular disease, which may potentially be fatal if they are acute ones.[53] The remaining rows in Panel D in Table 5 confirm the patterns in the figures. While I do not find any increases for chronic diseases such as cancer, I find large increases for heart disease and cerebrovascular disease. The jump in inpatient admissions for heart disease and cerebrovascular disease in Figure 7 corresponds to 11.5 percent and 10.5 percent increases, respectively.

I further divide heart disease and cerebrovascular disease into finer diagnoses to see whether these are acute ones recognizing the disadvantage of small sample size. The results reveal that most of the increase in admissions for heart disease come from ischemic heart disease - but chronic and not acute ones since I do not find any increase in heart attacks (clinically referred to as an acute myocardial Infarction or AMI) - and most of the increase in cerebrovascular disease, comes from the cerebral infarction, which is consistent with the increase in admissions for the occlusion of cerebral arteries. On the other hand, I do not find statistically significant change in Ambulatory Care Sensitive Conditions (ACSCs).[54]

Interestingly, the observed patterns by admission diagnoses I find here are similar to the findings in Card et al. (2008), which examines the Medicare eligibility at age 65; they find smaller increases for conditions that are typically treated with medication or bed rest (heart failure, bronchitis, and pneumonia), and large increases for those are treated with specific procedures (chronic ischemic heart disease, and osteoarthrosis). While I do not find an increase in admissions for respiratory diseases, and ACSCs that are typically treated with medication, I also find increases for cataracts, cerebral infarction (including occlusion of cerebral arteries), (chronic) ischemic heart disease, which may require procedures, such as intraocular lens implantation, open-head or open-heart surgery.[55] These results imply that diagnoses that are treated with expensive but elective procedures are quite price sensitive, probably due to its large cost, and hence patients delay to reduce the out-of-pocket expenditures.

Finally, I also examine the interaction between the outpatient visits and inpatient admissions by looking at the route before admission to hospitals. Panel E in Table 5 shows that there is statistically significant 9.7 percent increase in admissions that come from the outpatient visits within the same hospitals. This increase is slightly larger than the overall increase in admissions (8.2 percent), implying that patients wait and switch from outpatient visits to inpatient admissions within the hospital once

[52] The three leading causes of death in Japan are cancer, heart disease, and cerebrovascular disease.

[53] Unfortunately, the discharge data in the Patient Survey do not collect data on route into the hospital or whether the admission was for elective, urgent, or emergency care.

[54] The RD estimates for COPD is 1.6 percent (t-stat=0.34) and for hypertension is 3.2 percent (t-stat=0.58).

[55] The fact that I did not find any decline in inpatient admissions for ACSCs is potentially interesting. If the outpatient care takes care of these conditions, and hence replace inpatient admissions, I should see a corresponding decline in inpatient admissions for these conditions. On the other hand, if seemingly "effective" care at outpatient visits still includes some moral hazard, I may not see any change in inpatient admissions from these conditions.

cost-sharing for inpatient admissions is reduced drastically at age 70. This pattern is consistent with the possibility that physicians take the financial burden on patients into account when they provide expensive medical services.[56]

Appendix Table E shows the results of alternative specifications for selected outcome variables. The table shows that the results are quite robust to different specifications such as limiting the sample to narrower age window (ages 67–73) and including a cubic polynomial in age, fully interacted with a dummy for age 70 or older. However, specifications with a cubic polynomial in age sometimes give larger estimates due to a drop-off in number of inpatient admissions just prior to 70.

5 Results on Benefit

To look at the benefit side of cost-sharing, I first explore whether lower cost-sharing benefits the health of those above age 70, and next examine risk reduction.

5.1 Health Outcomes

A priori, the impact of cost-sharing on mortality is ambiguous. On the one hand, cheaper access to health care services may reduce mortality.[57] On the other hand, lower cost-sharing may increase mortality if those who are just below 70 delay life-saving treatment. Most importantly, if the marginal patient is not severely ill, I may find no effects on mortality.

Figure 8 shows the age profiles of the log of overall deaths among those between the ages of 65 and 75 using pooled 1987-2006 mortality data. Even though there is slight decline at age 70 in the log counts of mortality, first entry in Column (1) in Table 6 shows that the size of the estimates (-0.7 percent) is not statistically significant at conventional level. I also estimated different specifications, including local-linear regressions, but they yield similar results as shown in the remaining columns.[58]

I also examine cause-specific deaths for three leading causes of death among the elderly in Japan: cancer, heart disease, cerebrovascular disease, plus respiratory disease. Appendix Figure E show the there are no disenable patterns for any causes of death. The remaining rows in Table 6 confirm that there is no clear change in the cause-specific mortality at age 70, even though in some specifications the estimates become marginally statistically significant. These results are to some extent as expected,

[56] I also divide the inpatient admissions by the characteristics of hospitals in Appendix Table F. Consistent with the notion that patients can freely choose medical institutions, patterns do not differ by hospital ownership. This result is in stark contrast to the U.S.; Card et al. (2008) finds that with the onset of medical eligibility, hospital admissions to both private non-profit and private for-profits hospitals experience relatively large increases in admissions, while hospitals owned by large and long-established HMOs show little change, and county hospitals experience a sharp decline. Another possibility for this difference is that there is not much difference in the quality of hospitals by ownership or size in Japan. Also note that there are no for-profit hospitals in Japan since the hospitals are not allowed to issue shares and distribute the earnings.

[57] Also it is possible that more frequent interactions with physicians could increase peoples' awareness of the health consequences of behavioral risk factors such as smoking. Alternatively, it is also possible that by reducing the adverse financial consequences of poor health, lower cost-sharing may discourage investments in health and health-related behaviors, and thereby worsen health outcomes (*ex-ante* moral hazard).

[58] For bandwidth selection, I use rule of thumb bandwidth procedure proposed by the Fan and Gijbels (1996) assuming a triangular kernel. I then estimate the local linear regression using the triangular kernel with the estimated bandwidth, and also report asymptotic standard errors (Porter, 2003).

since in general, it is hard to detect the effect on health in a regression discontinuity framework, since health is stock (Grossman, 1972); thus it may take a while for most observable effects to be realized, unless the causes of death are acute, such as heart attacks or stroke (see e.g., Card et al., 2009; Chay et al., 2010). I also examined more acute causes of death such as heart attacks or stroke but did not find any disenable patterns in age profile (not shown).[59]

Next, I examine trends in self-reported health as a morbidity measure before and after age 70.[60] The respondents to the CSLC report health on a five-point scale (very poor, poor, fair, good, or very good). Appendix Figure F shows the age profiles of the fraction of the people who report themselves to be in good, or very good health (31 percent of the population), based on pooled 1984-2008 CSLC samples. The graph shows that self-reported health is gradually declining with age but I do not find any observable change at age 70. Appendix Table G confirms this age pattern. Column (2) presents estimates from linear probability models for the probability that people report that their health is good or better. Column (4) reports estimates from a simple linear regression for the mean assessment of health (assigning 1 to poor health and 5 to very good). Consistent with the patterns in Figure F, none of the estimates in Table G are associated with statistically significant changes in any of self-reported health. In the remaining columns, I also look at the mental health, but I did not find any changes in mental health outcomes either.[61]

Overall, I do not find any evidence that lower cost-sharing leads to a discrete jump in morbidity or mortality. These results are not surprising, since the findings in the utilization imply that the marginal patient receiving health care because of lower cost-sharing is not severely ill, and also it is unlikely that people delay life-saving procedures.

5.2 Risk Reduction

Other than improved health, another benefit of lower cost-sharing is a lower risk of unexpected out-of-pocket medical spending. As Finklestein and McKnight (2008) point out, this benefit is often overlooked in the literature. Some claim that protection against large medical expenditure risk is arguably the primary purpose of health insurance (e.g., Zeckhauser, 1970). Indeed, for risk averse individuals, the largest welfare gains from lower cost-sharing come from reducing catastrophic negative shocks to consumption.

To examine the effect of cost-sharing on risk reduction, I use self-reported out-of-pocket medical expenditure in the CSLC. Unfortunately, CSLC started collecting this information in 2007, thus I only have one survey year of individual out-of-pocket expenditures. The out-of-pocket medical expenditure includes any medical expenses such as over-the-counter drug spending which is not covered by health insurance, and does not distinguish the outpatient visits and inpatient admissions. With these caveats in

[59] Results are available from author.

[60] It is also not clear whether self-reported health will improve. On one hand, it is possible that more preventative care leads to improvements in subjective health if certain health problems can be resolved quickly, or if uncertainty about a chronic condition can be resolved. On the other hand, it may worsen subjective health if increasing contact with the physicians causes individuals to learn about previously unrecognized health problems (Card et al., 2004).

[61] Card et al. (2004) also did not find any impact of Medicare eligibility on self-reported health, while Finkelstein et al. (2011) find large improvement among the Medicaid beneficiaries in Oregon. The difference may arise from the fact that Medicaid recipients in Oregon are poorer and less healthy, so there is a large scope for improvement of self-reported health.

mind, my primary interest is to examine total individual out-of-pocket medical expenditures, regardless of how they were spent. Therefore in the analysis in this section, I focus on the data in year 2007. My analysis is based on 66,112 individuals between age 65 and 75 with non-missing out-of-pocket medical expenditure. The average annual out-of-pocket spending among those aged 65-69 is 142 thousand Yen ($1,420) while median out-of-pocket medical expenditure is 48 thousand Yen ($480).

Figure 9A shows that lower cost-sharing at age 70 overwhelms the utilization effect. The graph compares the distribution of out-of-pocket medical expenditure in 2007 for 65-69 year olds (not covered by Elderly Health Insurance) and 70-74 year olds (covered by Elderly Health Insurance) in 2007. The graph reveals that 70-74 year-olds at the top of the distribution spend substantially less than 65-69 year-olds despite the large benefits from stop-loss for 65-69 year-olds. This result is consistent with other studies in the US that show a pronounced decline in a right-tail in the distribution of the out-of-pocket medical expenditures through Medicare Parts A and B (Finkelstein and McKnight, 2008), Medicare Part D (Englehardt and Gruber, 2011), and Medicaid (Finkelstein et al., 2011). These studies look at the effect of insurance coverage rather than changes in generosity.

One concern in the above analysis is that I may merely pick up an underlying change in the spending distribution that differs systematically by age group. Figure 9B examines out-of-pocket medical expenditures among an adjacent age group (age 60-64) to the near-elderly (age 65-69), neither of whom benefit from lower cost-sharing. The figure shows that out-of-pocket medical expenditures among 65-69 year-olds is higher than among 60-64 year-olds, showing that medical expenditure tend to increase with age. This finding is reassuring; it suggests that that I am not measuring any systematic change in spending by age groups.

I start with presenting an RD estimate at the mean on out-of-pocket medical expenditures by estimating (1) where the model assumes quadratic in age fully interacted with post 70 dummy. First row in Table 7 shows that lower cost-sharing is associated with decline in out-of-pocket medical expenditure by 52 thousands Yen ($520), but the estimate is close to but not marginally statistically significant at the conventional level (t-stat = -1.47). However, the mean impact may miss the distributional impact of the lower cost-sharing. As is well known, the distribution of out-of-pocket spending is highly right-skewed. Among those age 65-69, the top 5 percent of spenders account for almost 40 percent of the out-of-pocket medical spending, while 72 percent of the sample has out-of-pocket spending below 100 thousands Yen ($1,000) in a year.

Figure 10A shows the age profiles of the out-of-pocket medical expenditures at 75th, 90th, and 95th percentiles. Out-of-pocket medical expenditures steadily increase prior to age 70, reflecting worse health as people age, and then decline sharply at age 70 at all three percentiles, with the largest decline at the highest percentile. To gauge the magnitude of the decline, I estimate the following equation for each quantile q

$$M_i^q = \alpha_0^q + \alpha_1^q Post70_i + f^q(a) + X_i^{'}\gamma^q + \varepsilon_i, \quad (4)$$

where M_i^q is the out-of-pocket medical expenditure at quantile q, and $f^q(a)$ is a quantile-specific smooth function of age, where age a is normalized to zero at age 70. X_i are demographic controls in the form of dummy variables for marital status, gender, region and birth month.

Figure 10B plots the RD estimates at age 70 on each quantile (α_1^q), along with their 95 percent

confidence interval. The standard error is computed based on the empirical standard deviation of 200 bootstrap repetitions of quantile treatment estimates.[62] Note that the coefficient and standard errors on the post70 dummy are not multiplied by 100 throughout this section. The figure shows that lower cost-sharing at age 70 is associated with declines in out-of-pocket spending at almost all (non-zero) quantiles of the distribution.

Table 7 reports the RD estimate (α_1^q) of each tencile above 40 percentile, and 95th and 99th percentile in column (2), with a value just below age 70 (α_0^q) in column (1). While the lower cost-sharing has a very small effect at the low quantiles, it grows consistently with baseline spending. At the median, the impact on out–of-pocket spending is a reduction of 23.5 thousands Yen; at the 95th quantile it grows to 115 thousands Yen, roughly a 30 percent decline from the value just below age 70. Note that the estimates reflect the effect of treatment on the distribution, not the effect of treatment on any particular individual without a rank invariance assumption.

6 Cost-Benefit Analysis

In this section, I carry out a simple cost-benefit analysis. Since it requires making a number of assumptions, the results here are more speculative. But the exercise provides a rough estimate on the social costs and benefits of marginal change of the cost-sharing at age 70.

To understand the costs and benefits in this framework, I first describe the items of social costs and benefits associated with the change in the price of the health care services at age 70. The program incurs two types of the costs. First is extra spending for mechanical reasons, i.e., the government has to bear additional payments due to higher reimbursements for the consumers above age 70 (denote this item #1). The other is efficiency costs from moral hazard on increased health spending (#2). The sum of #1 and #2 is the amount of the increase in spending out of government funds. Since there are marginal costs associated with raising public revenue, these numbers have to be multiplied by the marginal cost of funds (MCF) to estimate the total social cost. On the benefit side, there are two benefits. First is the mechanical gain by the lower cost-sharing accrued to the consumers, which is exactly the mirror image of the increase in the government reimbursement (i.e., #1). The other benefit is risk protection against unexpected out-of-pocket medical spending which I explain in length later (#3). Note that health benefit is not included in the social benefit here since I did not find any short-term health effects.

[62] See Frandsen, Froelich and Melly (2010) that propose the nonparametric estimator for quantile treatment effects in a RD design. Recognizing the potential bias due to the misspecification, I choose to use parametric approach since I also want to obtain the coefficients on other controls variables that are used to derive the distribution of out-of-pocket medical expenditure at each quantile conditional on individual characteristics later in the welfare analysis. In fact, I also estimate the proposed non-parametric estimators, and compare it to the parametric ones. The estimates are quite similar throughout the percentile except for slight deviation among the top 3 percentile. The results are available from the author. The stata code for the non-parametric estimator is available at Frandsen's website. http://econ-www.mit.edu/grad/frandsen/software

Thus net benefit can be written as follows.

$$\begin{aligned} Net\ Benefit &= (Total\ Benefit) - (Total\ Cost) \\ &= (\#3 + \#1) - MCF * (\#1 + \#2) \\ &= \#3 - (MCF - 1) * \#1 - MCF * \#2 \end{aligned} \qquad (5)$$

Note that the mechanical cost is multiplied by the (MCF-1), which is the excess burden of the public fund or dead weight loss, while the moral hazard is multiplied by MCF, since there is no benefit accrued by consumers to offset the cost. In the following, I estimate each component, #1, #2, and #3 accordingly.

6.1 Social Cost

The first cost is the mechanical cost. Since the out-of-pocket medical expenditures reported in CSLC do not distinguish the outpatient visits and inpatient admissions, I need to make an assumption to estimate the out-of-pocket spending distribution that mechanically adjusts for what the Elderly Health Insurance would have covered if it were applied to those just below age 70. Since the coinsurance rate for both inpatient admissions and outpatient visits is 30 percent for those below 70, and 10 percent for those above age 70 in 2007, I assume that two thirds of the out-of-pocket medical expenditures just below age 70 is the mechanical cost (i.e., I assume that the cost-sharing would have been one third if Elderly Health Insurance was mechanically applied to those just below age 70).[63] Since the average out-of-pocket medical expenditure just below age 70 from the first row of Table 7 is 152 thousand Yen, the average mechanical cost is 102 thousand Yen ($1,020).

Second, there are efficiency costs from the moral hazard on increased health spending. As seen from the results on utilization, most of the increased spending may have been socially inefficient. However, it is difficult to know exactly what would be the socially efficient use of the medical services. By treating all of the increase in utilization as a social cost, I provide an upper bound on the efficiency costs of the lower cost-sharing. The difference between the counterfactual and actual out-of-pocket medical expenditure just above age 70 should be moral hazard. From first row in column (1) in Table 7, the counterfactual mean value of the out-of-pocket medical expenditure is 51 thousand Yen (=152/3). The actual out-of-pocket medical expenditure just above the cut-off is 100 thousand Yen (152-52) from the first row of Table 8, and therefore moral hazard is remaining 49 thousand Yen.

