Dynamics of Consumer Responses to Medical Price Changes

By Norihiro Komura and Shun-ichiro Bessho*

How individuals respond to coinsurance rates is fundamental for insurance market design, but most existing estimates speak only to short-run responses. We exploit a unique policy experiment that increased the coinsurance rate some elderly individuals face when they are aged 70-74 but not before or after. Higher coinsurance rates have an immediate and persistent effect on healthcare expenditure, and a sizable share of this effect persists after age 75. We find no evidence that higher coinsurance rates affect health. These results suggest healthcare utilization depends on dynamic factors other than health stock, such as habits.

JEL: I11, I12, I13, I18, J14

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Understanding how people react to medical care prices is critical for de-

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signing health insurance; it guides the optimal structure of patient cost sharing. Existing studies tend to investigate short-term responses,[1] but a cost-sharing based on such responses may be sub-optimal if healthcare utilization is dynamic, contingent upon past behaviors. For example, past utilization and health behaviors can shape health stock (Grossman, 1972). Higher cost sharing reduces utilization immediately, which could exacerbate health problems and increase healthcare demand over time, offsetting the initial decline in utilization (Chandra, Gruber and McKnight, 2010; Fang and Gavazza, 2011). Cost sharing guided by the short-run response should be excessively high because it overlooks adverse impacts on health. Another possibility is habit formation. Higher cost sharing may create habits inducing individuals to use fewer healthcare services in the future. Short-term responses may underestimate the fiscal savings from increased cost sharing. However, the questions of whether healthcare utilization is dynamic and what drives the dynamics remain unanswered, because identifying response dynamics is challenging due to the absence of exogenous price variation over time (Finkelstein, Mahoney and Notowidigdo, 2018).

This study employs a policy change to the coinsurance rate in Japan's public health insurance system, offering a valuable opportunity to address the aforementioned challenge. The system provides a universal coverage with a comprehensive benefit package; private insurance plays a relatively minor role. Patient cost sharing is a fixed-rate coinsurance with a cap on out-of-pocket expenditure but without deductibles.[2]. The Japanese gov-

[1]For a recent review on consumer responsiveness to medical care prices, see Baicker and Goldman (2011), McGuire (2011), Einav and Finkelstein (2018), and Finkelstein, Mahoney and Notowidigdo (2018).

[2]Deductibles are common in health insurance and give rise to dynamic incentives (Klein, Salm and Upadhyay, 2022) The RAND HIE examines dynamic incentives, though not sufficiently because of the small sample size (Aron-Dine, Einav and Finkelstein, 2013;

ernment implemented a policy change in April 2014, resulting in exogenous variation in coinsurance across cohorts over time. Prior to the policy change, individuals below age 70 were subject to a rate of 30%, while those above age 70 were subject to a rate of 10%. Subsequent to the policy alteration, the rate for individuals aged 70-74 and born in or after April 1944 increased from 10% to 20%, while those aged 70-74 and born before April 1944 had a rate of 10%. Upon reaching age 75, the rate for those born in or after April 1944 decreased to 10%, aligning it with the rate for those born before April 1944.

To estimate the longer-run effect of cost sharing on utilization, we use a difference-in-differences (DID) design, defining the treated group as those born in or after April 1944 and the control group as those born before April 1944. The dataset spans 13 years, from 2009 to 2021, allowing for the examination of response dynamics during the five years with varying coinsurance rates and before and after these years when the rates are the same. Outcomes we explore include healthcare spending (outpatient services, prescription drugs, and inpatient services), health outcomes (mortality), and health behaviors (eating, exercise, sleep, smoking, and drinking).

This paper has four main findings. First, lower coinsurance rates increase expenditure for outpatient services and prescription drugs. The magnitude remains constant or slightly increases over the five years. Second, inpatient services are less responsive to coinsurance rates, with a magnitude that is

Einav and Finkelstein, 2018). Aron-Dine, Einav and Finkelstein (2013), Alpert (2016), Guo and Zhang (2019), Klein, Salm and Upadhyay (2022), and Johansson et al. (2023) detect consumer responses to dynamic incentives including annual deductible, nonlinear cost sharing, and future changes in out-of-pocket payments. Brot-Goldberg et al. (2017) and Dalton, Gowrisankaran and Town (2020) do not find consumers respond to dynamic incentives. These studies focus on the changes in cost sharing in the near future, typically in one year, but we focus on the effects of cost sharing in the past.

only about 50% of the outpatient response. These findings align with those of the RAND Health Insurance Experiment (HIE) that find time-invariant consumer responses to healthcare prices (Newhouse, RAND Corporation. Insurance Experiment Group and Insurance Experiment Group Staff, 1993) and smaller effects on inpatient spending (Aron-Dine, Einav and Finkelstein, 2013). Third, the treatment group, who had higher coinsurance rate at ages 70-74, uses fewer outpatient services and prescription drugs after age 75. Fourth, we do not find impacts on health status and health behaviors.

