Patient Cost-sharing and Health Care Utilization among Children*

Toshiaki Iizuka†
The University of Tokyo

Hitoshi Shigeoka ‡
Simon Fraser University
and NBER

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Abstracts: This paper examines the effect of the patient cost-sharing on health care utilization among children. By exploiting the drastic expansion of subsidy for child health care in Japan, we find that reduced cost-sharing significantly increases utilization of outpatient care. The arc-price elasticity is relatively constant around -0.1 for all ages 7-14, which is smaller than the conventional estimate for adults. We also provide suggestive evidence that most increases in utilization reflect moral hazard. In fact, increases in the "beneficial" outpatient care for the Ambulatory Care Sensitive Conditions (ACSCs)—diagnoses for which proper and early outpatient treatment reduces subsequent avoidable admissions—does not lead to reduce hospitalization by ACSC. Furthermore, the reduced cost-sharing increases inappropriate use of antibiotics. Taken together, our finding at least suggests that the benefit of such generous subsidy for child health care is unclear.

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† Faculty of Economics, The University of Tokyo, 7-3-1 Hongo, Bunkyo-ku, Tokyo 113-8654, JAPAN. Email: iizuka@e.u-tokyo.ac.jp

‡ Corresponding author: Department of Economics, Simon Fraser University, 8888 University Drive, Burnaby, BC V5A1S6, CANADA, and NBER. Email: hitoshi_shigeoka@sfu.ca

1. Introduction

A large body of evidence indicates that childhood health conditions have long-lasting impacts on individuals' outcomes, suggesting a large return in programs aimed at improving children's health (Heckman *et al*. 2013; Ludwig and Miller 2007). The government acknowledges such social return of investment on child health, and therefore public health insurance often provides generous support for child health care. For example, the federal government in the US regulates the patient cost-sharing level —the fraction of medical costs for which the beneficiary is responsible out of the pocket—in the Children's Health Insurance Program (CHIP).[1] Similarly, child health care is heavily subsidized in many countries.[2]

The generous subsidy—and hence lower patient cost-sharing—however, face clear tradeoff. On one hand, it may increase the beneficial care which may be forgone without subsidy. On the other hand, it may increase unnecessary health care services, resulting in waste of governmental resources. Furthermore, once the universal coverage is achieved, almost only demand-side approaches by the government to contain the medical cost is to fine-tune the level of patient cost-sharing. Thus, to help determine the appropriate level of patient cost-sharing, there is an urgent need for knowledge on how patient cost-sharing affects utilization among children.

Credible evidence on the price sensitivity of health care utilization is very scarce in general, and especially for children. Most of past studies on price responsiveness are concentrated among the elderly.[3] Children may show distinct utilization pattern than adults since the nature of diseases are more acute (e.g., asthma) than those for the elderly (e.g., diabetes), and children (and often mothers) may seek health care regardless of prices. Furthermore, because of longer life expectancy, the return from the medical intervention can be larger for child health than adult health.

So far, most of our knowledge on children's price sensitivity to health care and its impact on health come from the RAND Health Insurance Experiment or HIE (Manning *et al*. 1987; Newhouse 1993), which demonstrates little difference in child health across various cost-sharing plans. However, this study is conducted 30 years ago and thus may not be directly applicable to the situation today,

[1] See Baicker and Goldman (2011) for the summary of literature on patient cost-sharing. Hossein and Gerard (2013) documents that the level of patient cost-sharing has been increased in many high income countries between 2000 and 2010.

[2] For example, health care for children below 3 is exempted from payment in Taiwan, and similarly those below age 6 are subsidized in Korea.

[3] See for example, Chandra *et al.* (2010), Card *et al.* (2004, 2008, 2009) and Chay *et al.* (2012) for the US, and Shigeoka (2014) and Fukushima *et al.* (2016) for Japan.

especially to countries other than the United States. The notable exceptions are recent papers by Han *et al*. (2016) which examine the effect of patient cost-sharing at age 3 in Taiwan in regression discontinuity framework, and Nilsson and Paul (2015) which examine similar question for children in Sweden.

This paper examines the effect of the patient cost-sharing on health care utilization among children. We exploit the drastic expansion of subsidy for child health care, which substantially differ by municipality, age, and time in Japan. This very unique regional variation in subsidy generosity enables us to estimate the price elasticity at different ages in a difference-in-difference framework. We further investigate whether the increases in utilization mainly reflect just moral hazard or include beneficial and preventive care by examining the health outcomes and utilization patterns in various dimensions.

Our paper contributes to the literature on demand for health care among children in several ways. First and most importantly, our unique regional variation in the level of patient cost-sharing, which is always tied to age of children, enables us to estimate price elasticity even at each age in months from 7-14 years-old. The price elasticity at various ages can be informative for policy makers to design more flexible patient cost-sharing schedule. Second, we can examine whether children *asymmetrically* respond to the changes in price of health care since patient cost-sharing sometimes increase, and other times decrease even *at the same age* in our setting. These asymmetry responses, if any, may have some policy implications as the price sensitivity estimated from just one direction of price change may not be applicable if the policy maker wants to implement the policy with the opposite direction of change in patient cost-sharing.

Third, the unique institutional background in Japan offers a clean setting to arguably isolate behavioral parameter of patient from influences by insurers and medical providers. As for insurances, there is no adverse selection as everyone is insured because of universal coverage. In addition, there are no restrictions by insurers on patients' choices of medical providers such as managed care in the US. Therefore, patients can freely choose any medical providers and thus have direct access to specialist care without going through a gatekeeper or a referral system. As for medical providers, they cannot price discriminate patients as physician and hospital's payments are solely based on the same national fee schedule regardless of insurance type or age of patients. Relatedly, our insurance claim data *inherently* include price information which allows us to easily quantity the monetary values of (excess) utilization unlike the case in the US which is notoriously known for the complex price schedule.

Finally, our unique panel dataset which observe *both* outpatient and inpatient spending for the same individual in the same data over time allows us to examine the possibility of the "offset" effect—whether beneficial *outpatient* care prevents avoidable *inpatient* admissions in the future. For example, if

patients respond to price increase in outpatient care by reducing the outpatient spending for preventive care and, consequently, need to be hospitalized later, then saving through reduction in outpatient spending can be eventually "offset" by the subsequent increase in costly inpatient admissions.[4] To our knowledge, there is no study which examines the substitution effects of outpatient and inpatient care for children except for RAND HIE. To summarize, our study may arguably entail broader policy implications than past studies on patient cost-sharing among children.

The findings of this paper are summarized as follows. First, we find that children are also price sensitive to health care but probably less so than adults. The overall arc-elasticity among children is relatively constant throughout ages 7-14, and is roughly -0.10, which is smaller than conventional estimate of -0.20 for non-elderly in RAND HIE (Manning *et al*. 1997). Second, we find the evidence of asymmetric responses to the direction of price changes. Overall, the price sensitivity is higher when the price of health care goes down than goes up. However, this result masks the heterogeneity of asymmetric responses by procedure categories. The medication—which accounts for roughly as much as half of total outpatient spending—shows the opposite pattern: children spend substantially *more* on medication when the price becomes lower than spend less when price becomes higher. This result is plausible since one can easily stock medicine unlike other type of health services such as non-surgical procedure.

Third, we also provide the suggestive evidence that most increases in utilization reflect moral hazard rather than beneficial care. While we find that reduced patient cost-sharing also increases the "beneficial" care such as the Ambulatory Care Sensitive Conditions (ACSCs)—diagnoses for which proper and early outpatient treatment reduces subsequent avoidable admissions—they does not seem to reduce hospitalization by ACSC. More generally, we do not find any evidence of offset effects: substantial increases in outpatient spending do not accompany with the reduction in inpatient spending. Furthermore, the reduced patient cost-sharing increases inappropriate use of antibiotics and costly after-hour visits. Finally, we do not find any evidence of positive effect on child mortality. Taken together, our finding at least suggests that the benefit of such generous subsidy for child health care is unclear.

This paper is related to large literature on health insurance and child health (e.g., Gruber and

[4] In fact, whether outpatient care is a substitute or complement for inpatient care is an important but unsettled question in health economics. Most of the literature has found that outpatient and inpatient care are complements (e.g., Manning *et al.* 1997; Kaestner and Lo Sasso 2015) except for a study by Chandra *et al.* (2010) which 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 among the elderly in California. See also Trivedi *et al.* (2010).

Dafny 2005; Currie and Gruber 1996; Finkelstein *et al.* 2012).[5] However, these papers examine the effect of health insurance provision per se (extensive margin) such as expansion of Medicaid rather than the effect of changes in health insurance generosity (intensive margin). The provision of health insurance may entail large income effects. In addition, the beneficiaries of these studies are often limited to a particular population (i.e., low income mothers and their children). Furthermore, in countries with the universal coverage, one limited demand-side approach on containing the medical cost is to increase patient cost-sharing through deductibles, coinsurance, and copayments.

The rest of the paper is organized as follows. Section 2 provides the institutional background in subsidy to child health care. Section 3 describes the data, and Section 4 presents our identification strategy. Section 5 reports our main findings, and Section 6 examines health outcomes. Section 7 reports additional analysis, and Section 8 concludes.

2. Background

The unique institutional background in Japan offers several advantages in separating the behavioral parameter of patient since the roles of insurers and medical providers are relatively restricted. First of all, Japanese citizens are mandatorily covered by health insurance so there is no adverse selection. Patients have unrestricted choices of medical providers; for example, patients have direct access to specialist care without going through a gatekeeper or a referral system. Also, patients can go to either hospitals or clinics for outpatient visits, unlike in the United States, where those who lack insurance use hospitals for primary care. There is also no limit on the number of visits. Furthermore, patients cannot be price discriminated by physicians as their payments are solely based on the same national fee schedule regardless of insurance type or age of patients.[6]

Patient cost-sharing—share of cost paid by patients—has been set nationally at 30% except for the following two populations: young children and the elderly. Specifically, the cost-sharing is set at 20% for children below age 6, and at 10% for the elderly over age 70 (c.f., Shigeoka 2014; Fukushima *et al*. 2015).[7] The insurer pays the remaining fraction of expenses until the beneficiary meets the stop-loss

[5] In addition, recent studies examine the long-term effects of Medicaid in the US, either through expansion (Brown *et al*. 2016; Wherry *et al*. forthcoming; Miller and Wherry 2017) or through introduction (Goodman-Bacon 2016a, 2016b).
[6] This prevents cost shifting (Cutler 1998), where medical providers charge private insurers higher prices to offset losses from the beneficiaries of government-funded health insurance.
[7] The central government lowered the coinsurance rate from 30% to 20% for children below age 3 in October 2002, and expanded the policy to age 6 (till the start of primary school) in April 2008.

(also known as the maximum out-of-pocket), and then the insurer pays all expenses above the stop-loss.[8] Unlike a typical health insurance plan in the United States (Brot-Goldberg *et al.* 2017), there is no deductible in Japan.

Importantly, each municipality often additionally provide a subsidy for child health care. It is called Medical Subsidy for Children and Infants (MSCI), and it drastically expanded in last decade. Children (and hence mothers) receive a new insurance card, which is different from the regular insurance card that everybody possesses. Crucially, this card is only effective for the municipalities of residence, thus we can identify the level of subsidy (and hence level of patient cost-sharing) by which municipality a child currently lives. Children present the card at medical institutions to receive the discount.

3. Data

3.1. Explanatory variables: subsidy for child health care

Since the MSCI is set by each municipality, the level of patient cost-sharing depends on 1) where children live (municipality); 2) when children visit the medical providers (time); and 3) how old children are at the time of visit (age). The variations in these three dimensions are the sources for our identification strategy.

For each municipality, we collected the following information on subsidy for outpatient care for 10 years from April 2005 to March 2015 at each age in months from ages 0 to 18 years-old: 1) age till the subsidy is offered; 2) the level of patient cost-sharing (equivalently the level of municipal subsidy); 3) whether the subsidy is refund or in-kind; and 4) whether there are any household income restrictions for subsidy eligibility.[9] We explain each component in detail below.

First, the generosity of subsidy is largely reflected by the maximum age till which the subsidy is provided. Second, the level and the form of patient cost-sharing (equivalently the level of municipal subsidy) differ by municipality. For example, while some municipalities take the form of coinsurance rate such as 10%, 15% or 20%, while other municipalities take the form of copayment, such as 200, 300,

[8] The supplementary health insurance that covers the remaining out-of-pocket spending virtually does not exist in Japan probably because the stop-loss prevents the catastrophic loss of income upon illness. The probability of reaching stop loss in our sample is as low as 0.067%.

[9] We also collected information on subsidy for *impatient* care. However, most of the municipalities had already covered inpatient care till age 15 (the end of junior high school), and thus there is not much variation in eligibility of subsidy for impatient care. In fact, while we examine the effect of subsidy for inpatient care on impatient spending, we do not detect any meaningful results (results available upon request). Therefore, we focus on subsidy for outpatient care throughout this paper to save space.

or 500 JPY (roughly 2,3 or 5 USD) per visit. Third, the method of payment for subsidy can take two different forms: refund vs. in-kind. If subsidy is provided in the form of in-kind, children only need to pay the discounted amount set by the municipalities and no further action is necessary. On the other hand, if subsidy is provided in the form of refund, patients pay full amount of coinsurance /copayment at the medical institutions, and file the required documents to municipal office in order to get refunded. While the amount of patient cost-sharing can be identical in two cases as long as the children (of mothers) submit the required document, patients may prefer in-kind to refund because of opportunity cost, and if households are credit-constrained.[10] Finally, some municipalities impose income restrictions on eligibility for the subsidy. While we cannot identify the individuals who are ineligible for subsidy since income is not available in our insurance claim data, the fraction of municipalities which has income restriction is very small in our data. In our empirical model, we include a dummy for income restriction.

One contribution of this paper is that we newly collected detailed information on subsidy at each age×time×municipality level (where both age and time are measured in months).[11] Since such information was not formally collected at either prefecture or national level, we hand-collect through a variety of sources and directly verify the information collected with each municipality. For practical reasons, we limit data collection to municipalities in the six largest prefectures in Japan which result in 323 municipalities.[12] According to national statistics, these six prefectures cover as much as 44.9% of children ages 0–15. While our data is clearly not nationally representative, one benefit of restricting to these large prefectures is that municipalities are probably more comparable, which may be useful for our difference-in-difference identification strategy.

Figure 1 plots the share of municipalities in our subsidy data by the maximum eligibility age for

[10] For example, suppose the coinsurance rate is reduced from 30% to 10% due to the municipality's subsidy. In case of refund payment, the patient still pays full 30% at the medical institutions, but then is reimbursed the difference between the payment and coinsurance rate, which is 20%. On the other hand, in case of in-kind payment the patient only pays 10% at the medical institutions, and no further actions are necessary.

[11] Collecting such information at each age×time×municipality cell is indeed challenging as no formal collection of such data was done at national level. While some prefectures collect such subsidy information once a year from all municipalities in the prefecture (e.g., every April), we need information on *monthly* basis for our identification strategy. We use the varieties of sources to collect such information such as municipality web page, local newspaper, and municipal ordinance. We finally verify with each municipality that our information collected is accurate by either sending letters or calling municipal offices. This gives us another reason to limit our sample to large prefectures since such information for this long period (10 years) is not well kept in record in small municipalities.

[12] This includes municipalities that merged during this sample period. The estimates are essentially the same if we exclude them since these municipalities tend to be very small (results available upon request). There are total of 47 prefectures, and 1,719 municipalities in Japan as of January 2015.

the subsidy during April 2005–March 2015 (10 years) among 165 municipalities, which is used in this paper as explained later in Section 3.3. Note that this figure reflects the compositional changes of municipalities as the number of municipality increases at the later period in our data. Importantly, within the municipalities, the subsidy expansion is always monotonic, that is, there are *no* single municipalities that *lower* the maximum age during this period (April 2005-March 2015).

The graph clearly indicates that the subsidy expanded rapidly to upper ages. For example, while none of the municipalities provide subsidy till age 15 (end of junior high school) in April 2005, this number reaches nearly 80% of the municipalities by March 2015, the end of our sample period. The spike in April 2008 is explained by the fact that the central government has expanded the eligibility age for national-level subsidy (i.e., 20% coinsurance rate) from age 3 to 6 (till the start of primary school). While Figure 1 clearly shows that most of the municipalities in our sample have already had covered till age 6 by the time, this national-level subsidy expansion definitely eases the budgetary burden on municipalities as the central government financially covers more than before. For this reason, we see the highest number of municipality-level subsidy expansions in April, 2008 to ages higher than age 6.[13] While the exact reasons for such rapid expansion of MSCI are not fully understood, a few justifications mentioned in the literature are to attract more young couples with children for tax revenues, boost low fertility rate, and combat recent increases in child poverty (Bessho 2012).[14] We discuss potential endogeneity of subsidy expansions in Section 4.2.

3.2. Outcome variables: JMDC data

Our outcome data come from the Japan Medical Data Center (JMDC), which collects and analyzes administrative insurance claims data on behalf of large corporate health insurers.[15] Since parents of the children in the data work for large firms, our sample does not include children with extremely low household income like those who receive public assistance. As of November 2015, the JMDC claims

[13] See Appendix Figure A1 for the precise timing of all policy changes among 165 municipalities in our final sample. While the policy changes are rather concentrated in April which is the start of the fiscal/school year in Japan, there are reasonable variations in the timing of implementation across months. This figure also demonstrates that we need a *monthly* level data on both explanatory variable (subsidy level) and outcome variable (health care utilization).

[14] Shigeoka and Watanabe (2017) examine whether political cycle and spatial competitions across municipalities affects the expansion of subsidy for child health care (work in progress).