6.2 Social Benefit: Welfare Gains from Risk Protection

To estimate the value of the reduction in risk exposure, I combine the expected utility framework with the quantile RD estimates in the previous section, and calculate the change in the risk premium associated with out-of-pocket expenditure as a measure of the welfare gain from the lower cost-sharing

[63] This assumption is reasonable since only 2 percent of those aged 65-69 pay beyond the stop-loss in the sample. Note that Table 3 shows that 14.6 percent of those ages 65-69 reach stop-loss conditional on being admitted.

at age 70. This approach is akin to Feldstein and Gruber (1995), Finkelstein and McKnight (2008), and Englehardt and Gruber (2011).[64]

Specifically, I assume that each individual has utility $U(C)$ that is the function of net non-health consumption C. I then assume the individual must satisfy a budget constraint each period $C = Y - M$, where Y is per-period income and M is individual's out-of-pocket medical expenditures. M is a random variable with probability density function $f(M)$ with support $[0, \bar{M}]$.

I calculate the change in the risk premium associated with lower cost-sharing by computing the risk premium for both just below (denoted as zero) and above 70 (denoted as one). For those just below age 70, the risk premium (or certainty equivalence) π_0 can be defined by a fixed amount such that

$$U(Y - \pi_0) = \int_0^{\bar{M}} U(Y - M_0) f(M_0) dM_0, \tag{6}$$

and measures the amount a risk-averse individual would be willing to pay to insure against random variation in out-of-pocket spending.

For those just above age 70, lower cost-sharing at age 70 reduces not only the variance but also the mean of the out-of-pocket spending distribution. However, since the difference between the mean values of M_0 and M_1 is simply a transfer between the insured and insurers (or government), I calculate the certainty equivalence for the out-of-pocket risk distribution just above age 70 with an adjustment to make the mean of the risk distribution just above age 70 equal to that of just below age 70 distribution (i.e., I evaluate the mean preserving spread in risk).

Thus I define the risk premium π_1 for those just above age 70 as

$$U(Y - \pi_1) = \int_0^{\bar{M}} U(Y - M_1 + \mu_1 - \mu_0) f(M_1) dM_1, \tag{7}$$

where μ_0, and μ_1 are the mean of M_0, and M_1 respectively.

A decrease in risk exposure just above relative to just below 70 is reflected as decline in the risk premium; the absolute value of this decline Δ provides a measure of the insurance value and hence welfare gain of the lower cost-sharing:

$$\Delta = |\pi_1 - \pi_0|. \tag{8}$$

I measure Δ in the two steps as follows. First, I use the quantile estimates of the parameters in (4) to calculate for each individual i in the sample the quantiles of the out-of-pocket spending distribution $\hat{M}_i^q$, conditional on individual's characteristics X_i' just below and above age 70.

Specifically, for each $i = 1, ..., N$ in the sample, $\hat{M}_{i0}^q$ for those below age 70 can be written as

$$\hat{M}_{i0}^q = \hat{\alpha}_0^q + X_i' \hat{\gamma}^q, \tag{9}$$

respectively for $q = 1, ..., 99$ where $\hat{\alpha}_0^q$ and $\hat{\gamma}^q$ come from equation (4) at each quantile q.

[64] My welfare estimates may be bound to be lower than those in the US since it is much less likely to have catastrophic health expenses in Japan due to stringent control of national fee schedules by the government (Ikegami and Campbell, 1995).

For those above age 70, I compute the counterfactual out-of-pocket spending distribution the individual faces once the quantile treatment estimates of lower cost-sharing estimated in equation (4) are applied. Therefore $\hat{M}_{i1}^{q}$ for those above age 70 can be written as

$$\hat{M}_{i1}^{q} = \hat{M}_{i0}^{q} + \hat{\alpha}_{1}^{q}, \tag{10}$$

where $\hat{\alpha}_1^q$ is the RD estimate from equation (4) for each quantile q. Because there are 99 quantile estimates for each individual i, to make sure that the sum of the probabilities is one, I set conditional out-of-pocket spending at the very bottom of the distribution to zero, $q = 0$, i.e., $\hat{M}_{i1}^{0} = \hat{M}_{i0}^{0} = 0$. Then I now have 100 points of equal probability of occurrence in the out-of-pocket spending distribution for each individual. Following Finkelstein and McKnight (2008), and Englehardt and Gruber (2011), I truncate predicted out-of-pocket spending from below at zero and from above at 80 percent of individual income as a benchmark.

Finally, I calculate the risk premium π_{0i} for those below age 70 for each individual i by solving

$$U(Y - \pi_{0i}) = \frac{1}{100}\left[\sum_{q=1}^{99} U(Y_i - \hat{M}_{0i}) + U_0\right], \tag{11}$$

where $U_0 = U(Y_i)$, and the right hand side is the average utility given its income Y_i for each individual. In a similar vein, I calculate the risk premium π_{1i} for just above age 70 by solving

$$U(Y - \pi_{1i}) = \frac{1}{100}\left[\sum_{q=1}^{99} U(Y_i - \hat{M}_{1i} + \hat{\mu}_1 - \hat{\mu}_0) + U_1\right],$$

where $U_1 = U(Y_i + \hat{\mu}_1 - \hat{\mu}_0)$, and I made an adjustment by subtracting from the individual's income the average difference in out-of-pocket expenditures between one's 100 estimates for the original distribution just below age 70 ($\hat{\mu}_0$) and one's 100 estimates for the counterfactual distribution ($\hat{\mu}_1$).

Following the literature, I specify constant relative risk aversion (CRRA) utility function $U(C) = -\frac{1}{\phi-1}C^{1-\phi}$, which implies Arrow-Pratt measure of relative risk aversion of $\phi = -\frac{CU''}{U'}$. For a typical risk aversion of 3 in CRRA utility (see e.g., McClellan and Skinner, 2006), I estimate that this decline in risk premium, or welfare gain, is 20 thousands Yen ($200) per person. This is just half of the average cost through moral hazard.

However, it is important to note that the previous estimate on the decline in risk exposure is understated since the out-of-pocket expenditures include the behavioral response of increased utilization of the health care services. Here I once again assume that the cost-sharing would have been one third if Elderly health Insurance was mechanically applied to those just below age 70. For a typical risk aversion of 3 in CRRA utility using this mechanically adjusted out-of-pocket spending, I estimate that this decline in risk premium is doubled from 20 to 46 thousands Yen per person.

These estimates are somewhat sensitive to two particular assumptions: risk aversion and maximum level of out-of-pocket medical expenditures as a share of income. Table 8 shows the sensitivity of the welfare gain to these two parameters compared to the baseline case. First, I examine the sensitivity

to the choice of risk aversion coefficient (assuming the cap on out-of-pocket spending is 80 percent of income). Compared to an estimated welfare gain of 46 thousand Yen per person with a relative risk aversion of 3, the welfare gain falls to about 7 thousand Yen with relative risk aversion of 1, and rises to 110 thousand Yen with the relative risk aversion of 5.

Next, the welfare estimates are also sensitive to the assumption I make about the maximum level of out-of-pocket medical expenditures as a share of income (assuming relative risk aversion of 3). If I replace my baseline 80 percent cap with a cap of 60 percent, the estimated welfare gain falls from 46 thousand Yen to 22 thousand Yen, and if I impose a cap of 90 percent the welfare estimate rises to 74 thousand Yen.

Finally, the row B in Table 8 shows the risk premium at other percentiles. Recall that my central estimate of risk premium on average is 46 thousand Yen. I assume a relative risk aversion of 3 and out-of-pocket expenditure cap at 80 percent of income here. The median is 25, suggesting that benefits accrue more to those on the right tail. The 95th percentile is 126 thousand Yen. The results suggest that the risk-reduction gain was modest for most elderly, but sizeable for those at the highest risk of spending.

6.3 Discussion

My central estimate of risk reduction is 46 thousand Yen per person ($460). One way to gauge the size of the estimate is to simply plug estimated benefits and costs into equation (5) and calculate the MCF that would have for the two to be equal each other. Since I have the estimated values for all components (#1, #2, and #3), it is straightforward to derive that such MCF is equal to 0.98, or in other words, the MCF should be less than 0.98 to have positive net benefits. This value is smaller than the most of the estimates of MCF in 1990s like 1.3 (see e.g., Poterba, 1996).[65] Put differently, assuming the MCF is 1.3, the sum of the program financing costs and moral hazard suggests that the total annual social cost was 94.3 thousands Yen (102*0.3+ 49*1.3) per elderly beneficiary; the deadweight loss associated with program financing is responsible for one third of the total cost, and moral hazard accounts for two-thirds. Therefore, with a relatively high risk aversion of five where risk reduction is 110 thousand Yen is the only case I examined here that average social benefit outweighs average social cost.

7 Conclusion

A simple cost-benefit analysis shows that the welfare gain of risk protection from the lower cost-sharing is relatively small compared to the deadweight loss of program financing, suggesting that the social costs may outweigh the social benefits. However, there are a number of caveats to my welfare calculation. On the one hand, the stylized welfare calculations may overstate the welfare gains since the use of a one-

[65] There is no consensus estimate of MCF since MCF depends on behavioral responses to taxation and may differ by every country at every point in time. Nonetheless, to have a rough estimate, I here focus on income tax since it is a major source of taxes. The simplest formula is $\frac{1}{(1-\rho*(\frac{t}{1-t}))}$ where ρ is the elasticity of taxable income and t is the income tax rate (Kopczuk, 2005). Assuming that both the elasticity of taxable income and the tax rate are 0.4, MCF would be 1.36, which is close to 1.3 used here.

period model ignores the possibility that individuals can use savings or other mechanisms to smooth expenditure risk over several periods, which may lead me to over-state the welfare gains from lower cost-sharing. This may be the case since the elderly seem to have some savings.[66] On the other hand, the welfare gains may be understated because the calculations were based on an annual, rather than lifetime, measure of medical expenditure risk. In fact, there is some evidence that out-of-pocket medical expenditures are positively serially correlated (Feenberg and Skinner, 1994; French and Jones, 2004). These studies suggest that the lifetime distribution of out-of-pocket spending may be even more right-skewed than the annual distribution; therefore, the reduction in risk exposure in the lifetime scale may be even greater.[67] Furthermore, my welfare calculation does not incorporate the welfare gains from the health improvements. While I do not find any *short-term* reduction in mortality or improvement in any self-reported health measures, it is possible that preventive care induced by the lower cost-sharing may prevent future severe health events, and thus improve health in the long run. Estimating the long-term effect of cost-sharing on health is beyond the scope of the current paper, but it clearly remains an important topic for future research.

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[66] Average net savings at age 69 is 5,418 thousands Yen, which is roughly two and half times of average annual income (1,860 thousand Yen). Since saving and debt is only reported at the household level, I divide the net saving (i.e., saving minus debt) by the number of household members.

[67] Also the stylized model treats medical expenditures as affecting the budget constraint only and does not allow for any utility change from increased medical expenditures.

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A Appendix

A.1 Derivation of Out-of-Pocket Health Expenditures

This section in the appendix describes how I convert the cost-sharing formula in Table 1 into the actual monthly out-of-pocket health expenditures in Table 2. It is ideal if we have information on actual out-of-pocket expenditures at the individual level, such as Medical Expenditure Panel Survey (MEPS) in the US. In the absence of such data, I derive this myself.

Fortunately, I know the exact formula for cost-sharing (Table 1) and have individual level insurance claim data, which is the monthly summary of medical expenditures claimed for insurance reimbursement to medical institutions (called the Survey of Medical Care Activities in Public Health Insurance). Since a portion of this monthly total medical expenditure is paid as patient cost-sharing, using the formula in

Table 1, I can compute the average out-of-pocket medical expenditures at each age for each survey year of the Patient Survey.[68]

The insurance claim data is monthly since reimbursements to the medical institutions are conventionally paid monthly in Japan. Thus the stop-loss is set by monthly rather than annually unlike the US. The age of patients is measured in years in this data.

The steps I compute the average monthly out-of-pocket expenditures are as follows. Note that cost-sharing formula differs by outpatient visits and inpatient admissions; since inpatient admissions are more expensive and put more financial burden on patients, the coinsurance rate of inpatient admissions tend to be set lower than those of outpatient visits.

Those below age 70

First, I compute the average monthly out-of-pocket health expenditures for 69-year-old patients. For those below age 70, the coinsurance rate is determined by the type of health insurance: NHI, employees in employment-based health insurance, and dependent of employees in employment-based health insurance. Among those in NHI, the coinsurance rate differs among those who are still employed, retired former employees, and dependents of retied employees. I use information from the CSLC to compute the rate of those employed among NHI recipients. Also, assuming that males who are not employed are retired former employees and females who are not employed are dependents of retied employees, I compute the weighted average of the coinsurance rate for NHI. This assumption does not make any major differences for this computation, since the fraction of retired former employee is quite small. In fact, the coinsurance rate for only outpatient visits during 1984-2002 differs by 10 percent between retired former employees and dependents of retied employees, and the computed weighted coinsurance rate for NHI is around 28 percent, which is very close to the coinsurance rate for the employed and dependents of retired employees among NHI (30 percent). For inpatient admissions, this assumption plays no role, since the coinsurance rate for inpatient admissions is the same (20 percent) for retired former employees and dependents of retired employees.

Then, actual out-of-pocket medical expenditures, AM_{ipt}, for individual i whose health insurance plan p (p=1-3, where 1: NHI, 2: employees in employment-based health insurance, and 3: dependent of employees in employment-based health insurance), and types of services use j (j=1-2, where 1: inpatient admissions, 2: outpatient visits) in survey year t, is given as follows:

$$AM_{ipt} = min(EM_{ijpt}, SL_{jpt})$$

where EM_{ijpt} is the expected payment without stop loss (or maximum amount of out-of-pocket expenditures), and SL_{jpt} is stop-loss for each plan p for each service use j in survey year t.

Suppose there is an individual whose total medical expenditures for inpatient use in June 2008 is 1,000,000 Yen, and the coinsurance rate is 30 percent. This indicates that EM_{ijpt} of 300,000 Yen. On the other hand, SL_{jpt} is 87,430, which is 80,100+(1,000,000-267,000)*0.01, according to the formula in Table 2. Since SL is smaller than EM, AM is 87,430 Yen. I compute AM for each individual level claim data, and take the simple average to compute the average expenditure AM_{jpt}, by each plan type

[68] The rest of medical expenditures are paid by insurance societies. The source of the money is a fund of the pooled premiums of insured members and assistance from the government.

p, for each service j in survey year t.

Finally, I take a weighted average of each insurance type W_{pt}, obtained from the CSLC. Therefore, the average monthly out-of-pocket medical expenditure AM for age 69 is:

$$AM_{jt}(age69) = \sum_{p=1}^{3}(W_{pt} * AM_{jpt})$$

for use of type j in each survey year t of Patient Survey. I take W_{pt} for each year t, from the CSLC in year $t-1$ since CSLC is conducted a year before the Patient Survey. The exception is the Patient Survey year of 1984, when the fraction from 1987 of the CSLC is used as a weight since it is the closest year of information available. The majority of 69 year-olds (roughly 70-80 percent) belongs to NHI, and the rest belongs to employment-based health insurance.

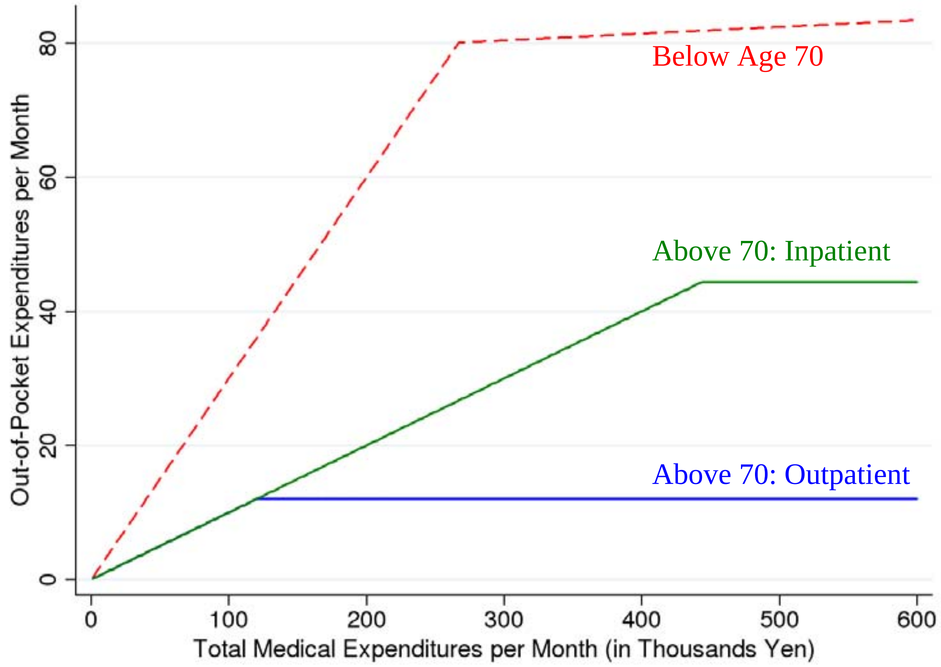
Those above age 70

Next, I compute the average out-of-pocket health expenditures for 70-year-old patients, who all receive Elderly Health Insurance. Since utilization is endogenous (i.e. observed out-of-pocket medical expenditure already reflects the change in cost-sharing), I compute a counterfactual out-of-pocket expenditure for 70-year-old patient if they had the same amount of utilization as the average 69-year-old. I compute the average monthly frequency of visits for outpatient visits, and average length of stay for inpatient admissions for age 69, and applied the formula for age 70 to compute the monthly average out-of-pocket medical expenditures, in the same manner as those for age 69 described above.