These results, particularly the persistent differences in medical spending after age 75, challenge a simple static model that depends solely on the current factors, such as prices, and predicts no differences in utilization as long as the factors are common to the both groups. They are also inconsistent with dynamic models predicting the offset effect mentioned above, including Fang and Gavazza (2011), who argue better health insurance reduces future healthcare expenditures. Although these models suppose patient cost sharing shifts future healthcare demand through the change-of-health stock, we do not find impacts on health status and do find higher prices today reduce future utilization, against the prediction of those models.[3]

Our results require an explanation of how individuals demand different levels of health care given the same current price, health status, and health behaviors, suggesting dynamic factors other than health stock are necessar-

[3]Chandra, Gruber and McKnight (2010) and Newhouse, RAND Corporation. Insurance Experiment Group and Insurance Experiment Group Staff (1993) test the offset hypothesis examining the effect of the changes in the price of outpatient visits and prescription drugs on inpatient admissions. Chandra, Gruber and McKnight (2010) find an increase in the price of outpatient services and prescription drugs is associated with an increase in inpatient admissions. Newhouse, RAND Corporation. Insurance Experiment Group and Insurance Experiment Group Staff (1993) compare deductible and free plans, both of which fully cover inpatient admissions, and find an increase in outpatient prices is not associated with an increase in inpatient admissions.

ily for describing healthcare utilization. One candidate is habit formation in the sense of Becker and Murphy (1988). Past utilization affects consumer preferences today. Patients with higher cost sharing might gradually become less anxious about and more accustomed to using fewer medical services. Different past cost sharing can lead to different habits and healthcare demand at the same price and health status today.

Our results do not support the offset hypothesis and its policy implication that fiscal savings by higher cost sharing get smaller over time and cost sharing based on short-term responses is excessively high; fiscal savings may be larger in the long run. Moreover, if habit formation drives healthcare utilization, additional policy implications are available. First, optimal cost sharing should depend on parameters governing habit formation, such as how quickly habit stock decays. Similar implications could apply to other instruments. For example, if supply-side factors, such as access to medical institutions, influence future healthcare spending through the change-of-habit stock, optimal supply-side policies should depend on the persistence of such effects. Second, insights in the literature on habit formation might be useful to control the use of medical services. For example, front-loaded incentives produce larger habit stock and greater persistence of behaviors than interventions spread out over time (Hussam et al., 2022).

Our paper is related to studies estimating consumer responsiveness to medical prices. For example, Shigeoka (2014) and Fukushima et al. (2016) use a regression discontinuity design with age as the cutoff to estimate how patients respond to a drop in the coinsurance rate at age 70 in Japan. We also focus on coinsurance rates assigned by age in Japan but exploit their difference by cohort for ages 70-74. Building upon these studies, our study contributes to the literature by estimating the response dynamics to medical prices under favorable conditions, compared with other studies, including the RAND HIE. First, we use a natural experiment from 2014 involving nearly all Japanese individuals aged approximately 70 who require significant healthcare resources. Our study is a more contemporary and larger study, targeting older individuals, than the RAND HIE, which was the RCT of 5,800 individuals aged under 62 years from 1974 to 1981 (Newhouse, RAND Corporation. Insurance Experiment Group and Insurance Experiment Group Staff, 1993; Aron-Dine, Einav and Finkelstein, 2013) Second, because Japan's public insurance system is universal and provides comprehensive benefits, self-selection and attrition bias minimally affect our analysis. Such bias represents a challenge when researchers estimate the effects of cost sharing (Baicker and Goldman, 2011; Ellis, Martins and Zhu, 2017). The RAND HIE is not free from such bias, because individuals can refuse enrollment and participants may drop out of the experiment. Aron-Dine, Einav and Finkelstein (2013) show completion rates were systematically higher for better insurance plans. Third, the difference in coinsurance rates is exogenously determined by the date of birth. Fourth, we observe healthcare utilization over five years, with varying coinsurance rates. This length of time is comparable to the RAND HIE, which created the variation of cost sharing over three to five years, and longer than other studies.[4] Fifth, we observe patient behaviors after the five years of varying coinsurance, when cost sharing is once again equal. If dynamic factors, such as health stocks or

[4]For example, Chandra, Gruber and McKnight (2010) estimates effects of copayments one and a half years later. The studies using an age regression discontinuity design estimate the effect immediately after price changes (Card, Dobkin and Maestas, 2008, 2009; Anderson, Dobkin and Gross, 2012; Shigeoka, 2014; Fukushima et al., 2016; Nilsson and Paul, 2018; Han, Lien and Yang, 2020).

habits, are at play, utilization is unlikely to be the same even if cost sharing converges again. This variation provides a unique opportunity that is not available even with the RAND HIE. We find the persistent differences in utilization after age 75, indicating dynamic elements characterize healthcare utilization. Furthermore, we do not find effects on health and health behaviors, narrowing down the key driver of response dynamics.

In the remainder of this paper, section I describes the Japanese public healthcare system and the 2014 policy change in coinsurance. Section II covers data, and section III explains our empirical strategy. Section IV shows results, and section V concludes the paper with discussions about the driver of our findings and policy implications.

I. Background

A. Japanese Healthcare System

Japan's public health insurance system provides coverage to all citizens.[5] The system offers a comprehensive benefits package that encompasses outpatient services, prescription drugs, and inpatient services. Two types of public insurance are available: employer- and region-based insurance, and many elderly individuals have the latter. All insurers offer the same benefits with the same fees, and therefore, the type of insurance is unimportant for our study. The role of private insurance is relatively insignificant.

Patients are not required to go through a gatekeeper or obtain a referral letter to access medical providers. For instance, patients can visit large hospitals for outpatient care even for less serious conditions.[6]

[5]For a more detailed understanding of the Japanese healthcare system, see Ikegami et al. (2011), Kondo and Shigeoka (2013), Shigeoka (2014), and Fukushima et al. (2016).

[6]Outpatient visits to certain large hospitals, such as university hospitals, may require

The Japanese government establishes a national fee schedule for medical services. The same fee schedule always applies regardless of the patient or medical provider involved. When patients use medical services, they are responsible for paying a portion of the fee (patient cost sharing) at the medical institution, and insurers cover the remainder.