[15] Japan's public health insurance system consists of two parallel subsystems: employment-based health insurance and the National Health Insurance (NHI), which is a residential-based system that covers anyone who lives in the covered area and who does not have employment-based health insurance (e.g., employees of small firms, self-employed workers and their families, the unemployed, and the retired elderly). See Kondo and Shigeoka (2013) for details.

database contains more than 3 million enrollees. The unit of data is monthly as the reimbursement to medical institutions occurs on a monthly basis in Japan.

JMDC data consists of administrative enrollment data, and claim data. For each person, the enrollment data comprise patient ID, gender, as well as age and municipality of residence. The age and municipality of residence in each month are crucial in our study as the level of patient cost-sharing are uniquely determined by them. The claim data report the monthly spending, including prescription drug spending.[16] Specifically, the claim data contain the year and month of the visit, and detailed information on the medical services provided including diagnoses, types of services, quantity of each service, and fees charged for each service. For example, when a prescription drug was dispensed, we have detailed information on the drug, including the name, ATC code, retail price, and quantity, along with when (in months) the drug is prescribed.

There are a few advantages of this data. The biggest advantage is that the data observe both outpatient and inpatient care, *and* also follow the same individual over time, which allows us to test the possibility of the "offset" effect—whether beneficial *outpatient* spending prevents avoidable *inpatient* spending in the future. In contrast, the outpatient and inpatient data are often separated in the US as the physicians and hospitals are normally distinct entities. Relatedly, the claim data in Japan inherently includes price information, since the national fee schedule sets uniform prices for each procedure which is applied to all patients (regardless of insurance type and age), which enables us to easily quantity the monetary values of (excess) utilization.

Our dataset is constructed in the following way. We provide the subsidy information we hand-collected to JMCD, and JMCD merges it with their insurance claim data in-house by municipality and year-month, and return it to us where municipality ID and patient ID are scrambled for confidential reason. Thus, we cannot examine the heterogeneity by the characteristics of the municipality (e.g., average household income, or average level of maternal education) as municipality ID is scrambled. Another drawback—albeit is usual for insurance claim data—is that the data do not include any individual characteristics (except for gender and age of children) such as maternal education and household income.

[16] The data do not, however, contain dental claims, and inpatient food and housing costs. The latter is small since the length of stay is short unlike the case of elderly.

3.3. Sample restriction

We impose the sample selection in the following ways. Our data cover the period of 10 years between April 2005 and March 2015 (120 months). We focus on ages 7-14 years-old (96 months) since as shown in Figure 2 we do not have many observations without subsidy below age 7 and with subsidy above age 15. This happens because majority of the municipalities (81.3%) have already covered till age 6 (the start of primary school) at the beginning of our sample period, and also most of the municipalities do not cover beyond age 15 (the end of junior high school) at the end of our sample period. Therefore, we limit our sample to 6-15 years-old (one year-old wider on both sides of ages of interest) to identify the effect of patient cost-sharing at ages 7-14.[17]

Finally, we limit the sample to 165 municipalities which only have either 0% (full subsidy) or 30% (no subsidy) of coinsurance rate during our sample period for following reasons. First, while the non-linearity itself is an important empirical question, our sample does not have many other coinsurance rates (such as 10%, 20%) other than 0% or 30%. This indicates that the non-linearity—even if successfully estimated—comes from a very particular set of municipalities. Second, the other patient cost-sharing takes the form of copayment (e.g., 100 JPY per visit) which requires us to convert it to the fraction of total medical expenditures to be comparable with coinsurance. However, estimating the counterfactual number of monthly visits unavoidably introduces measurement errors.[18] Finally, the transitions of "30% to 0%" and "0% to 30%" in subsidy status are by far the top two variations which account for two-thirds (66%) of all the combinations of changes in patient cost-sharing at municipality-age-time cell (including the change from coinsurance to copayment or vice versa). In fact, we still maintain as many as 3,727 changes in subsidy status at municipality-age-time cell, which is the level of the variation for identification in our empirical analysis.[19]

Table 1 reports selected summary statistics of our sample separately for municipality, individual, and year-month level in Panels A, B, and C respectively. Panel A shows that each municipality is observed on average 76.6 months, and 68.5% of the municipalities have at least one subsidy expansion.

[17] While we control for the subsidy status at ages 6 and 15 in the regressions, we do not report these estimates to save space as they are very noisy.

[18] We need to compute the counterfactual monthly visits for age a (in months), time t (in months), and living in municipality m. To do so, while we can keep two of them fixed, we need to relax the remaining one. For example, we may want to use the frequency of visits at age a and time t, but from other municipality m' or the frequency of visits at age a, municipality m, but from different time t'.

[19] One technical issue with limiting our sample to municipalities with 0% coinsurance rate (i.e., free care) is that as the price starts from zero, the arc-elasticity (which is widely used in health economics) does not reflect the prices as discussed later.

Importantly as discussed in Section 4.1, the source of variation for identification does not simply come from the *expansion* of subsidy but also *expiration* of the subsidy at certain age. At the individual level (Panel B), we have total of 63,590 individuals, and each individual is observed on average 36.2 months, and 21.8% experience at least one subsidy expansion. Gender is well balanced (48.8% is female).

Finally, Panel C reports some key variables at the unit of our analysis (year-month). We have a total of 2,303,335 year-month over the sample period of 120 months. Almost all the subsidy is provided in the form of in-kind (99.9%), and very few municipalities impose income restriction for eligibility criteria (1.5%). In terms of utilization, 40.7% of children make at least one outpatient visit per month on average, and spend 6.09 thousand JPY (roughly USD60.9) per month including zero-spending, and 14.95 thousand JPY (roughly USD149.5) conditional on visit. Children visits outpatient care by 0.83 times per month including the months with zero visits, and 2.04 per month conditional on at least one visit in the month. Inpatient admission for this age range is very low (only 0.28%) but it is much more costly when admitted (406.52 thousand JPY or USD4065.2) than outpatient visits.

As for the outcome variables, we mainly focus on two outpatient outcomes to save space: a dummy which takes one if there is at least one outpatient visit per month (an outpatient visit dummy, hereafter), and monthly outpatient spending (outpatient spending, hereafter) measured in thousand JPY (roughly USD10). In fact, total outpatient spending in each month can be decomposed as:

$$\text{Outpatient spending} = 1[\text{Visit} > 0] \times \text{frequency of visits} \times \text{spending per visit} - [1]$$

Thus, an outpatient visit dummy ($1[\text{Visit} > 0]$) broadly captures the extensive margin and the outpatient spending captures the intensive margin of health care utilization. In the online appendix, we include the results from frequency of visits, and spending per visit.

3.4. Raw data

The simple plots of raw data already reveal interesting patterns. Panel A of Figure 3 plots the raw mean of outpatient outcomes for children who live in municipalities with subsidy (labeled “subsidized”) and those who live in the municipalities without subsidy (labeled “no subsidy”). The graph on the left in Panel A presents the age profile of an outpatient visit dummy. While both age profiles show the declining trends in age since the average health may improve at older ages, the line with subsidy is always higher than the line without subsidy by 8-11 percentage points. The graph on the right in Panel A also demonstrates a similar pattern for outpatient spending. The average outpatient spending is roughly 2 to 3 thousand JPY (USD20-30) higher when children are subsidized compared to those without subsidy,

or higher by 40-60%, which is substantial. While this figure does not account for compositional changes in the sample, the main message from the more detailed analysis below is similar. Panel B of Figure 3 plots the age profile of impatient outcomes, which are aggregated in age in years as inpatient admissions are very rare event. In contrast to outpatient outcomes, we see no clear difference in inpatient admissions and inpatient spending with and without subsidy.

4. Identification Strategy

4.1. Asymmetry in patient cost-sharing level

Before presenting our estimation equation, it is important to clarify the two sources of variations used in our identification strategy. Importantly, the subsidy (hence patient cost-sharing) is uniquely determined by municipality, age, and time. Put differently, each cohort (defined by municipality and birth in months) experience own price schedule as long as they do not move across municipalities. Figure 4 illustrates one example of patient cost-sharing schedule in a particular municipality. By drawing the two separate price schedules for two cohorts that are just born one month apart in this municipality before and after subsidy expansion, we illustrate our unique source of variations in subsidy at different ages and concept of asymmetry in price changes.

Panel A shows the price schedules of two cohorts *before* subsidy expansion. The solid line draws the price schedule for cohort born in July 2001, and the dotted line draws it for cohort in June 2001, a month before the previous cohort. Suppose that the maximum eligibility age is set at the beginning of primary school (or roughly age 6). Both cohorts enjoy the free care since they are born. Ten when the cohorts starts the primary school in April 2008, which is the start of school year, the cohort born in July 2001 is 6 and 8 months old, while the cohort born in June 2001 is 6 and 9 months old.[20] Above this age, children have to pay national level of 30% coinsurance rate.

Suppose that policy is implemented in October 2009 which expands the maximum eligibility age for free care from the start of primary school (or roughly age 6) to end of junior high school (or roughly age 15). Panel B shows the price schedules after subsidy expansion. Importantly, any cohorts that are between ages 6 and 15 are benefited from this subsidy expansion at different age in months. The cohort

[20] In Japan, School Education Law (SEL) obliges parents to send their children to primary schools as soon as their children turn six years of age before the school starting month, which is April. Thus, the school cohort is defined by those born in April to those born in March next year. This school entry rule is strictly enforced in Japan and, thus, students rarely delay or start primary school earlier than the scheduled date (more than 99% enforcement rate). See Shigeoka (2015) for more details about the school starting rule in Japan.

born in July 2001 (solid line) pays 30% from age 6 and 8 months to age 9 and 3 months at the time of policy change in October 2009. Thanks to subsidy expansion, the cohort enjoys the free care from 9 and 3 months to age 15 and 8 months when the cohort graduates from junior high school. Again, once the cohort reaches age 15 and 8 months, they pay at the national level of 30%. On the other hand, price schedule for the cohort born a month before (dotted line) is shifted by one month to the right as the cohort is one month older than previous cohort when he enters primary school, when policy change happens, and when he graduate from junior high school. For example, this cohort is age 9 and 4 months at the time of policy change instead of age 9 and 3 months.

There are two important points to make from this simple illustration. First, since the subsidy expansion and expiration can affect the price schedule of each cohort at different ages, we can estimate the price elasticity for very broad age ranges (age 7-14). Second, we can examine whether there are *asymmetric* responses to the price of health care: subsidy expansion (labeled "better") that lowers the price from 30% to 0%, as well as subsidy expiration (labeled "worse") that raises the price from 0% to 30%. Since our data include the variation in which cost-sharing changes in both directions even *at the same age*, we can examine whether elasticity differs by the direction of the changes. If asymmetric price responsiveness is observed, it implies that we should be careful in making inference from one direction of price change (e.g., price decreases) to the other direction of price change (e.g., price increases) in the counterfactual policy analysis. Out of 3,727 changes in subsidy status at municipality-age-time, 2,429 changes (65.2%) are the expansion of the subsidy ("better") while 1,294 changes (34.8%) are the expiration of the subsidy ("worse").

4.2. Identification strategy

We exploit the unique variation in subsidy for child health care across municipality, age, and time combined with the longitudinal claim data in difference-in-difference framework. Specifically, our basic estimation equation is:

$$Y_{iamt} = \alpha + \sum_{a=85}^{179} \beta_a subsidized_{iamt} + \gamma X'_{mt} + \delta_a + \varphi_m + \pi_t + \theta_i + \varepsilon_{iamt} \text{ –[2]}$$

where Y_{iamt} is the health care utilization by a child i whose age is a (measured in months), in time t (measured in months), and living in municipality m. $subsidized_{iamt}$ is a dummy, which takes one if the child health care is subsidized at age a. δ_a, φ_m, π_t are fixed effects for age, municipality, and time respectively. Also, η_i is the individual FE which captures the unobserved time-invariant characteristics of patients and also address the compositional changes of individuals in the unbalanced panel data. We

also control for two time-varying municipality variables: a dummy that takes one if subsidy is in-kind rather than refund and a dummy takes one if there exists income restriction on eligibility for the subsidy recognizing the lack of the statistical power. Standard errors are clustered at the municipality level to account for serial correlation in the error terms within the municipalities.

While we can technically estimate β_a (treatment effects in age in months a), as shown later, the monthly estimates β_a are relatively stable within age in year. Thus, we instead estimate β_A (average treatment effect of age A where A is integer) as below to obtain more statistical power without losing much information:

$$Y_{iamt} = \alpha + \sum_{A=7}^{14} \beta_A \{subsidized_{iamt} \times 1(Age\ A)\} + \gamma X'_{mt} + \delta_a + \varphi_m + \pi_t + \theta_i + \varepsilon_{iamt} \quad -[3]$$

where $1(Age\ A)$ is an indicator variable which takes one if the person is more than age A but less than age $A+1$ (or equivalently $1(Age\ A) = 1(A \leq a < A+1)$).[21] Our coefficients of interest are series of β_A (A=7-14).

For our main analysis, we focus on the sample of non-movers (95.4% of the sample), and we specifically discuss the inter-municipality migration in Section 6.5. For non-movers, since φ_m and θ_i are identical, our final estimation equation is written as[22]:

$$Y_{iamt} = \alpha + \sum_{A=7}^{14} \beta_A \{subsidized_{iamt} \times 1(Age\ A)\} + \gamma X'_{mt} + \delta_a + \pi_t + \theta_i + \varepsilon_{iamt} \quad -[4]$$

To measure the price responsiveness, we report arc-elasticity for each age in year A defined by

$$arc\text{-}elasticity_A = \left(\frac{Q_{1A}-Q_{0A}}{Q_{0A}+Q_{1A}}\right) \Big/ \left(\frac{P_{1A}-P_{0A}}{P_{1A}+P_{0A}}\right) = \left(\frac{\beta_A}{Q_{0A}+Q_{1A}}\right) / \left(\frac{0-0.3}{0.3+0}\right) = -\frac{\beta_A}{Q_{0A}+Q_{1A}} \quad -[5]$$

where Q_{1A}, Q_{0A} are quantity or health care utilization for subsidized (denoted by 1), and unsubsidized (denoted by 0), and P_{1A}, P_{0A} are defined in the same way for prices. β_A is the estimates from equation [4]. One caveat of arc-elasticity is when the starting price is zero, arc-elasticity does not reflect the prices as they cancel out (i.e., no P_{1A}, P_{0A} in equation [5]). We nonetheless report these statistics as they are widely used and also comparable to estimates from RAND study, which also have the plan for free care. Alternatively, to account for starting from zero price, Brot-Goldberg *et al.* (2017) report the *semi* arc-elasticity which is defined by

[21] We construct age in year dummies in this way so that age corresponds to the school cohort. In Japan, age 6 corresponds to just before start of primary school, age 12 corresponds to the last year of elementary school, age 15 corresponds to the last year of junior high school.

[22] For non-movers, since time=birth+age, the municipality and birth defines the cohort, which experiences exactly the same patient cost-sharing schedule.

$$\textit{semi arc-elasticity}_A = \left(\frac{Q_{1A}-Q_{0A}}{Q_{0A}+Q_{1A}}\right)/\left(\frac{P_{1A}-P_{0A}}{2}\right) = \left(\frac{\beta_A}{Q_{0A}+Q_{1A}}\right)/\left(\frac{0-0.3}{2}\right) = \textit{arc-elasticity}_A/0.15 \quad -[6]$$

Thus, *semi* arc-elasticity is simply arc-elasticity divided by 0.15.

In addition, we can exploit the two opposite directions of changes in subsidy status to examine the asymmetric price responses of children to health care. Thus, a subsidized dummy in equation [4] is decomposed to two sets of dummies as:

$$Y_{iamt} = \alpha + \sum_{A=7}^{14} \beta_A^{Better}\{subsidized_{iamt} \times 1(Age\ A) \times better_{iamt}\} + \sum_{A=7}^{14} \beta_A^{Worse}\{subsidized_{iamt} \times 1(Age\ A) \times worse_{iamt}\} + \gamma X'_{mt} + \delta_a + \pi_t + \theta_i + \varepsilon_{iamt} \quad -[7]$$

where $better_{iamt}$ is an indicator equal to zero before subsidy is not available, and equal to one in all period after the subsidy is introduced, even if the subsidy expires. Similarly, $worse_{iamt}$ is an indicator variable equal to zero before subsidy expires, and equal to one in all years after the subsidy expires, even if the subsidy becomes available.[23] Because of the way that the indicators are defined, the interaction of a subsidy dummy with $better_{iamt}$ tests the effect of *decrease* in patient cost-sharing on utilization, relative to individuals in other municipalities without subsidy, after the subsidy is expanded, relative to the period when the subsidy was not available; on the other hand, the interaction of a subsidy dummy with $worse_{iamt}$ tests the effect of *increases* in patient cost-sharing on utilization, relative to individuals in other municipalities with subsidy, after the subsidy is expired at the age, relative to the period when the subsidy was available.

For the analysis of asymmetric responses, we report semi *point*-elasticity instead of *arc*-elasticity as we exactly know the starting quantity, and also the direction of the changes. Specifically, we report

$$\textit{semi point-elasticity}_A^{Better} = \left(\frac{dq}{q}\right)/dp = -\left(\frac{\beta_A^{Better}}{Q_{0A}}\right)/0.3 \quad -[8]$$

$$\textit{semi point-elasticity}_A^{Worse} = \left(\frac{dq}{q}\right)/dp = \left(\frac{\beta_A^{Worse}}{Q_{1A}}\right)/0.3 \quad -[9]$$

where β_A^{Better} and β_A^{Worse} are estimates from equation [7] above. For arc-elasticity and semi point-elasticity, standard errors clustered at municipality are bootstrapped with 200 repetitions.

