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The Effect of Patient Cost Sharing on Utilization, Health, and Risk Protection†

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This paper exploits a sharp reduction in patient cost sharing at age 70 in Japan, using a regression discontinuity design to examine its effect on utilization, health, and financial risk arising from out-of-pocket expenditures. Due to the national policy, cost sharing is 60–80 percent lower at age 70 than at age 69. I find that both outpatient and inpatient care are price sensitive among the elderly. While I find little impact on mortality and other health outcomes, the results show that reduced cost sharing is associated with lower out-of-pocket expenditures, especially at the right tail of the distribution. (*JEL* G22, I11, I12, I13, I18, J14)

Rising medical expenditures due to an aging population and coverage expansion are increasingly posing an acute fiscal challenge to governments. For example, 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] 1/3

One main strategy for the government to contain health care costs is higher patient cost sharing, that is, requiring patients to pay a larger share of the cost of care. However, cost sharing has clear trade-offs. While cost sharing may reduce direct costs by decreasing the moral hazard of health care services, it may also reduce

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1 Examples of attempts by the US government to control supply side costs include the introduction of prospective payments for hospitals and reductions in provider reimbursement rates (Cutler 1998).

2 Patients aged over 65 years consume 36 percent of health care in the United States while they account for 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 5 and 6 percent of the GDP (Congressional Budget Office 2011). Likewise, in Japan, the elderly consume five times as many health care services as the non-elderly (Okamura, Kobayashi, and Sakamaki 2005).

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, namely financial protection against large out-of-pocket medical expenditure. Thus, to help determine the appropriate level of cost sharing, there is an urgent need for knowledge on how patient cost sharing affects utilization, health, and risk protection, especially among the elderly.

Credible evidence on the price sensitivity of health care consumption and its effect on health among the elderly are scarce. Individuals above the age of 62 years were excluded from the well-known RAND Health Insurance Experiment (Newhouse and the Insurance Experiment Group 1993)—henceforth, RAND HIE—Card, Dobkin, and Maestas (2008, 2009) found that Medicare eligibility at 65 years of age discontinuously increases health care utilization and also has a modest positive effect on the health of elderly patients above 65 years. However, these studies did not conclusively address whether these changes at the age of 65 are the result of health insurance provision per se (extensive margin) or changes in health insurance generosity (intensive margin), given that turning 65 years in the United States entails a number of coincident changes.[3] Chandra, Gruber, and McKnight (2010) examined the effect of an increase in copayments for physician office visits and prescription drugs in a supplemental Medicare insurance policy for Californian civil servants, but the change in copayments was very small and limited to office visits and prescription drugs. Only a few studies in the United States have examined the effect of health insurance on the distribution of out-of-pocket medical expenditures (Feldstein and Gruber 1995; Finkelstein and McKnight 2008; Engelhardt and Gruber 2011; Finkelstein et al. 2012). However, these studies examined the effect of insurance provision rather than that of changes in generosity.

My research design exploits a sharp reduction in cost sharing for patients aged over 70 in Japan, to examine its effect on utilization, patient health, and financial protection against risk. Due to the prevailing 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.[4] This reduction is substantial, especially for inpatient admissions: out-of-pocket medical expenditures for inpatient admissions can reach as much as 27 percent of the average monthly income of a 69-year-old patient.[5] By exploiting this price variation, I compare the outcomes of patients just below 70 versus those just over that age using a regression discontinuity (RD) design.

[3] These changes include 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, Dobkin, and Maestas (2009) concluded that it is not clear whether reductions in mortality are due to health insurance provision or generosity.

[4] Japan introduced free care for the elderly aged over 70 years in January 1973. However, this policy substantially increased the utilization of health care services and medical expenditure. In fact, medical expenditure rose by 55 percent in just one year. In February 1983, 10 years after the Japanese government had introduced its generous policy, it imposed cost sharing on the elderly aged over 70 years. Despite this, the large discrepancy in cost sharing between those just above and below the age of 70 persists. Due to data availability, this study focuses on the period after the implementation of cost sharing for the elderly.

[5] Note that inpatient admissions are associated with hospitalizations, while outpatient visits refer to visits that do not require an overnight stay in clinics or hospitals.

This setting offers a number of advantages over previous empirical settings. First, there are no confounding factors at age 70, and thus, I can plausibly isolate the effect of patient cost sharing on demand for health care services; under universal health insurance coverage in Japan, the change at age 70 only reflects increases in benefit generosity, rather than the combined effect, of health insurance coverage and generosity. Also, as shown later, turning 70 in Japan does not coincide with changes in any other factors such as employment or receiving pension. Second, I can estimate the elasticities of inpatient admissions of the elderly as well, since cost sharing for inpatient admissions also changes abruptly at age 70. Third, since I have detailed information on outpatient visits, I can investigate the price sensitivity of preventive care in the outpatient setting. In contrast, most existing datasets capture either outpatient visits or inpatient admissions. Fourth, I examine the effect of cost sharing, rather than health insurance per se, on exposure to out-of-pocket medical expenditure risk.

Finally, the unique setting in Japan allows me to separate the demand elasticities of patients from responsive behavior by insurers and medical providers, because they typically play a small (if any) role in patients' demand for health care services; physicians' payments are based on a national fee schedule that does *not* depend on patients' insurance type, and thus prevents cost shifting, where medical providers charge private insurers higher prices to offset losses from the beneficiaries of government-funded health insurance (Cutler 1998). Also, there are no restrictions by insurers on patients' choices of medical providers.

(1)

I reach three conclusions. First, I find that reduced cost sharing at age 70 discontinuously increases health care utilization. The corresponding elasticity is modest, at around −0.2 for both outpatient visits and inpatient admissions. Examining patterns of utilization in more detail, I also find that lower patient cost sharing is associated with increases in the number of patients presenting both serious and nonserious diagnoses. 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 reduces subsequent avoidable admissions.

Second, in terms of benefits, I do not find that lower patient cost sharing improves any of the health measures I examine, such as mortality and self-reported physical and mental health. Since health is a stock, it may take some time for the most observable health effects to be realized. Therefore, it is challenging to address it using the RD approach unless the causes of death are acute. Nonetheless, I do not find any change even in acute cause-specific mortality. The lack of differences in health in spite of utilization changes implies that patient cost sharing can reduce health care utilization without adversely affecting health, at least in the short run. (2)

Finally, I do find that lower cost sharing at 70 yields reductions in out-of-pocket expenditure, especially at the right tail of the distribution, because the reduction in price at age 70 overwhelms offsetting increases in utilization. This finding suggests that patients with high medical spending benefit substantially from financial protection against risk due to lower cost sharing.

The rest of the paper is organized as follows. Section I briefly describes the institutional background. Section II describes the data and presents the identification strategy. Section III shows the main results on utilization. Section IV refers to the analysis on benefit and examines the health outcomes as well as risk reduction. Section V discusses the implications of the findings, and Section VI concludes.

I. Background

A. *Institutional Setting*

All Japanese citizens are mandatorily covered by health insurance.[6] Patients have unrestricted choices of medical providers; for example, it is common for the Japanese to visit hospitals rather than clinics for outpatient care (similar to physician office visits in the United States).[7] Patients have direct access to specialist care without going through a gatekeeper or a referral system. There is also no limit on the number of visits. Patients may either go to hospitals or clinics for outpatient visits and to hospitals for admissions, unlike in the United States, where those who lack insurance use hospitals for primary care.

A patient pays coinsurance, which is the percentage of medical costs for which the beneficiary is responsible. Since inpatient admissions are more expensive than outpatient visits, the coinsurance rate for inpatient admissions tends to be set lower than that for outpatient visits. 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. Unlike a normal health insurance plan in the United States, there is no deductible in Japan.

The elderly become eligible for lower cost sharing on the first day of the next month after they turn 70. They receive a new insurance card and a notice from the government indicating that they are eligible for Elderly Health Insurance. They can present the card at medical institutions to receive the discount. Elderly Health Insurance is also provided to bedridden people between the ages of 65 and 70, but the proportion of such people is not substantial. According to a report by the Ministry of Health, Labour and Welfare (2009), the fraction of bedridden people between the ages of 65 and 70 was 4.2 percent on average during 1984–2001. Nonetheless, since those covered by Elderly Health Insurance at a younger age should have relatively worse health, the price elasticity and health consequences I estimate may be interpreted as the lower bound.

Table 1 displays the cost sharing formulas for those below and above age 70 for outpatient visits and inpatient admissions for each survey year of the Patient Survey (described in detail in Section II). 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 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 the employees' dependents. National Health Insurance (NHI) is a resident-based system that provides coverage to everyone else, mainly the employees of small firms, self-employed

[6] Japan achieved universal health insurance coverage in 1961. See Kondo and Shigeoka (2013) for more details about the effect of the introduction of universal health insurance on utilization and supply side responses.

[7] In Japan, hospitals are defined as medical institutions with 20 or more beds, and clinics are medical institutions with less than 20 beds.

Table 1—Formula for Patient Cost Sharing below and above Age 70

	Below 70				Above 70	
	Coinsurance				Coinsurance	
Year	NHI (percent)	Employment-based (employee, percent)	Employment-based (dependent, percent)	Stop-loss (thousand yen)	All	Stop-loss (thousand yen)
Panel A. Outpatient visits[a]						
1984	30(1)	10	30	51.0	0.4/month	—
1987	30(1)	10	30	54.0	0.8/month	—
1990	30(1)	10	30	57.0	0.8/month	—
1993	30(1)	10	30	63.0	1.0/month	—
1996	30(1)	10	30	63.0	1.02/month	—
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
Panel B. Inpatient admissions[b]						
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

Notes:

[a] (1) Among the retired, former employees pay 20 percent, and their dependents, 30 percent. (2) Up to four times per month. TC stands for total cost per month. All monetary values (i.e., values not expressed as percent) are in thousand yen (roughly US$10 in 2008).