B. *Cost Sharing and the Change Made to Coinsurance in 2014*

Table 1 illustrates patient cost sharing for our sample period. Coinsurance rates, accompanied by caps on out-of-pocket payments, characterize cost sharing, and no deductible exists. The columns titled "CO" report coinsurance rates, which vary according to age; individuals face each rate immediately after their birth month. Those aged 6-69 years have a rate of 30%. Before April 2014, once individuals reached the age of 70, the rate fell to 10%. With the policy change starting in April 2014, the coinsurance rate rose from 10% to 20% for those aged 70-74. Importantly, this new rate of 20% was exclusively applicable to those born in or after April 1944. Conversely, those born prior to April 1944 continued to enjoy the reduced rate of 10%. For individuals reaching the age of 75, the rate fell to 10% for those born in or after April 1944, thereby eliminating the rate difference. Leveraging this variation, we identify effects of coinsurance rates during the five years when the two groups faced different rates between 10% and 20% and after the period when both groups faced the same rate again at 10%.

The coinsurance rate for high-income earners is 30%, regardless of their age. If an individual is categorized as a high-income earner, she did not experience the aforementioned changes in coinsurance rates. Our data can-

a co-payment in the absence of a referral letter.

not distinguish between high-income earners and others. However, only a few patients above age 70, approximately 7%, are classified as high-income earners (Ikegami et al., 2011; Shigeoka, 2014). Accordingly, although we may underestimate demand elasticity when employing the rate of change in the coinsurance rate as the denominator for its calculation, such bias should be minimal.

The cap imposes a limit on monthly out-of-pocket payments, with the amount varying according to age and income. Similar to the coinsurance rate, patients face each cap immediately after the birth month. The columns titled "Total Cap" and "OP Cap" of Table 1 list caps for regular-income earners. For those aged under 70, a cap applies solely to the total payments made by the household. Those aged 70 or above have a lower cap on total household payments and a new cap on individual outpatient payments. As with high-income earners, caps limit the impact of the change in coinsurance rates and result in an underestimation of price elasticity.

The data on the proportion of elderly individuals who reached the cap in our sample are not available. Annual reports of public insurance suggest only a small portion of outpatient visits reached the cap, whereas a non-negligible portion of inpatient admissions did so. For example, in the region-based insurance in 2014, the fraction of claims that reached the cap was 4.5% for all claims (including outpatient services, prescription drugs, and inpatient services) but 44% for inpatient claims[7]. Caps may limit the impact of the change in coinsurance rates, but they only affect inpatient admissions. Note that because the cap setting is slightly more complicated than the aforementioned description, the ratios provided are rough estimates.[8]

[7]For inpatient claims, 3.5 million out of 8.0 million inpatient claims reached the cap.
[8]Shigeoka (2014) argues the cap is high and the probability of reaching the cap is not

II. Data

Healthcare Utilization

We source our data from the National Database of Health Insurance (NDB), which covers almost all Japanese public health insurance claims. We do not have access to micro data, but obtain semi-aggregated data by the month and year of birth. Data are also aggregated over a three-month period from September to November of each year.[9] Our data cover 2009 to 2021. The dataset comprises an annual panel, with a cohort defined by the month and year of birth. The number of observations for a single cohort is 13 (= 13 years $\times$ 1 period (the sum of the three months)). In analysis, we need to exclude observations that have different coinsurance rates from September to November in a given year. For example, a cohort born in October 1944 faced 30% coinsurance in September 2014 (69 years old), but they faced a 20% coinsurance rate in November 2014 (70 years old).

Our data include expenditures and the number of claims. By expenditure, we refer to the total cost of medical services, not out-of-pocket expenditures. We use expenditures and spending interchangeably. Each medical provider issues one claim per month if a patient uses any medical services it provides. Even if a patient visits the same clinic more than once per month, the clinic generates a single claim. We acquire data on the breakdown according to three types of services: outpatient services, prescription drugs, and inpatient services.

large even for inpatient admissions. He estimates the probability using individual-level insurance claim data in 2008, when the same system was applied in the row titled "Before April 2014" in Table 1. His estimate is 13.5% for inpatient admissions at age 69, whereas it is 0% at age 70 because not only the cap but also the coinsurance rate is lower (see Shigeoka (2014), Appendix Table K).

[9] Data for other months are unavailable.

Table 2 shows the descriptive statistics of the monthly medical spending and the monthly number of claims per capita for the three types of medical services by cells defined by three age groups (65.5-69, 70-74, and 75-77.5) and two coinsurance groups (control group and treatment group).[10] The control group consists of cohorts born between April 1941 and March 1944, whereas the treatment group consists of cohorts born between April 1944 and March 1947. We use the same definitions of the two groups throughout the main body of this paper. Table 2 also lists differences in outcomes between the two coinsurance groups for each age group (the row titled "Difference") and differences in the differences compared with the age group of 65.5-69 (the row titled "DID").

The rows titled "control group" and "treatment group" illustrate the level of utilization. For the control group, for example, total spending for patients aged 70-74 is 44.3 thousand yen (428 USD) per capita and month. Outpatient services, prescription drugs, and inpatient services account for approximately 39% (17.2 thousand yen; 167 USD), 21% (9.4 thousand yen; 91 USD), and 40% (17.7 thousand yen; 171 USD) of the total spending, respectively. As for the number of claims, patients aged 70-74 in the control group use around 1.10 medical institutions for outpatient services, 0.71 institutions for prescription drugs, and 0.03 institutions for inpatient services per capita and month.