The identifying assumption in our difference-in-difference framework is that there are no unobserved municipality specific changes that (1) are correlated with changes in subsidy in the municipality and (2) are correlated with municipality specific changes in the health care utilization.

[23] This way of constructing variables only makes sense when the changes of subsidy status within the individual are less than or equal to two. Thus, we remove 921 individuals (1.45%) who experience more than two changes in subsidy status. We confirm that our baseline estimates are almost identical once we remove these individuals from the sample (results available upon request).

Since the level of variation for both age and time are measured in months and thus there are as many as 3,727 changes in subsidy level at municipality-age-time cell, it is difficult to imagine that such omitted variables are likely to influence our estimates. Nonetheless, it is still possible that the municipality with different pre-trend health care utilization may implement the subsidy expansion at the different timing, which may bias our estimates. For example, the municipalities that are improving financial condition are more likely to implement the subsidy expansion, and the better financial condition at the municipality may have direct impact on health care utilization through income effects, our estimates can be upward biased.

To account for such concern, we take at least three approaches. First, we conduct the event-study that normalize the data to the timing of the policy change, and examine whether there is any systematic differences in pre-trend outcomes between treated and control municipalities before the subsidy expansion. Second, we add municipality time trend and even municipality-by-year month FEs, to examine the robustness of our baseline estimates. Finally, we limit our sample to only those individuals which experienced at least one change in subsidy status. Since we only exploit the *timing* of the changes in subsidy status, we can to some extent mitigate the concern that individuals in the treatment and control municipalities can be different. In short, our results are robust to these different specifications.

5. Basic Results

5.1. Graphical evidence

Before presenting the regression results, we provide the graphical evidence on changes in outpatient outcomes in the form of an event-study. More concretely, we replace the subsidized dummy in estimation equation [4] by a series of dummy for each month ranging from 12 months prior to the change in subsidy status to 12 months after the change (T=-12 to +11, where T=0 is the change in subsidy status).

Figure 5 present the results of event-study for an outpatient visit dummy (Panel A), and outpatient spending (Panel B) separately for subsidy expansion (“better”) and subsidy expiration (“worse”). The reference month is three months before the change in subsidy status (T= -3). Note that the scales of y-axis are set the same within the panels so that two figures for opposite directions of subsidy changes are visually comparable.

There are a few important points to make from these graphs. First, it is reassuring that there does not seem to show any pre-trend as the estimates are mostly close to zero before the changes in subsidy

status. Importantly, this result addresses the concern that the municipalities that expand the subsidy may have different trend in health care utilization than the municipalities that does not.

Second, the utilizations measured by an outpatient visit dummy and outpatient spending are clearly influenced by the level of patient cost-sharing. The utilization abruptly increases from $T=0$ on when the subsidy is expanded (graphs on the left), and the utilization shows the opposite pattern when subsidy expires (graphs on the right).

Third, there is substantial intertemporal substitutions as we see huge drops for subsidy expansion ("better") and surge for subsidy expiration ("worse") just before $T=0$. Children rush to visit outpatient care and spend more just before the subsidy is over, and also conversely delay outpatient visits and spending till the subsidy becomes available. This pattern reveals that children (and hence mothers) are aware of the changes in subsidy status, and incorporate these changes in their behavior. Furthermore, the intertemporal substitution is much larger in case of subsidy expiration ("worse") than that of subsidy expansion ("better"). On one hand, the existence of the intertemporal substitution is rather surprising as children's diseases tend to be more acute than those of adults. On the other hand, the fact that the magnitude of such intertemporal substitution is larger for subsidy expiration than subsidy expansion indicates that most of the diseases are acute and thus cannot delay too much. Since intertemporal substitution seems to be concentrated within two months from $T=0$, we exclude two months of the data from both sides ($\pm$2months or 4 months in total) throughout the paper. In fact, as shown later, the estimates and hence elasticity are barely affected after removing more than 2 months.

Finally and perhaps most importantly, the effect of patient cost-sharing seem to be permanent rather than transitory since the level of the utilization after $T=0$ does not revert to the level before $T=0$. Appendix Figure A2 expands the window of the event-study to $\pm$24 months (instead of $\pm$12 months) from the subsidy change. It is reassuring that the estimates are relatively stable even 24 months (2 year) after the change in subsidy status. This result justifies the use of the difference-in-difference strategy as the effect of the patient cost-sharing on utilization is not temporary, and thus we do not need to rely on observations only around $T=0$. Technically, we can do the event-study for each age recognizing the loss of the statistical power. Appendix Figures A3 show the event-study for age 9 and age 12, respectively. The fact that we observe opposite signs of changes in utilization for subsidy expansion and expiration even *at the same age* indicates that we are unlikely to capture something that is particular at that age (e.g., finishing elementary school at age 12).

5.2. Main results

Figure 6 demonstrates the graphical presentation of estimating equation [4] which plots β_A for each age (A=7-14) in the upper half, and the corresponding *arc-elasticity*$_A$ from equation [5] in the lower half.[24] Panels A and B present the results of an outpatient visit dummy, and outpatient spending respectively. Table 2 reports the estimates and the resulting arc-elasticity that correspond to Figure 6.

Panel A of Figure 6 reveals that the estimates (β_A) on an outpatient visit dummy are relatively stable across ages 7-14. With subsidy, the chance of seeing a doctor at least once per month increases by 6-8 percentage points compared to the chance without subsidy. As the mean of the outpatient dummy without subsidy among age 7-14 is 0.32, these increases translate into 19-25% increases in the probability of visits per month. The corresponding arc-elasticity, which is graphically presented at the bottom half of Figure 6, indicates that arc-elasticity ranges from -0.07 to -0.10. While caution is necessary to compare the elasticity across the countries and different periods, the arc-elasticity we find is smaller than the conventional estimate of -0.20 for non-elderly from the RAND HIE (Manning *et al*. 1997).

Panel B of Figure 6 shows that estimates of outpatient spending slightly declining as one gets older. With subsidy, the outpatient spending increases by 1.38 thousand JPY (13.8 USD) at age 7, and by 0.998 thousand JPY (9.98 USD) at age 14 than those without subsidy. These estimates correspond to 18-31% increases from 4.49 thousand JPY, which is the mean value for ages 7-14 without subsidy. Since the mean outpatient spending—which is the denominator of arc-elasticity—is relatively stable across ages, arc-elasticity ($= -\beta_A/(Q_{0A} + Q_{1A})$) is largely governed by the size of β_A. Hence, arc-elasticity on lower right is also slightly declining in ages, which goes from -0.12 at age 7 to -0.08 at age 14.[25]

Since the total number of children aged 7-14 in Japan is roughly 8.8 million according to the Population Census in 2015 (Statistics Bureau 2015), if the free care is expanded to all the municipalities, the back-of-the-envelope calculation suggests that the annual outpatient spending increases by 9.77 billion JPY or 81.2 million USD.[26]

Table 2 also shows that the estimates on a dummy for in-kind payment, and a dummy for income

[24]See Appendix Figure A4 which plots the monthly estimates (β_a) instead of yearly estimates (β_A). In both outcomes, since monthly estimates are relatively stable within age in year, we do not lose much information by reporting β_A.

[25] Appendix Figure A5 shows the sensitivity of our estimates to the size of the "donut-hole". The estimates and hence elasticity are barely affected after excluding 2 months from both sides of T=0. The results are summarized in Appendix Table A2.

[26] We multiply each β_A by the number of children in the age A in 2015 and sum them up. Then, we convert all figures at 120.39 yen (JPY) to the dollar (USD), the average exchange rate in March 2015.

restrictions take the expected sign: in-kind payment increases the outpatient visits by 4.7 percentage points, which is more than half the size of the estimates in patient cost-sharing from 30% to 0%, and decrease by 2.0 percentage points when there is income restriction on eligibility for the subsidy.[27] For outpatient spending, the signs of these coefficients are also as expected, but not statistically significant at the conventional level.

We also report the results on frequency of outpatient visits and the outpatient spending per visit in Appendix Figure A6, and the corresponding estimates in Appendix Table A1. The estimates for frequency of visits follow similar age patterns as that of outpatient spending. Interestingly, while both spending and frequency of visits increase, the average spending *per visit* is also positive and statistically significant at the conventional level. This result suggests that the increases in outpatient spending are not purely driven by the increases in the frequency per se but also the increase in spending per visit.

5.3. Robustness

We subject these results to a series of robustness checks. Critically, the results in Figure 6 (and Table 2) on the causal effects of patient cost-sharing to be robust across all specifications considered. Appendix Figure A7 plots the estimates of key robustness checks together with our baseline estimates. The corresponding results are summarized in Appendix Tables A4 and A5 for an outpatient visit dummy and outpatient spending where Columns (1) in both tables present the estimates from our baseline model of equation [4] for the ease the comparison.

First, we address the potential concern that our control group—namely municipalities without changes in subsidy—exhibits a different time trend than municipalities with subsidy. For example, municipality with better economic environments may be more likely to expand the subsidy, and also the higher income leads to more health care utilization. Since the estimates in event-study before $T=0$ seems to be reasonably smooth and close to zero, this does not seem to be a serious concern. Nonetheless, we conduct several robustness checks to address this concern. First, we add the municipality specific time trend in Column (2) and even time-by-municipality FEs (where time is measured in months) in Column (3) to account for the time-varying municipality characteristics that are correlated with both the expansion of the subsidy and the health care utilization. The latter is especially stringent as these fixed effects capture any municipality specific policy change or event in a particular month such as income transfer or other subsidies. Row (i) in Appendix Figure A7 shows that the estimates are almost

[27] This result is consistent with Zhong (2011) which show that subsidy in the form of in-kind increases the health care utilization compared to subsidy in the form of refund. This point is not well studied in health economics.

unchanged.

Another way to account for the potential endogenity is to restrict the sample to only those individuals which experienced at least one change in subsidy status, thereby, dropping individuals which remain either subsidized or unsubsidized throughout the sample period. Importantly, this identification strategy only exploits the *timing* of the changes in subsidy status. In this way, we can to some extent mitigate the concern that individuals in the treatment and control groups are different. Row (ii) in Appendix Figure A7 shows that the estimates are somewhat noisier due to smaller sample but are qualitatively similar.

Third, we collapse the data at age×time×municipality cells, which is the level of variation, to partially account for zero spending at the individual-monthly level. Then, we estimate analogous to equation [4] where the number of observations in each cell is used as a weight. Row (iii) in Appendix Figure A7 shows the results. It is reassuring that the estimates from underlying individual micro data are almost identical to the cell level analysis.

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5.4. Estimates from asymmetric responses

So far, we show that children are also price sensitive to health care but arguably not so much as the elderly. In this subsection, we investigate whether children asymmetrically respond to price of health care by exploiting the unique variation of price changes in opposite directions. This asymmetry, if it exists, may have some policy implications as the price sensitivity estimated from just one direction of price change may not be simply applicable if the policy maker wants to implement the policy with the opposite direction of change in patient cost-sharing.

Figure 7 demonstrates the graphical presentation of estimating equation [7] which plots β_A^{Better} and β_A^{Worse} for each age (A=7-14) in the upper half, and the corresponding *semi point-elasticity*$_A^{Better}$ and *semi point-elasticity*$_A^{Worse}$ from equations [8] and [9] in the lower half. Panels A and B present the results of an outpatient visit dummy, and outpatient spending, respectively. Table 3 reports the estimates and the resulting semi point-elasticities that correspond to Figure 7.

It is reassuring that the estimates take completely opposite signs for opposite direction of changes in subsidy status, and both are statistically significant at 1% level at any age ranges. For an outpatient dummy, two things are worthy of mentioning. First, the estimates for an outpatient dummy are nearly constant at each age for both directions of subsidy changes. Second, the absolute values of estimates for both directions are nearly in the same magnitude. Since the denominator of the semi point-elasticity for

"worse" (Q_{1A}) is larger than that of "better" (Q_{0A}) for an obvious reason while the numerators (β_A^{Better} and β_A^{Worse}) are similar as shown in the graph, the semi point-elasticity is larger in magnitude for subsidy expansion ("better") than subsidy expiration ("worse").

Interestingly, we do not find much difference in semi point-elasticity when the outcome is outpatient spending. While the magnitude of estimates for "worse" is larger than that of "better", the denominator for "worse" is also larger than that of "better". Thus, the resulting semi point-elasticity is similar in both directions. However, as shown in the next subsection, this result masks the large heterogeneity by procedure categories.

5.5. Estimates by procedure categories

In this subsection, we investigate the possibility that asymmetric responses we document in the previous section may mask heterogeneity by procedure categories. There are six broad categories: medication, consultation fees, laboratory tests, non-surgical procedure, surgical procedure, and others. Appendix Table A4 presents summary statistics of procedure categories. Column (2) shows that conditional on visit, consultation fees is charged at 94% of the time, and fees on medications are charged at 85% of the time.[28] Fees for laboratory tests and non-surgical procedure follow them, and are charged at 47% and 40% of the time. In terms of outpatient spending, Column (5) shows that the medication is by far the largest category of outpatient spending that accounts for nearly half (48.8%) of total spending. Consultation fees (23.6%), laboratory tests (17.3%), and non-surgical procedure (5.8%) are next three categories, and combined with medication, these four categories account for 95.5% of total outpatient spending. Thus, in what follows, we focus on these four main categories.

Figures 8-1 & 8-2 provide the graphical presentation of equation [4] separately for these four procedure categories on an outpatient dummy and outpatient spending, respectively.[29] The corresponding tables can be found in Appendix Table A5. Consistent with Figure 7 for an outpatient dummy, Figure 8-1 shows that for all procedure categories semi point-elasticity is larger in magnitude at subsidy expansion ("better") than the subsidy expiration ("worse").

However, Figure 8-2 on outpatient spending shows a different pattern. While all the categories

[28] In Japan, doctor fees and hospital fees are not separately defined. Thus, one can view this consultation fees as a part of the doctor fees in that sense that doctors spend time with the patients.

[29] See also Appendix Figure A8 which examines the sensitivity of the estimates and arc-elasticity to the sizes of donut holes for each procedure category. Consistent with intuition, the effect of intertemporal substitution is large in mediation and laboratory tests, suggesting that these are the procedure categories that can be more easily timed than say non-surgical procedure which is probably more urgent.

except for one show the same pattern that semi point-elasticity is larger for "better" than "worse", the medication shows the opposite pattern. The semi point-elasticity is larger for "worse" than "better", suggesting the asymmetrical responses in total outpatient spending makes the heterogeneity by procedure categories. Children spend substantially *more* on medication when the price becomes lower than spend less when price becomes higher. This result is plausible since one can easily stock medicine unlike other type of health services such as non-surgical procedure.[30] In any case, this asymmetry indicates that policy increasing or decreasing price of medications may have differential magnitude of responses by children (and hence mothers).

6. Health Outcomes

The remaining important question is whether the increases in outpatient care due to subsidy results in the increases in moral hazard or increases in beneficial care. While this is always a challenging task, we examine the health outcomes and heterogeneity of utilization patterns from a number of dimensions to answer this question to the extent possible.

6.1. Ambulatory Care Sensitive Conditions (ACSC)

Our insurance claim data include diagnosis code by ICD10. Appendix Table A6 lists the major diagnosis group and top 10 diagnoses at the ICD10 4-digit level. Compared to the elderly who tend to have more chronic diseases, the top ranked diagnoses are more acute such as acute bronchitis, and acute upper respiratory infection. In fact, the largest share comes from diseases of the respiratory system, which account for roughly one third of all the diagnosis.

Instead of looking at broad disease categories that are arbitrary chosen or each individual diagnosis, one useful set of diseases to investigate is so-called Ambulatory Care Sensitive Conditions (ACSC) or "avoidable conditions"—diagnoses for which timely and effective outpatient care can help to reduce the risks of hospitalization by either preventing the onset of an illness or condition (e.g., asthma).[31]

We employ the list from Gadomski *et al*. (1998) that specifically focus on child health care.

[30] Of course, it is difficult to distinguish whether this result stems from the patient-induced demand, that is, children or mothers ask more medications when price is low, or physician-induced demand, that is, doctors may provide aggressive medications stemming from their economic motives/benevolence.

[31] We also estimate equation [4] by the broad diagnosis groups but we do not find much interesting heterogeneity on this dimension except for the "Injury, poisoning and certain other consequences of external causes" which shows slightly smaller arc-elasticity as these conditions may be more urgent and thus less price sensitive (the results available upon request).

Appendix Table A7 provides the lists of the ACSC with corresponding ICD10 codes, and the fraction of each ACSCs in the data. Column (2) indicates that conditional on visit, as much as 41% belongs to ACSC which indicates the acute nature of diseases for children. Among the list of 17 ACSCs, severe ENT infections (56.9%) and asthma (31.5%) stands out, and account for as much as 88.4% of total ACSCs.

Therefore, to save space, Figure 9 plots the estimates in equation [4] when outcome is an outpatient visit dummy for (i) any ACSC, (ii) severe ENT infections, and (iii) asthma.[32] Panel A shows that outpatient visits for these diagnoses increase when subsidized, and all the estimates are statistically significant at the conventional level. Table 4 reports the estimates that are plotted in Figure 9. For example, the outpatient visit by any ACSC increases by 2-4 percentage points during ages 7-14 where the mean without subsidy is 0.11.

This result may add additional evidence to the idea that higher patient cost-sharing leads patients to cut spending across the board, not merely on non-essential or low-value care. However, most of past studies could not examine whether such seemingly beneficial care indeed lead to better health of patients. Here, one big advantage of our insurance claim data is that it include the information for both outpatient and inpatient care from the same individual. Thus, we can directly examine whether such increases in preventive care at outpatient setting indeed lead to the reduction in hospitalization from these diagnoses. Panel B in Figure 9 plots the estimates from equation [4] where the outcomes are now *inpatient* spending and an *inpatient* admission dummy while the explanatory variables are subsidy status for *outpatient* care as before. We do not see any declines in the hospitalization or inpatient spending associated with any ACSC or other individual ACSCs. Since the hospitalization among children are very rare events (0.28% of all year-months), the estimates are imprecise, but at least the point estimates are always positive instead of negative, implying that outpatient care and impatient care for these diagnoses can be complement rather than substitute.