[b] (1) Among the retired, both former employees and their dependents pay 20 percent. (2) Up to two months. TC stands for total cost per month. All monetary values (i.e., values not expressed as percent) are in thousand yen (roughly US$10 in 2008).

workers, the unemployed, and the retired. Employment-based health insurance had a lower coinsurance rate than NHI until 2003, after which both were equalized to a common coinsurance rate of 30 percent for outpatient visits as well as inpatient admissions.

At the age of 70, people switch to Elderly Health Insurance and, in principle, face the same cost sharing.[8] Importantly, on the other hand, all medical providers are reimbursed by the national fee schedule, which is uniformly applied to all patients

[8] In fact, high-income earners above 70 have been charged a higher coinsurance rate (20 percent instead of 10 percent) since October 2002. As the bar for "high income" is set quite high, a limited number of patients fall in this category (7 percent, according to Ikegami et al. 2011). Since income is not recorded in the Survey of Medical Care Activities in Public Health Insurance, which I use to derive monthly out-of-pocket expenditures, I compute expenditures considering a "normal" family. See Section A1 in the online Appendix for details.

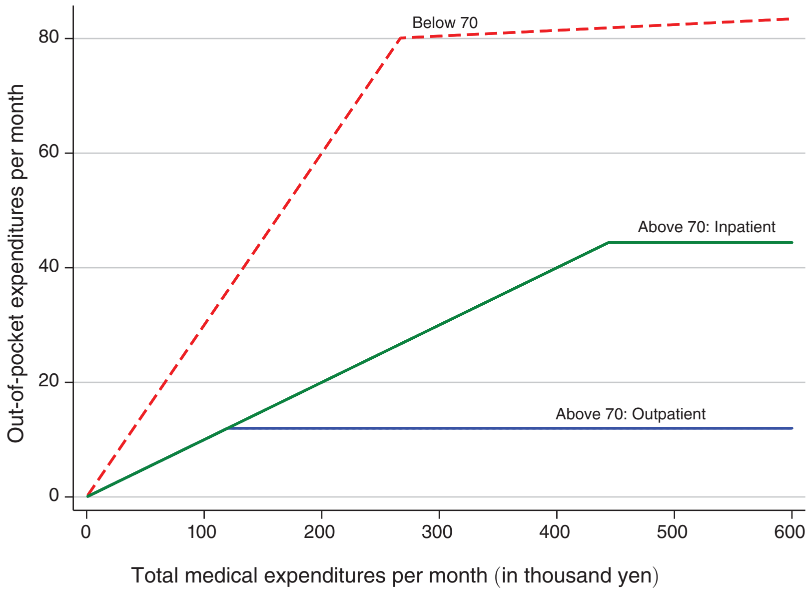

Figure 1. Patient Cost Sharing below 70 and above 70, 2008

Notes: See Table 1 for the formula used to calculate patient cost sharing. For those above age 70, since the coinsurance rate and stop loss differs by outpatient visits and inpatient admissions, I show two separate lines for each service. For those below 70, there was no distinction between outpatient visits and inpatient admissions in year 2008. One thousand yen roughly equaled US$10 in 2008.

regardless of their insurance type and age.[9] Since a patient's insurance type and age do not affect reimbursements, physicians have arguably few incentives to influence patient demand. For example, from the physician's perspective, in principle, there are few reasons to delay surgeries until age 70, as long as patients can pay, because reimbursements do not differ by the patient's age.

B. *Changes in Patient Cost Sharing at Age* 70

Figure 1 illustrates the out-of-pocket expenditures with respect to total monthly medical expenditures for 2008, as an example of the formula in Table 1. Unlike in the United States, the stop-loss is set monthly, rather than annually, in Japan. This is for purely administrative reasons. Reimbursements to medical institutions are conventionally paid monthly in Japan. The x-axis indicates total monthly medical expenditures, and the y-axis, the corresponding monthly out-of-pocket medical expenditures. Since the stop-loss differs for outpatient visits and inpatient admissions for those over 70, I show separate lines for the two services. For those below 70, there was no distinction between these two services in 2008. Figure 1 shows that the price schedule for those above 70 always lies below that of those below 70,

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

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

	Out-of-pocket medical expenditure (thousand yen)			Percent reached stop-loss among insurance claims	
Type of service	Below 70 (1)	Above 70 (2)	Percent reduction ((1)–(2))/(3)	Below 70 (4)	Above 70 (5)
Outpatient visits	4.0	1.1	73	0.1	0.6
Inpatient admissions	41.7	13.0	69	14.6	0.0

Note: All monetary values (i.e., values not expressed as percent) are in thousand yen (roughly US$10 in 2008).

suggesting that for any given medical expenditures, the out-of-pocket payment for those above 70 was always smaller than that for those below 70 in 2008.

Unfortunately, information concerning actual out-of-pocket expenditure of the general population is only available for year 2007, and these data do not distinguish between outpatient visits and inpatient admissions. However, I have access to individual level insurance claim data for outpatient visits and inpatient admissions, which summarizes the monthly 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 out-of-pocket medical expenditures for each insurance claim.

Table 2 summarizes the actual average monthly out-of-pocket expenditures of a 69-year-old and the counterfactual monthly out-of-pocket medical expenditures for a 70-year-old. For those aged 70, since the observed out-of-pocket medical expenditures already reflect the change in cost sharing (i.e., out-of-pocket medical expenditures are endogenous), I compute their counterfactual out-of-pocket expenditures by applying the cost sharing rules of Elderly Health Insurance to utilization by an average 69-year-old. See Section A1 in the online Appendix for details on these derivations.

In the main analysis, I do not exploit the year-to-year variation in cost sharing, and instead, I pool all the survey rounds to increase the statistical power and smooth out cohort size effects.[10] As a robustness check, I run separate regressions for periods before and after 2002. I choose 2002 since the price schedule for those above age 70 changes from flat monthly or daily copayment to coinsurance with stop-loss (as shown in Table 1), which could generate quite different utilization incentives. Overall, out-of-pocket medical expenditure, conditional on using health care services in Table 2, is the weighted average of out-of-pocket medical expenditure across all survey years, using the population of 69-year-olds in each survey year as weights.

[10] Due to the smaller sample size, the estimates from each year are noisy and do not have any consistent pattern. Also, these results should be viewed with caution, since fluctuations in cohort size due to events like the Spanish Flu pandemic and World War I may heavily affect the estimates in this RD framework, which are based on counts instead of rate. These results are available from the author upon request.

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 a 69-year-old is 1,822 yen (or roughly US$18,220), out-of-pocket medical expenditures for inpatient admissions can reach as much as 27 percent of a person's average monthly income.[11] On the other hand, once the patient turns 70, the counterfactual ratio of medical expenditures to average monthly income is reduced to as little as 8.6 percent.[12]

One complication in the above-mentioned calculations is the nonlinearity imposed by the stop-loss, which is a classic, but important, challenge in estimating elasticities and dates back to the RAND HIE (Keeler, Newhouse, and Phelps 1977; Ellis 1986). The problem is that although in many cases medical expenditure is caused by unpredictable illnesses, economically rational individuals who anticipate spending beyond the stop-loss may spend more when the price is low (Keeler and Rolph 1988). The size of the difference between true and nominal out-of-pocket prices 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 is reached takes the simple form $(1 - x)P$, where P is the nominal price, and x is the probability of exceeding the stop-loss (Keeler and Rolph 1988).

Accounting for nonlinearity associated with the stop-loss is challenging, since to fully understand the size of the difference between the true price and the 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 overutilization is probably much smaller in my case, unlike the RAND HIE, for the following two reasons. First, the probability of reaching the stop-loss is not high even for inpatient admissions—14 percent for those admitted (see column 4 in Table 2) and 2 percent for the non-conditional population. Second, the stop-loss is set monthly in Japan, rather than annually like for the RAND HIE and most health insurances in the United States. To the extent that illnesses are unpredictable, this shorter interval may make it harder for people to time and overuse medical services. In fact, even under an annual stop-loss, Keeler and Rolph (1988) empirically showed that people in the RAND HIE responded myopically to the stop-loss, i.e., people do not appear to change the timing of their medical purchases to reduce costs.[13]

Nonetheless, to partially account for this effect, I simply apply the formula $(1 - x_t)P_t$ for those whose out-of-pocket medical expenditures exceed the 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 inpatient admissions, the nominal price (41,000 yen) for those just below age 70 is not so different from the true price (38,000 yen, not shown). Therefore, the

[11] One thousand yen is roughly equal to US$10. The rate of 27 percent was calculated by the author using the Comprehensive Survey of Living Conditions (CSLC), i.e., $41.7/(1822/12) = 0.27$.

[12] This rate was calculated by the author using the CSLC, i.e., $13.0/(1822/12) = 0.086$.

[13] Aron-Dine et al. (2012) also showed that while there are some forward-looking aspects in health care utilization, individuals' behavior is much closer to full myopia, such that they respond only to the spot price instead of looking forward as individuals responding only to the future price. See also Kowalski (2012) and Marsh (2012) on the recent application of nonlinear budget set estimation to analyze the effect of health insurance contracts.

bias coming from the nonlinearity associated with the stop-loss may be negligible in this case.

II. Data and Identification

I use one of the most comprehensive health-related data sources ever assembled on Japan. In this section, I summarize the most important datasets used in the study. Further details on the same appear in Section A3 in the online Appendix. My main outcomes are health care, health outcomes, and out-of-pocket expenditures.

A. *Data*

The dataset for health care utilization is the Patient Survey, a nationally representative repeated cross-sectional survey that collects administrative data from hospitals and clinics. 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 it also includes information on outpatient visits, unlike most existing datasets that 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 avoidable inpatient admissions. In my case, I directly look at changes in the number of patients for beneficial and preventive care in the outpatient setting. The disadvantage of this data is that like most discharge data, it only includes limited individual demographics, such as gender and place of residence. There is no record of education and 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, inpatient admissions. Outpatient data are collected during one day in the middle of October of the survey year and provide information on all patients who made outpatient visits to the surveyed hospitals and clinics on the day of the survey.[14] These data include patients' exact dates of birth and the survey dates, which is equivalent to the exact dates 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.[15]

As health outcomes, I examine both mortality and morbidity. I examine mortality, since it is one of the few objective and well-measured health outcomes, the data for which are often easily available and comparable across different countries. I use the universe of death records between 1984 and 2008, which report the exact dates of birth and death, place of death, and cause of death using the International Classification of Diseases (ICD) 9 or 10. The main advantage of the death records

[14] Since data concerning outpatient visits are collected on one day only, the survey is susceptible to external factors such as the weather. This short survey period is another reason I do not exploit the year-to-year variation in cost sharing in this paper.