Finally, the overall out-of-pocket medical expenditure in Table 2 is the weighted average of the out-of-pocket medical expenditure across all survey years for outpatient visits and inpatient admissions respectively, using the population of age 69 in each survey year as weights. For reference, Appendix Table H shows the estimated out-of-pocket medical expenditure for each survey year.

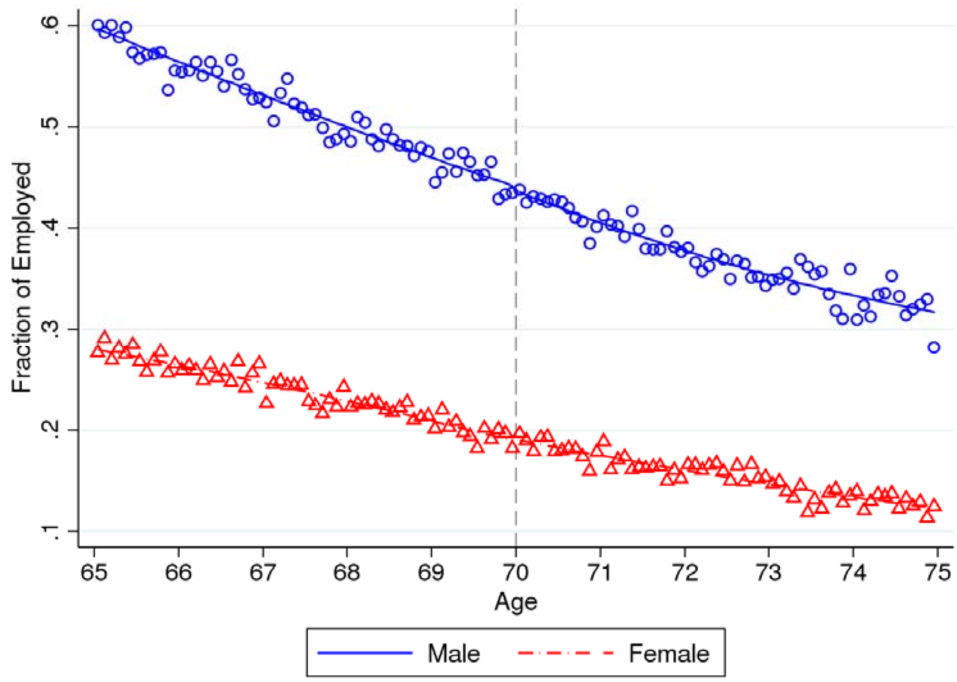
It is worth mentioning that these figures I compute is a rough estimate of actual out-of-pocket medical expenditures since the actual cost-sharing is a little bit more complicated than this simple exercise. For example, different coinsurance rates are applied to specific populations, and there is another way to reduce out-of-pocket medical expenditures. For example, in October 2002, the coinsurance rate for those over age 70 with high income – 7 percent according to Ikegami et al. (2011) - was raised from 10 percent to 20 percent. Also for all ages, the stop-loss is set lower for very low-income people. Nonetheless, since most of the patients are under the basic cost-sharing formula, the cost-sharing I estimate should be within an acceptable range.

Fig.1 Cost-Sharing Below 70 and Above 70: Year 2008 as an Example



Note: See Table 1 for the formula for cost-sharing below and above 70. For those above 70, since the coinsurance rate and stop loss differs by outpatient visits and inpatient admissions, there are two separate lines for each outpatient visits and inpatient admissions. For those below 70, there is no distinction between outpatient visits and inpatient admissions in year 2008. One thousands Yen is roughly $10 US dollars.

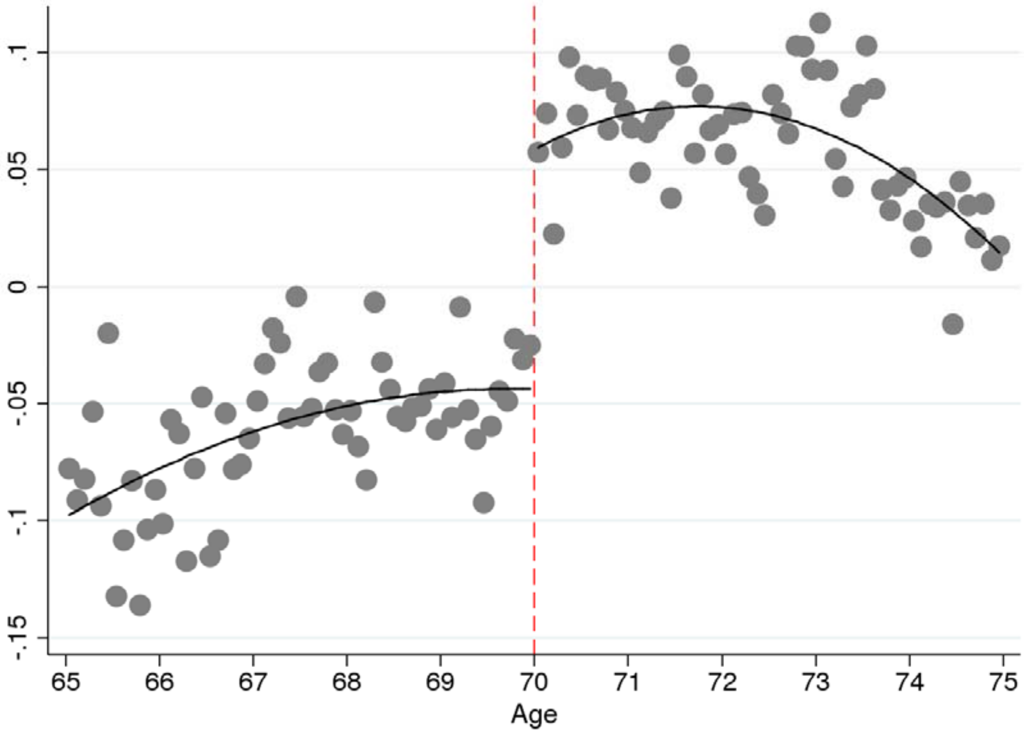
Fig.2 Age Profile of Employment by Gender (1987–2007 CSLC)



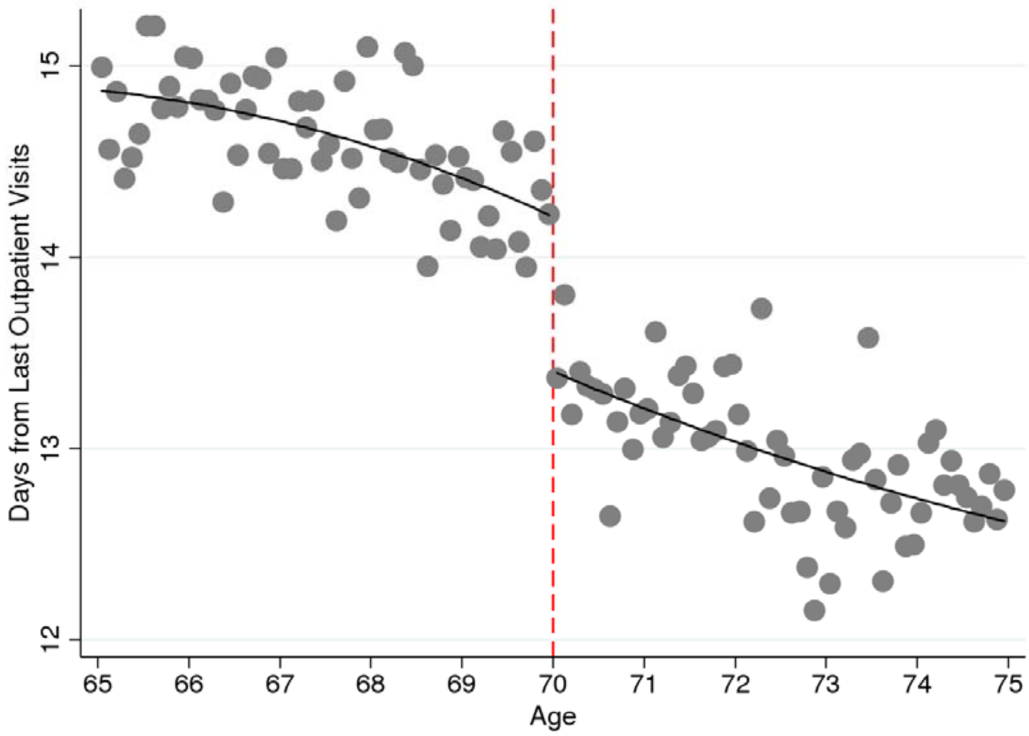
Note: The data come from the pooled 1986-2007 Comprehensive Survey of Living Conditions. The markers represent actual averages (age in month), and the lines represent fitted regressions from models that assume a quadratic age profile fully interacted with a dummy for age 70 or older for male and female separately.

Fig.3 Age Profile of Outpatient Visits

3A. Overall Outpatient Visits (log scale)

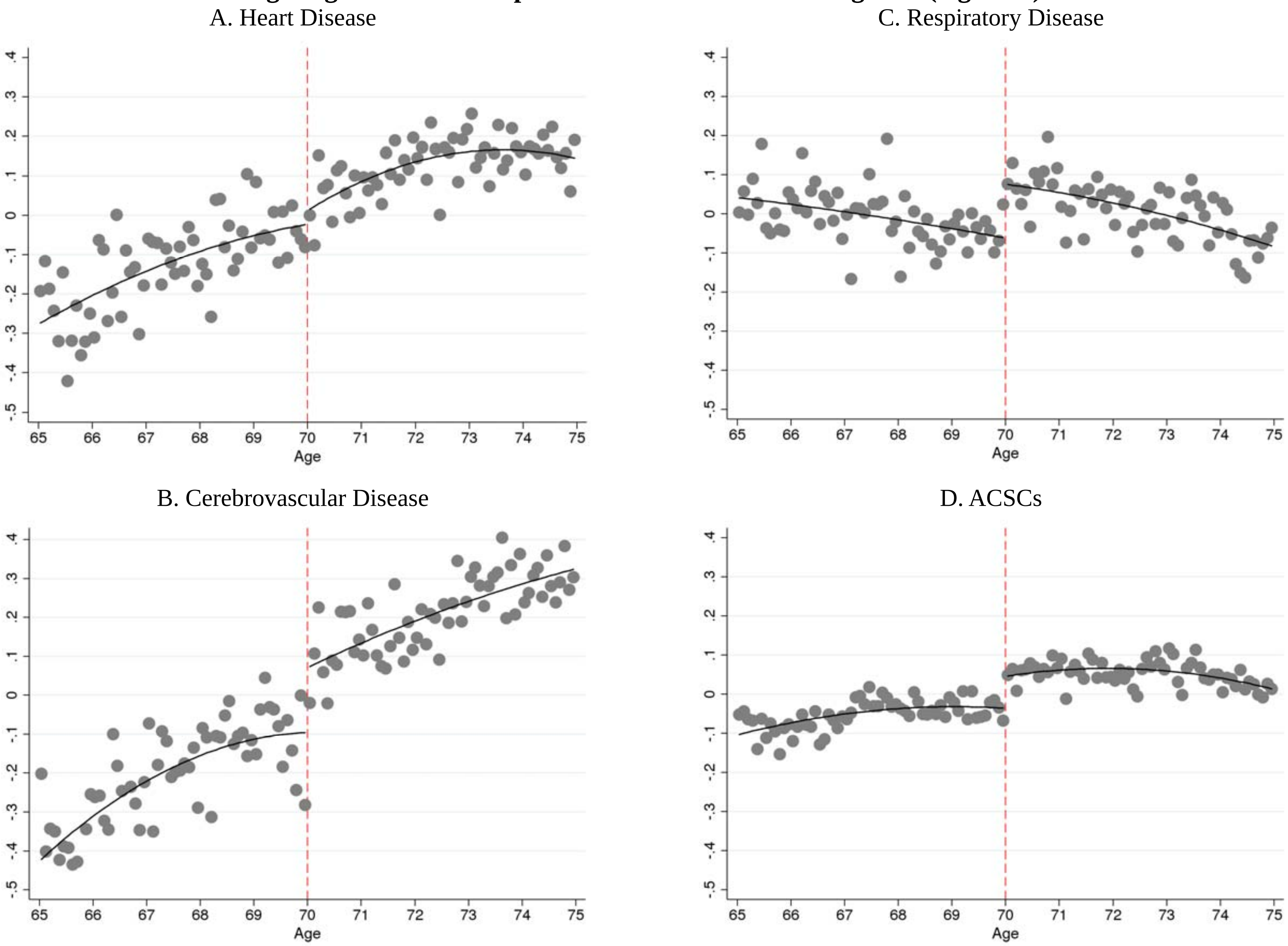


3B. Days from Last Outpatient Visits for Repeated Patients



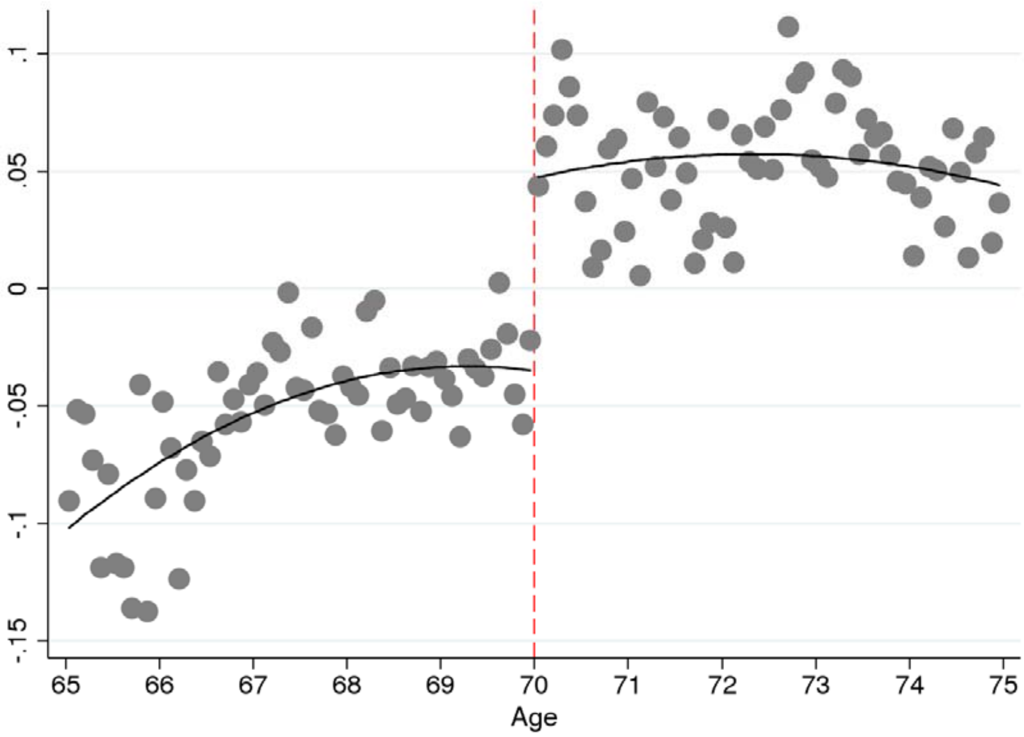
Note: The data come from pooled 1984-2008 outpatient visits data in the Patient Survey. The markers in 3A represent the averages of residuals from a regression of the log outcome on birth month fixed effects and survey year fixed effects (aggregated by age in month), and the simple average in 3B. The lines represent fitted regressions from models that assume a quadratic age profile fully interacted with a dummy for age 70 or older.

Fig.4 Age Profile of Outpatient Visits for Selected Diagnosis (log scale)



Note: The data come from pooled 1984-2008 outpatient data in the Patient Survey. The corresponding RD estimates at age 70 are statistically significant at 5 % level except for Panel A. The markers represent the averages of residual from a regression of the log outcome on birth month fixed effects and survey year fixed effects (aggregated by age in month). The lines represent fitted regressions from models that assume a quadratic age profile fully interacted with a dummy for age 70 or older. ACSCs stand for Ambulatory Care Sensitive Conditions developed by AHRQ. See Appendix Table C for the list of ACSCs.