The Difference and DID rows roughly illustrate the dynamics of consumer response to changes in coinsurance. For outpatient services and prescription drugs, the treatment group uses more than the control group for those aged under 70, whereas the opposite is true for those aged 70-74. Interestingly,

[10]We estimate the population size for each cohort in each time period using the 2015 Census and vital statistics.

the treatment group uses fewer outpatient services and prescription drugs among those aged 75 and over. For inpatient services, the patterns are qualitatively similar but with smaller differences.[11]

Mortality and Health Behavior

As modeled in Grossman (1972), health status and health behavior can drive the dynamics of healthcare utilization. An objective and well-measured health outcome is the mortality rate. We calculate monthly mortality rates per 100,000 people for each cohort, using the universe of death records from January 2004 to December 2021 as in Shigeoka (2014). The dataset comprises a monthly panel, with a cohort defined by the month and year of birth.

Regarding health behavior, we use the micro data from the Comprehensive Survey of Living Conditions (CSLC) by the Ministry of Health, Labour, and Welfare (MHLW). The MHLW conducts the CSLC health-related survey in June every three years, and we use the waves in 2013, 2016, and 2019. We employ the six binary measures: (1) eating regularly, (2) exercising regularly, (3) sleeping enough, (4) not smoking, (5) not drinking, and (6) doing something to improve health.

III. Empirical Strategy

A. Age Profiles

We first plot healthcare utilization and health outcomes against age from 65.5 to 77.5 for the treatment and control groups. To compare different co-

[11]Because our data cover the period between October 2009 and November 2021, the average age of the treatment group is lower than the average age of the control group in columns “65.5-69” and “75-77.5.”

horts at the same age, we control for a set of fixed effects (FEs), as described below.

To analyze health utilization, we regress the log of the outcome on a quadratic function of age, a dummy for age 70 or older, the interaction between a quadratic function of age and a dummy for age 70 or older, a dummy for age 75 or older, and the interaction between a quadratic function of age and a dummy for age 75 or older, all of which are interacted with a dummy for the treatment group, in addition to year FEs and birth-month FEs.

To analyze health outcomes, we regress the mortality rate on a cubic function of age, FEs for the month and year of death, and birth-month FEs to control for death-related events such as earthquakes, seasonality of death, and heterogeneity of death by the month of birth. We choose this specification based on AIC and BIC criteria, although the results hardly change when we employ a similar specification to that used for utilization (replacing year FEs by FEs for the month and year of death).[12]

B. *Difference-in-Differences*

To examine the effects of coinsurance rates more rigorously, we employ a DID by focusing on the policy change in April 2014. The policy change differentiated coinsurance rates between the treatment and control groups during ages 70-74, when the treatment group had a rate of 20% while the control group enjoyed a rate of 10%. Once they reached age 75, both groups faced the same 10% rate.

The regression equation is as follows:

[12]We report the results using the specification similar to the utilization in Appendix Figure 4.

$$Y_{ca} = \sum_a \beta_a D_c T_a + \gamma D_c + \sum_a \delta_a T_a + \theta_t + \theta_{bm(c)} + \varepsilon_{ca}, \tag{1}$$

where Y_{ca} is the outcome of the cohort born in c at age bin a, in years. We use the log of medical spending per capita, the log of the mortality rate, and a binary outcome for health behavior. D_c is a dummy for the treatment group, and T_a is an indicator for age bin a. The bin $a = 70.5$ includes $70.0 \leq$ age in months < 71.0, and we define other bins similarly, except for the bin $a = 77.5$, where $77.0 \leq$ age in months < 77.5[13]. The omitted category is 69.5. θ_t is year FEs for utilization and health behavior and FEs for the month and year of death for mortality. $\theta_{bm(c)}$ is birth-month FEs. ε_{ca} is the unobserved component. The standard errors are clustered at the level of cohort.

Our coefficients of interest are β_as. For $a \in [65.5, 68.5]$, the estimates of β_a tell us whether the trends in outcomes prior to the treatment differ between the two groups who faced the rate of 30%. For $a \in [70.5, 74.5]$, they capture differences in outcomes under different coinsurance rates (20% vs 10%). Finally, for $a \in [75.5, 77.5]$, they represent differences in outcomes after the coinsurance rates returned to the same at 10% for both groups.

Our key identification assumption is parallel trends: the treatment group would have used the same level of healthcare services and enjoyed the same level of health outcomes without the policy change in April 2014, conditional on a dummy for the treatment group, time FEs, and the control variables.

[13]Those born in April 1944, the oldest cohort in the treatment group, were 75.5 years old in October 2021.

This assumption appears reasonable because the two groups are neighboring cohorts and the Japanese government did not decide the target of higher coinsurance rates based on utilization or health status of cohorts, as far as we know. We can test the parallel-trends assumption indirectly by assessing whether β_as are zero prior to the assignment of different coinsurance rates.

IV. Results

A. Outpatient Services

Figure 1 illustrates the age profiles and DID estimates for healthcare expenditures by type of medical services. Panel A shows the age profiles on outpatient service spending for the treatment and control groups. Four points are worth mentioning. First, below the age of 70, the levels and trends of the two groups are similar. This finding is consistent with the parallel-trends assumption. Second, at age 70, medical spending jumps up discontinuously for both groups. The rise of the treatment group, whose rate decreased from 30% to 20%, is smaller than that of the control group, whose rate decreased from 30% to 10%. Third, for ages 70-74, when the two groups experience different rates, the difference in utilization appears to be constant or to diverge slightly. Fourth, at age 75, when the coinsurance rate for the treatment group drops to 10%, they increase outpatient expenditure, but the difference between the two groups does not fully disappear. The observed differences appear to narrow gradually after age 75. The difference in coinsurance at ages 70-74 has a lasting effect even after the rates become uniform.