[15] I describe these dates in chronological order for simplicity, but each unit of data is as per the discharge.

is that they cover all deaths that occur in Japan, unlike hospital discharge records, which only report in-hospital mortality by definition.

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 the Japanese population conducted every three years between 1986 and 2007, mostly in June. The survey asks questions about insurance coverage, self-reported physical and mental health, stress levels, and so forth. Age is reported by month in this dataset. Descriptive statistics for the Patient Survey, CSLC, and mortality data are reported in Table A in the online Appendix.

B. *Identification Strategy*

My identification strategy is very similar to studies from the United States that use an RD design to examine the effect of turning 65 (Card, Dobkin, and Maestas 2004, 2008, 2009; Chay, Kim, and Swaminathan 2010). However, in Japan, the change at age 70 only reflects increases in benefit generosity rather than the combined effects of change in health insurance coverage and benefit generosity. Moreover, as shown later, turning 70 in Japan does not coincide with changes in any observable factors, such as employment or receiving pension.

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

$$Y_{iat} = f(a) + \beta Post70_{iat} + X'_{iat}\gamma + \varepsilon_{iat}, \tag{1}$$

where Y_{iat} is a measure of morbidity or out-of-pocket medical expenditure 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 the value one if individual i is over age 70. My parameter of interest is the coefficient β. 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 with samples aged 65–75 years. As robustness checks, I limit the sample to a narrower age window (ages 67–73) and add cubic terms in age. To account for common characteristics within cells of the same age, following Lee and Card (2008), the standard errors are clustered at age in months.

Unlike the CSLC in which I see all individuals, the unique features of the Patient Survey and mortality data is that I only observe individuals who are present in the medical institutions or are deceased, respectively. My approach to deal with this issue is to assume that the underlying populations at risk for outpatient visits, inpatient admissions, and deaths trend smoothly with age. Since I pool several years of data, this assumption seems plausible.[16] Therefore, I use the log of counts

[16] See Card, Dobkin, and Maestas (2004) for formalization of this approach. Since I am using nine rounds of the Patient Survey, the patients at each age in my samples are actually drawn from nine different age cohorts, smoothing any fluctuations in cohort size.

as the dependent variable for these datasets and modify the regression equation as follows:

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

where Y_{at} indicates the count of patients or deaths at age a in year t. Throughout the paper, for regressions where the dependent variable is either binary or log, the coefficients on *Post*70 and their standard errors are multiplied by 100 to make them easier to interpret as percentage changes.

There is one remaining empirical issue in estimating equation (2) using the Patient Survey. As seen in Figure A in the online Appendix, there is substantial seasonality and heaping in the reported birthdays of patients observed in the Patient Survey. First, I observe heaping on the first day of the month, which is likely due to reporting.[17] 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 the winter, when there is less work, but evidence proving this notion is scant (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 in one month (September) for inpatient admissions. 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 seventieth birthday, this approach allows me to code age in months and the post age-70 dummy using dates of birth and dates of visits without error. To account for 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, Lindo, and Waddell 2011; Carneiro, Løken, and Salvanes 2010). Thus, the cell indicates the birth month for each age for each survey year. There are 120 observations (12 birth months for each year times 10 years of age (65–75) windows) per survey round, and there are nine rounds of surveys. Thus, there are 1,080 cells in the estimation for outpatient visits.

I also try two different approaches to account for the heaping and seasonality. One approach is to collapse the data into age in quarters and then convert the counts into rates, since I have population data by the quarter of the birth month from the population censuses that 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 those in the main approach, probably due to measurement error in the population estimates. Another approach is to collapse the data into age in days and include 365 day-of-birth fixed effects as well as year-of-birth fixed effects into equation (2), so as to account for seasonality and cohort size effects where age in days at the time of the outpatient visit or inpatient admission is the running variable (Gans and Leigh 2009; Barreca, Lindo, and Waddell 2011). The disadvantage of this approach is that when I divide the sample into finer subsamples (e.g., by diagnoses), there are

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

many birthdays without any observations, which may introduce noise in the running variable. The approach of using age in months does not suffer much from this problem 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 the approach I first described. Some of the results using age in days as the running variable are shown in Table E in the online Appendix.

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 patients are discharged in September. To avoid including patients with unusually long hospital 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. Later, I show that the estimates are robust to using different windows from the discharge date. The cell for discharge indicates the year of birth, month of birth, month of admission, and survey year, the latter being identical to the admission year. Since there are 1,080 cells for each admission month, there are a total of 3,240 cells in the estimation of inpatient admissions. The estimations include birth month fixed effects, admission month fixed effects, and survey year fixed effects.

For the mortality data, I estimate the same equation (2), replacing Y_{at} with death counts. While I observe that deaths occur throughout the year, seasonality remains an issue. As shown in Figure B in the online Appendix, more births as well as more deaths are observed in winters. Thus, if I just plot the raw number of deaths by age, I mechanically observe more deaths around each patient's birthday. To account for seasonality (as well as heaping in birthdays, similar to the observation made in the Patient Survey), I collapse the mortality data into birth year/birth month/death year/death month (i.e., age in months) and include birth months and death months fixed effects. This approach is analogous to the estimation of inpatient admissions, with the admission month being replaced by the death month. Since mortality data spans 1984–2008, I limit the sample to those born during 1919–1933, so that I can trace the deaths throughout ages 65–75.[18] There are 21,600 cells.[19] The main drawback of using death records is that in those records I only observe the exact date of death. In contrast, in the hospital discharge data, I observe the exact date of admission, which (unlike the date of death) determines the price schedule applicable to the patient. Note that this may attenuate the estimates, since people who died immediately after their seventieth birthday may not be eligible for Elderly Health Insurance at the time of admission even though I consider them as treated.

Importantly, "age RD design" is distinct from the standard RD design. Because all individuals will eventually age into the program (age 70 in this case), assignment to treatment is inevitable. Therefore, individuals who anticipate a price change at age 70 may behave in a certain way before treatment is provided (Lee and Lemieux

[18] The results using all deaths that occurred between the ages of 65 and 75 during 1984–2008 are quantitatively similar.

[19] This calculation is a result of 15 birth years (1919–1933), 12 birth months, and 12 death months for 10 years of age (65–75) windows ($21,600 = 15 \times 12 \times 12 \times 10$).

2010). This issue is particularly relevant for inpatient admissions, since there is a possibility that people may delay some expensive medical procedures until they become 70, which may accentuate the size of the discontinuity.[20]

However, the age RD setting allows me to visually examine whether the discontinuity is accentuated; if the increase is transitory rather than permanent, I should observe a tendency to revert to the previous level after age 70 as well as a drop-off just shy of age 70. Indeed, as I show later, the 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 it. 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 (Barreca, Lindo, and Waddell 2011). 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 catch-up effects or intertemporal substitution.

The underlying assumption of a typical RD model still applies to the age RD design; in this case, the assumption is that expected outcomes below and above age 70 are continuous at age 70 (Hahn, Todd, and Van der Klaauw 2001). Continuity requires that all other factors that might affect the outcome of interest trend smoothly at age 70. Following Lee and Lemieux (2010), I simply fit the same models as equation (1) for confounding variables and testing for discontinuities at age 70.

Figure C in the online Appendix 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 at age 70 for both genders.[21] Row 1 in Table B in the online Appendix confirms that there is no jump in employment at age 70. In the remaining rows in the table, I also investigate age profiles of marriage and income in the CSLC, but neither outcome shows any discontinuities at age 70. Therefore, employment, marriage, and income are unlikely to confound the impact of cost sharing at that age.

III. Utilization Results

In this section, I examine the effect of changes in patient 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.

[20] It is not always the case that such anticipation accentuates the magnitude of the discontinuity; it can also mute the discontinuity (Lee and Lemieux 2010).

[21] The mandatory retirement age in Japan used to be either 55 or 60 years. Pension receipts start at either 60 or 65 years, depending on the type of job. Also, long-term care (LTC) health insurance was introduced in Japan in 2000, but it does not specify the age of eligibility as 70. Indeed, I do not see any change at age 70 in the probability of receiving LTC, as shown in Table B in the online Appendix.

A. *Outpatient Visits*

I examine changes in the number and characteristics of outpatient visits at age 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 counts on birth month fixed effects and survey year fixed effects.

Panel A of Figure 2 shows the actual and fitted age profiles of outpatient visits based on pooled outpatient data. The markers in the figure represent 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 smoothly increase prior to age 70 and then jump sharply at age 70. Also, the increase appears to be permanent rather than transitory since I do not observe any tendency after age 70 to revert to the previous level.

Panel A in Table 3 shows that the jump in panel A of Figure 2 corresponds to a 10.3 percent increase. The implied elasticity of the outpatient visits is $-0.18(= 0.103/(\log(1.1) - \log(4.0)))$, where the denominator is the log difference in price between ages 69 and 70 from the first row in Table 2.[22] Since I do not visually observe catch-up effects and stop-loss is rarely reached, the bias on estimating the elasticity of outpatient visits seems minimal.

Panel B of Table 3 divides the sample before and after 2002, when the price schedule for those above age 70 changes from the flat monthly or daily copayment to coinsurance with stop-loss, which could generate quite different utilization incentives. Even though the RD estimates are larger pre-2002 than post-2002 (12.0 versus 6.9 percent, respectively), the corresponding price elasticity is relatively similar across periods (-0.19 versus -0.15, respectively), since price reduction at age 70 was larger in the period before 2002 (see Table K in the online Appendix). In addition, the null hypothesis that RD estimates are the same for pre- and post-2002 cannot be rejected at the conventional level.