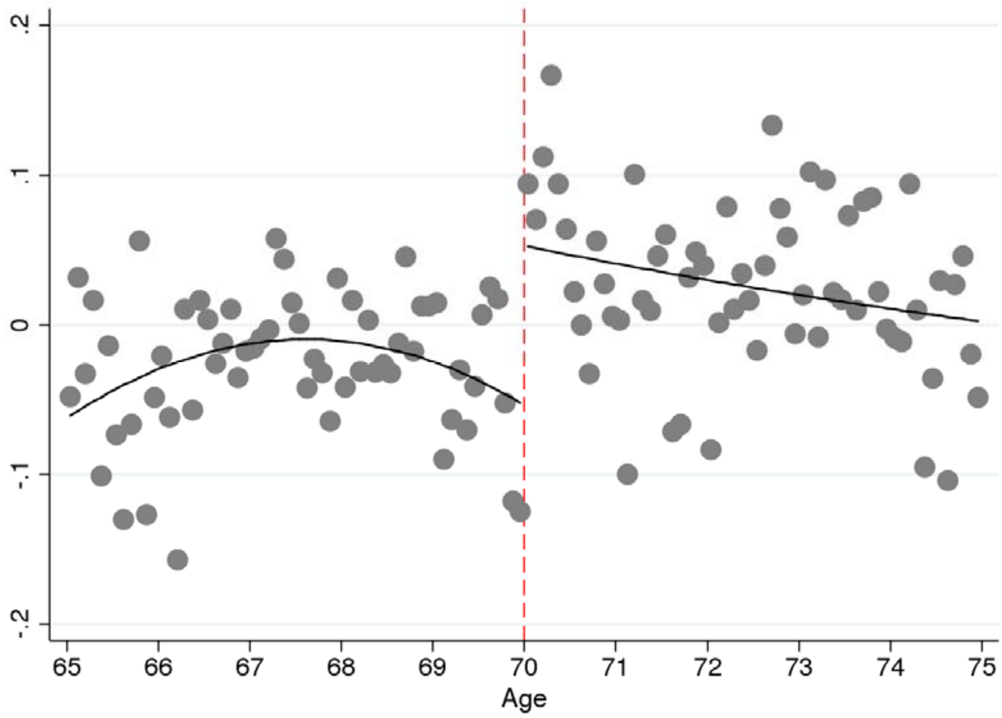
Fig.5 Age Profile of Inpatient Admissions (log scale)



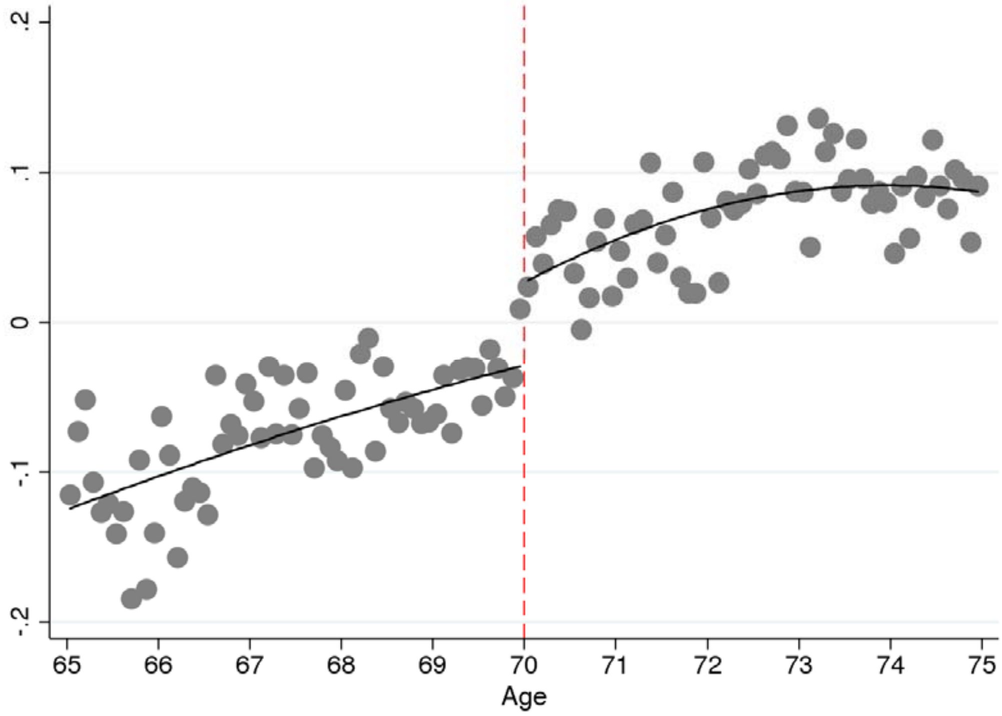
Note: The data come from pooled 1984-2008 discharge data in the Patient Survey. The markers represent the averages of residual from a regression of the log outcome on birth month fixed effects, admission month fixed effects and survey year fixed effects (aggregated by age in month). The lines represent fitted regressions from models that assume a quadratic age profile fully interacted with a dummy for age 70 or older.

Fig.6 Age Profile of Inpatient Admissions with and without Surgery (log scale)

6A. With Surgery



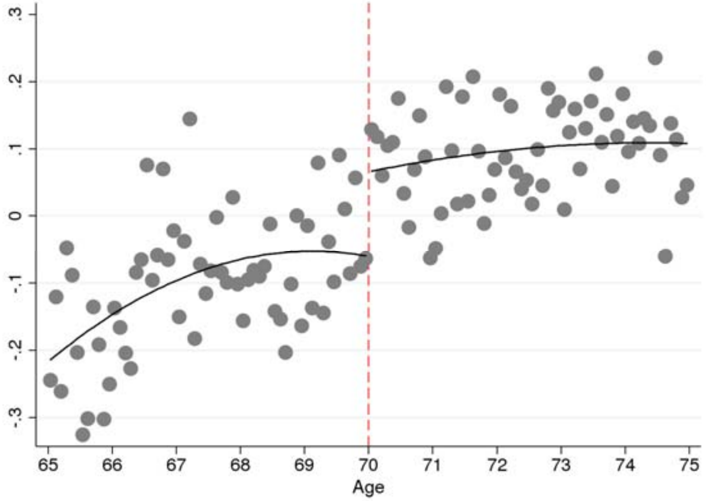
6B. Without surgery



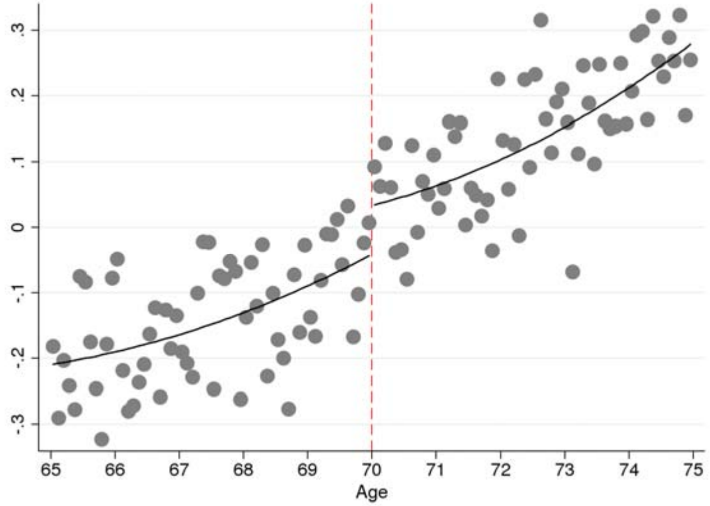
Note: The data come from pooled 1984-2008 discharge data in the Patient Survey. The markers represent the averages of residual from a regression of the log outcome on birth month fixed effects, admission month fixed effects and survey year fixed effects (aggregated by age in month). The lines represent fitted regressions from models that assume a quadratic age profile fully interacted with a dummy for age 70 or older.

Fig.7 Age Profile of Inpatient Admissions for Selected Diagnosis (log scale)

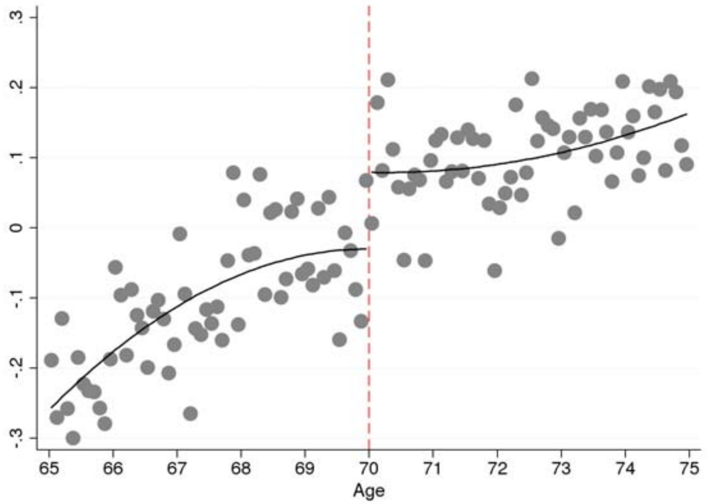
A. Heart Disease



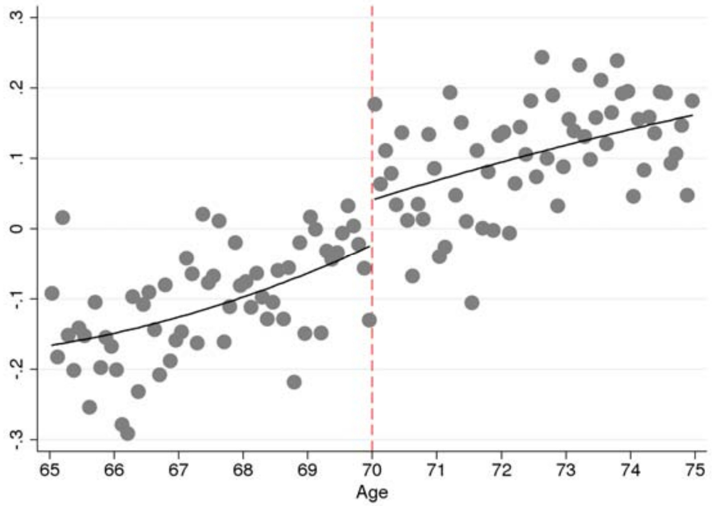
C. Respiratory Disease



B. Cerebrovascular Disease

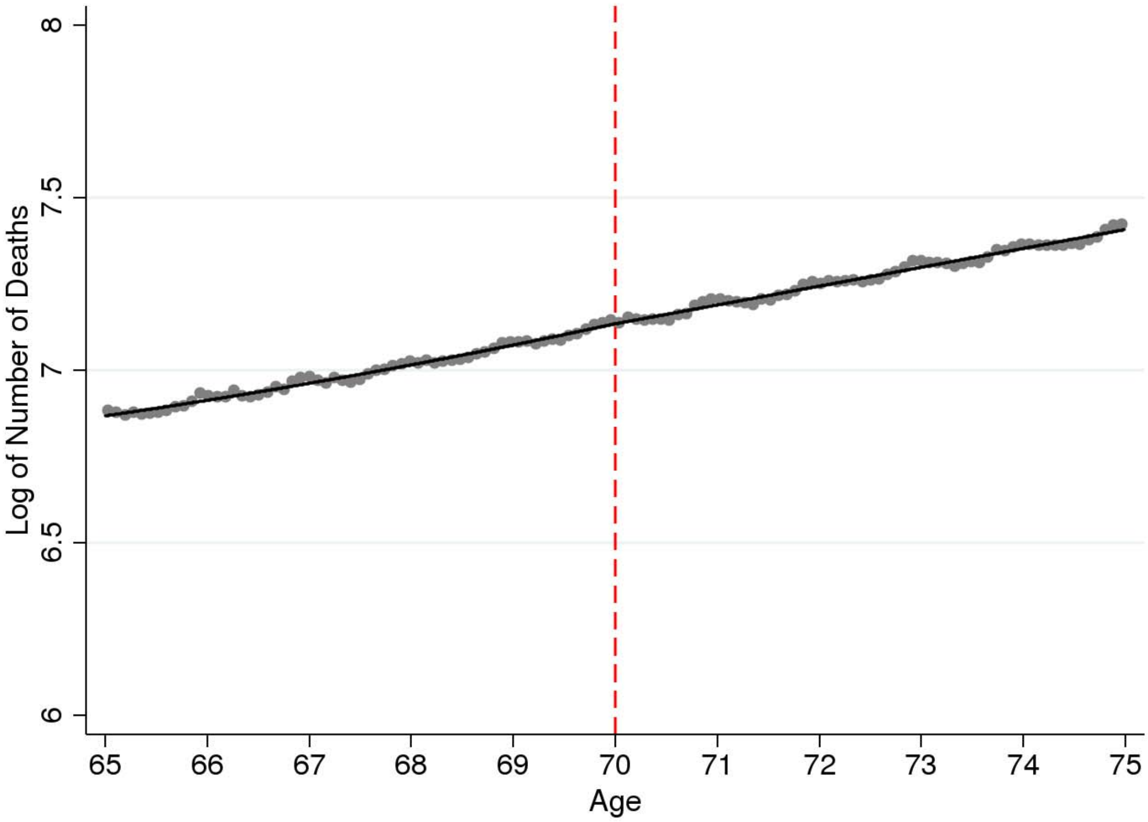


D. ACSCs



Note: The data come from pooled 1984-2008 discharge data in the Patient Survey. The corresponding RD estimates at age 70 are statistically significant at 5 % level for Panel A and B only. The markers represent the averages of residual from a regression of the log outcome on birth month fixed effects, admission month fixed effects, admission of month fixed effects, and survey year fixed effects (aggregated by age in month). The lines represent fitted regressions from models that assume a quadratic age profile fully interacted with a dummy for age 70 or older. ACSCs stand for Ambulatory Care Sensitive Conditions developed by AHRQ.