Panel B illustrate the DID estimates, where the horizontal axis represents ages and the vertical axis represents the estimates of β_a multiplied by 100 to facilitate interpretation as percentage changes. We explain our results for the following three periods. First, below age 70, all point estimates are small and statistically insignificant, demonstrating the differences in utilization between the two groups did not change over time. The results support the parallel-trends assumption of DID. Second, for ages 70-74, the outpatient service utilization of the treated group was 4% lower than the control group. This finding corresponds to an elasticity of -0.06.[14] The effects appear to increase during this period, but the differences in estimates for ages 70-74 are not statistically significant. Third, above age 75, when both groups faced the same coinsurance, the treatment group used the outpatient services 2.5% less than the control group, and this effect is statistically significant. The difference in outpatient spending between the two groups decreased gradually and became statistically insignificant at age 77.5. The cohorts who face higher prices in the earlier period utilize fewer outpatient services even after the coinsurance rates of the two groups become the same, and a sizable share of the effect of coinsurance rates persists.[15]

[14] This is the arc-elasticity dividing 0.04 by $(0.1-0.2)/((0.1+0.2)/2)$. Our arc-elasticity may be underestimated because of the cap on out-of-pocket expenditure.

[15] Appendix Figure 1 shows the age profiles and DID estimates for total medical spending. The results also suggest the effect of coinsurance persists at ages 75 and above.

Table 1—: Patient Cost Sharing in Japan

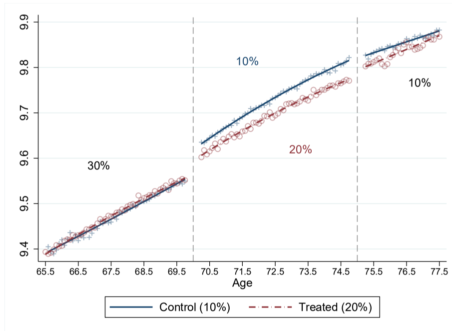
	Below Age 70		Between Ages 70-74					
			Born before Apr 1944			Born in or after Apr 1944		
	CO (%)	Total Cap in JPY K [USD]	CO (%)	Total Cap in JPY K [USD]	OP Cap in JPY K [USD]	CO (%)	Total Cap in JPY K [USD]	OP Cap in JPY K [USD]
Before Apr 2014	30	80.1+	10	44.4	12.0	–	–	–
		[774+]		[429]	[116]		–	–
Apr 2014-July 2017	30	80.1+	10	44.4	12.0	20	44.4	12.0
		[774+]		[429]	[116]		[557]	[135]
Aug 2017-July 2018	30	80.1+	10	57.6	14.0	20	57.6	14.0
		[774+]		[557]	[135]		[557]	[135]
After July 2018	30	80.1+	10	57.6	18.0	20	57.6	18.0
		[774+]		[557]	[174]		[557]	[174]
			Age 75 or Above					
			CO (%)	Total Cap in JPY K [USD]	OP Cap in JPY K [USD]			
Before Apr 2014			10	44.4	12.0			
				[429]	[116]			
Apr 2014-July 2017			10	44.4	12.0			
				[429]	[116]			
Aug 2017-July 2018			10	57.6	14.0			
				[557]	[135]			
After July 2018			10	57.6	18.0			
				[557]	[174]			

Note: CO stands for the coinsurance rate (%). The rate for high-income earners above age 70 remains 30% instead of 20% or 10%. Two types of caps on out-of-pocket payments exist. First, caps on the total out-of-pocket expenditure are imposed at the household level (Total Cap). Second, caps on the out-of-pocket expenditure for outpatient services are imposed at the individual level (OP Cap). Caps are expressed in thousand JPY (JPY K) and in US dollars [USD] converted by the PPP rate in 2015 (1USD = 103.47JPY) calculated by the World Bank. Caps for those below age 70 are set by the following formula: $80.1 + (\mathrm{TC} - 267) \times 1\%$, where TC means household's total medical costs per month; thus, out-of-pocket spending for those aged below 70 increases by 1% as TC exceeds 267 JPY K. Caps are set on a monthly basis. Caps in this table are for regular-income earners.