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. As much as 94 percent of patients are repeat visit patients (i.e., visits for the same underlying health conditions *and* made at the same hospitals or clinics as last time) rather than first-time visitors, as shown in Table A in the online Appendix. Panel B of Figure 2 plots the age profile of days from the last outpatient visit for repeat patients. Consistent with the increase in outpatient visits, the duration from the last visit steadily decreases prior to age 70, and then drops sharply by roughly one day at age 70.

[22] Note that I used the average price rather than the marginal price in the denominator. 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, for 2008, the log marginal price difference would be $\log(0.1) - \log(0.3)$ without stop-loss (Table 1), while the log average price difference is $\log(1.1) - \log(4.0)$ for outpatient visits and $\log(13.0) - \log(41.7)$ for inpatient admissions (Table 2).

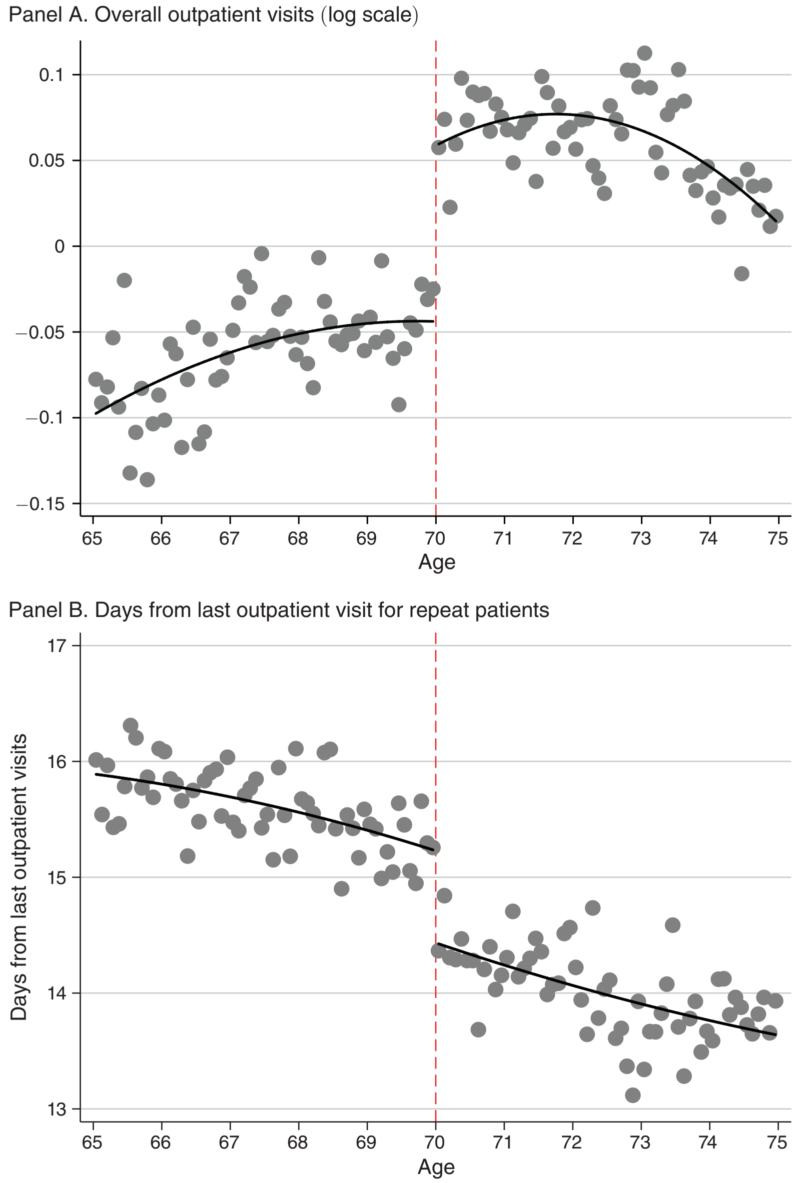

Figure 2. Age Profile for Outpatient Visits

Notes: I pool outpatient data for 1984–2008 from the Patient Survey. The markers in panel A represent the averages of residuals from regressions of log outcomes on birth month fixed effects and survey year fixed effects (aggregated by age in months). The markers in panel B represent the simple average. The lines represent fitted regressions from models that assume a quadratic age profile, fully interacted with a dummy for age 70 or older.

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, although distinguishing between the two is a very difficult task. To investigate this question, I divide the sample into various dimensions in the remaining rows in Table 3. In panel C, I divide outpatient

Table 3—RD Estimates on Outpatient Visits at Age 70

Panel A. All		*Panel F. By referral*	
	10.3***	Without referral	10.5***
	(1.8)		(1.9)
		With referral	6.4
Panel B. By period			(5.2)
Years 1984–1999	12.0***		
	(1.8)	*Panel G. By gender*	
Years 2002–2008	6.9*	Male	11.3***
	(3.6)		(2.2)
		Female	9.7***
Panel C. By visit type			(1.9)
First visits	12.7***		
	(3.3)	*Panel H. By diagnosis*	
Repeated visits	10.3***	Heart disease	3.0
	(1.9)		(4.6)
		Cerebrovascular disease	15.2***
Panel D. Days from last outpatient visits among repeated visits			(5.9)
1 day	17.9***	Respiratory disease	14.3***
	(2.5)		(3.6)
2–3 day	16.4***	Ambulatory care sensitive conditions	8.2***
	(4.4)		(2.3)
4–7 day	13.3***	Cancer	6.1
	(2.8)		(8.0)
15–30 day	2.8	Diseases of nervous and sense organs	10.4***
	(2.9)		(2.8)
31–60 day	−1.5	Diseases of genitourinary system	14.9***
	(4.3)		(5.4)
		Diseases of skin	17.4***
Panel E. By institution			(4.9)
Hospital	5.1**	Diseases of musculoskeletal system	18.6***
	(2.0)		(2.5)
Clinic	13.8***		
	(1.8)		

Notes: Each cell is the estimate from separate estimated RDs at age 70. The specification is 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 outpatient data. Sample size is 1,080. Robust standard errors are in parentheses. As all coefficients on *Post*70 and their standard errors have been multiplied by 100, they can be interpreted as percentage changes.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

visits by first visit or a repeat visit. Interestingly, not only repeat visits but first visits also increase by more than 10 percent.[23] Since repeat visits account 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

[23] Figure D in the online Appendix shows the age profiles for first-time and repeat outpatient visits. The age profiles of first visits show a very interesting trend; the number of first 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 repeat visits are very similar to those of total outpatient visits, since most of total outpatient visits are repeat visits.

receiving outpatient care for the first time may avoid outpatient visits before turning 70 due to their cost.

For repeat visits, panel D in Table 3 shows that most of the increases are concentrated within a short interval from the last visit. In fact, most of the increase is concentrated among those who received their last outpatient care within seven days, and the largest increase of 17.9 percent is observed within one day from the last visit, indicating that some of these visits may be less beneficial.[24] Panels E and F show that the increase in outpatient visits is concentrated at clinics and at visits without referrals. Since people have much easier access to small clinics (rather than large hospitals) without referrals, these results imply that these outpatient visits are more discretionary and less serious.

Most of the findings so far suggest that those who visit medical institutions for outpatient care once they turn 70 are less seriously ill than those who visit these institutions at the age of 69. To further investigate this point, I examine the size of discontinuity at age 70 by type of diagnoses. Panel H in Table 3 presents the RD estimates for selected diagnoses. Although the majority of large increases are not likely to be for life-threatening diagnoses, these conditions, such as diseases of the genitourinary system, skin, and musculoskeletal system, probably require treatment to enhance the quality of life. However, I also find an increase in potentially more serious diagnoses, such as a 15.2 percent increase for cerebrovascular disease and 14.3 percent increase for respiratory disease, both of which are statistically significant at the 1 percent level. Figure 3 displays the age profile for these commonly examined diagnoses (see, e.g., Chay, Kim, and Swaminathan 2010).

Further, I look at diagnoses listed as ACSCs, for which proper and early outpatient care reduces subsequent avoidable admissions. ACSCs are developed by the AHRQ to study preventive care in an outpatient setting using inpatient data and to identify admissions that should not occur in the presence of sufficient preventive care (see Table D in the online Appendix for a list of ACSCs).[25] Since I *do* have the outpatient datasets, I can directly look at changes in the number of patients for such beneficial and preventive care. In fact, I find a statistically significant 8.2 percent increase in ACSCs.[26] Panel D in Figure 3 confirms that there is a modest jump at age 70 for ACSCs.

In sum, while I find a modest increase for diagnoses, such as ACSCs, indicating the need for beneficial and preventive care, I find much a larger increase for discretionary diagnoses. However, I need to view this result with considerable caution, since any conclusion based only on the diagnoses is unwarranted, due to the large heterogeneity of severity within the diagnoses.

[24] The average number of days from the last outpatient visit for patients aged 65–75 years is 13.6 days, as shown in Table A in the online Appendix.

[25] The leading ACSC is hypertension, which is by far the most frequent diagnosis of all outpatient visits (see Table C in the online Appendix). 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).

[26] I also try to investigate each ACSC separately, but due to smaller sample sizes, I cannot obtain precise estimates for most ACSCs. The two exceptions are Chronic Obstructive Pulmonary Disease (COPD), a progressive disease that makes it hard to breathe, and hypertension. The increase for patients with COPD and hypertension is 17.2 percent (t-stat $= 2.10$) and 8.5 percent (t-stat $= 3.54$), respectively.