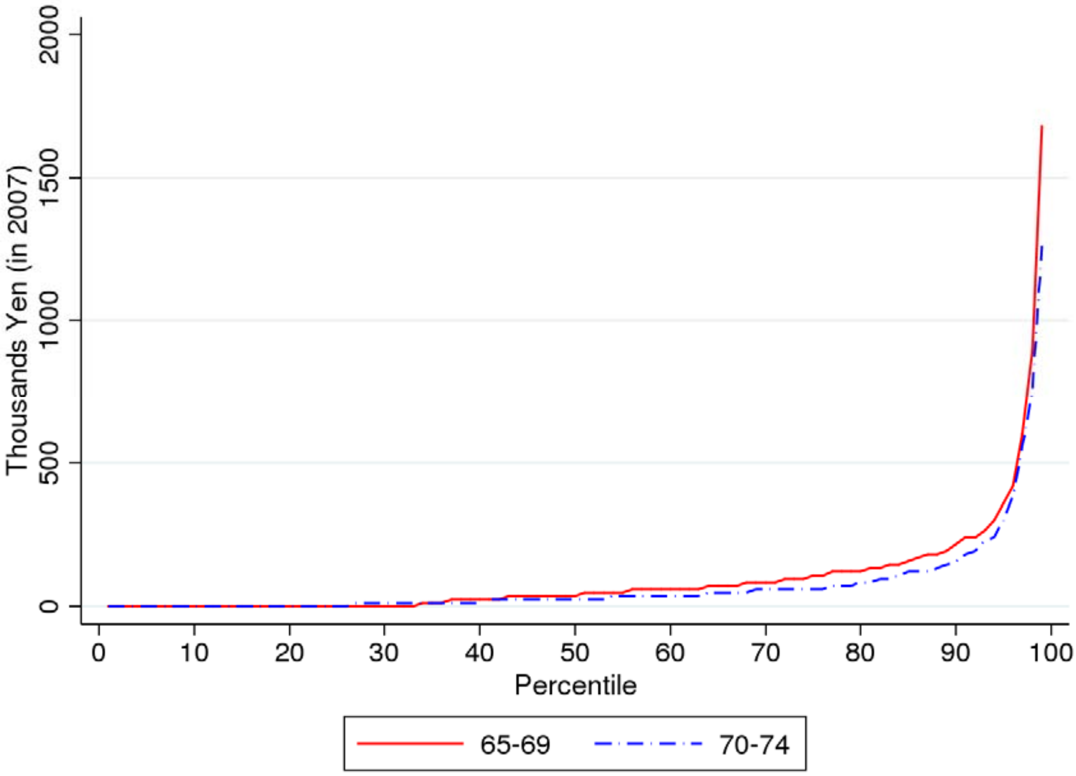
Fig.8 Age Profile of Overall Mortality



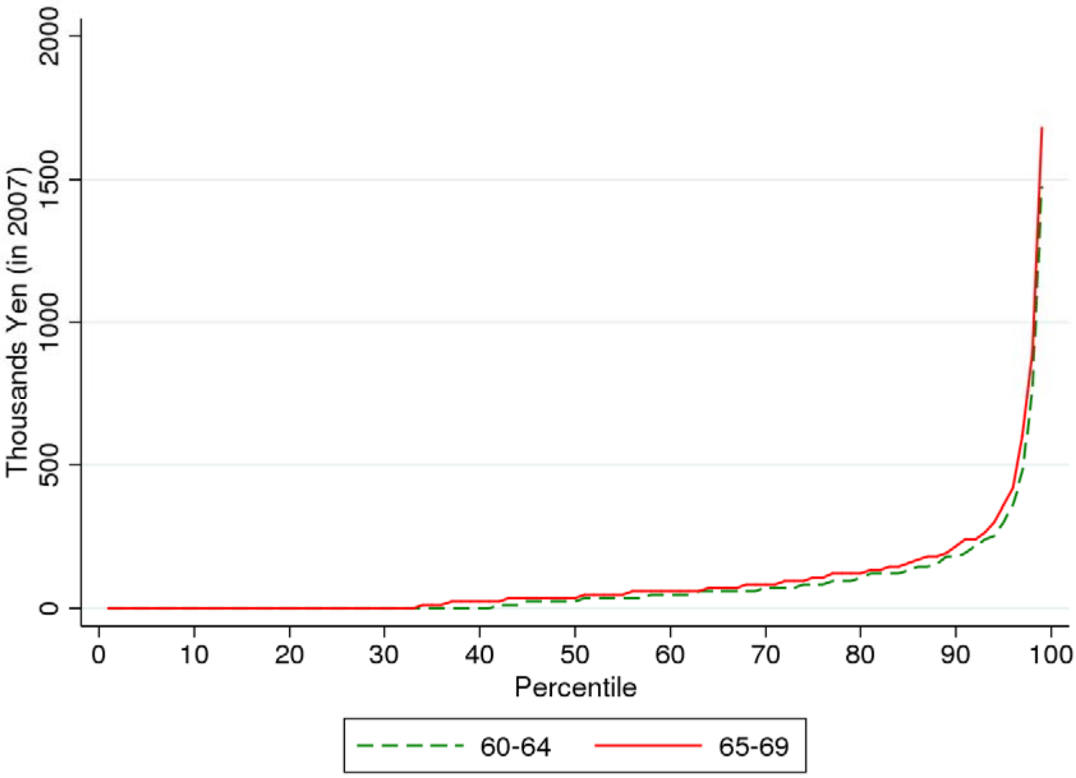
Note: The data come from pooled 1984-2008 mortality data. I use days to eligibility for the Elderly Health Insurance as a running variable. The cell is each 30 days interval from the day of eligibility at age 70. The markers represent the averages, and the lines represent fitted regressions from models that assume a quadratic age profile fully interacted with a dummy for age 70 or older.

Fig.9 Distribution of Out-of-Pocket Medical Expenditure in 2007

9A. Ages 65-69 (Near Elderly) and Ages 70-74 (Elderly)



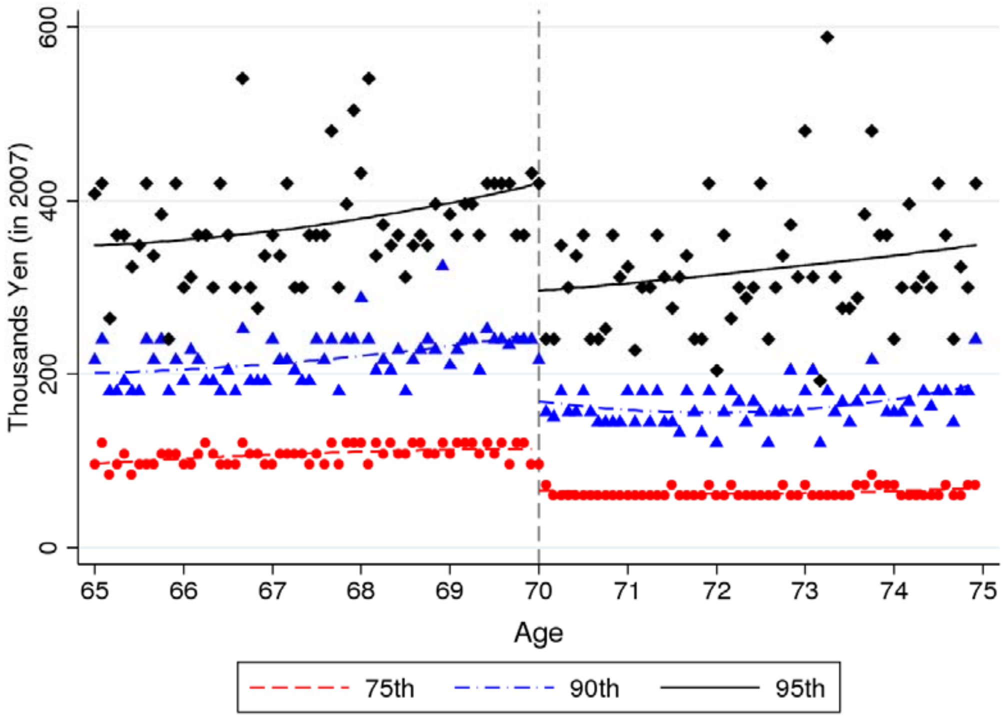
9B. Ages 60-64, and Ages 65-69 (Near Elderly)



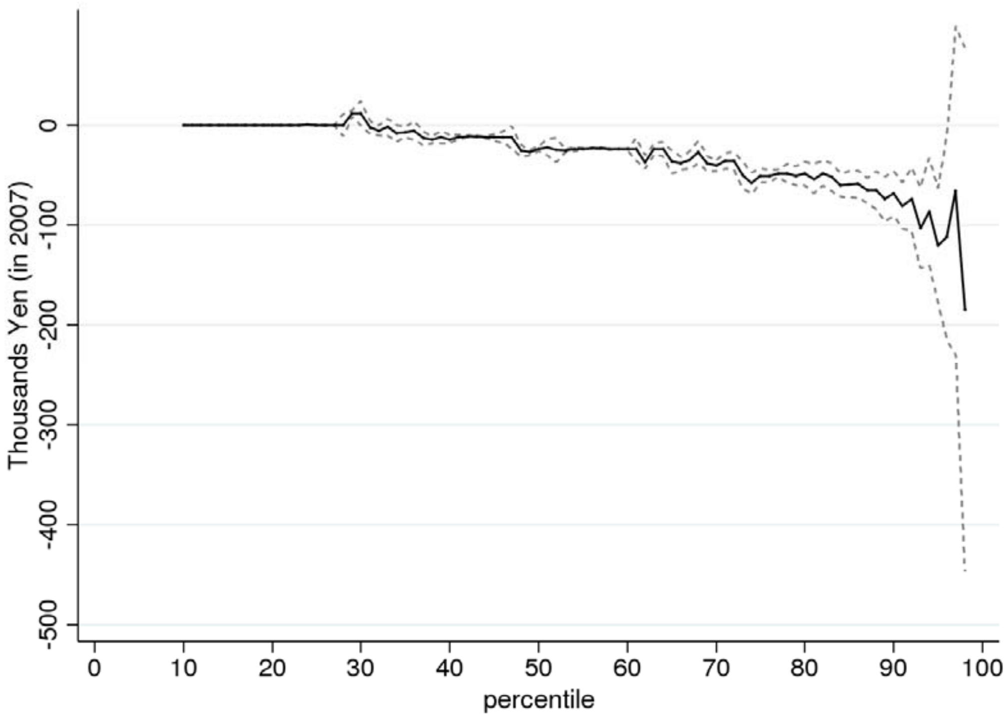
Note: The data come from 2007 Comprehensive Survey of Living Conditions. I have multiplied the monthly out-of-pocket expenditures by twelve to convert to annual basis. One thousands Yen is roughly $10 US dollars.

Fig.10 Age Profile of Out-of-Pocket Medical Expenditures in 2007

10A. At 75th, 90th and 95th percentile



10B. RD Estimates at Each Quantile



Note: The data come from 2007 Comprehensive Survey of Living Conditions. I have multiplied the monthly out-of-pocket expenditures by twelve to convert to annual basis. One thousands Yen is roughly $10 US dollars.
10A: The markers represent actual averages (age measured in month), and the lines represent fitted regressions from models that assume a quadratic age profile fully interacted with a dummy for age 70 or older.
10B: This figure plots the RD estimates at each quantile along with their 95 percent confidence interval. I do not show 99th percentile in the graph.

Table 1: Formula for Cost-Sharing Below and Above Age 70

A. Outpatient Visits

	Below 70				Above70	
	Coinsurance				Coinsurance	
Year	NHI	Employment-based (Employee)	Employment-based (Dep)	Stop-loss	All	Stop-loss
1984	30%(1)	10%	30%	51.0	0.4 /mon	-
1987	30%(1)	10%	30%	54.0	0.8 /mon	-
1990	30%(1)	10%	30%	57.0	0.8 /mon	-
1993	30%(1)	10%	30%	63.0	1.0 /mon	-
1996	30%(1)	10%	30%	63.0	1.02 /mon	-
1999	30%(1)	20%	30%	63.6	0.53 /day (2)	-
2002	30%(1)	20%	30%	63.6+(TC-318) *0.01	10%	12.0
2005	30%	30%	30%	72.3+(TC-241) *0.01	10%	12.0
2008	30%	30%	30%	80.1+(TC-267) *0.01	10%	12.0

Note: (1) Former employees pay 20% and dependent of former employees pay 30% among the retired (2) Up to 4 times/month. TC stands for total cost per month. All money values without percentage sign are in thousand Yen (roughly 10 US dollar in 2008).

B. Inpatient Admissions

	Below 70				Above70	
	Coinsurance				Coinsurance	
Year	NHI	Employment-based (Employee)	Employment-based (Dep)	Stop-loss	All	Stop-loss
1984	30%(1)	10%	20%	51.0	0.4 /day (2)	-
1987	30%(1)	10%	20%	54.0	0.4 /day	-
1990	30%(1)	10%	20%	57.0	0.4 /day	-
1993	30%(1)	10%	20%	63.0	0.7 /day	-
1996	30%(1)	10%	20%	63.0	0.71 /day	-
1999	30%(1)	20%	20%	63.6	1.2 /day	-
2002	30%(1)	20%	20%	63.6+(TC-318) *0.01	10%	37.2
2005	30%	30%	30%	72.3+(TC-241) *0.01	10%	40.2
2008	30%	30%	30%	80.1+(TC-267) *0.01	10%	44.4

Note: (1) Former employees pay 20% and dependent of former employees also pay 20% among the retired (2) Up to 2 months. Also see the note above.

Table 2: Estimated Out-of-Pocket Medical Expenditure per Month

	Out of Pocket Medical Expenditure (thousand Yen)			% reached stop-loss among insurance claims	
	Below 70	Above70	% reduction	Below 70	Above70
Type of Service	(1)	(2)	((1)-(2))/(3)	(4)	(5)
Outpatient Visits					
	4.0	1.0	74%	0.1%	0.6%
Inpatient Admissions					
	38.0	12.4	67%	14.6%	0.0%

Note: All money values without percentage sign are in thousand Yen (roughly 10 US dollar in 2008).

Table 3: RD Estimates at Age 70 on Employment, and Family Structure

		By Gender		Data	
	All	Male	Female	Years Available	Sample Size for "All"
A. Employment related					
(1) Employed	0.3	0.5	0.1	1986-2007	573,104
	(0.4)	(0.5)	(0.5)		
(2) Retired	-0.1	0.8	-0.7	1986-2007	573,104
	(0.5)	(0.7)	(0.6)		
(3) Hours/wk	0.0	0.1	0.0	2004-2007	39,978
	(0.0)	(0.1)	(0.2)		
(4) Family Income (thousand Yen)	-54.9	-212.0	88.1	1986-2007	77,967
	(113.0)	(174.9)	(144.9)		
(5) Income (thousand Yen)	-32.3	-29.9	-34.1	2004-2007	18,757
	(89.8)	(179.9)	(54.3)		
B. Family Structure					
(6) Married Spouse Present	0.5	0.5	0.4	1986-2007	573,104
	(0.5)	(0.5)	(0.7)		
(7) Head of Household	0.0	-0.1	0.1	1986-2007	573,104
	(0.4)	(0.4)	(0.6)		
C. Other					
(8) Receiving Pension	0.3	0.2	0.4	1986-2007	573,104
	(0.3)	(0.4)	(0.4)		
(9) Long Term Care Insurance	-0.1	-0.5	0.2	2001-2007	232,928
	(0.3)	(0.4)	(0.3)		

Note: Estimated regression discontinuities at age 70 are shown, from models that include a quadratic of age, fully interacted with dummy for age 70 or older among people between ages 65-75. The exception is a pension dummy since there is a discrete jump at age 65 for probability of receiving the pension, and thus I limit the sample to age 66-74. Other controls include indicators for gender, region, marital status, birth month, and sample year. I use pooled samples of comprehensive survey of living condition (CSLC) conducted every three year since 1986. Sample sizes differ by variables since some variables are only collected for a shorter period. Note that income is collected for roughly 15 % of all samples. Standard errors (in parentheses) are clustered at the age in month level as this is the most refined version of the age variable available. All regressions are weighted to take into account the stratified sampling frame in the data. ***, **, * denote significance at the 1%, 5% and 10% levels respectively. All coefficients on Post70 and their standard errors have been multiplied by 100, so they can be interpreted as percentage changes.

Table 4: RD Estimates at Age 70 on Outpatient Visits

A.	All	10.3***	F	By Diagnosis	
		(1.8)		Top 5	
B.	By Visit Type			Essential hypertension	8.0***
	First visits	12.7***			(2.4)
		(3.3)		Spondylosis	23.7***
	Repeated visits	10.3***			(3.6)
		(1.9)		Diabetes	1.7
C.	Days from Last Outpatients Visits				(4.4)
	Among Repeated Visits			Osteoarthrosis	25.3***
	1 day	17.9***			(4.2)
		(2.5)		Cataract	12.0**
	2-3 day	16.4***			(4.9)
		(4.4)		Other	
	4-7 day	13.3***		Heart disease	3.0
		(2.8)			(4.6)
	15-30 day	2.8		Cerebrovascular disease	15.2***
		(2.9)			(5.9)
	31-60 day	-1.5		Respiratory disease	14.3***
		(4.3)			(3.6)
D.	By Institution			Ambulatory Care Sensitive Conditions	8.2***
	Hospital	5.1**			(2.3)
		(2.0)		Cancer	6.1
	Clinic	13.8***			(8.0)
		(1.8)		Diseases of nervous and sense organs	10.4***
E.	By Referral				(2.8)
	Without Referral	10.5***		Diseases of genitourinary system	14.9***
		(1.9)			(5.4)
	With Referral	6.4		Diseases of skin	17.4***
		(5.2)			(4.9)
				Diseases of musculoskeletal system	18.6***
					(2.5)

Note: Each cell is the estimate from separate estimated regression discontinuities at age 70. The specification is a quadratic in age, fully interacted with dummy for age 70 or older among people between ages 65-75. Controls are dummies for each survey year and each month of birth. I use pooled samples of 1984-2008 Patient Survey conducted every three years since 1984. Sample size is 1080. Robust standard errors are in parenthesis. ***, **, * denote significance at the 1%, 5% and 10% levels respectively. All coefficients on Post70 and their standard errors have been multiplied by 100, so they can be interpreted as percentage changes.

Table 5: RD Estimates at Age 70 on Inpatient Admissions

A All	8.2***	<u>Other</u>	
	(2.6)	Heart disease	11.5**
B Surgery			(5.7)
W/o surgery	5.4*	Hypertensive disease	4.8
	(2.9)		(5.5)
With surgery	10.8***	Ischemic heart disease	14.5**
	(3.8)		(7.1)
C Type of Surgery		Cerebrovascular disease	10.5***
Open-head surgery	11.7		(3.9)
	(8.8)	Intracerebral hemorrhage	8.0
Open-heart surgery	4.1		(6.1)
	(8.5)	Cerebral infarction	12.8***
Open-stomach surgery	11.4**		(4.6)
	(5.6)	Respiratory Diseases	6.8
Musculoskeletal surgery	5.6		(4.8)
	(5.0)	Ambulatory Care Sensitive Conditions	7.6
Endoscopic surgery: stomach	9.3		(5.0)
	(7.3)	Cancer	6.6
Intraocular lens implantation	19.6***		(4.6)
	(6.2)	E Location Before Admission	
D By Diagnosis		Outpatients in Same Hospital	9.7***
<u>Top 5</u>			(2.9)
Cataract	22.6***	Other places	1.6
	(6.5)		(5.4)
Angina pectoris	11.4		
	(7.3)		
Occlusion of cerebral arteries	13.7***		
	(4.6)		
Diabetes	7.4		
	(5.8)		
Malignant neoplasm of stomach	4.9		
	(6.1)		

Note: Each cell is the estimate from separate estimated regression discontinuities at age 70. The specification is a quadratic in age, fully interacted with a dummy for age 70 or older among people between ages 65-75. Controls are dummies for each survey year, each month of birth, and each month of admission. I use pooled samples of 1984-2008 Patient Survey conducted every three year since 1984. Sample size is 3,240 except Panel C, and E. Sample size for C is 1,440 (4 yr, 1999-2008), and sample size for F is 1,800 (5 yrs, 1996-2008) since these information is only collected in the later years. Robust standard errors are in parenthesis. ***, **, * denote significance at the 1%, 5% and 10% levels respectively. All coefficients on Post70 and their standard errors have been multiplied by 100, so they can be interpreted as percentage changes.