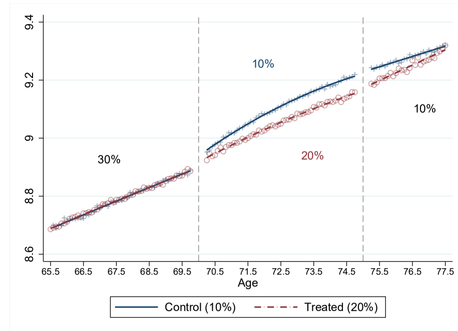
Table 2—: Descriptive Statistics

	Spending in JPY K [USD]			Number of Insurance Claims		
	65.5-69	70-74	75-77.5	65.5-69	70-74	75-77.5
A. Outpatient Services						
control group	11.85	17.24	20.27	0.79	1.10	1.23
	[114.5]	[166.6]	[195.9]			
treatment group	13.06	17.21	20.16	0.85	1.05	1.16
	[126.2]	[166.3]	[194.9]			
Difference	1.20	-0.03	-0.10	0.07	-0.05	-0.07
	[11.6]	[-0.3]	[-1.0]			
DID	–	-1.23	-1.31	–	-0.11	-0.14
		[-11.9]	[-12.6]			
B. Prescription Drugs						
control group	6.30	9.39	10.85	0.52	0.71	0.83
	[60.8]	[90.8]	[104.9]			
treatment group	6.64	8.79	10.23	0.54	0.69	0.78
	[64.1]	[84.9]	[98.9]			
Difference	0.34	-0.60	-0.62	0.01	-0.02	-0.04
	[3.3]	[-5.8]	[-6.0]			
DID	–	-0.95	-0.96	–	-0.04	-0.05
		[-9.1]	[-9.3]			
C. Inpatient Services						
control group	12.35	17.65	23.08	0.024	0.032	0.039
	[119.4]	[170.6]	[223.0]			
treatment group	12.78	17.84	22.74	0.024	0.030	0.036
	[123.5]	[172.4]	[219.8]			
Difference	0.42	0.19	-0.34	0.000	-0.001	-0.003
	[4.1]	[1.8]	[-3.2]			
DID	–	-0.23	-0.76	–	-0.001	-0.003
		[-2.3]	[-7.3]			

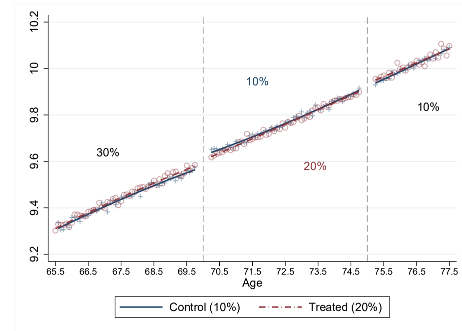
Note: This table summarizes (1) monthly medical spending per capita in thousand JPY (JPY K) and in US dollars [USD] converted by the PPP rate in 2015 (1USD = 103.47JPY) calculated by the World Bank and (2) the monthly number of health insurance claims per capita by age (65.5-69, 70-74, and 75-77.5) and by medical services (outpatient services, prescription drugs, and inpatient services). The rows titled "control group" and "treatment group" show the average of the outcomes, where the former includes those born between April 1941 and March 1944, and the latter includes those born between April 1944 and March 1947. The rows named "Difference" represent the value of the row "treatment group" minus the value of the row "control group." The rows named "DID" represent the value of the row "Difference" in the columns named "70-74" or "75-77.5" minus the value of the row "Difference" in the column named "65.5-69."



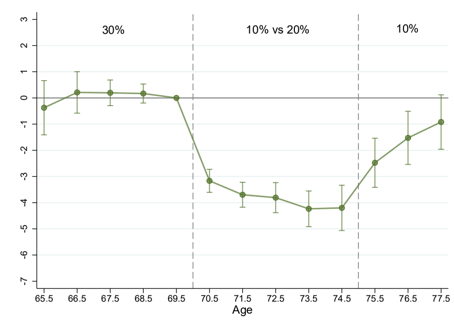
Panel A. Profiles (Outpatient Services)



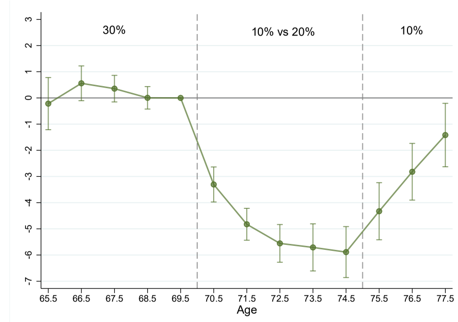
Panel C. Profiles (Prescription Drugs)



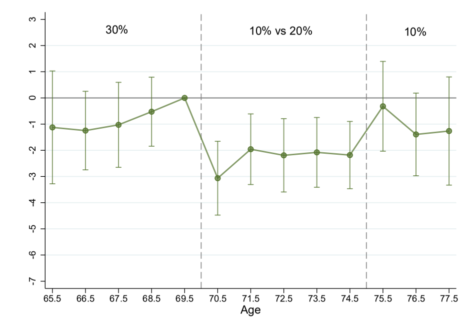
Panel E. Profiles (Inpatient Services)



Panel B. Estimates (Outpatient Services)



Panel D. Estimates (Prescription Drugs)



Panel F. Estimates (Inpatient Services)

Figure 1. : Results. Medical Spending by Type of Services

Note: We define the control group as those born between April 1941 and March 1944 and the treatment group as those born between April 1944 and March 1947. Panels A, C, and E (Profiles) are age profiles plotting the log of outcomes (spending on outpatient services, prescription drugs, and inpatient services, respectively) per month and capita, excluding year fixed effects (FEs) and birth-month FEs, against age from 65.5 to 77.5 for the control group (solid line in blue) and for the treatment group (dashed line in red). Because each marker represents the average of utilization over three months (from September to November), the age in months in these panels represents the one in October, and we exclude markers around ages 70 and 75. We use quadratic fits below age 70 and between ages 70 and 74, and linear fits above age 75. In Panels B, D, and F (Estimates), each marker denotes the estimate of β_a in equation (1) with a 95% confidence interval. We employ age bin 69.5 as the reference. We multiply estimates and standard errors by 100 so that they can be interpreted as percentage changes. Standard errors are clustered at the cohort (the month and year-of-birth) level.

B. Prescription Drugs

Panels C and D of Figure 1 illustrate the age profiles and DID estimates for expenditures on prescription drugs. Our findings are similar to those for outpatient services. Notably, the treated group utilizes fewer prescription drugs after age 75, when both groups are subject to the same coinsurance.