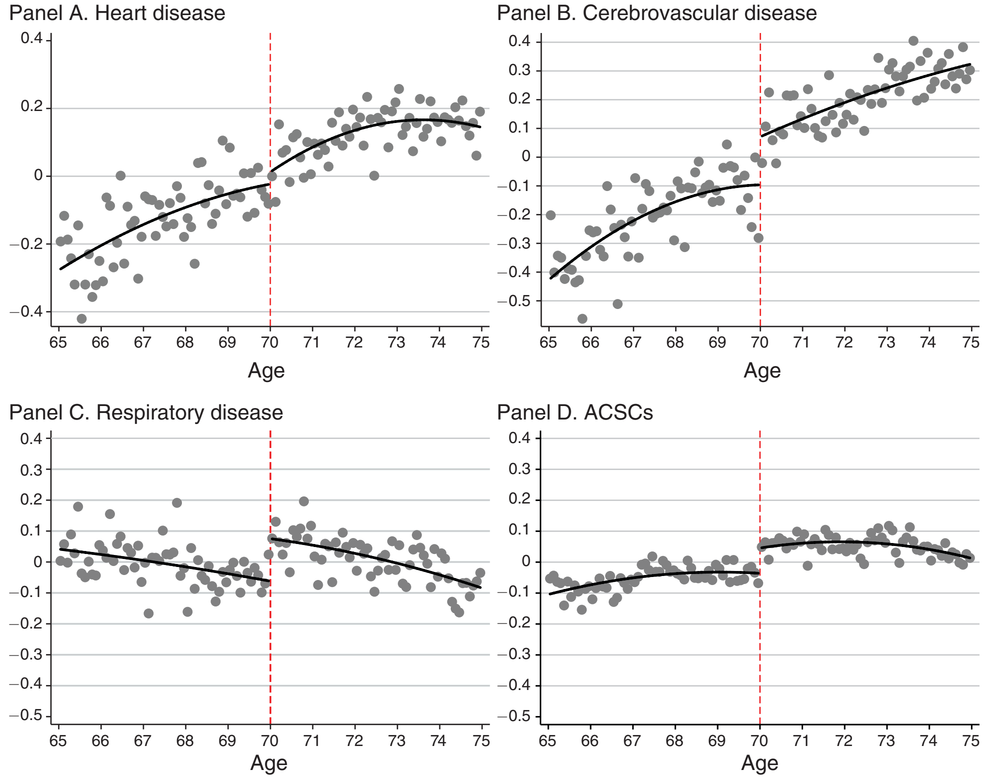

Figure 3. Age Profile for Outpatient Visits for Selected Diagnoses (*log scale*)

Notes: I pool outpatient data for 1984–2008 from the Patient Survey. Except for panel A, the corresponding RD estimates at age 70 are statistically significant at the 5 percent level. The markers represent the averages of residuals from regressions of log outcomes on birth month fixed effects and survey year fixed effects (aggregated by age in months). The lines represent fitted regressions from models that assume a quadratic age profile, fully interacted with a dummy for age 70 or older. See Table D in the online Appendix for the list of ACSCs.

Table E in the online Appendix summarizes the results of alternative specifications that use age in days as the running variable with birthday fixed effects and shows quantitatively similar results for most of the outcomes.[27] As a falsification test, I also run the same estimation for other ages that should not have any discontinuity (each single age between 66 and 74 years) and do not find any statistically significant changes in them (results available upon request). This result is not surprising, since I do not see any visible discontinuity in other ages in either Figures 2 or 3.

B. *Inpatient Admissions*

Panel A of Figure 4 shows the actual and fitted age profiles of inpatient admissions based on the pooled discharge data for 1984–2008. The plotted average is the

[27] I choose some outcomes that do not have zero cells for any age in days in Table E in the online Appendix. It is conventional to add one or a small positive value before taking the log value of such cells, but zero cells introduce noises and hence, attenuate the estimates. In fact, as the number of zero cells increases, the estimates obtained by using age in days as the running variable start to deviate from those of age in months.

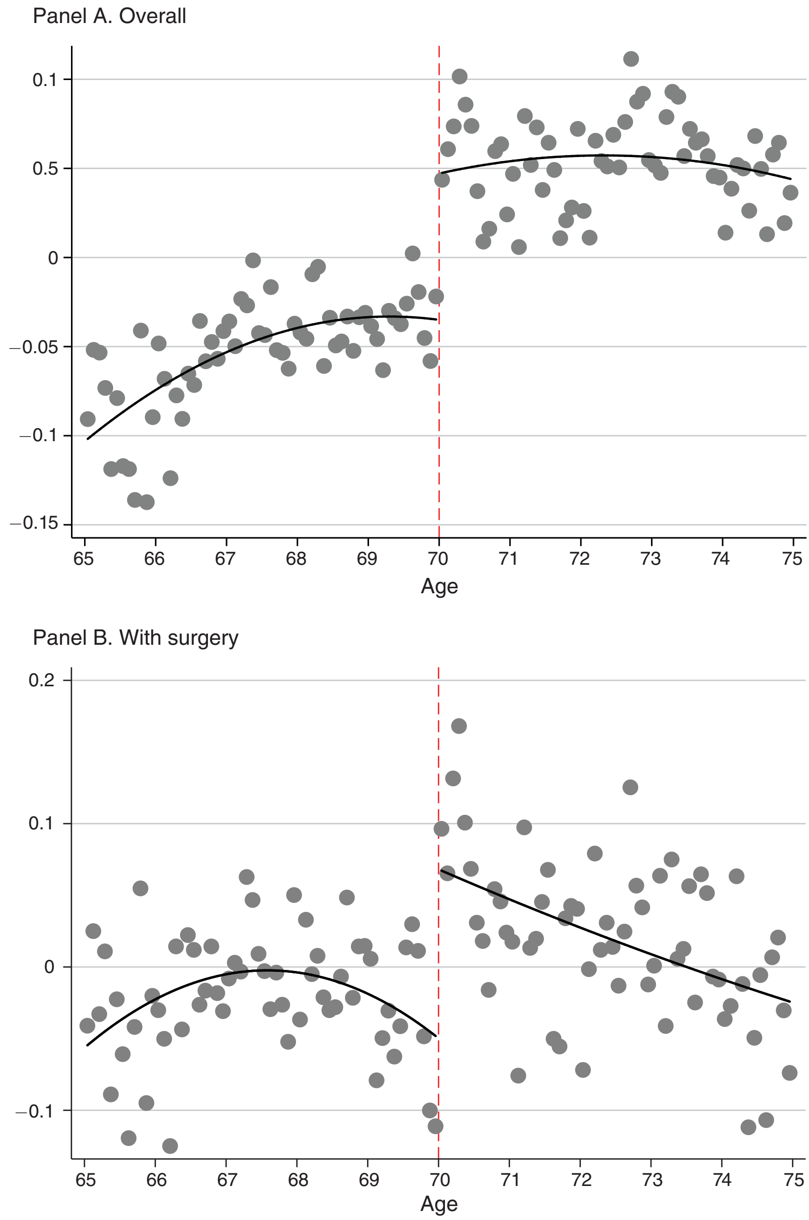

FIGURE 4. AGE PROFILE FOR INPATIENT ADMISSIONS (*log scale*)

Notes: I pool discharge data for 1984–2008 from the Patient Survey. The markers represent the averages of residuals from regressions of log outcomes on birth month fixed effects, admission month fixed effects, and survey year fixed effects (aggregated by age in months). The lines represent fitted regressions from models that assume a quadratic age profile, fully interacted with a dummy for age 70 or older.

residual from a regression of log counts 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 for outpatient visits, with no tendency to return to prior levels.

Since the sharp change in cost sharing in inpatient admissions coincides with that of outpatient visits, it may be difficult to conclusively distinguish if the change in inpatient admissions for a certain condition is the result of lower inpatient cost sharing per se or of substitution with increased outpatient visits. For example, preventive and beneficial outpatient care may replace avoidable admissions in the future. Alternatively, more frequent checkups at outpatient visits allow detection of serious conditions and, hence, increase subsequent admissions. However, since I do not see a discontinuity with time lag in the graph for inpatient admissions, it is more likely that the jump I observe is the reflection of lower cost sharing rather than any interaction with outpatient visits. I will return to this point in Section V.

The first entry in Table 4 shows that the jump in overall inpatient admissions in panel A of Figure 4 corresponds to an 8.2 percent increase. The implied elasticity of inpatient admissions is -0.16 ($= 0.082/(\log(13.0) - \log(41.7))$), where the denominator is the log difference in price between ages 69 and 70 (from the second row in Table 2). Panel B presents the RD estimates from the sample before and after 2002 (similar to what was done for outpatient visits). While the RD estimates are larger for the period before 2002 than after 2002 (9.6 versus 5.3 percent, respectively), the corresponding price elasticities become relatively similar across periods (-0.17 versus -0.12, respectively), since price reduction at age 70 was larger in the former period (see Table K in the online Appendix). Moreover, the null hypothesis that the RD estimates are the same pre- and post-2002 cannot be rejected at the conventional level.

As I discussed earlier, there is a potential bias in estimating elasticity, especially due to the catch-up effect. To account for this effect, I run a donut-hole RD by excluding a few months of observations around the threshold. There is no guide as to the size of the donut-hole statistically or economically, because it is not clear what magnitude of delay is fathomable/medically low-cost for patients. Thus, I experiment with a threshold of zero to six months. However, removing six months from either side of age 70 may be too drastic, since it would essentially mean comparing patients aged 69.5 and 70.5. Figure D1 in the online Appendix shows that the estimates get smaller and the standard errors larger as the hole is expanded. But as long as the removal of the data is within three months of age 70, the estimates are statistically significant at the 5 percent level. Taking the conservative RD estimate from the three-month donut-hole RD, the lower bound of implied elasticity is -0.14 ($= 0.072/(\log(13.0) - \log(41.7))$), which is not so different from naïve elasticity.

Figure D2 in the online Appendix presents the RD estimates by different windows from the discharge date. Since the applicable price schedule changes monthly in Japan, those who enter the scheme before age 70 and stay until after 70 may see a price reduction in the middle of a spell. This fact implies that the RD estimates may get smaller as I include longer stay, since the expected price for those below age 70 can be lower than the nominal price. However, Figure D2 shows that the results are stable across the length of windows from the discharge date.