6.2. Mortality

Next, we examine whether outpatient subsidy may affect more drastic but objective outcome: mortality. While we recognize that mortality rate among this age range is extremely low (in fact, the mortality rate is as low as 0.0039 percent), the mortality rate is arguably most objective outcome.

[32] Unfortunately, insurance claim data in Japan until recently lists all the ICD10 that are diagnosed in the month instead of diagnosis for each visit, which makes us difficult to examine the other outcomes such as spending and frequency of visits by ICD10 unless we make a strong assumption.

Figure 10 plots the estimates from equation [4] where the outcome is a mortality dummy (multiplied by 1000). The corresponding table is presented in Appendix Table A8. While the estimates are somewhat noisy due to low mortality rate, none of the estimates at any ages are statistically and economically significant. Thus, at least in the short-run, we do not see that subsidy for outpatient care reduces mortality of children.

6.3. Misuse of antibiotics

Finally, another concern of generous subsidy is that it may increase the inappropriate use of the drugs. Since more than half of the outpatient spending is occupied by medication, this is a valid concern worth investigating. Specially, the biggest concern is that use of inappropriate use of antibiotics for diagnoses that are not recommended.

Fleming-Dutra *et al.* (2016) list the three tiers of diseases (with corresponding ICD9-CM) in which the appropriateness of antibiotics use substantially differs. Specifically, Tier 1, 2, and 3 are diagnostic categories where antibiotic use is always recommended, is occasionally recommended, and finally not recommended, respectively. We convert ICD9-CM to ICD10, and Appendix Table A9 presents the list of diagnostic categories for each tier.[33] Appendix Table A10 provides the summary statistics of antibiotic use by each tier and more detailed diagnostic categories for each tier. Aggregated at the tier level, the share of Tier 3 is roughly half (53.7% = 0.218/(0.052+0.136+0.218)), followed by Tier 2 (33.5 %) and Tier 1 (12.8%).[34]

Column (2) in Appendix Table A10 shows the use of antibiotics conditional on being diagnosed to one of these diagnostic categories. Importantly, while the antibiotic use is not recommended in Tier 3, roughly 20% of the children diagnosed in Tier 3 (i.e., none of the diagnoses in Tiers 1 or 2) are prescribed with antibiotics, indicating the misuse of the antibiotics for children even without subsidy.[35] For Tier 3, the average spending on antibiotics is 0.24 thousands JPY as in Column (3) and the frequency of antibiotics prescriptions is 0.94 per year-month as in Column (4). Both numbers are far from zeros.

[33] One may have multiple diagnoses. To assign each patient at each month to mutually exclusive tiers, we assign a patient to Tier 1 when the patient has any diagnosis in Tier 1 in the month and to Tier 2 when the patient has any diagnosis in Tier 2 but not Tier 1, and the rest to Tier 3. In this way, Tier 3 only includes the patient in the month when antibiotics should not be recommended as none of the diagnoses include the ones from Tier 1 and Tier 2.
[34] Within each tier, the largest share of diagnoses are miscellaneous bacterial infections for Tier 1 (4.7% of year-months), sinusitis (7.1%) for Tier 2, and asthma (5.8%) for Tier 3 excluding the "other diseases".
[35] While the antibiotics use is recommended in Tier 1, the average use of antibiotics is only 40%. The corresponding number of Tier 2 is 62%, which is higher than that of Tier 1.

We are concerned if children in Tier 3 who are prescribed with antibiotics increases due to subsidy. To investigate this, we estimate the equation [4] where the outcome is the interaction of being in Tier 3 and also using the antibiotics (which takes the values in the last three columns in Appendix Table 11).[36] Figure 11 plots the estimates in the upper half, and the corresponding arc-elasticity in the lower half. The outcome in Panels A and B is monthly outpatient spending on antibiotics, and frequency of antibiotics prescriptions per month. The corresponding estimates are reported in Table 5.

We find that the lower patient cost-sharing increases the spending on antibiotics as well as frequency of antibiotics prescriptions. For outpatient spending, the subsidy increases the spending on antibiotics by 0.009 to 0.020 thousands JPY. Since the mean of the outcome is 0.052 without subsidy, the estimates indicate that generous subsidy increases the spending on antibiotics by 17-38% among children aged 7-14. The frequency of antibiotics prescriptions shows very similar pattern.[37]

Taken individually, each piece of empirical evidence in subsections 6.1-6.3 may not be sufficient to establish the existence of moral hazard. But taken together, the weight of the evidence supports the notion that the aggressive expansion of child health care subsidy may lead to the increases of the unnecessary and costly outpatient visits.

7. Additional analysis

7.1. "Urgent" visits

Another concern of generous subsidy is that children (and hence mothers) increases the "urgent" visits which place a burden on the workload of the physicians as well as increase in spending for expensive care as the urgent visits are set higher fees by national fee schedule. This point was repeatedly raised in the media but there is no formal analysis on this aspect.

The insurance claim data includes the billing ID which enables us to examine the timing of outpatient visits in a day. Since the national fee schedules are applied regardless of insurance type or ages, we exactly know the additional fees charged associated with these visits.

Under the national fee schedule, the fees for non-regular hour visits can be expressed by addition to the fees for regular-hour visits. Appendix Table A8 provides the list of billing codes for these "urgent"

[36] The estimates on each diagnostic category in Tiers 1-3 are available upon request while the statistical power is always the issue.

[37] For the sake of completeness, Appendix Figure A9 plots the estimates on Tier 1 and Tier 2, and Appendix Table A11 is the corresponding table. The estimates for Tier 1 and Tier 2 for both outcomes are also positive and statistically significant at the conventional level, implying that subsidy increases the use of antibiotics in all tiers.

visits (after-hour visits and midnight/holiday visits) and corresponding additional fees. As a benchmark, fees for regular-hour visits during the sample period are roughly 0.7 for initial visit, and 0.5 for revisits measured in thousands JPY (roughly USD10). Compared to fees for regular-hour visits, the additional fees charged for non-regular hour visits are relatively high, suggesting that non-regular hour visits are costly. Also, the additional fees for midnight/holiday visits are on average set higher than that of after-hour visits.[38]

Figure 12 plots the estimates (β_A) for regular-hour visits (for references), after-hour visits, and midnight/holiday visits. The corresponding estimates are reported in Table 6. To ease the interpretation, the outcome here is the frequency of visits by each type of visit and the results on outpatient spending is reported in Appendix Figure A10 and Appendix Table A13.[39]

Since the majority of the visits are regular-hour visits (0.41 visits per month or 89.1% of total visits), Panel A shows the similar pattern as our baseline estimates reported in Figure 6. Interestingly, Panel B shows that the costly after-hour visits—which account for 8.4% of total visits (0.023 visits per month)—also increase due to subsidy. The estimates are slightly increasing in age, and are statistically significant at the conventional level at least above age 9. Thus, as shown in Table 6, arc-elasticity is also increasing in age, that go from as low as -0.076 at age 7 to -0.184 at age 14.

In contrast, we do not see any increases in midnight/holiday visits (which only accounts for 2.5 % of total visits) in Panel C. This is plausible as the visits at midnight or holidays may be indeed very serious cases, and thus children and mothers are less price elastic for these unavoidable visits. In sum, the subsidy for child health care seems to increase not only the regular-hour visits but also costly after-hour visits, which raise some concern that generous subsidies may increase the workload of physicians, and also costly visits by children.[40]

[38] For example, suppose the regular hours of a clinic are registered from 9 am to 5 pm. First of all, the midnight visits are defined by visits between 10 pm and 6 am. Thus, the visits outside of regular hours but not during midnight visits—which are between 5 pm to 10 pm and 6 am to 9 am—are considered to be the after-hour visits. Holiday visits are visits in the holiday. Importantly, the medical institutions can charge only one billing code from the list for additional fees on top of the regular-hour fee.

[39] Note that the spending here only includes consultation fees, and does not include any treatments during the visits. Consultation fees are the sum of fee for regular-hour visits and any additional fee listed in Appendix Table A12. Note that medical providers can only charge one billing code listed on top of fee for regular-hour visits.

[40] It is possible that cost of after-hour visits may be partially offset by the opportunity cost of working mothers who may need to leave the work to take children to outpatient care during the regular-hour. Ultimately, the availability of free after-hour visits may affect the labor supply of parents. Unfortunately, since our data do not include any parental information, we cannot investigate such possibilities.

7.2. Offset

More generally, we examine the possibility of the "substitution" effect between outpatient and inpatient care, that is, whether preventive and beneficial *outpatient* spending replaces *inpatient* spending. To our knowledge, there is no study which examines the substitution effects for child health care. To do so, we replace the outcome in equations [4] by inpatient spending while explanatory variables are a series of subsidy dummy for outpatient care. In this way, we can investigate whether the change in subsidy for outpatient care has any impact on impatient care.

Panel A of Figure 13 plots the estimates on the probability of hospitalization, and Panel B plots the estimates on inpatient spending. Table 7 shows that out of 16 estimates (8 for each age for each outcome), none of the estimates except for one (age 7 on an inpatient admission dummy) are statistically significant at the conventional level. Also, the estimates are mostly positive albeit statistically insignificance, which imply that the generous subsidy for outpatient care do not seem to reduce the utilization of inpatient care in general, despite the large increases in the outpatient visits and spending documented so far. These results echo with the findings on ACSC in Section 6.1; while the outpatient visits for ACSC increases, they do not seem to translate into the reduction in hospitalization of ACSC.

Of course, inpatient care is just one short-term and extreme outcome, and we cannot rule out the possibility of improvement in health in the long-run. Nonetheless, at least in our data, we do not find any offset effects on inpatient spending despite the substantial increases in outpatient spending.

7.3. Inter-municipality migration

So far, we focus on the individuals that do not move across municipalities as there are only 3,046 children which are only 4.6% of all children (63,530 vs. 66,576). This is because our migration rate is lower than the actual migration since intra-municipality migration is not counted as migration since the subsidy level is the same. However, if a family with very sick children is more likely to move to more generous municipality, our estimates which cannot control for the time-varying unobserved health conditions, can be potentially biased. We think that this is very unlikely for a couple of reasons. First, the migration rate is declining function of age of children and is already low by age 7 as parents tend to move before their children enter primary school. It is also difficult to imagine that children aged 7-14 move by themselves based on their health conditions. Second, there may be so many municipality characteristics other than subsidy generosity that may affect the decision of migration such as other childrearing support (Nakajima and Tanaka 2014), availability of daycare, and quality of school districts.

Nonetheless, we include those who moved across municipalities into the sample and estimated the equation [4].[41] Appendix Figure A11 shows that the estimates are hardly changed.[42] This is totally plausible since out of 3,046 children who move across municipalities, majority (86.3%) moves to the same level of subsidy as before move. Only 8% moves to municipalities with more generous subsidy, and 5.7% moves to municipalities with less generous subsidy. Thus, only 0.37% (=0.457*0.08) of all children aged 7-14 moves to more generous municipalities. Therefore, it is unlikely that movers play any large role in our estimation.

8. Conclusion

We examine the effect of patient cost-sharing on health care utilization among children by exploiting the substantial regional variation on subsidy level. Importantly, the eligibility for subsidy is always tied to the age of the children, allowing us to estimate the price elasticity at each age from 7 to 14. We find that children are also price sensitive but probably less so than adults. The price elasticity is relatively stable around -0.1 across these age ranges. While we have to be careful in comparing the elasticity across countries or different sample, the price elasticity for children estimated in this paper is smaller than that of RAND HIE for adults in the US, and Shigeoka (2014) and Fukushima et al. (2017) for the elderly in Japan, which we believe is a new contribution to the literature. Also, we find some evidence of asymmetric responses in price sensitivity. Children (and hence mothers) may view the gain from increases in generosity and loss from the decrease in generosity differently and respond accordingly.

We further examine the health outcomes as well as utilization patterns by a number of dimensions to understand whether changes in utilization simply reflect the moral hazard or include the beneficial care. While reduced cost-sharing seems to increase the beneficial care such as Ambulatory Care Sensitive Conditions (ACSCs)—diagnoses for which timely and effective outpatient care can help to reduce the risks of hospitalization, they do not lead to reduce hospitalization by these avoidable conditions. The outpatient subsidy does not seem to reduce mortality either while caution is necessary to interpret this result as the mortality is very low among children in this age range. Furthermore, we find

[41] Adding municipality FE has almost no impact on the estimates.

[42] We also investigate whether those who move to municipalities with more generous subsidy have very bad health conditions before the move. To do so, we run multinomial logistic regression where the outcome is whether to move to more generous (better) or less generous (worse) municipalities where the omitted category is the same level. The regressor is the average spending in the last 12 months before the move. If anything we find that the past spending reduces the probability of moving to more generous municipalities, and furthermore the magnitude is economically very small (results available upon request).

the increases in inappropriate use of antibiotics for patients with diagnosis for which such use should not be recommended. Taking these results combined, we conclude that the most of the increases in the outpatient visits—thanks to generous subsidy for child health care—end up with the increases in moral hazard rather than the increases in beneficial and preventive care.

Additionally, we document that generous subsidy for outpatient care increases the costly after-hour outpatient visits. Finally, we do not find any evidence of offset effects: the increases in outpatient spending do not seem to reduce the spending for inpatient care.

This paper faces a number of limitations. The biggest issue is that we cannot investigate other form of short-term health outcomes (e.g., headaches or self-reported health) as well as any long-term health outcomes. It is plausible that the increases in the preventive care during childhood or adolescents may translate into the improvement in the long-run health, which can potentially justify the generous subsidy for outpatient care. Another limitation is that the insurance claim data do not include basic family characteristics especially that of mothers. Thus, we cannot investigate the heterogeneity along this important dimension especially for younger children as their decision making is likely to be heavily affected by mother (or parents). For example, it is an important empirical question whether the price sensitivity may differ by household income, or by the level of maternal education. To the best of our knowledge, such monthly data with age in month, municipality of residence, health care utilization, and any household characteristics, do not exist in Japan but this definitely leaves an avenue for future research.

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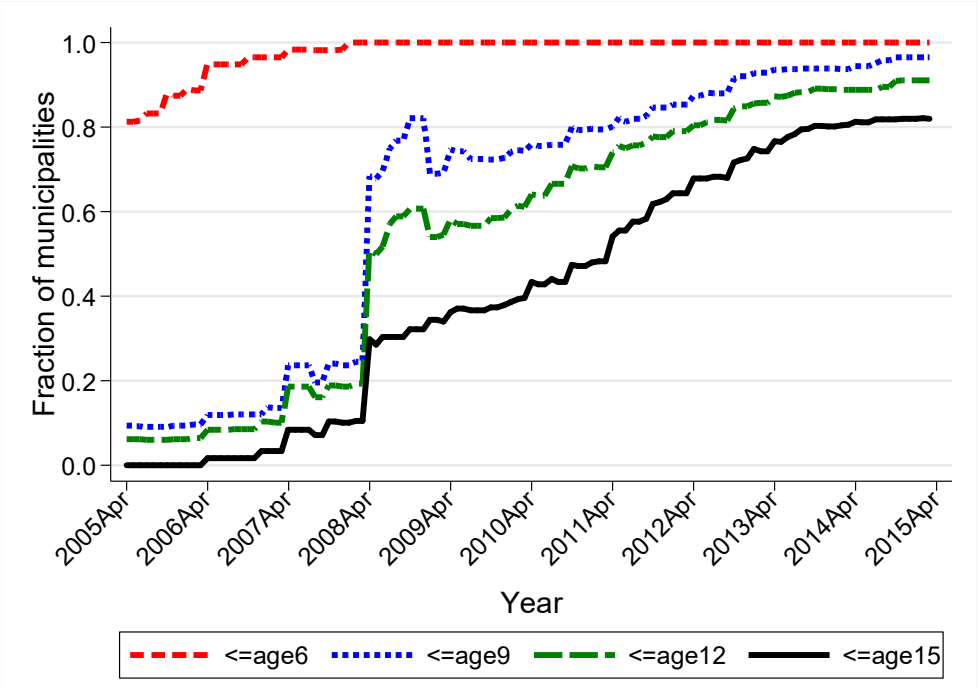
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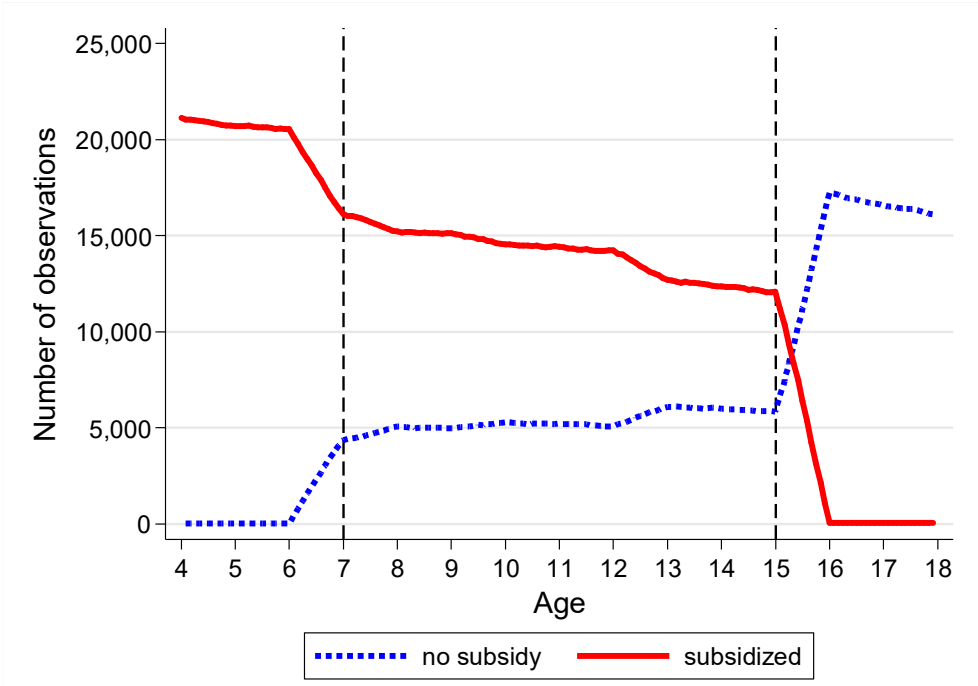
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Figure 1: Time series of maximum age fully covered by child care subsidy



Notes: The data is unbalanced monthly panel where the unit of observation is municipality. There are total of 165 municipalities. Importantly, this figure reflects the compositional changes of municipalities as the number of municipalities in our sample increases at the later period. Within the municipalities, the expansion is always monotonic, that is, there are no single municipalities in our sample that *lower* the maximum age during this period (April 2005-March 2015).