As shown in Panel D, the differences in prescription drug spending between the treatment and control groups at ages 70-74 are 3% to 6%, respectively, and generally greater than those of outpatient services. This difference indicates spending on prescription drugs is more price responsive, perhaps because the use of prescription drugs involves more adjustment margins. Individuals can request from physicians a larger (smaller) amount of medicine considering remaining stock at home, may choose new drugs (generics), might not obtain medicines by using prescriptions provided by outpatient visits, and can alternatively use over-the-counter medicines. By contrast, patients may not have many alternative options to see a doctor to deal with their symptom(s).

C. Inpatient Services

Panels E and F of Figure 1 show the age profiles and DID estimates for expenditures on inpatient services. The age profiles in Panel E indicate the levels and trends of the treated and control groups are similar at all ages. We find statistically significant responses of inpatient services to the change in the coinsurance rate for ages 70-74 (Panel F). The responses are relatively small, approximately 2%, compared with the ones for outpatient services (4%) and prescription drugs (5%-6%).

The age profiles in Panel E show slight increases observed at age 70 for the control group and at age 75 for the treatment group, both of which experienced a reduction in the coinsurance rate to 10% (see Appendix Table 2 for the results of a formal regression discontinuity test). The surges suggest patients exhibit relatively large responses to price changes instantaneously, yet the responses do not persist for an extended period.

Overall, our findings indicate a smaller impact on inpatient admissions. Our results are intuitive and consistent with those of the RAND HIE, which found small and statistically insignificant responses to inpatient service prices, with the exception of the free plan (Aron-Dine, Einav and Finkelstein, 2013). Inpatient services may be less responsive to the coinsurance rate because the admissions decision involves much less discretion. Additionally, the out-of-pocket spending cap may attenuate the responses to the coinsurance rates, because if the out-of-pocket spending is sufficiently higher than the cap, a decrease in the coinsurance rate does not change the out-of-pocket spending. As described in section I, a non-negligible portion, possibly more than 40%, of inpatient admissions reached the cap.

D. Mortality and Health Behaviors

Panels A and B of Figure 2 illustrate the age profiles and DID estimates for mortality. Our dependent variable is the log of the monthly mortality rate (per 100,000 people). The age profiles in Panel A demonstrate a lack of a discernible difference between the treatment and control groups at any given age. The DID estimates in Panel B, multiplied by 100, show estimates are small and that positive and negative estimates are mixed. The implemented increase in coinsurance rates may result in either a decrease or an increase in mortality rates by 1%. The confidence intervals are not wide, between

-4% to 4%, and all estimates are statistically insignificant. These results suggest higher coinsurance rates do not have large and systematic impacts on mortality rates.

Table 3 shows DID estimates for health behaviors, wherein the positive coefficients indicate the treatment group engages in the healthy behavior more by facing higher prices at ages 70-74. Similar to mortality, estimates are small and positive and negative estimates are mixed. Standard errors seem relatively large, 1-2 percentage points, and most estimates are statistically insignificant at the conventional level. We do not believe any major or systematic changes in health behaviors would explain the impact on the use of medical services that we have discovered in this paper.

Our results are not consistent with the offset hypothesis based on Grossman-type health stock models. For example, Fang and Gavazza (2011) argue as follows. First, a reduction in the price of health care increases healthcare utilization. Second, the increased healthcare utilization improves health status. Third, healthier people use fewer healthcare services. The results on health and health behavior in this subsection do not support the second step. The persistent differences in utilization after age 75 we show in the previous subsections are against the third step. In addition, our findings of no positive effects on health behavior are not consistent with the ex-ante moral-hazard hypothesis that those who face a high coinsurance rate engage in healthy behaviors, decreasing healthcare utilization.[16]

[16]Appendix Figures 2 and 5 and Appendix Table 1 show our results on healthcare spending, mortality, and health behaviors are robust to controlling for a linear or cubic function of age in month and to a narrower or wider sample cohort choice. Appendix Figure 3 shows results on utilization measured by the number of claims are similar to the spending results.

Table 3—: Results. Estimates (Health Behavior)

	(1) Eating Regularly	(2) Doing Exercise	(3) Sleeping Enough	(4) Not Smoking	(5) Not Drinking	(6) Doing Something
Age 70	0.77	1.36	-0.62	0.77	1.47	0.35
	(0.90)	(1.11)	(1.09)	(1.14)	(1.03)	(0.55)
Age 71	0.59	1.06	0.63	0.21	0.57	-0.02
	(0.92)	(0.97)	(1.15)	(1.07)	(0.99)	(0.51)
Age 72	0.13	1.82	0.96	0.81	-0.31	1.61
	(0.60)	(1.29)	(2.28)	(1.43)	(0.93)	(0.58)
Age 73	0.96	2.60	0.11	-0.38	-0.22	1.27
	(1.07)	(1.38)	(2.32)	(1.79)	(1.16)	(0.73)
Age 74	-0.02	1.90	0.34	0.48	-0.36	2.02
	(1.00)	(1.46)	(2.30)	(1.69)	(1.25)	(0.74)
Sample Mean	74.4	50.8	46.2	49.9	30.2	94.3
Observations	129,303	129,303	129,303	129,303	129,303	129,303

Note: This table shows the estimate of β_a in equation (1) with the standard error. We employ age bin 69.5 as the reference. We multiply estimates and standard errors by 100 so that they can be interpreted as percentage changes. Standard errors are clustered at the cohort (the month and year of birth) level. Column (1)-(6) use different measures of health behavior. Column (1) uses a binary measure that takes the value of 1 if respondents eat meals regularly. Column (2) uses a binary measure that takes the value of 1 if respondents exercise. Column (3) uses a binary measure that takes the value of 1 if respondents get enough sleep. Column (4) uses a binary measure that takes the value of 1 if respondents do not smoke. Column (5) uses a binary measure that takes the value of 1 if respondents do not drink. Column (6) uses a binary measure that takes the value of 1 if respondents do something to improve health.