Another source of bias due to forward-looking behavior is the timing of admission within a month. To the extent that patients are forward looking, they may time their admissions early in the month to fully exploit the monthly nature of stop-loss, and hence, those who enter hospitals at different times within a month may have different characteristics. To investigate this possibility, I divide the sample into those

Table 4—RD Estimates on Inpatient Admissions at Age 70

Panel A. All		*Panel F. Gender*	
	8.2***	Male	8.1***
	(2.6)		(2.8)
		Female	9.0***
			(2.8)
Panel B. By period			
Years 1984–1999	9.6***		
	(2.2)	*Panel G. By diagnosis*	
Years 2002–2008	5.3**	Heart disease	11.4**
	(2.6)		(5.7)
		Hypertensive disease	4.8
Panel C. By admission day			(5.5)
First half of the month	9.8***	Ischemic heart disease	14.5**
	(2.8)		(7.1)
Second half of the month	8.7***	Cerebrovascular disease	10.5***
	(3.2)		(3.9)
		Intracerebral hemorrhage	8.0
Panel D. Surgery			(6.1)
Without surgery	6.4**	Cerebral infarction	12.8***
	(2.6)		(4.6)
With surgery	12.0***	Respiratory diseases	6.9
	(3.5)		(4.8)
		Ambulatory care sensitive conditions	5.6*
Panel E. Type of surgery			(5.2)
Open-head surgery	11.3	Cancer	6.5
	(7.9)		(4.6)
Open-heart surgery	8.1	Cataract	22.6***
	(8.0)		(6.5)
Open-stomach surgery	12.6**		
	(5.3)	*Panel H. Location before admission*	
Musculoskeletal surgery	5.6	Outpatients in the same hospital	9.7***
	(5.0)		(2.9)
Endoscopic surgery: stomach	8.7	Other	4.3
	(7.1)		(2.7)
Intraocular lens implantation	22.9***		
	(5.2)		

Notes: Each cell is the estimate from separate estimated RDs at age 70. The specification is 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 discharge data. Sample size is 3,240 excluding panels E and H. Sample size for panel E is 1,440 (4 years, 1999–2008) and that for panel H is 1,800 (5 years, 1996–2008), since these data were only collected in later years. Robust standard errors are in parentheses. As all coefficients on *Post*70 and their standard errors have been multiplied by 100, they can be interpreted as percentage changes.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

who are admitted in the first half and the second half of the months, and I run RD regressions separately. Panel C in Table 4 shows that the estimates are very similar and in fact, not statistically distinguishable. Therefore, the timing of the admissions does not seem to affect the compositions of patients and RD estimates.

So far, I have shown that estimates on inpatient admissions are pretty robust. Next, I examine the characteristics of inpatient admissions in the remaining rows in

Table 4. First, in panel D, I divide the sample by whether the patients received surgery. Interestingly, I find that the increase in admissions for people who received surgery is larger than the overall growth in admissions (12.0 percent versus an overall increase of 8.2 percent, respectively), while estimates from non-surgery admissions are smaller in magnitude (6.4 percent). Indeed, close inspection of the age profile of patients with surgery in Figure 4, panel B reveals a drop-off just prior to age 70, coupled with a temporary surge shortly after age 70. This pattern suggests that some people who are close to 70 years of age delay surgery until they become eligible for Elderly Health Insurance, so as to reduce out-of-pocket expenditures.

In panel E, I further investigate the sizes of discontinuities across types of surgeries. Unfortunately, this information was 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 precise estimates. While the estimates on any procedures are positive, I find that open-stomach surgery and intraocular lens implantation, the latter with substantial overlaps with admissions for cataracts (clouding of the lens of the eye), show statistically significant increases at age 70. Figure F in the online Appendix displays the age profile of inpatient admissions for these two procedures. Similar to the overall age profiles for inpatient admissions with surgery, I find a drop-off just prior to age 70 coupled with a temporary surge shortly after age 70 for both procedures. These results are plausible since on the one hand, these procedures, such as cataract surgeries are easily deferred, and on the other, they may substantially improve the quality of life (Card, Dobkin, and Maestas 2008).

These findings raise two possibilities for physicians' and patients' roles in the demand for health care services. First, it may imply that physicians may consider the financial effects of treatments on patients, since there are no financial incentives for physicians to delay surgeries until age 70, because reimbursements do not differ by patient age. Alternatively, it may raise the possibility of patients playing a more active role in determining their treatments. Indeed, Fang and Rizzo (2009) pointed 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) might have fostered patient-initiated requests for specific treatments.

Next, I examine patients' heterogeneous responses by the severity of the conditions. Figure 5 plots the RD estimates at age 70 on the y-axis and the severity measure on the x-axis. While there is no perfect measure of the severity of an illness, following Dobkin (2003), I use the fraction of weekend admissions as a severity measure.[28] The idea behind this measure is that if the condition is urgent and serious, admission occurs even during the weekend without triage, and thus, weekend admissions tend to be higher for these diagnoses. Since three digits of ICD9 are insufficient in providing precise RD estimates for each diagnosis, I group diagnoses into roughly 60 groups based on the Basic Tabulations of Diagnoses (see Table G in the online Appendix for lists of diagnosis groups). I omit diagnosis groups with less than 1 percent of total observations, because such sample sizes are too small to provide credible estimates. This leaves me with roughly 20 diagnosis groups. The graph presents a

[28] Unfortunately, the discharge data in the Patient Survey do not record whether the admission was elective, urgent, or for emergency care.

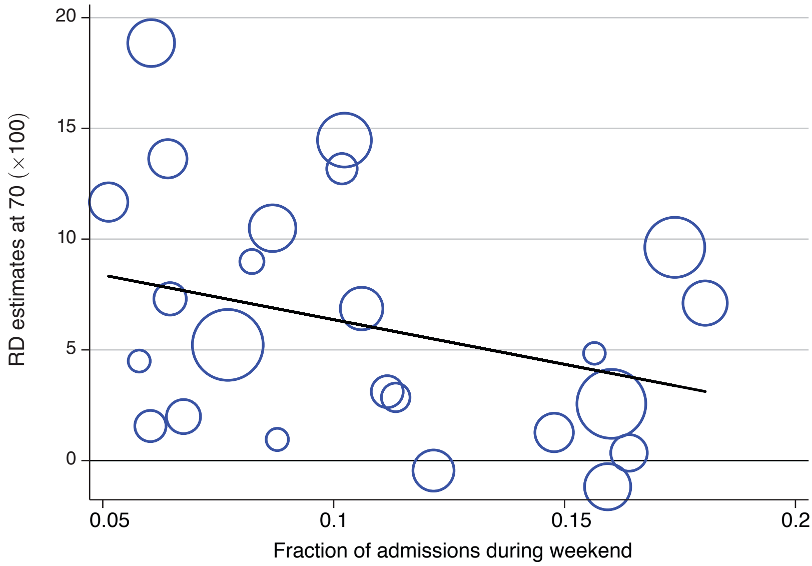

Figure 5. RD Estimates and Fraction of Weekend Admissions

Notes: I pool discharge data for 1984–2008 from the Patient Survey. The *y*-axis represents the RD estimates at age 70, and the *x*-axis is the fraction of admissions during weekends for each diagnosis group. The size of each dot reflects the number of observations in the discharge data for the control group (those aged 69). See Table G in the online Appendix for the list of diagnosis groups. I omit diagnosis groups with less than 1 percent of the total observations because their sample sizes are too small to provide credible estimates. The solid line is a linear fit, using the reciprocal of the variance of each RD estimate as weight for the observation.

clear negative relationship: the higher the severity, the smaller the RD estimates, suggesting that patients are less price sensitive for more serious conditions.

Panel G in Table 4 presents the RD estimates for selected diagnoses.[29] Interestingly, the observed patterns by admission diagnoses are similar to the findings in Card, Dobkin, and Maestas (2008), which examined Medicare eligibility at age 65; they found smaller increases for conditions typically treated with medication or bed rest (heart failure, bronchitis, and pneumonia) and large increases for those treated with specific procedures (chronic ischemic heart disease and osteoarthrosis). While I do not find an increase in admissions for respiratory diseases and the ACSCs that are typically treated with medication, I do find increases for cataracts, cerebral infarction, and (chronic) ischemic heart disease, which may require procedures, such as intraocular lens implantation, open-head surgery, and open-heart surgery, respectively.[30] These results imply that diagnoses that are treated with expensive but elective procedures are quite price sensitive, probably due to their large cost, and hence, patients delay treatment so as to reduce out-of-pocket expenditures.

[29] Table C in the online Appendix lists the top five diagnoses in 3-digit ICD9 codes and the corresponding RD estimates. Also, Figure G in the online Appendix displays the age profile of inpatient admissions for the commonly examined broad set of diagnoses.

[30] Note that estimates on ischemic heart disease are mostly driven by chronic, rather than acute, heart attacks (clinically referred to as an acute myocardial infarction or AMI).

Finally, I also examine the interaction between outpatient visits and inpatient admissions by looking at the route before admission to hospitals. Panel H in Table 4 shows that there is a statistically significant 9.7 percent increase in admissions that come from outpatient visits to the same hospitals, implying that patients wait to switch from outpatient visits to inpatient admissions within the hospital till they reach the age of 70.

Table F in the online Appendix shows the results of alternative specifications for selected outcome variables. The results are quite robust to different specifications, such as limiting the sample to a 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 the number of inpatient admissions just prior to age 70.

IV. Benefits

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

A. *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. 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 6 shows the actual and fitted age profiles of the log of overall deaths among those aged between 65 and 75 using pooled mortality data from 1987–2008. The plotted average is the residual from a regression of log outcome on birth month and death month fixed effects. The first entry in panel A in Table 5 shows that the estimate (−0.2 percent) is not statistically significant at the conventional level. The remaining columns in panel A present similar results from different specifications. It is important to note that while none of the point estimates are statistically significant, the 95 percent confidence interval for the mortality effects includes declines of elderly mortality up to 2.6 percent (based on the first entry in panel A). In addition, panel G (Table 3), panel F (Table 4), and panel B (Table 5) are stratified by gender, but none of the estimates are statistically different from each other between male and female patients.[31]

Further, I examine cause-specific deaths for three leading causes of death among the elderly in Japan (cancer, heart disease, and cerebrovascular disease) and also respiratory disease.[32] Figure H in the online Appendix shows the there are no discernible patterns for any causes of death. Panel C in Table 5 confirms that there is no clear change in cause-specific mortality at age 70.