Figure 2: The number of observations by subsidy status

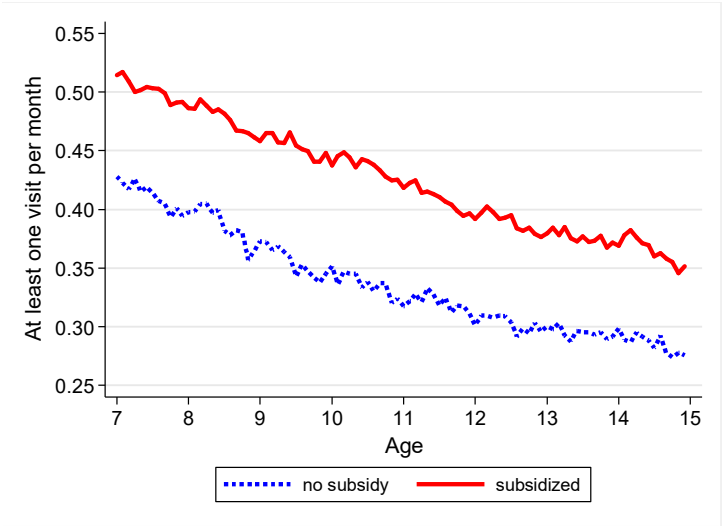


Notes: The sample used in this paper is children aged from 7 to 15 as indicated by the two vertical dotted lines since there are few variations below age 7 and above age 15 during our sample period (April 2005-March 2015).

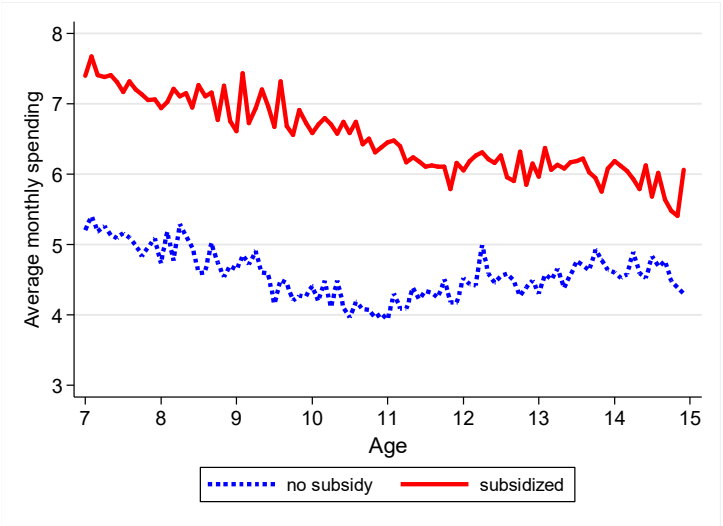
Figure 3: Age profiles of utilizations by subsidy status

A. Outpatient care (monthly)

Outpatient visit dummy

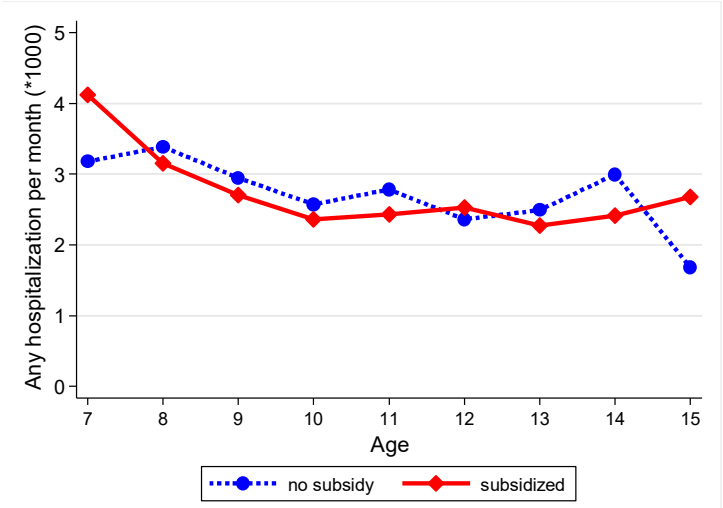


Outpatient spending (in 1K JPY)

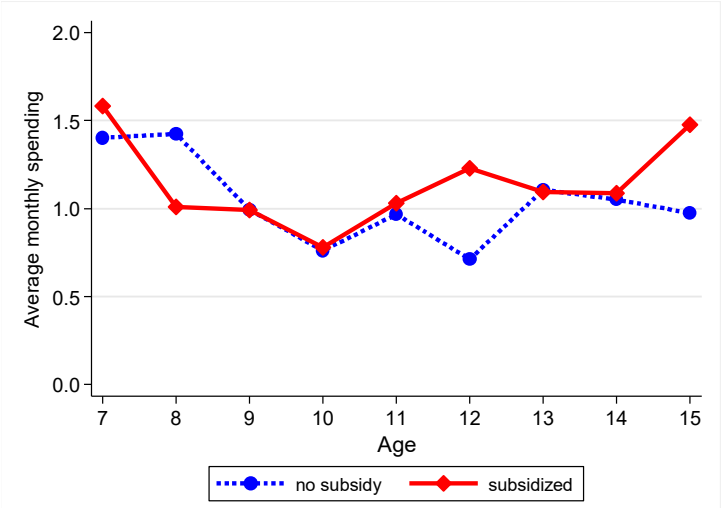


B. Inpatient care (yearly)

Inpatient admission dummy

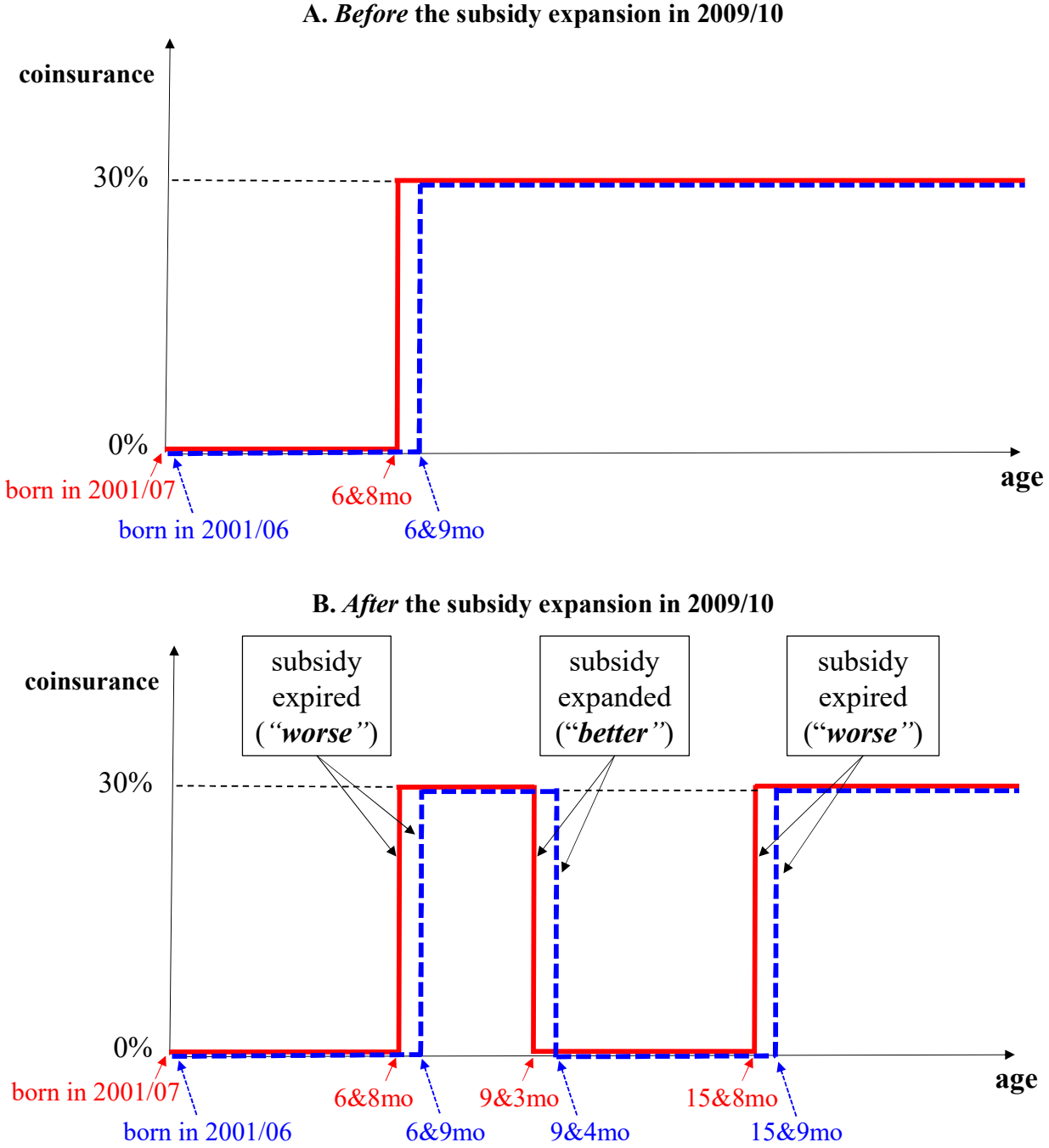


Inpatient spending (in 1K JPY)



Notes: Panel A plots the monthly mean of outpatient outcomes, and Panel B plots the yearly mean of inpatient outcomes as inpatient admission is a rare event. An outpatient visit dummy takes one if there is at least one outpatient visit per month, and an inpatient admission dummy takes one if there is at least one hospitalization per month. The outpatient spending is the monthly spending on outpatient care and the inpatient spending is monthly spending on inpatient care, both of which are measured in thousand JPY (roughly USD10). The dotted lines are age profiles of utilization without subsidy (labeled "no subsidy"), and the solid lines are age profiles of utilization with subsidy (labeled "subsidized").

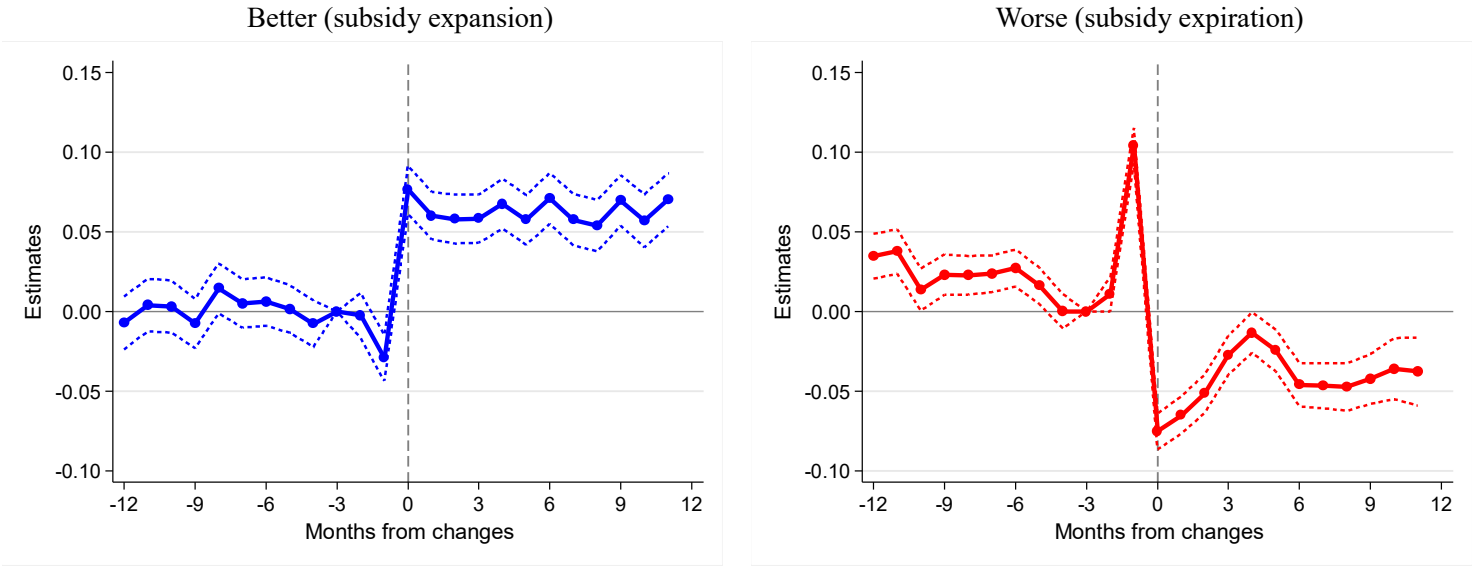
Figure 4: An example of *asymmetry* in subsidy change



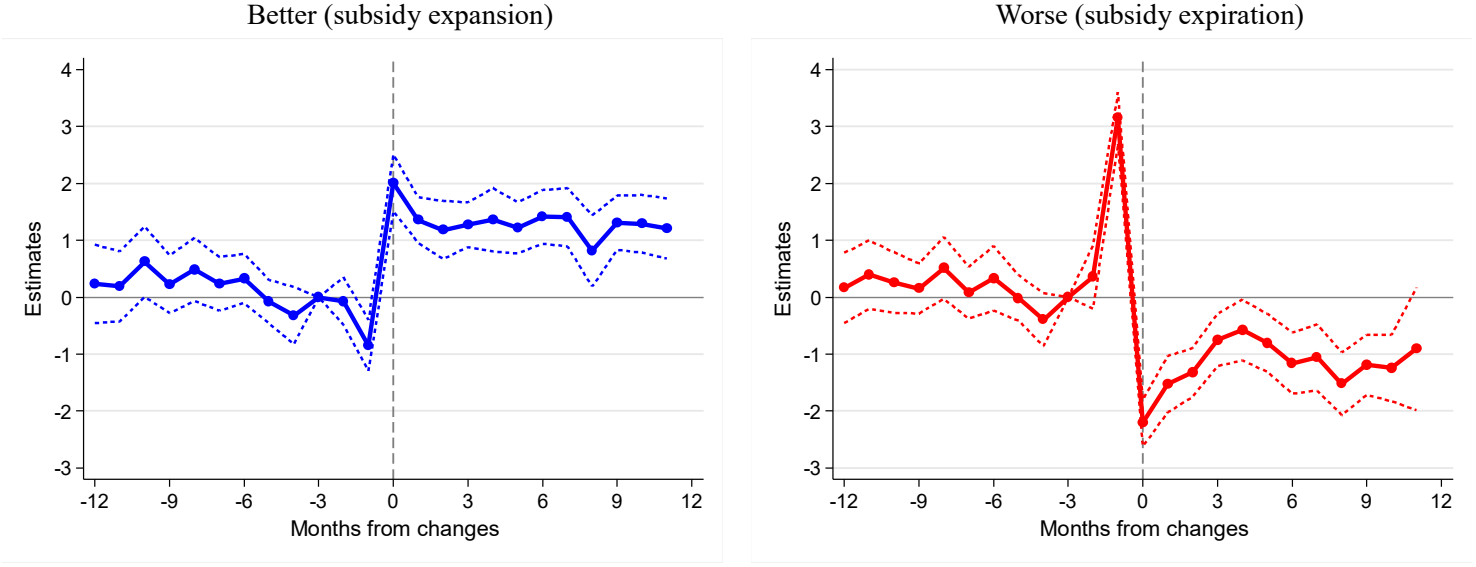
Notes: The solid line is the price schedule for cohort born in July 2007 while that of dotted line is the price schedule for cohort born in June 2007, a month before the previous cohort. In this example, the subsidy expansion from age 6 (before the start of primary school) to 15 (end of junior high school) occurs in October 2010.