Table 6: RD Estimates at Age 70 on Mortality

		Basic	67-73 yrs	Cubic	LLR
		(1)	(2)	(3)	(4)
A	All	0.0	-0.3	-0.8**	-0.3
		(0.3)	(0.4)	(0.4)	(0.3)
B	By Diagnosis				
	Cancer	-0.5	-1.4***	-2.0***	-0.8
		(0.4)	(0.6)	(0.6)	(0.5)
	Heart disease	0.5	0.5	-0.7	0.1
		(0.8)	(1.0)	(1.0)	(0.9)
	Cerebrovascular disease	0.1	0.3	-0.1	0.3
		(0.8)	(1.1)	(1.2)	(1.0)
	Respiratory diseases	0.5	0.0	0.2	0.4
		(1.3)	(1.6)	(1.7)	(1.5)

Note: Each cell is the estimate from separate estimated regression discontinuities at age 70. The dependent variable is the log of the number of deaths that occurred x days from the person' eligibility to the Elderly Health Insurance See Data Appendix for the ICD codes for each of the categories above. I use pooled 1984-2008 mortality data. LLR (local liner regression) estimates use a triangular kernel and the rule-of-thumb bandwidth selection procedure suggested by Fan and Gijbels (1996). Robust standard errors are in parenthesis. ***, **, * denote significance at the 1%, 5% and 10% levels respectively. All coefficients on Post70 and their standard errors have been multiplied by 100, so they can be interpreted as percentage changes.

Table 7: RD Estimates at Age 70 on Out-of-Pocket Medical Expenditure

	Out-of-Pocket Expenditure just Below age 70	RD Estimates at Age 70
	(1)	(2)
Mean	152	-52
40th Percentile	30	-14***
Median	52	-24***
60th Percentile	65	-24***
70th Percentile	96	-40***
80th Percentile	139	-49***
90th Percentile	247	-68***
95th Percentile	419	-115***
99th Percentile	1,793	-502*

Note: All money values are thousand Yen in 2007 (roughly 10 US dollar). I omit the 10, 20, and 30 percentile since the out-of-pocket expenditure is zero for those percentiles. ***, **, * denote significance at the 1%, 5% and 10% levels respectively.

Table 8: Welfare Gain from Risk Protection

		Distribution adjusted	
		using quantile estimates	"mechanically"
		(1)	(2)
<u>A. At mean</u>			
1. Risk Aversion			
(80% income cap)	1	3	7
	3	**20**	**46**
	5	41	110
2. Cap on percent of income			
(Risk aversion=3)	60	11	22
	90	31	74
<u>B. Distribution</u>			
(80% cap, risk aversion=3)			
	25th percentile	5	11
	Median	13	25
	75th percentile	31	85
	90th percentile	50	112
	95th percentile	63	126
	99th percentile	97	153

Note: All estimates are thousands Yen in year 2007. One thousands Yen is roughly 10 US dollars in 2007.

Appendix Figures and Tables
(Not for Publication)

FIGURES

Fig. A Seasonality in Day of Birth in the Patient Survey Data

This figure shows that there is substantial seasonality and heaping in the reported birthdays of patients observed in the Patient Survey. First, heaping on the first day of the month is observed, which is likely due to reporting. Second, there are many more births in the first quarter than in the other three quarters throughout the sample period. I observe the same pattern in the mortality data as well.

Fig. B Age Profiles for First Time and Repeated Outpatient Visits

These figure display the age profiles for first time and repeat outpatient visits, respectively. Panel 1 shows that the number of first time visits steadily decreases prior to age 70, reflecting the trend of deteriorating health as people get older, and then jumps sharply at age 70. Panel B shows that the age profiles of repeated visitors are very similar to that of overall outpatient visits, since 94 percent of total outpatient visits are repeat visits.

Fig. C Robustness of Results on Inpatient Admissions

Two graphs show the robustness of the results on inpatient admissions. Panel 1 shows that the results on inpatient admissions are not driven by how I limit the sample by admission dates. The results are pretty robust to the length of windows from the discharge date. Note that more than 90% of inpatient admissions occurred within three months from discharges. Panel 2 shows the results on the donut-hole RD by excluding a few months of observations around the threshold (Barreca et al. 2011). The figure shows that the estimates get smaller and standard errors get larger as the “hole” is expanded. But as long as the removal of the data is within three month from both side of age 70, the estimates are statistically significant at 95 percent level.

Fig. D Age Profile for Inpatient Admissions for Selected Surgery

This figure displays the age profile of inpatient admissions for these two procedures: open-stomach surgery and intraocular lens implantation. I find a drop-off just prior to 70, coupled with a temporary surge shortly after 70 for both procedures. This pattern suggests that some people who are close to 70 delay surgery until they become eligible for Elderly Health Insurance to reduce the out-of-pocket expenditures.

Fig. E Age Profile for Cause-Specific Mortality

This figure plots age profiles for mortality of cause-specific deaths for three broad leading cause of death among the elderly: cancer, heart disease, cerebrovascular disease, plus respiratory diseases. The figure shows that there are no disenable patterns for all causes of deaths.

Fig. F Age Profiles for Fraction in Good or Very Good Health

This figure shows the age profiles of the fraction of the people who report themselves to be in good, or very good health (31 percent of the population), based on pooled 1984-2008 CSLC samples. The graph shows that health is gradually declining with age but I do no find any observable change in the self-reported health at age 70.

TABLES

Table A: Top 10 Diagnosis for Outpatient Visits, and Inpatient Admissions

This table summarizes descriptive statistics for Patient Survey (outpatient data and discharge data respectively) and CSLC.

Table B: Top 10 Diagnosis for Outpatient Visits, and Inpatient Admissions

This table list top 10 diagnoses for outpatient visits, and inpatient admissions.

Table C: Robustness of RD Estimates on Outpatient Visits for Selected Outcomes

This table reports alternative specifications for RD models of outpatient visits for selected outcomes. There are 3 alternative estimates of the RD at age 70: (1) the basic RD estimates from the main tables

in the paper; (2) an RD estimate from a model fit to data for people who are 67-73 years old; (3) an RD estimate from a cubic polynomial in age, fully interacted with dummy for age 70 or older. Both age in months as well as age in days are used as the running variable. Outcomes are selected so that there is no "zero" cells for any age in days for these outcomes.

Table D: List of PQI (Ambulatory-Care-Sensitive Conditions)
This table list PQI indicators developed by AHRQ.

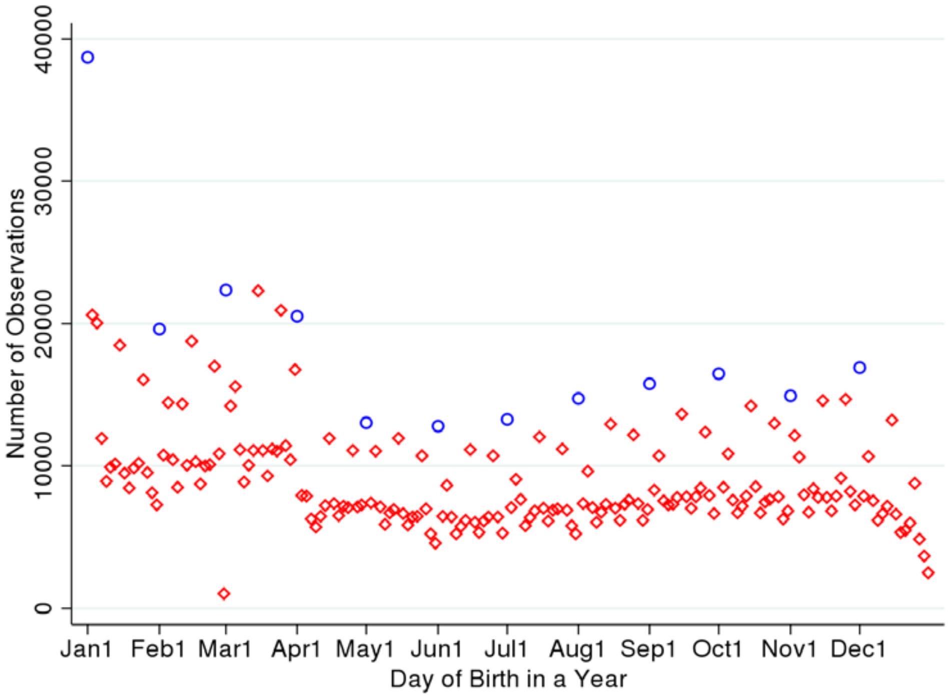
Table E: Robustness of RD Estimates on Inpatient Admissions for Selected Outcomes
This table reports alternative specifications for RD models of inpatient admissions for selected outcomes. There are 3 alternative estimates of the RD at age 70: (1) the basic RD estimates from the main tables in the paper; (2) an RD estimate from a model fit to data for people who are 67-73 years old; (3) an RD estimate from a cubic polynomial in age, fully interacted with dummy for age 70 or older.

Table F: RD Estimates of Inpatient Admissions by Characteristics of Hospital
This table reports the RD estimates on inpatient admissions by the characteristics of hospitals. Consistent with the notion that patients can freely choose medical institutions in Japan, patterns do not differ by hospital ownership. This result is in stark contrast to the U.S.; Card et al. (2008) finds that with the onset of medical eligibility, hospital admissions to both private non-profit and private for-profits hospitals experience relatively large increases in admissions, while hospitals owned by large and long-established HMOs show little change, and county hospitals experience a sharp decline. Another possibility for this contrast is that there is not much difference in quality among hospitals by ownership or size in Japan. Also, it is important to note that there are no for-profit hospitals in Japan since the hospitals are not allowed to issue shares and distribute the earnings.

Table G: RD Estimate at Age 70 on Morbidity
This table reports the RD estimates on morbidity using 1986-2007 Comprehensive Survey of Living Conditions (CSLC). Overall, I do not find any evidence that lower cost-sharing leads to a discrete jump in morbidity measures.

Table H: Estimated Out-of-Pocket Medical Expenditure per Month across Survey Years
This table reports the estimated out-of-pocket medical expenditure per month across survey years using Survey of Medical Care Activities in Public Health Insurance (See Data Appendix). The number used to compute the elasticity in the main text is the weighted average of the out-of-pocket medical expenditure across all survey years for outpatient visits and inpatient admissions respectively, using the population of age 69 in each survey year as weights. See Appendix A for details.

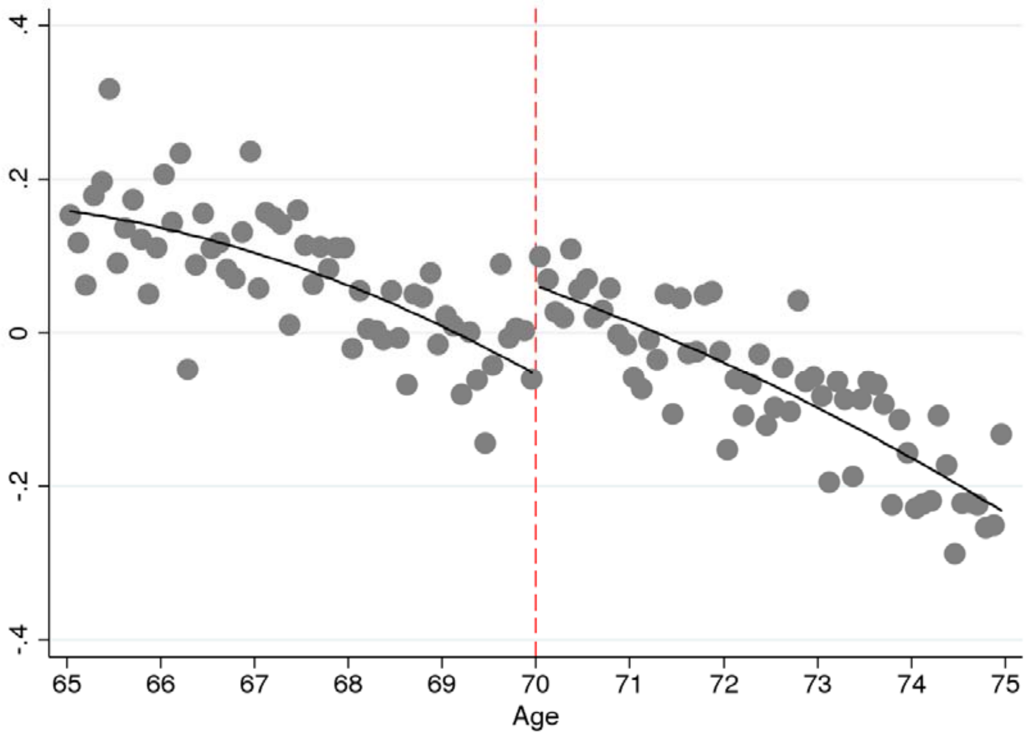
Fig. A Seasonality in Day of Birth in the Patient Survey Data



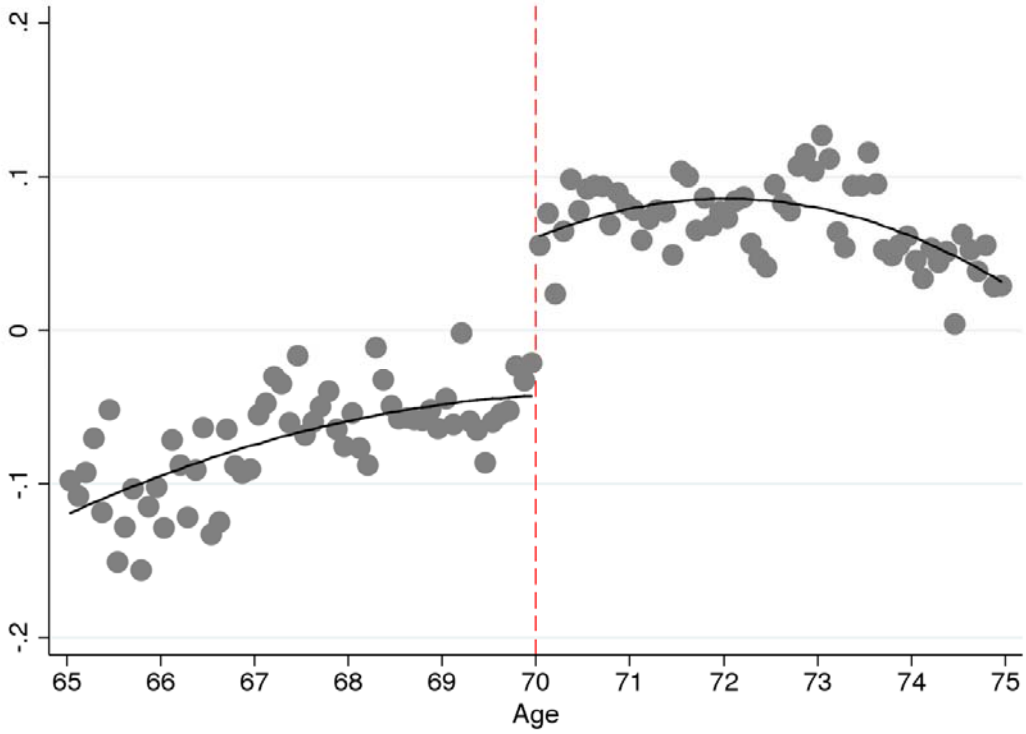
Note: The data comes from pooled 1984-2008 outpatient visit data in the Patient Survey. The circles indicate the first day of the month. Very similar patterns of birth distribution are observed in discharge data in the Patient Survey and mortality data as well.