[31] Unfortunately, as the Patient Survey and mortality data only include limited individual demographics except for gender, I could not examine heterogeneous effects based on individual characteristics.

[32] The corresponding 3-digit ICD9 codes are as follows: cancer (140–208), heart disease (390–398, 402, 404, 410–429), cerebrovascular disease (430–434, 436–438), and respiratory disease (460–519).

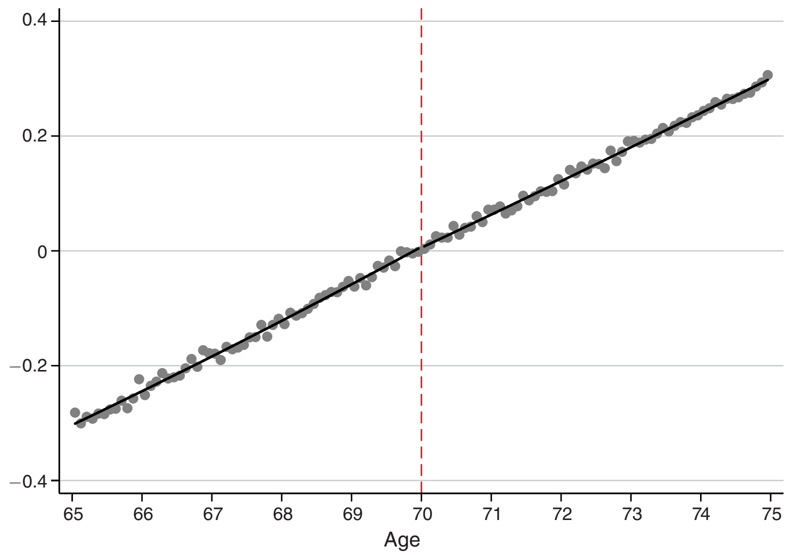

Figure 6. Age Profile of Overall Mortality

Notes: I pool mortality data for 1984–2008 for patients born during 1919–1933. The markers represent the averages of residuals from regressions of log outcomes on birth month fixed effects and death month fixed effects (aggregated by age in months). The lines represent fitted regressions from models that assume a quadratic age profile, fully interacted with a dummy for age 70 or older.

Table 5—RD Estimates on Mortality at Age 70

	Basic (1)	67–73 years (2)	Cubic (3)
Panel A. All	−0.2	0.1	0.0
	(1.1)	(0.8)	(0.9)
Panel B. Gender			
Male	−0.2	0.3	0.1
	(1.3)	(1.1)	(1.2)
Female	−0.2	0.1	−0.1
	(1.2)	(0.9)	(1.0)
Panel C. By diagnosis			
Cancer	−0.6	−0.6	−0.5
	(1.3)	(1.3)	(1.4)
Heart diseases	0.3	0.0	0.0
	(1.6)	(1.4)	(1.5)
Cerebrovascular diseases	0.3	1.2	2.1
	(1.6)	(1.6)	(1.7)
Respiratory diseases	1.5	1.9	0.0
	(2.4)	(2.6)	(2.7)

Notes: Each cell is the estimate from separate estimated RDs at age 70. The dependent variable is the log of the number of deaths. I use pooled 1984–2008 mortality data for patients born during 1919–1933. Sample size is 21,600. Robust standard errors are in parentheses. As all coefficients on *Post*70 and their standard errors have been multiplied by 100, they can be interpreted as percentage changes.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

These results are, to some extent, expected; in general, it is hard to detect the effect on health in an RD framework, because health is stock (Grossman 1972). Thus, it may take a while for the most observable effects to be realized, unless the causes of death are acute, such as heart attacks or strokes (see, e.g., Card, Dobkin, and Maestas 2009; Chay, Kim, and Swaminathan 2010). Following Card, Dobkin, and Maestas (2009), I also examine nondeferrable conditions (those with very similar weekend and weekday admission rates), but I do not find any discernible patterns in the age profile (results available upon request).

I also examine trends in self-reported physical and mental health as a morbidity measure before and after age 70, but I do not find any evidence that lower cost sharing leads to a discrete jump in morbidity as well (see Figure I and Table H in the online Appendix).[33] 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.[34]

It is worthwhile mentioning that the available health measures here are limited. In fact, several of the procedures that show large increases at age 70 are likely to yield substantial health benefits. For example, cataract surgeries may improve peoples' vision and reduce injury (Desapriya et al. 2010). While self-reported health measures should capture such health improvements, I may still underestimate the overall health benefit.

B. *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) pointed 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, the CSLC started collecting this information in 2007. Thus, I only have one survey year of individual out-of-pocket expenditures. Out-of-pocket medical expenditures include any medical expenses, such as over-the-counter drug spending, which is not covered by health insurance, and this expenditure does not distinguish between outpatient visits and inpatient admissions. With these caveats in 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 data for 2007. My analysis is based on 66,112 individuals aged between 65 and 75 years, with

[33] See also Nishi et al. (2012) on mental health.

[34] In contrast, Card, Dobkin, and Maestas (2009) showed that Medicare eligibility has a modest positive effect on the health of those above age 65. The difference in the two results is probably because supply side incentives differ significantly at age 65 in the United States. In fact, Card, Dobkin, and Maestas (2008) showed that both supply side incentives and shifts in insurance characteristics play an important role for the utilization of health care services at age 65 in the United States.

nonmissing out-of-pocket medical expenditure. The average annual out-of-pocket spending among those aged 65–69 is 142,000 yen (US$1,420), while the median out-of-pocket medical expenditure is 48,000 yen (US$480).[35]

I first present an RD estimate at the mean on out-of-pocket medical expenditures by estimating equation (1), where the model assumes quadratic in age fully interacted with a *Post*70 dummy. On average, lower cost sharing is associated with decline in out-of-pocket medical expenditure by 52,000 yen (US$520). The estimate is close to the conventional level, but it is not marginally statistically significant (t-stat $= -1.47$). However, the mean impact may miss the distributional impact of lower cost sharing. As is well known, the distribution of out-of-pocket spending is highly right-skewed. Among those aged 65–69, the top 5 percent of spenders account for almost 40 percent of out-of-pocket medical spending, while 72 percent of the sample has out-of-pocket spending below 100,000 yen (US$1,000) in a year.

Panel A of Figure 7 shows the age profiles of out-of-pocket medical expenditures at the seventy-fifth, ninetieth, and ninety-fifth percentiles. Out-of-pocket medical expenditures steadily increase prior to age 70, reflecting worse health as people age. Then, they decline sharply at age 70 at all three percentiles, with the largest decline at the highest percentile.[36] This result is consistent with other studies in the United States that showed a pronounced decline in the right tail of the distribution of out-of-pocket medical expenditures through Medicare Parts A and B (Finkelstein and McKnight 2008), Medicare Part D (Engelhardt and Gruber 2011), and Medicaid (Finkelstein et al. 2012). As noted previously, these studies looked at the effect of insurance coverage rather than changes in generosity.

To gauge the magnitude of the decline, I estimate equation (1) for each quantile q, where the outcome is out-of-pocket medical expenditure. Panel B of Figure 7 plots the RD estimates at age 70 on each quantile, 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.[37] Note that the coefficient and standard errors on the *Post*70 dummy are not multiplied by 100, because the outcome variable is a level rather than a log. The units for this coefficient are thousand yen.

The graph shows that lower patient cost sharing at age 70 is associated with declines in out-of-pocket spending at almost all (nonzero) quantiles of the distribution. While lower cost sharing has a very small effect at low quantiles, it grows consistently with baseline spending. At the median, the impact on out-of-pocket

[35] The data record out-of-pocket payments in the last month (May), whereas the survey is conducted in June. I multiply the data by 12 to convert the value to "annual" out-of-pocket costs. Note that seasonality in medical spending may introduce a measurement error. Moreover, this may overstate the likelihood of very high out-of-pocket payments if few patients visit a hospital every month.

[36] Figure J in the online Appendix compares the whole distribution of out-of-pocket medical expenditure in 2007 for different age groups.

[37] See Frandsen, Frölich, and Melly (2010), which proposed the nonparametric estimator for quantile treatment effects in an RD design. Recognizing the potential bias due to the misspecification, I choose to use the parametric approach, since I also want to obtain the coefficients on other control variables used to derive the distribution of out-of-pocket medical expenditure at each quantile, conditional on individual characteristics later in the welfare analysis in Section A2 in the online Appendix. In fact, I also estimate the proposed nonparametric estimators and compare them to the parametric ones. The estimates are quite similar throughout the percentile, except for a slight deviation among the top 3 percentile. The results are available from the author.