Figure 5: Event study

A. Outpatient visit dummy

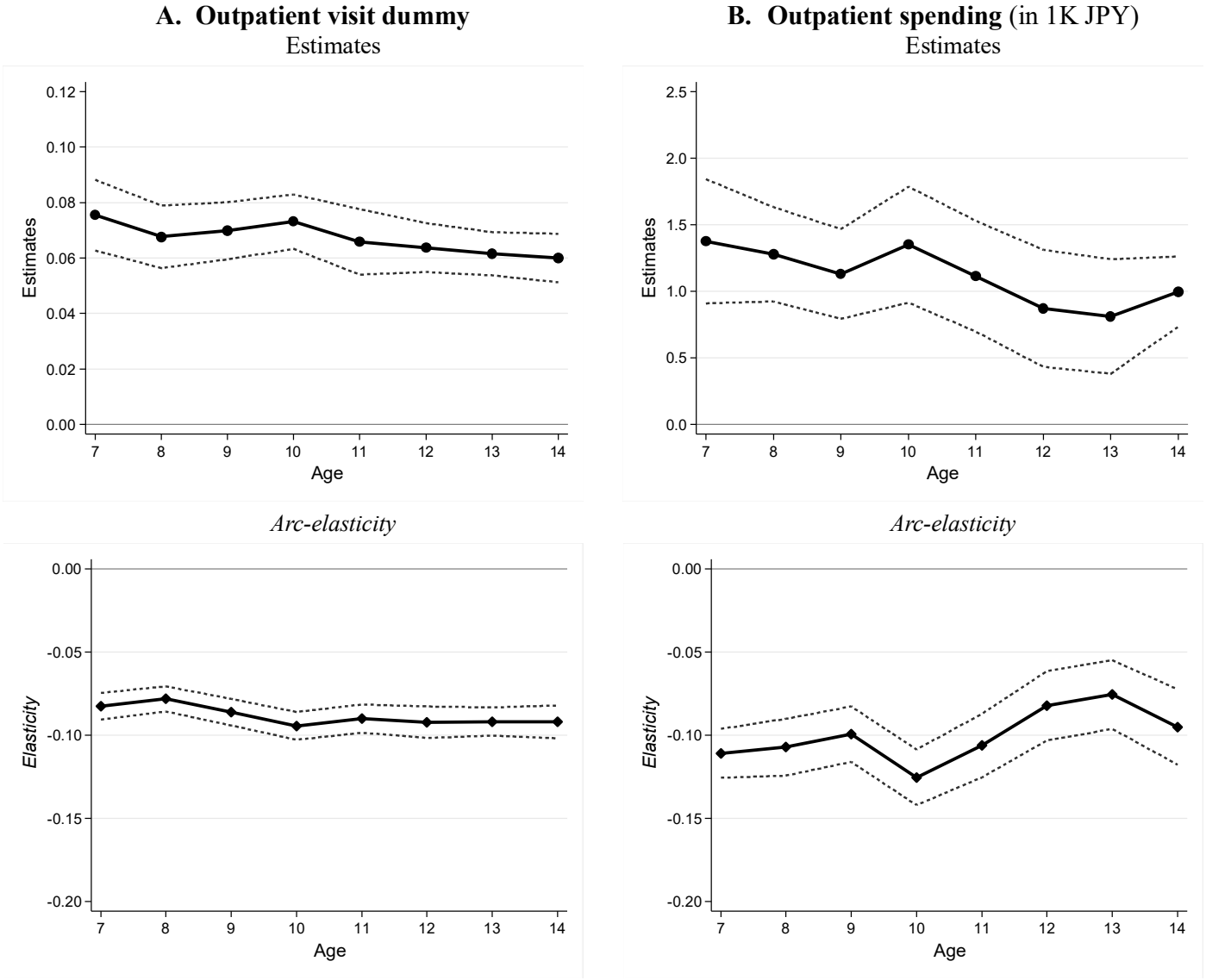


B. Outpatient spending (in 1K JPY)



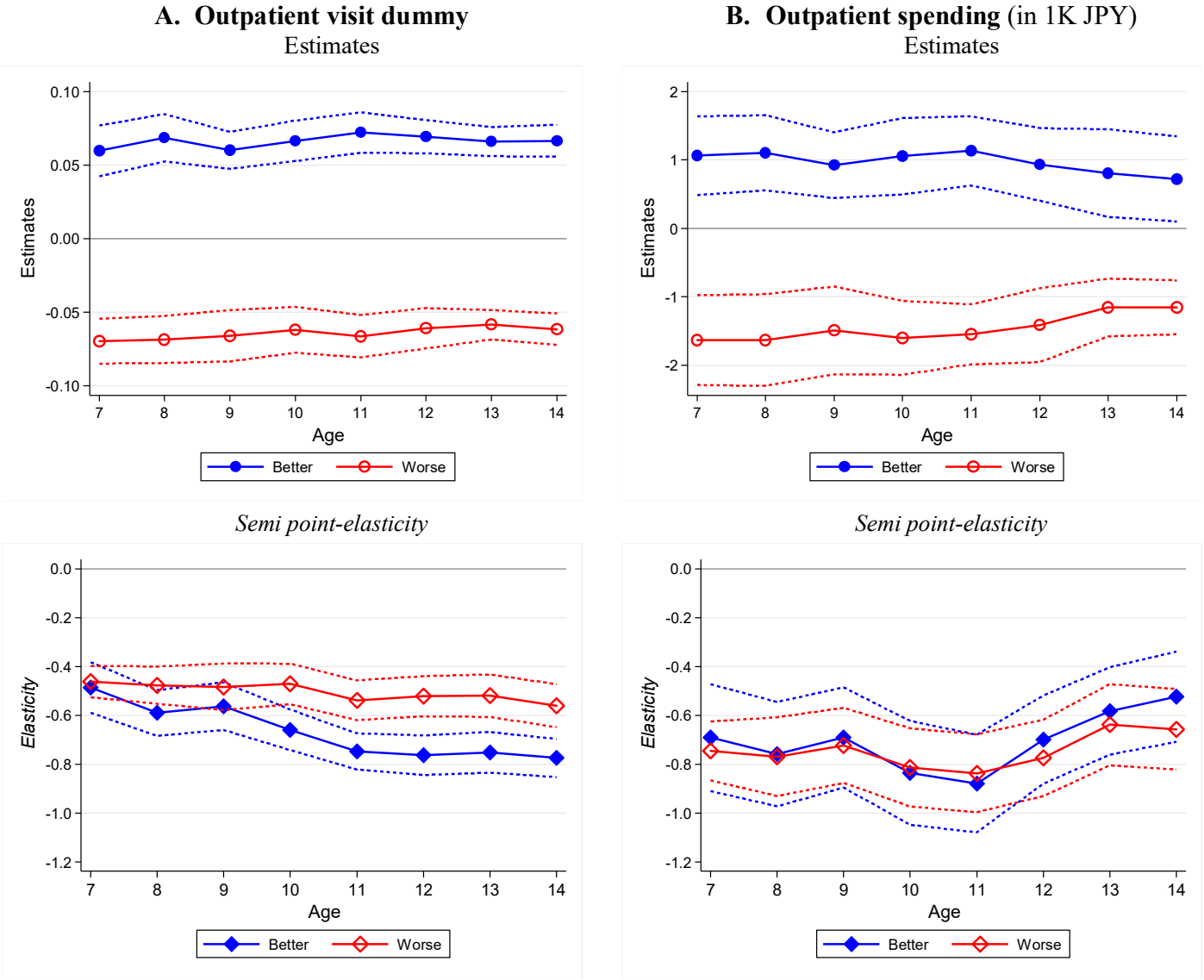
Notes: An outpatient visit dummy takes one if there is at least one outpatient visit per month, and outpatient spending is the monthly spending on outpatient care measured in thousand JPY (roughly USD10). "Better" indicates the subsidy expansion which lowers the price of health care from 30% to 0%, and "Worse" indicates subsidy expiration that raises the price from 0% to 30%. The solid lines plot the estimates from a variant of estimation equation [4] where the subsidized dummy is replaced by a series of dummy for each month ranging from 12 months prior to the change in subsidy status to 12 months after the change in subsidy status (T=-12 to +11, where T=0 is the change). The dotted lines are the 95th confidence intervals where standard errors clustered at municipality level are used to construct them. The reference month is 3 months before the subsidy changes (T=-3). The observations within two months from the subsidy changes of the opposite direction are excluded to account for intertemporal substitution. Note that the scales of *y*-axis are set the same within the panels so that two figures for opposite directions of subsidy changes are visually comparable.

Figure 6: Basic results



Notes: An outpatient visit dummy takes one if there is at least one outpatient visit per month, and outpatient spending is the monthly spending on outpatient care measured in thousand JPY (roughly USD10). The dotted lines are the 95th confidence intervals. The standard errors clustered at municipality level are used for estimates, and the bootstrapped standard errors clustered at municipality with 200 repetitions are used for the arc-elasticity. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. Note that the scales of *y*-axis on the arc-elasticity are set the same so that two elasticities are visually comparable.

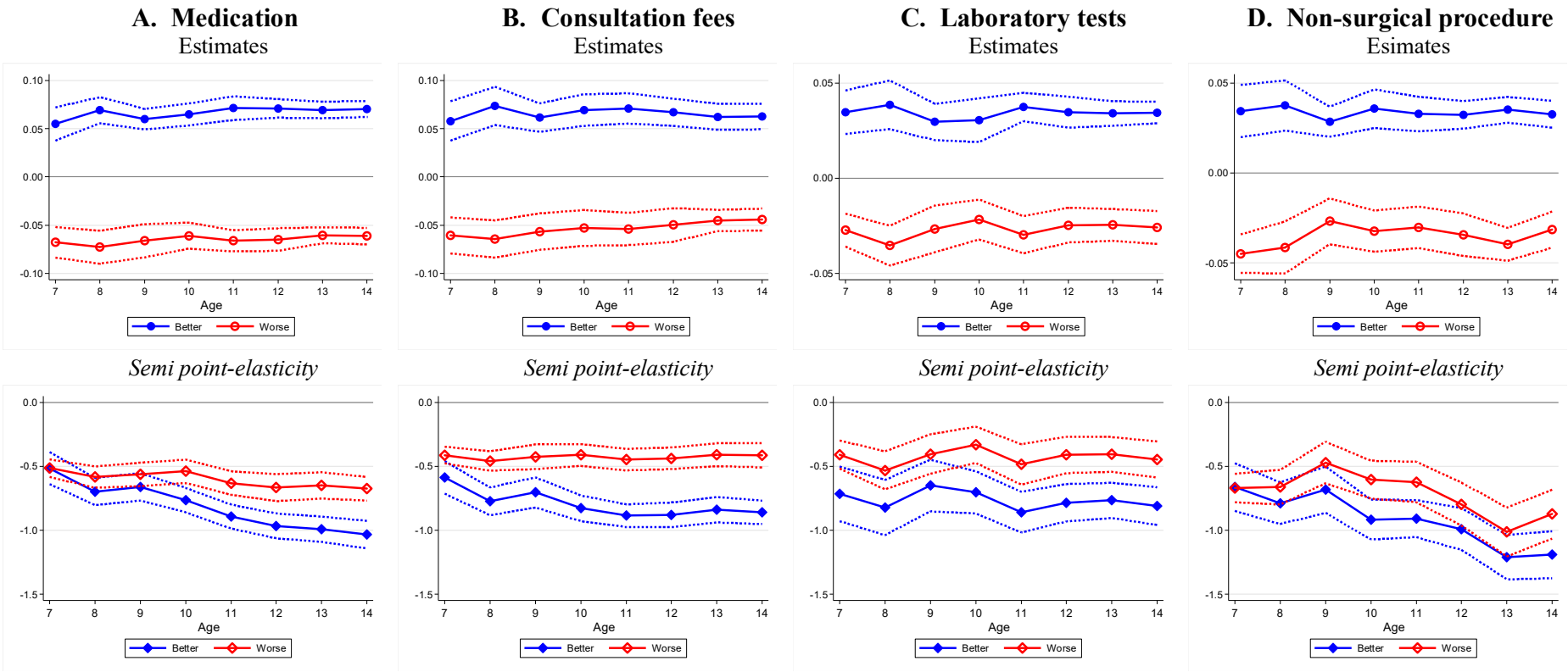
Figure 7: Asymmetric responses



Notes: An outpatient visit dummy takes one if there is at least one outpatient visit per month, and outpatient spending is the monthly spending on outpatient care measured in thousand JPY (roughly USD10). "Better" indicates the subsidy expansion which lowers the price of health care from 30% to 0%, and "Worse" indicates subsidy expiration that raises the price from 0% to 30%. The dotted lines are the 95th confidence intervals. The standard errors clustered at municipality level are used for estimates, and the bootstrapped standard errors clustered at municipality with 200 repetitions are used for the semi point-elasticity. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. Note that the scales of *y*-axis on the semi point-elasticity are set the same so that two elasticities are visually comparable.

Figure 8-1: By procedure categories

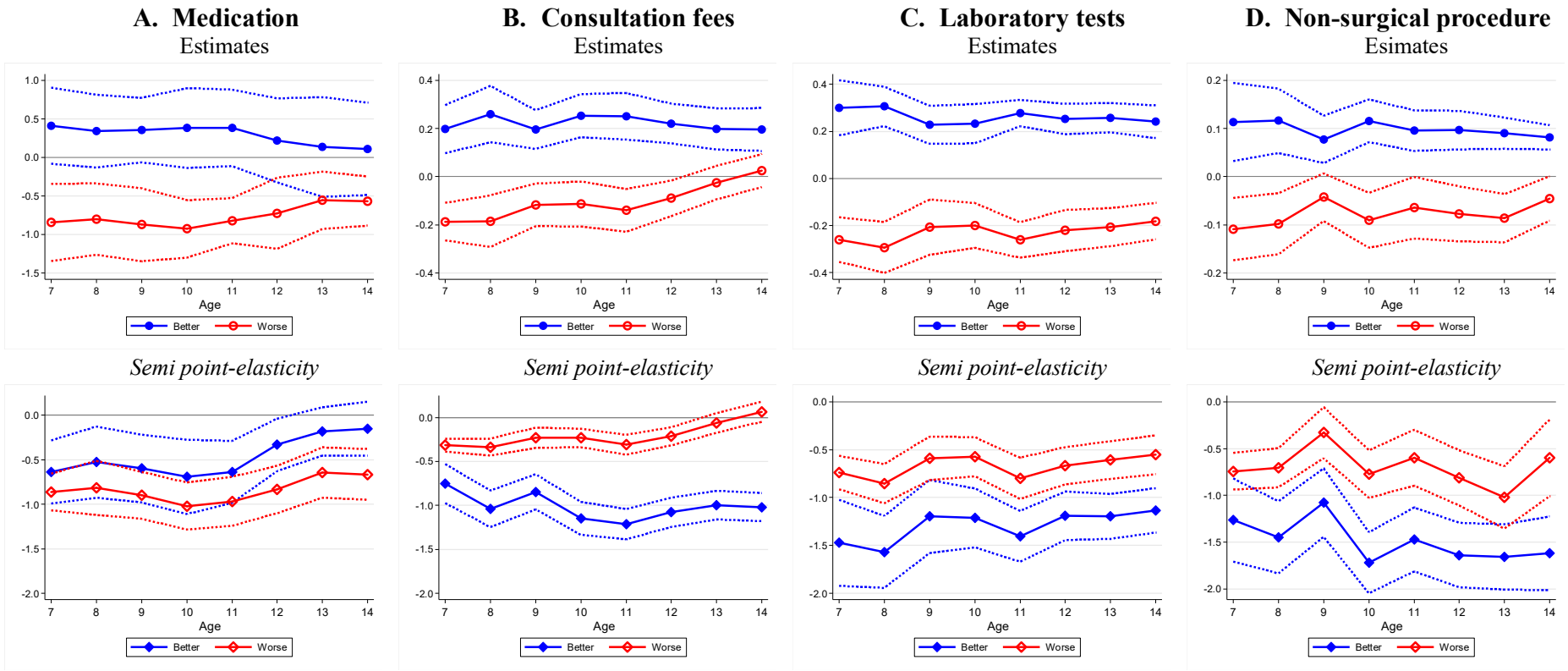
Outcome: Outpatient visit dummy



Notes: An outpatient visit dummy takes one if there is at least one outpatient visit per month. "Better" indicates the subsidy expansion which lowers the price of health care from 30% to 0%, and "Worse" indicates subsidy expiration that raises the price from 0% to 30%. The dotted lines are the 95th confidence intervals. The standard errors clustered at municipality level are used for estimates, and the bootstrapped standard errors clustered at municipality with 200 repetitions are used for the semi point-elasticity. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. See Appendix Table A4 for summary statistics of procedure categories. Note that the scales of *y*-axis on the bottom half are set the same so that semi point-elasticities across procedures are visually comparable.