Fig. B Age Profiles for First Time and Repeated Outpatient Visits

B1. First Time Visits



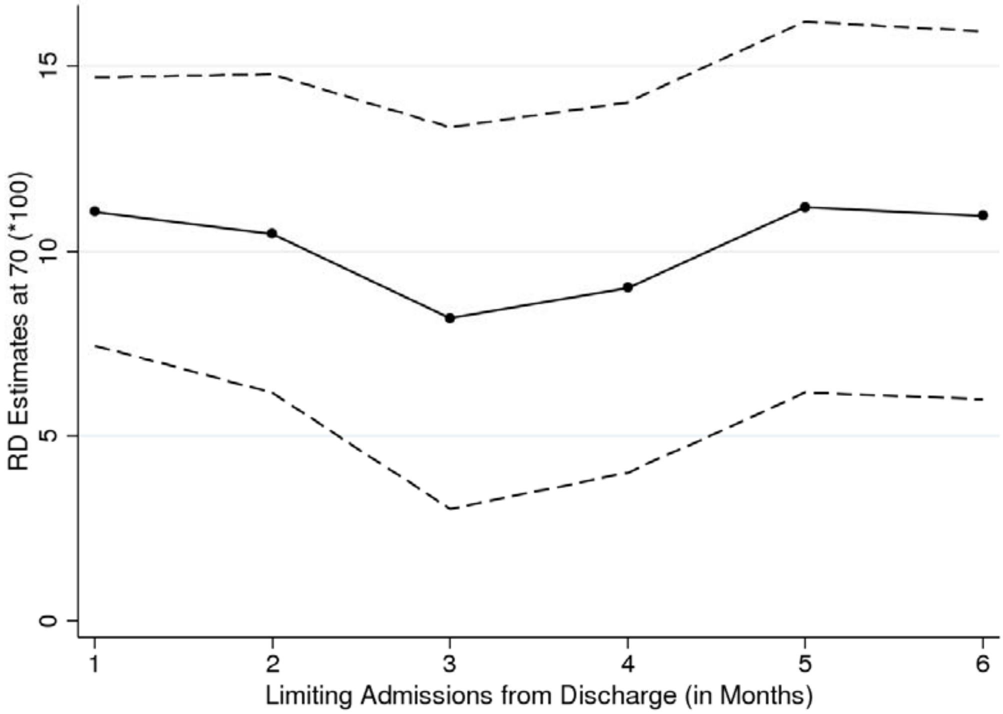
B2. Repeated Visits



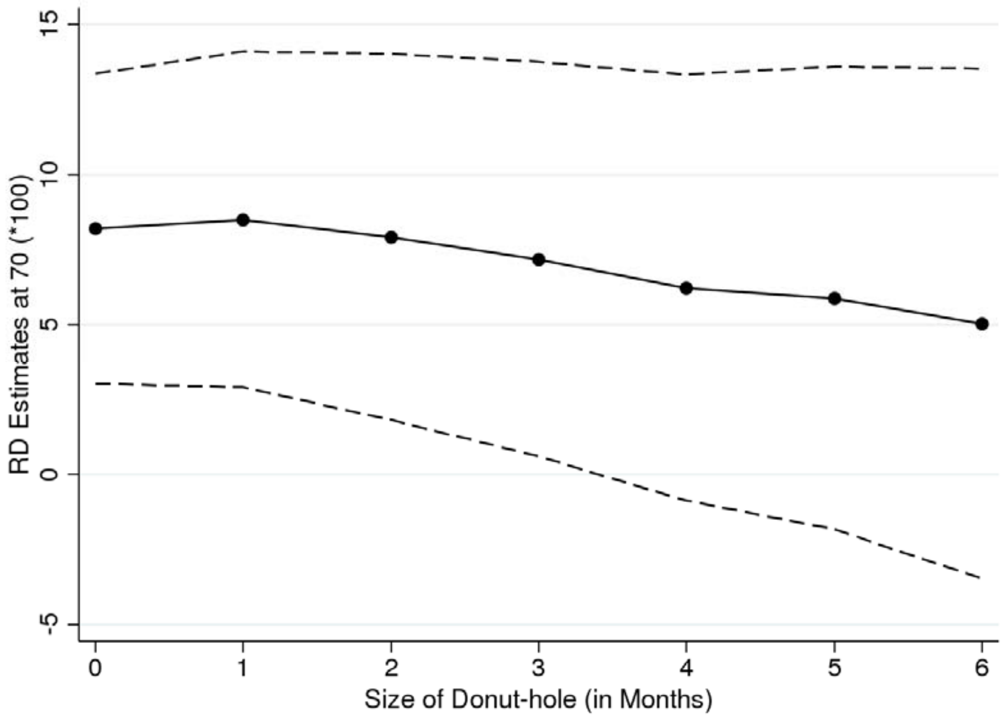
Note: The data come from pooled 1984-2007 outpatient data in the Patient Survey. The markers represent actual averages of residual of outcome that is regressed by birth month fixed effects and the survey year fixed effect to partial out the seasonality in birth and the underlying common shocks in the survey year. The lines represent fitted regressions from models that assume a quadratic age profile fully interacted with a dummy for age 70 or older.

Fig. C Robustness of Results on Inpatient Admissions

C1. Limiting the Sample by Different Windows from Discharge



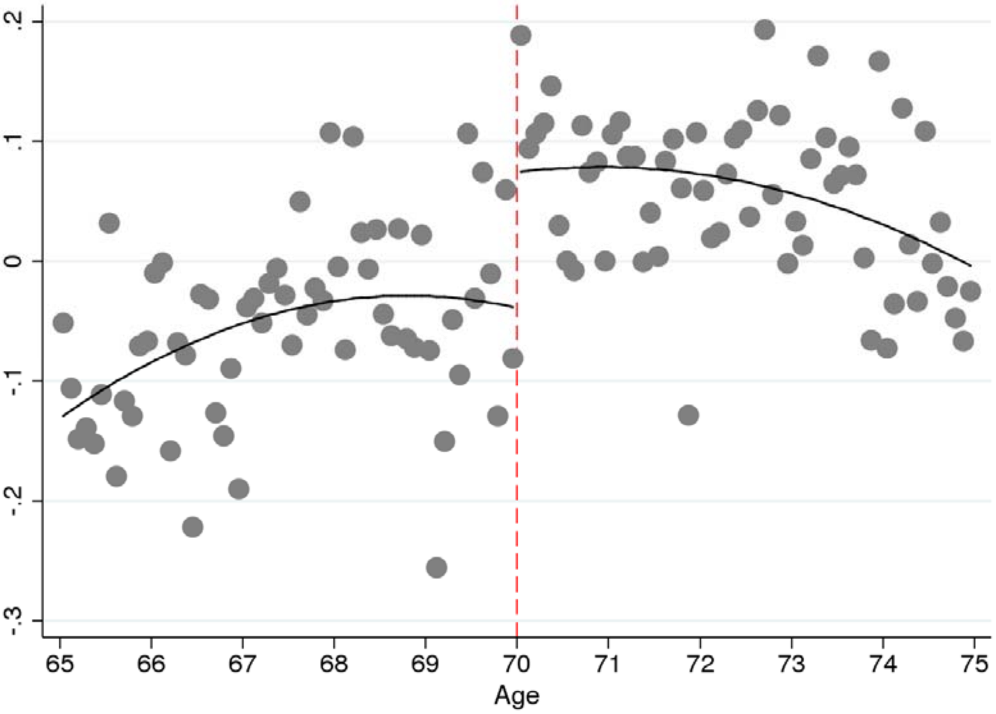
C2. Estimates from “Donut-hole” RD



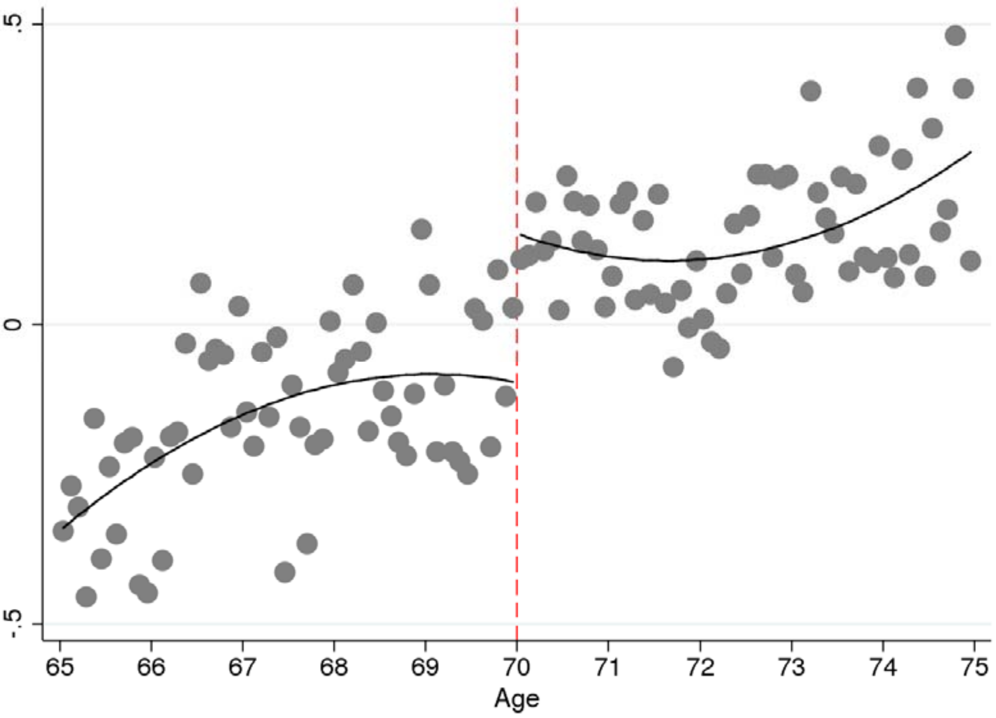
Note: The data come from pooled 1984-2008 discharge data in Patient Survey. The model here is quadratic age profile fully interacted with a dummy for age 70 or older. Dashed line is 95 percent confidence interval.

Fig. D Age Profile for Inpatient Admissions for Selected Surgery (log scale)

D1. Open-Stomach Surgery

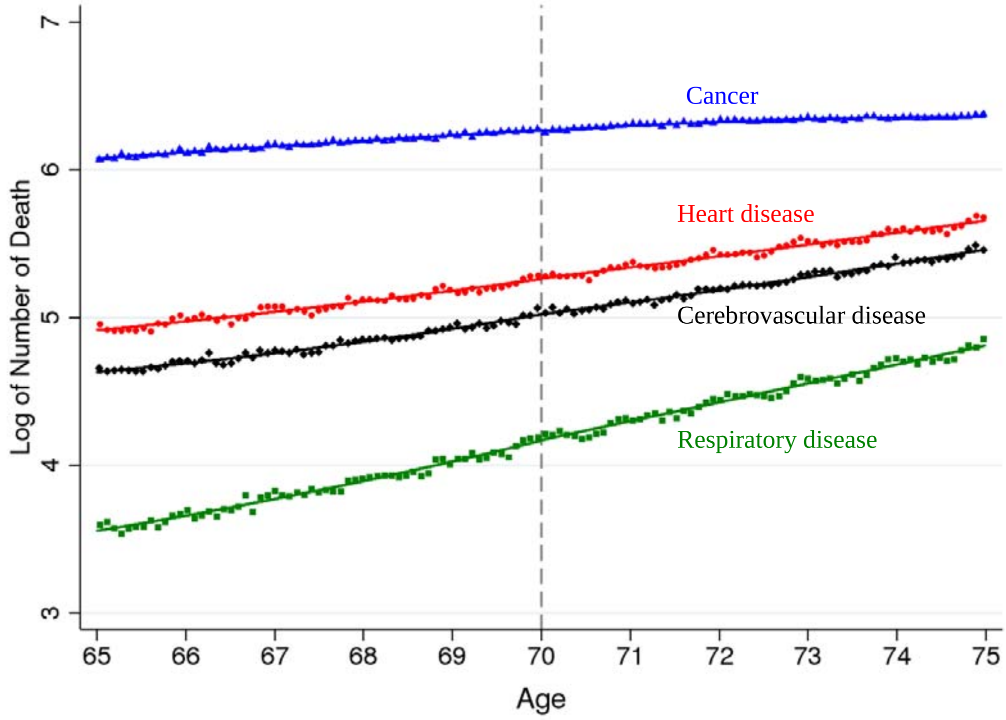


D2. Intraocular Lens Implantation



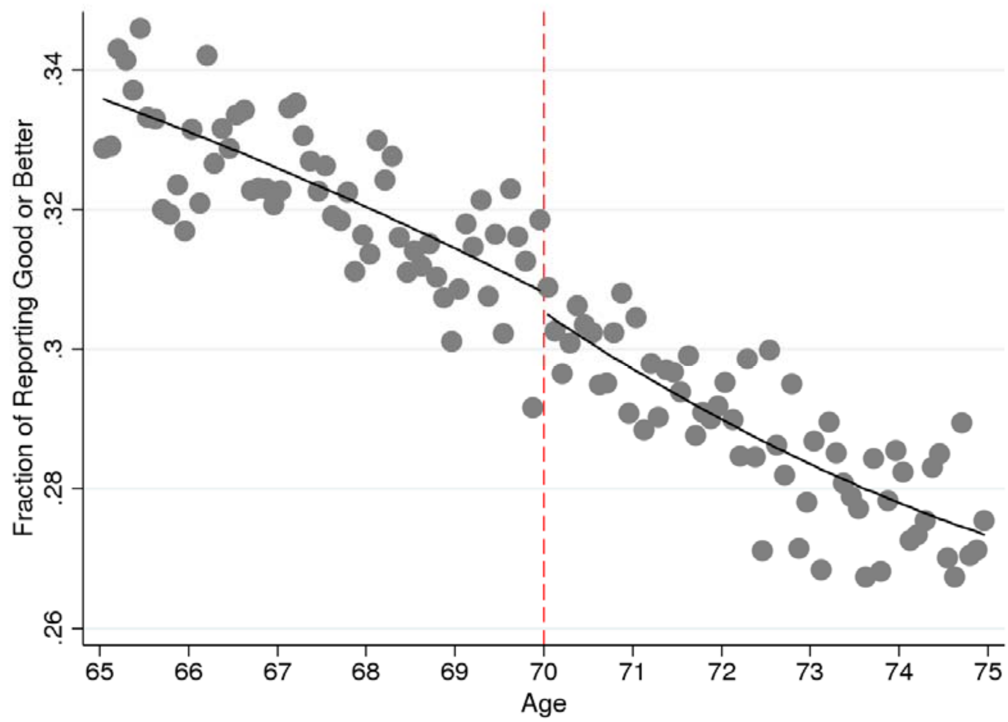
Note: The data come from pooled (1999, 2002, 2005, and 2008) discharge data in Patient Survey since specific surgery information is collected for only these four survey years. I use admissions within three months from discharge, and thus the sample size is 1,440. The markers represent actual averages of residual of log outcome that is regressed by birth month fixed effects, admission month fixed effects, and the survey year fixed effect to partial out the seasonality in birth and the underlying common shocks in the survey year. The lines represent fitted regressions from models that assume a quadratic age profile fully interacted with a dummy for age 70 or older.

Fig. E Age Profile for Cause-Specific Mortality



Note: The data come from pooled 1984-2008 mortality data. I use days to eligibility for the Elderly Health Insurance as a running variable. The cell is each 30 days interval from the day of eligibility at age 70. The markers represent the averages, and the lines represent fitted regressions from models that assume a quadratic age profile fully interacted with a dummy for age 70 or older.

Fig. F Age Profiles for Fraction in Good or Very Good Health



Note: The data come from pooled 1986-2007 Comprehensive Survey of Living Conditions. The markers represent actual averages (age in month), and the lines represent fitted regressions from models that assume a quadratic age profile fully interacted with a dummy for age 70 or older.

Table A: Summary Statistics (Ages 65-75)

	Variables	Mean (SD)
A	Outpatient Data	
	Repeated Visits	0.94
	Hospital	0.44
	Clinic	0.56
	Male	0.42
	With Referral	0.05
	Days from Last Outpatient Visits (Days)	13.6
		(20.2)
B	Discharge Data	
	With Surgery	0.35
	Hospital	0.99
	Clinic	0.01
	Open-head surgery	0.00
	Open-heart surgery	0.01
	Open-stomach surgery	0.04
	Musculoskeletal surgery	0.03
	Endoscopic surgery: stomach	0.01
	Intraocular lens implantation	0.02
	Length of stay (Days)	18.1
		(17.7)
C	CSLC	
	Self Reported Health: Good or Better	0.31
	Being Stressed	0.41
	Male	0.45
	Currently Married	0.74
	Employed	0.31
	Hours of Work per Week	6.82
	Income (Thousands Yen)	1,860
		(1,920)
	Receiving Pension	0.95
	With Long Term Health Insurance	0.03

Note: One thousands Yen is roughly $10 US dollars.

Table B: Top 10 Diagnosis for Outpatient Visits, and Inpatient Admission

B1. Outpatient Visits

rank	Name of diagnosis	Percentage	ICD9 (3digit)
1	Essential hypertension	16.1%	401
2	Spondylosis and allied disorders	4.7%	721
3	Diabetes mellitus	4.7%	250
4	Osteoarthrosis and allied disorders	4.3%	715
5	Cataract	3.4%	366
6	Other and unspecified disorders of back	3.3%	724
7	Gastritis and duodenitis	2.3%	535
8	Occlusion of cerebral arteries	2.1%	434
9	Other disorders of bone and cartilage	1.9%	733
10	Disorders of lipoid metabolism	1.8%	272

Note: The data come from the pooled 1984-2008 outpatient visits data in the Patient Survey.