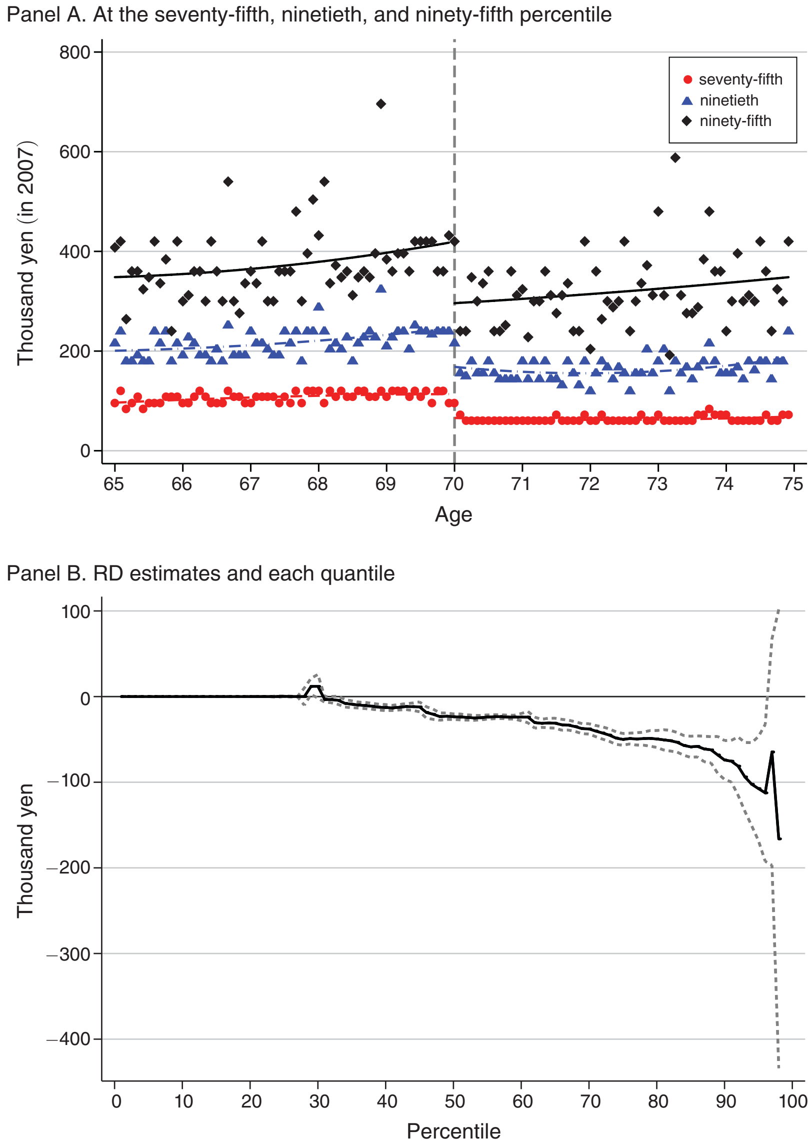

Figure 7. Age Profile of Out-of-Pocket Medical Expenditures (2007)

Notes: The data are sourced from the Comprehensive Survey of Living Conditions for 2007. I multiply the monthly out-of-pocket expenditures by 12 to convert the values to an annual basis. One thousand yen roughly equaled US$10 in 2007. The markers in panel A represent actual averages (age measured in months), and the lines represent fitted regressions from models that assume a quadratic age profile, fully interacted with a dummy for age 70 or older. Panel B plots the RD estimates at each quantile along with their 95 percent confidence interval. The confidence interval for the ninety-ninth percentile (−989.38, −9.25) is not shown on the graph.

spending is a reduction of 23,500 yen; at the ninety-fifth quantile, it grows to 107,000 yen, a 26 percent decline from the value just below age 70 (see Table I in the online Appendix). These results show that patients at the right tail of the distribution in particular are substantially benefited from lower cost sharing, since the reduction in price at age 70 overwhelms offsetting increases in utilization.

V. Discussion

A. *Implications of Price Elasticities*

I estimated the price elasticities of outpatient and inpatient care separately, since the price schedule of patient cost sharing differs for the two services. The data I use in this paper do not generally allow me to distinguish own- from cross-price effects, because the prices of outpatient and inpatient care both drop by roughly 70 percent at age 70. Thus, the behavioral responses of roughly 10 percent increases in visits for both outpatient and inpatient care may be driven in principle by both effects.[38] However, for some diagnosis groups, cross-price effects should be nearly zero, because for these diagnosis groups nearly all treatment is outpatient or nearly all treatment is inpatient.

Figures K1 and K2 in the online Appendix show RD estimates by diagnosis group (see Table G in the online Appendix for the list) as they relate to the fraction of visits in each group using outpatient or inpatient care at age 69, respectively. In each figure, the RD estimates are generally driven by both own- and cross-price effects. However, the right-hand limit of each figure covers diagnosis groups where nearly all patients use outpatient or inpatient care, respectively. For these diagnosis groups, the RD effects should be driven almost entirely by own-price effects. The bottom line is that these own-price effects are about 10 percent, which is in line with the total effects given in Table 3 and Table 4.

Specifically, the diagnosis group with highest fraction of outpatient care in Figure K1 is hypertensive disease (diagnosis group 26), where the fraction is 94.2 percent. In fact, hypertension, which is included in this diagnosis group, is the leading cause for outpatient visits at the 3-digit ICD9 level (see Table C1 in the online Appendix). The RD estimate for this diagnosis group is 8.2 percent, and it is not statistically different from the overall estimate of 10.3 percent (see panel A in Table 3).

I conduct the same exercise for inpatient care. The diagnosis group with the highest fraction of inpatient care in Figure K2 is benign neoplasm (diagnosis group 15), with a fraction of 78.5 percent. Compared to the result for outpatient care, the claim that nearly all patients are treated as inpatients does not really fit—nearly a quarter of patients in this group are outpatients. The RD estimate for this diagnosis group is 11.7 percent, while the overall estimate is 8.2 percent (see panel A in Table 4). Here, we see that the overall estimate is somewhat lower than the estimate for this diagnosis group (although not statistically significantly different).

Taken together, the results for inpatient and outpatient care show that for diagnosis groups where cross-price effects are a priori small, the overall behavioral effect of the price change (RD estimate) is an approximately 10 percent increase in visits, which is similar to the overall estimate, which includes both cross- and own-price effects. To the extent that the magnitude of own-price effects is similar

[38] Whether outpatient and inpatient care are substitutes or complements is an important, but unsettled, question. Most of the literature, including that pertaining to the RAND HIE, has found that outpatient and inpatient care are complements (e.g., Kaestner and Lo Sasso 2012). A recent study by Chandra, Gruber, and McKnight (2010) is an exception: it found evidence of substitution effects, namely that while the copayment increase in outpatient visits reduces the number of such visits, it leads to an increase in subsequent hospitalizations.

across diagnosis groups, this suggests that own-price effects are the dominant factor in the RD estimates presented in this paper.

B. *Comparison to Prior Literature*

While the elderly are the most intensive consumers of health care, credible evidence on price elasticities for this group is very scarce. It is not clear a priori whether the elderly are expected to have larger or smaller price elasticities of demand for health care services than the non-elderly. The former's price elasticities may be larger if they are poorer or more credit-constrained than the latter, and smaller if their health problems are more severe than those of the latter (Finkelstein 2007).

One notable exception is Chandra, Gruber, and McKnight (2010), which examined the price elasticity of physician office visits among the recipients of a supplemental Medicare insurance policy in the United States. My estimate for outpatient visits (-0.16) is slightly larger than the estimates in Chandra, Gruber, and McKnight (2010) (-0.07 to -0.10). Also, while individuals over the age 62 are excluded from the RAND HIE, my estimate is similar to the estimates found therein for the non-elderly (roughly -0.2).[39] In any case, my estimate is within the range of similar estimates in prior literature.

Nevertheless, I need to view these comparisons with considerable caution since there are many institutional differences between Japan and the United States. For example, the ratio of medical expenditure to GDP was 6.5 percent in 1984 and 8.6 percent in 2008 in Japan, while the corresponding figures in the United States were much higher, namely 10.2 percent and 16.6 percent, respectively (OECD 2012). In fact, in 2008, Japan's ratio was the lowest (twentieth) among the OECD countries. This fact is interesting because given Japan's universal coverage without the need to go through a gatekeeper or a referral system, Japan has the highest per-capita number of physician visits among all OECD countries. Physician consultations per-capita per year are 13.2 in Japan, which are more than three times as large as those in the United States (3.9). Some argue that Japan's low medical spending is achieved through low reimbursements to hospitals, controlled by the stringent national fee schedule (e.g., Ikegami and Campbell 1995).

Interestingly, while there is a five-year age difference between the Medicare population in the United States (those over age 65) and individuals covered under Elderly Health Insurance in Japan (those over age 70), there is some indication that the underlying population may be similar. In fact, in 2008, the life expectancy at birth was 82.7 in Japan and 78.1 in the United States (OECD 2012). Conditional on surviving until the eligibility age for public insurance for the elderly is reached, these figures for life expectancy are not much different.

[39] Also see Aron-Dine, Einav, and Finkelstein (2013), which reexamined the core findings of the RAND HIE, including the well-known elasticity estimate of -0.2. Chandra, Gruber, and McKnight (2014) also found price elasticities of about -0.16—similar to my estimates—for a low-income population sample in Massachusetts.

C. *Cost-Benefit Analysis*

Finally, I conduct a simple cost-benefit analysis associated with the change in the price of health care services at age 70. The details are summarized in Section A2 in the online Appendix. Since I needed to make a number of assumptions, the results from this exercise are mostly speculative. The social cost is the combination of the deadweight loss of program financing and the moral hazard, while the benefit is risk protection against unexpected out-of-pocket medical spending. My estimates suggest that the welfare gain of risk protection from lower patient cost sharing is comparable to the total social cost, indicating that the welfare gain from risk protection may fully cover the total social cost in this setting. One limitation of this welfare analysis is that it does not incorporate welfare gains from 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 lower cost sharing at age 70 may prevent severe future health events, thus improving health in the long run. It is infeasible to estimate long-run effects in this framework, because individuals eventually age into treatment.

VI. Conclusion

Previous studies of patient cost sharing have had difficulty separating its effect on patients from the responsive behavior by medical providers and insurers. In addition, the estimates are confounded by the joint effects of changes in health insurance coverage and benefit generosity. This paper attempted to overcome these limitations by examining a sharp reduction in patient cost sharing at age 70 in Japan, using an RD design. I find that the implied price elasticities are -0.2 for both outpatient visits and inpatient admissions. While I did not detect any effects on health, I did find reduced cost sharing benefits for patients at the right tail of the out-of-pocket distribution, lowering it by roughly 30 percent. One limitation of the paper is that I cannot take long-run health benefits into account in this empirical framework. Estimating the long-term effect of patient 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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