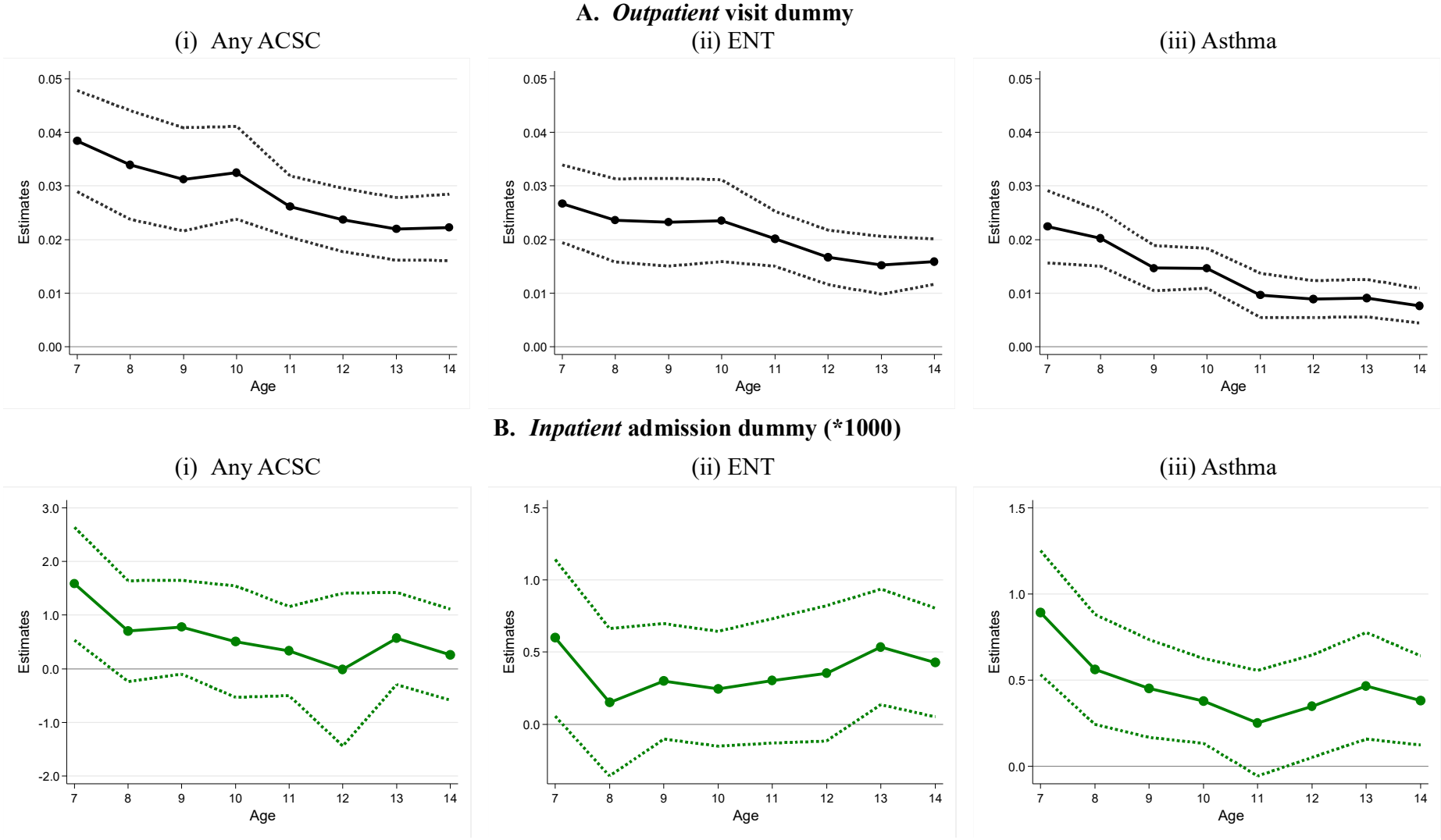
Figure 8-2: By procedure categories

Outcome: Outpatient spending (in 1K JPY)



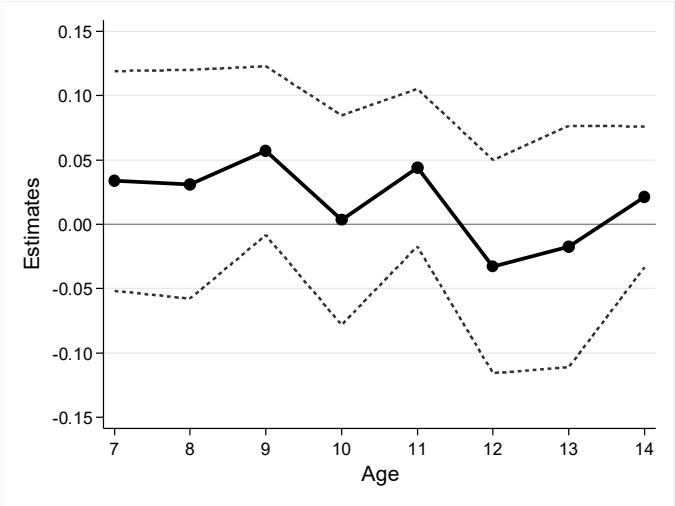
Notes: Outpatient spending is the monthly spending on outpatient care measured in thousand JPY (roughly USD10). "Better" indicates the subsidy expansion which lowers the price of health care from 30% to 0%, and "Worse" indicates subsidy expiration that raises the price from 0% to 30%. The dotted lines are the 95th confidence intervals. The standard errors clustered at municipality level are used for estimates, and the bootstrapped standard errors clustered at municipality with 200 repetitions are used for the semi point-elasticity. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. See Appendix Table A4 for summary statistics of procedure categories. Note that the scales of *y*-axis on the bottom half are set the same so that semi point-elasticities across procedures are visually comparable.

Figure 9: Ambulatory Care Sensitive Conditions (ACSC)



Notes: An outpatient visit dummy takes one if there is at least one outpatient visit per month, and an inpatient admission dummy takes one if there is at least one hospitalization per month (*1000). The dotted lines are the 95th confidence intervals and the standard errors clustered at municipality level are used to construct them. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. ENT stands for Ear, Nose, and Throat. See Appendix Table A7 for the list of ACSC and summary statistics.

Figure 10: Mortality (*1000)

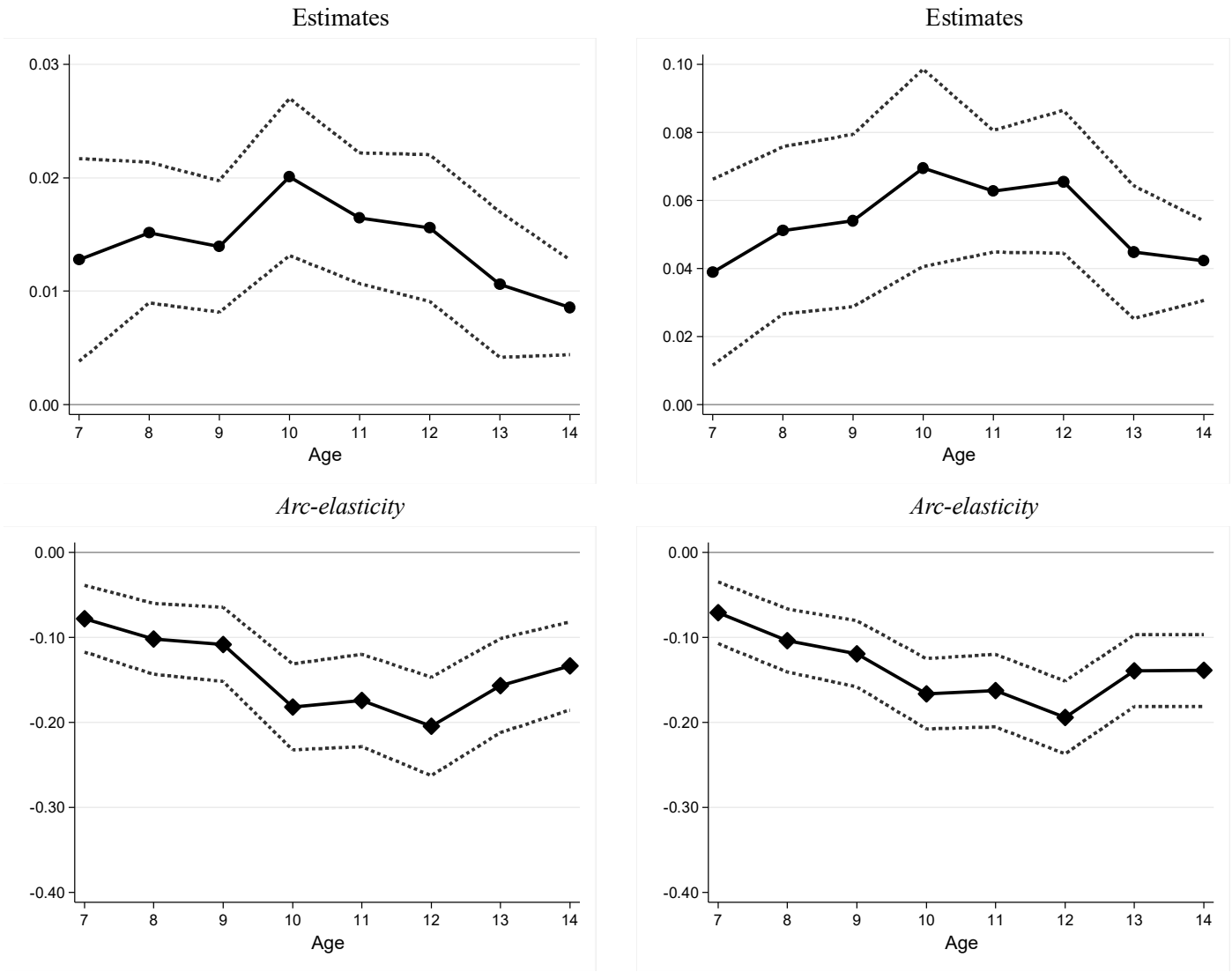


Notes: A mortality dummy is multiplied by 1000. The dotted lines are the 95th confidence intervals derived from standard errors clustered at municipality level. The observations within two months from subsidy changes are excluded to account for intertemporal substitution.

Figure 11: Antibiotics use (Tier 3)

A. Outpatient spending on antibiotic drugs (in 1K JPY)

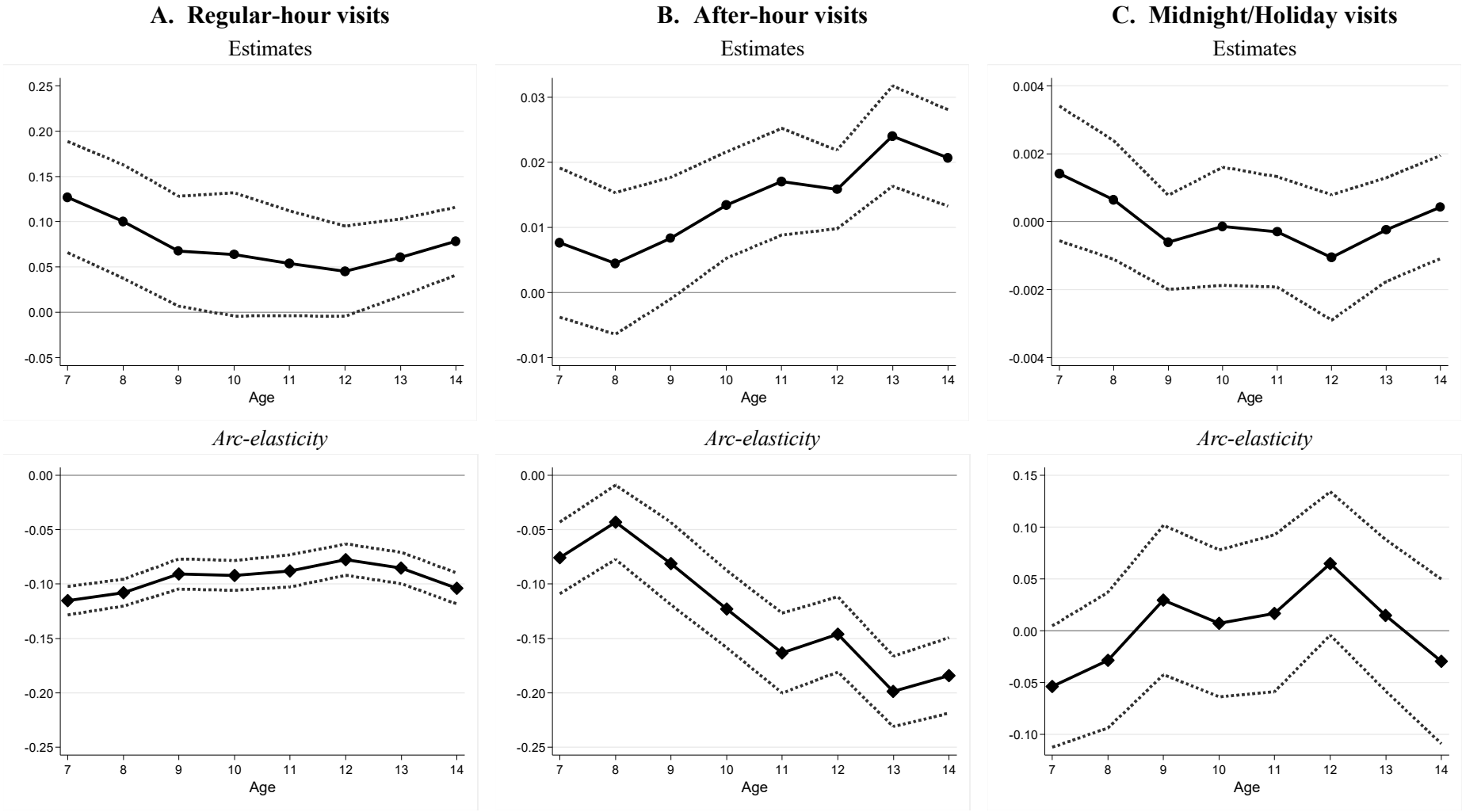
B. Frequency of antibiotics prescriptions



Notes: The outpatient spending on antibiotic drugs is the monthly spending on antibiotics measured in thousand JPY (roughly USD10), and the frequency of antibiotics prescriptions is the number of prescriptions for the antibiotic per month. See Appendix Table A9 for the list of ICD10 codes for each Tier and Appendix Table A10 for the summary statistics. The dotted lines are the 95th confidence intervals. The standard errors clustered at municipality level are used for estimates, and the bootstrapped standard errors clustered at municipality with 200 repetitions are used for the arc-elasticity. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. Note that the scales of *y*-axis on the arc-elasticity are set the same so that two elasticities are visually comparable.

Figure 12: Urgent visits

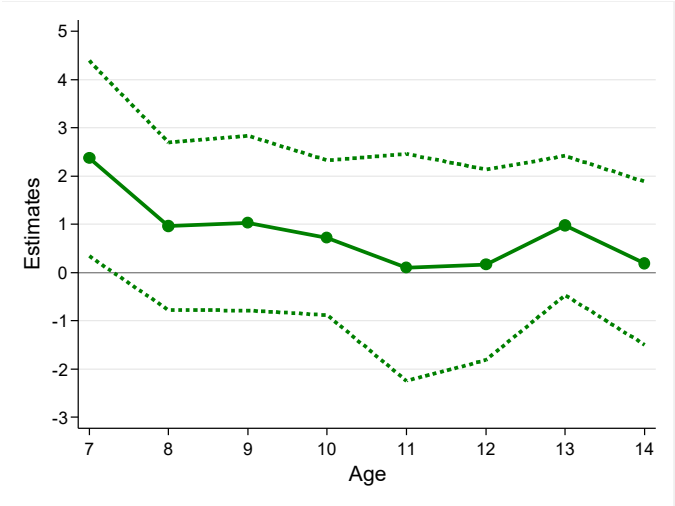
Outcome: Frequency of outpatient visits



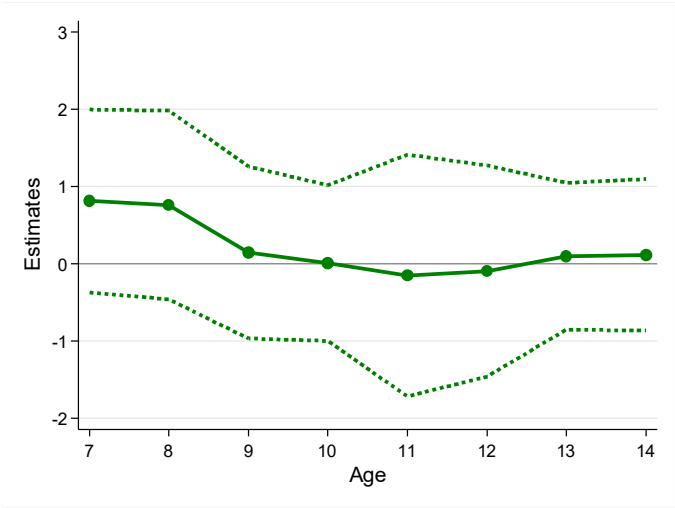
Notes: The frequency of outpatient visits is the number of outpatient visits per month. The dotted lines are the 95th confidence intervals. The standard errors clustered at municipality level are used for estimates, and the bootstrapped standard errors clustered at municipality with 200 repetitions are used for the arc-elasticity. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. See Appendix Table A12 which provides the list of billing codes for these urgent visits and corresponding fees that are additionally charged on top of fees for regular-hour visits. Note that the scales of *y*-axis on the arc-elasticity are set the same so that three elasticities are visually comparable.

Figure 13: Offset effects

A. *Inpatient* admission dummy (*1000)



B. ***Inpatient* spending** (in 1K JPY)



Notes: An inpatient admission dummy takes one if there is at least one hospitalization per month (*1000), and inpatient spending is the monthly spending on inpatient care measured in thousand JPY (roughly USD10). The dotted lines are the 95th confidence intervals derived from standard errors clustered at municipality level. The observations within two months from subsidy changes are excluded to account for intertemporal substitution.

Table 1: Summary statistics

Variable	Mean	SD	Min	Max
A. Municipality (N=165)				
Average length observed (months)	76.59	32.77	5	120
Subsidy info				
Number of policy changes	1.20	1.12	0	5
At least one policy change	68.5%	0.47	0	1
B. Individual (N=63,590)				
Average length observed (months)	36.22	31.14	2	119
Subsidy info				
Number of subsidy status changes	0.39	0.80	0	5
At least one subsidy status change	21.8%	0.41	0	1
Characteristics				
Female	48.8%	0.50	0	1
Age (in years)	10.86	2.85	6.08	15.92
C. Overall (N= 2,303,335 year-month)				
Subsidy info				
Subsidized	71.0%	0.45	0	1
In-kind (when subsidized)	99.9%	0.03	0	1
Income restriction (when subsidized)	1.5%	0.12	0	1
Utilization				
Outpatient visit dummy	40.7%	0.49	0	1
Outpatient spending (in 1K JPY)	6.09	25.33	0	9,336
Outpatient spending (outpatient visit >0)	14.95	37.98	0.08	9,336
# of outpatient visits	0.83	1.46	0	34
# of outpatient visits (outpatient visit >0)	2.04	1.65	0	34
Inpatient admission dummy	0.28%	0.05	0	1
Inpatient spending (in 1K JPY)	1.15	35.24	0	6,084
Inpatient spending (inpatient admission >0)	406.52	523.57	5.23	6,084

Notes: The outpatient and inpatient spending are measured in thousands JPY (roughly 10USD).