V. Discussion and Conclusion

This paper investigates the dynamics of healthcare utilization, using a natural experiment that differentiated the coinsurance rates at ages 70-74 for neighboring cohorts. Four main findings emerge. First, a higher coinsurance rate decreased outpatient and prescription drug spending, and the effects appeared to grow for five years during ages 70-74. Second, the cohorts that enjoyed lower coinsurance rates at ages 70-74 also had higher healthcare utilization even at ages 75 and older. Third, we find smaller responses of inpatient care. This result is intuitive, given that an inpatient admission is a less discretionary event than an outpatient visit or drug prescription. Fourth, we do not detect effects on mortality and health behavior. The cap on out-of-pocket payments may obscure the effect of coinsurance rates on inpatient admissions and mortality.

Our results appear to require some dynamic element (other than health stock and health behavior) to explain how healthcare demand can differ under the same current price, health status, and health behavior. One hypothesis is habit formation. Becker and Murphy (1988) assume consumer preferences today rely on consumption in the past. Those who face high coinsurance rates use fewer healthcare services, and such behavior becomes their habit. According to a body of research examining habit formation in the context of health-related behaviors (e.g.,Charness and Gneezy (2009), Hussam et al. (2022), and Agüero and Beleche (2017)), people might form habits in healthcare utilization behavior. Habit formation may apply to outpatient services and prescription drugs because these services are generally associated with mild disease and depend on discretionary decision-making, in contrast to inpatient admissions. Another explanation is attention, whereby individuals could only gradually be aware of a price change. In our case, only the treated group experienced a change in coinsurance at age 75, making their utilization different from the control group.

Policy implications are as follows. Our results are inconsistent with the offset hypothesis and its policy implication that the fiscal cost of generous health insurance gets smaller over time, and cost sharing based on short-term responses is higher than optimal. Moreover, more implications emerge depending on the driver of our findings. If it is habit formation, setting cost sharing should refer to parameters governing habit formation, such as the persistence of habits. In addition, the habit-formation literature might help policymakers encourage the appropriate use of medical services. For example, front-loaded incentives are more effective than interventions spread out over time, because the former generate larger habit stock (Hussam et al., 2022). Policymakers could create strong habits by offering generous incentives for the use of beneficial and preventive care for relatively younger individuals. Alternatively, if attention drives our findings, policymakers need to find a way to make coinsurance rates more noticeable in order to obtain the intended impacts of policy changes. Because policy implications are partly contingent on the exact mechanism behind our findings, as discussed, further investigation on mechanisms behind the persistent effect on utilization is necessary.

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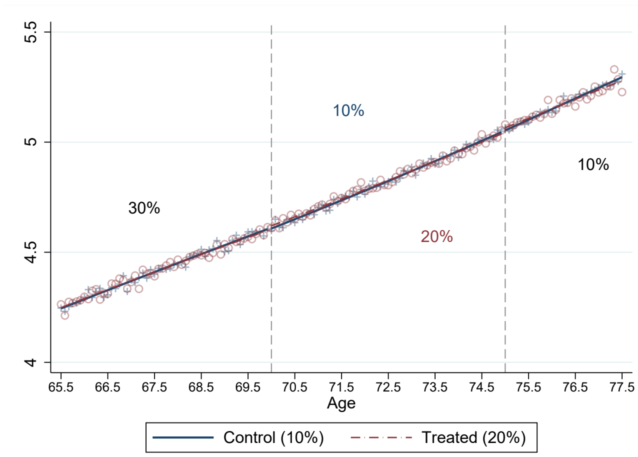
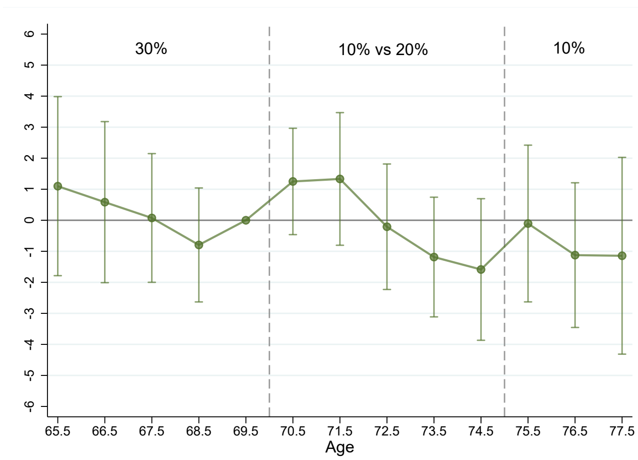


Panel A. Age Profiles (Mortality)



Panel B. Estimates (Mortality)

Figure 2. : Results. Mortality

Note: We define the control group as those born between April 1941 and March 1944 and the treatment group as those born between April 1944 and March 1947. Panel A (Age Profiles) plots the log of death per month per 100,000 people, excluding fixed effects (FEs) for month and year of death and birth-month FEs, against age from 65.5 to 77.5 for the control group (solid line in blue) and for the treatment group (dashed line in red). We use quadratic fits below age 70 and between ages 70 and 74, and linear fits above age 75. In Panel B (Estimates), each marker denotes the estimate of β_a in equation (1) with a 95% confidence interval. We employ age bin 69.5 as the reference. We multiply estimates and standard errors by 100 so that they can be interpreted as percentage changes. Standard errors are clustered at the cohort (the month and year-of-birth) level.