B2. Inpatient Admissions

rank	Name of diagnosis	Percentage	ICD9 (3digit)
1	Cataract	4.4%	366
2	Angina pectoris	4.1%	413
3	Occlusion of cerebral arteries	3.8%	434
4	Diabetes mellitus	3.2%	250
5	Malignant neoplasm of stomach	3.1%	151
6	Benign neoplasm of other parts of digestive system	2.9%	211
7	Malignant neoplasm of liver and intrahepatic bile ducts	2.3%	155
8	Malignant neoplasm of colon	2.1%	153
9	Malignant neoplasm of trachea, bronchus and lung	1.8%	162
10	Cholelithiasis	1.5%	574

Note: The data comes from the pooled 1984-2008 discharge data in the Patient Survey.

Table C: List of PQI (Ambulatory-Care-Sensitive Conditions)

Number	Name of Diagnosis
PQI 1	Diabetes, short-term complications
PQI 3	Diabetes, long-term complications
PQI 5	Chronic obstructive pulmonary disease
PQI 7	Hypertension
PQI 8	Congestive heart failure
PQI 10	Dehydration
PQI 11	Bacterial pneumonia
PQI 12	Urinary infections
PQI 13	Angina without procedure
PQI 14	Uncontrolled diabetes
PQI 15	Adult asthma
PQI 16	Lower extremity amputations among patients with diabetes

Note: I excluded PQ2 (Perforated appendicitis) from the analysis since this index is the number of admissions for perforated appendix as a share of admissions for appendicitis only. Also PQI 14 requires the fifth digit of the ICD9, which I don't have, since PQI 14 only include 25002 and 25003 (25000, 25001, and 25009 should not be included). To account for this, I only include diabetes (2500) which has secondary diagnosis.

Table D: Robustness of RD Estimates on Outpatient Visits for Selected Outcomes

Running Variable: Age in	Month			Day		
	Basic	Age 67-73	Cubic	Basic	Age 67-73	Cubic
	(1)	(2)	(3)	(4)	(5)	(6)
A. All	10.3***	11.3***	12.1***	11.4***	12.3***	12.7***
	(1.8)	(2.3)	(2.6)	(1.6)	(2.1)	(2.2)
B. By Visit Type						
Repeated visits	10.3***	11.2***	12.1***	11.4***	12.1***	12.5***
	(1.9)	(2.3)	(2.6)	(1.6)	(2.1)	(2.2)
C. Days from Last Outpatients Visits Among Repeated Visits						
1 day	16.4***	20.9***	21.6***	15.7***	17.1***	16.5***
	(4.4)	(6.1)	(6.5)	(2.1)	(2.7)	(2.9)
4-7 day	8.5***	6.6	8.7*	9.6***	11.7***	10.5***
	(3.0)	(4.1)	(4.6)	(2.3)	(3.1)	(3.2)
D. By Institution						
Clinic	13.8***	15.1***	16.0***	13.4***	14.2***	14.7***
	(1.8)	(2.3)	(2.6)	(1.1)	(1.5)	(1.5)
E. By Referral						
Without Referral	10.5***	11.6***	12.5***	11.5***	12.3***	12.8***
	(1.9)	(2.3)	(2.6)	(1.6)	(2.1)	(2.2)

Note: Each cell is the estimate from separate estimated regression discontinuities at age 70. "Basic" is the model that include quadratic of age, fully interacted with dummy for age 70 or older among people between ages 65-75. Controls are dummies for each survey year and each month of birth. I use pooled samples of the Patient Survey conducted every three year since 1984. Robust standard errors are in parenthesis. ***, **, * denote significance at the 1%, 5% and 10% levels respectively. All coefficients on Post70 and their standard errors have been multiplied by 100, so they can be interpreted as percentage changes.

Table E: Robustness of RD Estimates on Inpatient Admissions for Selected Outcomes

		Basic	Age 67-73	Cubic
		(1)	(2)	(3)
A	All	8.2***	10.0***	11.2***
		(2.6)	(3.4)	(3.6)
B	Surgery			
	With surgery	10.8***	17.4***	20.7***
		(3.8)	(5.0)	(5.2)
C	Type of Surgery			
	Open-stomach surgery	11.4**	17.4**	19.5***
		(5.6)	(7.0)	(7.4)
	Intraocular lens implantation	19.6***	18.9**	19.1*
		(6.2)	(8.0)	(9.8)
E	By Diagnosis			
	Cataract	22.6***	31.6***	46.4***
		(6.5)	(8.5)	(9.7)
	Occlusion of cerebral arteries	13.7***	16.3***	18.2***
		(4.6)	(5.9)	(6.3)
	Ischemic heart disease	14.5**	17.3*	16.4*
		(7.1)	(9.3)	(9.7)
	Cerebral infarction	12.8***	14.4**	14.5**
		(4.6)	(6.0)	(6.3)

Note: "Basic" is the model that include quadratic of age, fully interacted with dummy for age 70 or older among people between ages 65-75. Controls are dummies for each survey year, each month of birth, and each month of admission. I use pooled samples of Patient Survey conducted every three year since 1984. Robust standard errors are in parenthesis. ***, **, * denote significance at the 1%, 5% and 10% levels respectively. All coefficients on Post70 and their standard errors have been multiplied by 100, so they can be interpreted as percentage changes..

Table F: RD Estimates of Inpatient Admissions by Characteristics of Hospital

		Basic	Age 67-73	Cubic
		(1)	(2)	(3)
A	Ownership			
	Governmental hospitals	7.0**	9.5**	11.9***
		(3.2)	(4.2)	(4.4)
	Public hospitals	10.1**	13.8***	17.1***
		(4.0)	(5.2)	(5.4)
	Not-for-profit hospitals	8.5***	9.7***	10.0***
		(2.8)	(3.6)	(3.8)
B	Teaching			
	Teaching hospital	6.3	5.9	10.1
		(5.0)	(6.4)	(6.5)
	Non Teaching hospital	8.4***	10.2***	11.3***
		(2.6)	(3.4)	(3.6)
C	Emergency Department			
	With	8.3***	10.3***	12.3***
		(2.8)	(3.7)	(3.8)
	Without	7.7***	9.6***	9.6**
		(2.8)	(3.6)	(3.8)
D	Size of hospital			
	1-99 beds	12.5***	14.3***	14.8***
		(3.4)	(4.3)	(4.5)
	100-299 beds	4.9	4.7	4.6
		(3.1)	(4.1)	(4.3)
	300-3000 beds	9.9***	12.7***	15.5***
		(3.3)	(4.3)	(4.6)

Note: Each cell is the estimate from separate estimated regression discontinuities at age 70. The specification is a quadratic of age, fully interacted with dummy for age 70 or older among people between ages 65-75. Controls are dummies for each survey year, each month of birth, and each month of admission. I use pooled samples of Patient Survey conducted every three year since 1984. Sample size is 3,240. Robust standard errors are in parenthesis. ***, **, * denote significance at the 1%, 5% and 10% levels respectively. All coefficients on Post70 and their standard errors have been multiplied by 100, so they can be interpreted as percentage changes.

Table G: RD Estimates at Age 70 on Morbidity

	Self-reported Health				Stress-related			
	Good or Better Health		Linear Regression (1=poor 5=excellent)		Stress Dummy		Stressed due to own health and care	
	Age 68-9	RD at 70	Age 68-9	RD at 70	Age 68-9	RD at 70	Age 68-9	RD at 70
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. All	31.4	-0.3	2.8	1.1	41.1	0.4	25.3	0.2
		(0.6)		(1.3)		0.4		(0.7)
B By HH Income								
Above median	32.1	-0.1	2.7	2.3	39.2	-0.7	22.9	1.0
		(1.9)		(4.3)		(2.4)		(2.0)
Below median	30.1	1.4	2.8	-5.1	44.8	-3.2	29.2	-0.5
		(2.0)		(4.7)		(2.5)		(2.3)
years available	1986-2007				1995-2001			

Note: Entries in odd-numbered columns are the mean of age 68-69 years-olds of the outcome variables shown in column heading. Entries in even-numbered columns are estimated regression discontinuities at age 70, from models that include quadratic control for age, fully interacted with dummy for age 70 or older among people between age 65 to age 70. Other controls include indicators for gender, region, marital status, birth month, and survey year. Except column 4, estimates are based on linear probability model fit to pooled samples of CSLS conducted every three year since 1986. Standard errors (in parenthesis) are clustered at the age in month level as this is the most refined version of the age variable available. All regressions are weighted to take into account the stratified sampling frame in the data. ***, **, * denote significance at the 1%, 5% and 10% levels respectively. Available years for each outcome are described in the last row. Income is collected for roughly 15 % of all samples, and thus the sample size of Panel B is smaller than the full sample. All coefficients in even-numbered columns on Post70 and its standard error have been multiplied by 100 in order to interpret them as percentage changes.

Table H: Estimated Out-of-Pocket Medical Expenditure per Month across Survey Years

H1. Outpatient Visits

	Cost-Sharing			% reached stop-loss	
	Below 70	Above70	% reduction	Below 70	Above70
year	(1)	(2)	((1)-(2))/(3)	(4)	(5)
All	**3.99**	**1.02**	**74%**	**0.1%**	**0.6%**
1987	3.96	0.80	80%	0.1%	-
1990	4.26	0.80	81%	0.1%	-
1993	4.48	1.00	78%	0.1%	-
1996	4.23	1.02	76%	0.1%	-
1999	3.91	1.00	74%	0.2%	-
2002	3.61	1.30	64%	0.1%	0.5%
2005	3.97	1.28	68%	0.2%	0.7%
2008	3.69	1.20	68%	0.1%	0.5%

H2. Inpatient Admissions

	Cost-Sharing			% reached stop-loss	
	Below 70	Above70	% reduction	Below 70	Above70
year	(1)	(2)	((1)-(2))/(3)	(4)	(5)
All	**37.95**	**12.44**	**67%**	**14.6%**	**0.0%**
1987	44.52	7.86	82%	26.6%	0.0%
1990	42.21	7.42	82%	21.6%	0.0%
1993	40.78	11.91	71%	11.5%	0.0%
1996	39.70	10.65	73%	11.5%	0.0%
1999	38.65	15.09	61%	9.2%	0.0%
2002	35.86	15.54	57%	8.7%	0.0%
2005	46.39	15.73	66%	18.3%	0.0%
2008	45.64	15.63	66%	13.5%	0.0%

Note: All money values without percentage sign are in thousand Yen (roughly 10 US dollar).

Data Appendix

In this study, I use a variety of datasets collected mainly by the Ministry of Health, Labour and Welfare. A brief description of each dataset is provided in this data appendix. The English-Japanese crosswalks of the name of the datasets can be found at the following website from Ministry of Health, Labour and Welfare. http://www.mhlw.go.jp/toukei/itiran/eiyaku.html

	Name of Dataset	Period	Interval
1	Patient Survey	1984-2008	Every three year (9 rounds in total)
2	Survey of Medical Institutions	1984-2008	Every three year (9 rounds in total)
3	Comprehensive Survey of Living Conditions	1986-2007	Every three year (8 rounds in total)
4	Survey of Medical Care Activities in Public Health Insurance	1984-2008	Every year
5	Vital Statistics: Mortality data	1984-2008	Every year

1. Patient Survey

Detail: http://www.mhlw.go.jp/english/database/db-hss/dl/sps_2008_06.pdf

The Patient Survey is a national sample survey of hospitals and clinics that has gathered information on the utilization of medical institutions in Japan since 1948. The comprehensive version of the current Patient Survey is conduced every three years since 1984. It covers roughly 2000-7000 hospitals and 3000-6000 clinics per survey year. It collects information on ICD code, patients' principal sources of payment, and the limited socio-demographic characteristics such as gender and patients' place of living. The individual patient level microdata files are available starting from 1984.

There are two datasets in the Patient Survey, outpatient data, which I use to examine outpatient visits, and discharge data, which I use to examine inpatients admissions.

1.1 Outpatient data

The outpatient data in the Patient Survey is conducted one day in middle of the October (normally a weekday in the second week), and collects information on all patients that visit hospitals or clinics for outpatients reasons (i.e., visits to hospitals for non-hospitalization reasons). The datasets contain 75,000-100,000 individuals for outpatient visits. This data includes exact date of birth and the survey date, which is equivalent to the exact date of visits and enables me to compute age in days at the time of outpatient visits. The sample size of the outpatient data is about 500,000-1,500,000.

1.2 Discharge data

The discharge data in the Patient Survey reports all the inpatients record discharged in the surveyed hospitals and clinics within September in the survey year. The datasets contain about 180,000-970,000 inpatients records per each survey year. The sample size gets larger in more recent years. The data includes the exact day of birth, admission, discharge, and surgery. It also contains information whether the patient needed surgery, and several types of main surgery (collected from 1999 on). Unlike the Comprehensive Survey of Living Conditions, the discharge data include patients who die in the hospital as well as clinics.

2. Survey of Medical Institutions

Detail: http://www.mhlw.go.jp/english/database/db-hss/dl/01_Outline_of_Survey.pdf

The Survey of Medical Institutions collects information on all medical institutions in Japan that are in practice at the time of survey. The survey was conducted every year until 1972 and every three years since then. The individual hospital/clinic level microdata files are available starting from 1972. The data collect information on the ownership of institutions, number of beds permitted, notification of emergency, teaching school status, number of physicians, clinical specialties, machinery and equipment, and their working conditions. I merge this hospital and clinic information to the Patient Survey based on institution ID.

3. Comprehensive Survey of Living Conditions (CSLC)

Detail: http://www.mhlw.go.jp/english/database/db-hss/cslc.html

The Comprehensive Survey of Living Conditions (CSLC) is a nationwide repeated cross-section survey of households that has gathered information on the health of the Japanese people since 1986. The CSLC collects information on socio-demographic characteristics, and health related topics. The long version of CSLC used in this study is conducted every three years for randomly sampled individuals based on the 3000-5000 districts from the National Census conducted every five years ending with last digit of zero or five.

The microdata files are available starting from fiscal year 1986. The survey reports births in months, so I use this information to compute the age in month combined with the information on month of the survey. The long version of CSLC consists of three questionnaires: Household, Health, and Income and Savings. A long-term care questionnaire was added in 2004. I mainly use the data on the health questionnaire that collects information on self-reported physical and mental health, and activity limitations.

I also use the insurance type information in the household questionnaire, to compute the average health insurance coverage of each health insurance type, which is mapped to the Survey of Medical Care Activities in Public Health Insurance to derive the amount of out-of-pocket medical expenditures.

The household forms also include the basic individual-level socio-demographics such as gender, marital status, employment, and household size. The income and saving questionnaire asks the amount and source of income, and amount of saving and debt. Information on out-of-pocket medical expenditures at individual level is only collected in 2007. I use individual income and out-of-pocket medical expenditures to compute the welfare gains from risk reduction.

The survey covered 240,000-290,000 households and 740,000-800,000 household members in each survey round. The income and savings questionnaire is conducted for only around 15 percent of the whole sample.

4. Survey of Medical Care Activities in Public Health Insurance

Detail: http://www.mhlw.go.jp/english/database/db-hss/dl/shw-03.pdf

The Survey of Medical Care Activities in Public Health Insurance is a survey of health insurance claims data that gathers yearly information on detailed statements of medical fees and pharmacy dispensing fee. I use this information to derive the average monthly out-of-pocket medical expenditures for those who use medical institutions as described in Appendix A1.

Due to the monthly reimbursement to the medical institutions, the claim data is a summary of the medical expenditures per month per individual who uses medical institutions in June of the survey year. The data is collected from the prefectural branches of the Social Insurance Medical Fee Payment Fund for employment-based health insurance recipients and the Federation of National Health Insurance for National Health Insurance recipients. Health insurance claim data from the society-managed employment-based health insurance recipients is collected since 1999. Age is measured in year.

5. Vital Statistics: Mortality data

Detail: http://www.mhlw.go.jp/english/database/db-hw/outline/index.html

The 1984-2008 National Mortality Details Files is an annual census of deaths within Japan. The data contain the universe of deaths and information on the deceased's date of birth, and date of death, which enables me to compute age in days at the time of death. The data also include gender, nationality, place of the death, and cause of deaths according to the International Classification of Disease (ICD). ICD9 was used till 1994, and ICD10 is used since 1995 in Japan.

The ICD codes for each cause of death used in this paper are following;

Cause of Death	1984 -1994 (ICD-9)	1995-2008 (ICD-10)
Main Cause		
Cancer	140-208	C00-C97
Heart Disease	390-398, 402, 404 410-429	I00-I09, I11, I13, I20-I51
Cerebrovascular Disease	430-434, 436-438	I60-I69
Respiratory Disease	460-519	J00-J99
Sub diagnosis		
Hypertensive Disease	401-405	I10-I15
Ischemic Heart Disease	410-414	I20- I25
Intracerebral Hemorrhage	431-432	I61, I69.1
Cerebral Infarction	433, 434, 437.7a, 433.7b	I63, I69.3