Table 2: Basic results

	A. Outpatient visit dummy				**B. Outpatient spending** (in 1K JPY)			
	(1)		(2)		(3)		(4)	
	Estimate	(SE)	*Arc-elasticity*	[SE]	Estimate	(SE)	*Arc-elasticity*	[SE]
Subsidized ×								
Age7	0.075***	(0.006)	-0.083***	[0.005]	1.376***	(0.236)	-0.111***	[0.008]
Age8	0.068***	(0.006)	-0.078***	[0.004]	1.278***	(0.179)	-0.107***	[0.009]
Age9	0.070***	(0.005)	-0.086***	[0.004]	1.131***	(0.171)	-0.099***	[0.009]
Age10	0.073***	(0.005)	-0.094***	[0.004]	1.350***	(0.221)	-0.125***	[0.009]
Age11	0.066***	(0.006)	-0.090***	[0.004]	1.113***	(0.211)	-0.106***	[0.009]
Age12	0.064***	(0.004)	-0.092***	[0.004]	0.872***	(0.223)	-0.082***	[0.010]
Age13	0.062***	(0.004)	-0.092***	[0.004]	0.811***	(0.218)	-0.076***	[0.009]
Age14	0.060***	(0.004)	-0.092***	[0.004]	0.998***	(0.134)	-0.095***	[0.010]
In-kind	0.047***	(0.014)			0.440	(0.388)		
Income restriction	-0.020**	(0.009)			-0.561	(0.372)		
R-squared	0.23				0.51			
N	2,205,647				2,205,647			
N of Individual	63,530				63,530			
Mean wo subsidy	0.32				4.49			

Notes: An outpatient visit dummy takes one if an individual makes at least one outpatient visit per month and zero otherwise. The outpatient spending is total monthly spending on outpatient care measured in thousands JPY (roughly 10USD). All the regressions include age (in months) FE, time (in month) FE, and individual FE. In-kind is a dummy that takes one if the municipality offers the subsidy in the form of in-kind instead of refund, and income restriction is a dummy that takes one if the municipality imposes income restriction for subsidy eligibility. For the estimates, the standard errors clustered at the municipality level are reported in parenthesis. For the arc-elasticity, the bootstrapped standard errors with 200 repetitions clustered at municipality level are reported in brackets. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table 3: Asymmetric responses

	A. Outpatient visit dummy				B. Outpatient spending			
	(1)		(2)		(3)		(4)	
	Estimate	(SE)	*Semi point-elasticity*	[SE]	Estimate	(SE)	*Semi point-elasticity*	[SE]
Subsidized ×								
Age7 × Better	0.060***	(0.009)	-0.485***	[0.053]	1.064***	(0.291)	-0.691***	[0.112]
Age8 × Better	0.069***	(0.008)	-0.590***	[0.048]	1.106***	(0.278)	-0.759***	[0.109]
Age9 × Better	0.060***	(0.006)	-0.562***	[0.050]	0.925***	(0.244)	-0.691***	[0.105]
Age10 × Better	0.067***	(0.007)	-0.659***	[0.042]	1.056***	(0.283)	-0.836***	[0.109]
Age11 × Better	0.072***	(0.007)	-0.748***	[0.038]	1.135***	(0.257)	-0.880***	[0.102]
Age12 × Better	0.069***	(0.006)	-0.763***	[0.041]	0.936***	(0.269)	-0.700***	[0.092]
Age13 × Better	0.066***	(0.005)	-0.751***	[0.043]	0.809**	(0.325)	-0.582***	[0.091]
Age14 × Better	0.067***	(0.006)	-0.775***	[0.040]	0.724**	(0.315)	-0.524***	[0.094]
Subsidized ×								
Age7 × Worse	-0.070***	(0.008)	-0.462***	[0.033]	-1.633***	(0.333)	-0.746***	[0.062]
Age8 × Worse	-0.068***	(0.008)	-0.476***	[0.039]	-1.633***	(0.340)	-0.769***	[0.082]
Age9 × Worse	-0.066***	(0.009)	-0.483***	[0.049]	-1.493***	(0.326)	-0.723***	[0.079]
Age10 × Worse	-0.062***	(0.008)	-0.471***	[0.042]	-1.601***	(0.274)	-0.813***	[0.082]
Age11 × Worse	-0.066***	(0.007)	-0.538***	[0.042]	-1.551***	(0.222)	-0.837***	[0.081]
Age12 × Worse	-0.061***	(0.007)	-0.522***	[0.042]	-1.416***	(0.274)	-0.774***	[0.080]
Age13 × Worse	-0.058***	(0.005)	-0.519***	[0.044]	-1.157***	(0.214)	-0.639***	[0.085]
Age14 × Worse	-0.061***	(0.005)	-0.560***	[0.045]	-1.155***	(0.200)	-0.657***	[0.084]
In-kind	0.050***	(0.014)			0.452	(0.395)		
Income restriction	-0.020**	(0.009)			-0.731**	(0.346)		
R-squared	0.23				0.51			
N	2,144,756				2,144,756			
N of Individual	62,609				62,609			
Mean wo subsidy	0.32				4.49			

Notes: An outpatient visit dummy takes one if an individual makes at least one outpatient visit per month and zero otherwise. The outpatient spending is total monthly spending on outpatient care measured in thousands JPY (roughly 10USD). "Better" indicates the subsidy expansion which lowers the price of health care from 30% to 0%, and "Worse" indicates subsidy expiration that raises the price from 0% to 30%. All the regressions include age (in months) FE, time (in month) FE, and individual FE. In-kind is a dummy that takes one if the municipality offers the subsidy in the form of in-kind instead of refund, and income restriction is a dummy that takes one if the municipality imposes income restriction for subsidy eligibility. For the estimates, the standard errors clustered at the municipality level are reported in parenthesis. For the semi point-elasticity, the bootstrapped standard errors with 200 repetitions clustered at municipality level are reported in brackets. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table 4: Ambulatory Care Sensitive Conditions (ACSC)

	A. Any ACSC				B. ENT				C. Asthma			
	(1)		(2)		(3)		(4)		(5)		(6)	
	An *outpatient* dummy		An *inpatient* dummy (*1000)		An *outpatient* dummy		An *inpatient* dummy (*1000)		An *outpatient* dummy		An *inpatient* dummy (*1000)	
	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)
Subsidized ×												
Age7	0.038***	(0.005)	0.159***	(0.053)	0.027***	(0.004)	0.060**	(0.028)	0.022***	(0.003)	0.089***	(0.018)
Age8	0.034***	(0.005)	0.070	(0.048)	0.024***	(0.004)	0.015	(0.026)	0.020***	(0.003)	0.056***	(0.016)
Age9	0.031***	(0.005)	0.077*	(0.044)	0.023***	(0.004)	0.030	(0.020)	0.015***	(0.002)	0.045***	(0.014)
Age10	0.032***	(0.004)	0.051	(0.053)	0.024***	(0.004)	0.025	(0.020)	0.015***	(0.002)	0.038***	(0.012)
Age11	0.026***	(0.003)	0.033	(0.042)	0.020***	(0.003)	0.030	(0.022)	0.010***	(0.002)	0.025	(0.016)
Age12	0.024***	(0.003)	-0.002	(0.072)	0.017***	(0.003)	0.035	(0.024)	0.009***	(0.002)	0.035**	(0.015)
Age13	0.022***	(0.003)	0.056	(0.044)	0.015***	(0.003)	0.054***	(0.020)	0.009***	(0.002)	0.047***	(0.016)
Age14	0.022***	(0.003)	0.026	(0.043)	0.016***	(0.002)	0.043**	(0.019)	0.008***	(0.002)	0.038***	(0.013)
In-kind	0.030**	(0.015)	0.180*	(0.095)	0.021***	(0.005)	0.053***	(0.017)	0.010	(0.015)	0.058**	(0.025)
Income restriction	-0.008	(0.008)	-0.185***	(0.059)	-0.011	(0.007)	-0.060**	(0.027)	0.000	(0.004)	-0.079**	(0.035)
R-squared	0.24		0.14		0.16		0.06		0.35		0.16	
N	2,205,647		2,205,647		2,205,647		2,205,647		2,205,647		2,205,647	
N of Individual	63,530		63,530		63,530		63,530		63,530		63,530	
Mean wo subsidy	0.11		1.04		0.08		0.32		0.04		0.25	

Notes: An outpatient visit dummy takes one if there is at least one outpatient visit per month, and an inpatient admission dummy takes one if there is at least one hospitalization per month. All the regressions include age (in months) FE, time (in month) FE, and individual FE. In-kind is a dummy that takes one if the municipality offers the subsidy in the form of in-kind instead of refund, and income restriction is a dummy that takes one if the municipality imposes income restriction for subsidy eligibility. For even-numbered columns, we also control for a dummy that takes one if the municipality also offers subsidy for inpatient care. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. ENT stands for Ear, Nose, and Throat. See Appendix Table A7 for the list of ACSC and summary statistics. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table 5: Antibiotic use (Tier 3)

	A. Outpatient spending on antibiotics (in 1K JPY)				B. Frequency of antibiotics prescriptions			
	(1)		(2)		(3)		(4)	
	Estimate	(SE)	*Arc-elasticity*	[SE]	Estimate	(SE)	*Arc-elasticity*	[SE]
Subsidized ×								
Age7	0.013***	(0.005)	-0.078***	[0.020]	0.039***	(0.014)	-0.071***	[0.019]
Age8	0.015***	(0.003)	-0.102***	[0.021]	0.051***	(0.012)	-0.104***	[0.019]
Age9	0.014***	(0.003)	-0.108***	[0.022]	0.054***	(0.013)	-0.119***	[0.020]
Age10	0.020***	(0.004)	-0.182***	[0.026]	0.070***	(0.015)	-0.166***	[0.021]
Age11	0.016***	(0.003)	-0.174***	[0.028]	0.063***	(0.009)	-0.163***	[0.022]
Age12	0.016***	(0.003)	-0.205***	[0.030]	0.066***	(0.011)	-0.194***	[0.022]
Age13	0.011***	(0.003)	-0.157***	[0.028]	0.045***	(0.010)	-0.139***	[0.022]
Age14	0.009***	(0.002)	-0.134***	[0.026]	0.042***	(0.006)	-0.139***	[0.022]
In-kind	0.018**	(0.009)			0.087*	(0.052)		
Income restriction	-0.006	(0.005)			-0.029*	(0.017)		
R-squared	0.08				0.09			
N	2,205,647				2,205,647			
N of Individual	63,530				63,530			
Mean wo subsidy	0.052				0.193			

Notes: The outpatient spending on antibiotics is the monthly spending on antibiotics measured in thousand JPY (roughly USD10), and the frequency of antibiotics prescriptions is the number of prescriptions for the antibiotics per month. See Appendix Table A9 for the list of ICD10 codes for each Tier and Appendix Table A10 for the summary statistics. All the regressions include age (in months) FE, time (in month) FE, and individual FE. In-kind is a dummy that takes one if the municipality offers the subsidy in the form of in-kind instead of refund, and income restriction is a dummy that takes one if the municipality imposes income restriction for subsidy eligibility. For the estimates, the standard errors clustered at the municipality level are reported in parenthesis. For the semi point-elasticity, the bootstrapped standard errors with 200 repetitions clustered at municipality level are reported in brackets. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table 6: Urgent visits

Outcome: Frequency of outpatient visits

	A. Regular-hour visits				B. After-hour visits				C. Midnight/Holiday visits			
	(1)		(2)		(3)		(4)		(5)		(6)	
	Estimate	(SE)	*Arc-elasticity*	[SE]	Estimate	(SE)	*Arc-elasticity*	[SE]	Estimate	(SE)	*Arc-elasticity*	[SE]
Subsidized ×												
Age7	0.169***	(0.028)	-0.115***	[0.007]	0.008	(0.006)	-0.076***	[0.017]	0.001	(0.001)	-0.054*	[0.030]
Age8	0.148***	(0.030)	-0.108***	[0.006]	0.004	(0.006)	-0.043**	[0.017]	0.001	(0.001)	-0.028	[0.033]
Age9	0.115***	(0.027)	-0.091***	[0.007]	0.008*	(0.005)	-0.081***	[0.019]	-0.001	(0.001)	0.030	[0.037]
Age10	0.110***	(0.031)	-0.092***	[0.007]	0.013***	(0.004)	-0.123***	[0.018]	-0.000	(0.001)	0.007	[0.036]
Age11	0.096***	(0.026)	-0.088***	[0.008]	0.017***	(0.004)	-0.163***	[0.019]	-0.000	(0.001)	0.017	[0.039]
Age12	0.079***	(0.023)	-0.078***	[0.007]	0.016***	(0.003)	-0.146***	[0.018]	-0.001	(0.001)	0.065*	[0.035]
Age13	0.082***	(0.020)	-0.085***	[0.007]	0.024***	(0.004)	-0.199***	[0.017]	-0.000	(0.001)	0.015	[0.037]
Age14	0.096***	(0.018)	-0.104***	[0.007]	0.021***	(0.004)	-0.184***	[0.018]	0.000	(0.001)	-0.029	[0.040]
In-kind	0.035	(0.053)			0.031	(0.019)			-0.001	(0.004)		
Income restriction	-0.051	(0.032)			-0.005	(0.010)			-0.001	(0.002)		
R-squared	0.28				0.14				0.04			
N	2,205,647				2,205,647				2,205,647			
N of Individual	63,530				63,530				63,530			
Mean wo subsidy	0.401				0.023				0.006			
Share	89.1%				8.4%				2.5%			

Notes: The frequency of outpatient visits is the number of outpatient visits per month. See Appendix Table A12 which provides the list of billing codes for the urgent visits (after-hour visits and midnight/holiday visits) and the corresponding fees that are additionally charged on top of fees for regular-hour visits. All the regressions include age (in months) FE, time (in month) FE, and individual FE. In-kind is a dummy that takes one if the municipality offers the subsidy in the form of in-kind instead of refund, and income restriction is a dummy that takes one if the municipality imposes income restriction for subsidy eligibility. For the estimates, the standard errors clustered at the municipality level are reported in parenthesis. For the semi point-elasticity, the bootstrapped standard errors with 200 repetitions clustered at municipality level are reported in brackets. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table 7: Offset effects

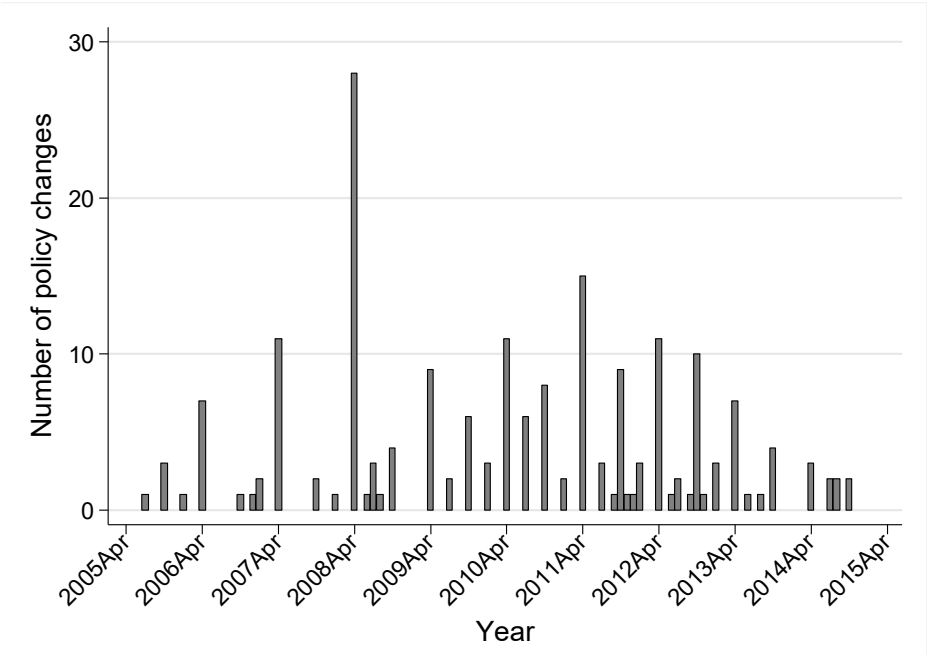
	Inpatient **dummy (*1000)**		***Inpatient*** **spending** (in 1K JPY)	
	(1)		(2)	
	Estimate	(SE)	Estimate	(SE)
Subsidized ×				
Age7	2.365**	(1.026)	0.814	(0.599)
Age8	0.958	(0.879)	0.761	(0.618)
Age9	1.023	(0.918)	0.147	(0.564)
Age10	0.721	(0.812)	0.009	(0.510)
Age11	0.104	(1.191)	-0.151	(0.792)
Age12	0.160	(1.001)	-0.094	(0.692)
Age13	0.974	(0.730)	0.098	(0.481)
Age14	0.193	(0.857)	0.116	(0.497)
In-kind	2.984***	(1.109)	0.316	(0.539)
Income restriction	-2.423***	(0.757)	-1.306***	(0.453)
R-squared	0.12		0.20	
N	2,205,647		2,205,647	
N of Individual	63,530		63,530	
Mean	2.41		1.00	

Notes: An inpatient admission dummy takes one if there is at least one hospitalization per month, and inpatient spending is the monthly spending on inpatient care measured in thousand JPY (roughly USD10). All the regressions include age (in months) FE, time (in month) FE, and individual FE. In-kind is a dummy that takes one if the municipality offers the subsidy in the form of in-kind instead of refund, and income restriction is a dummy that takes one if the municipality imposes income restriction for subsidy eligibility. We also control for a dummy that takes one if the municipality also offers subsidy for inpatient care. The standard errors clustered at the municipality level are reported in parenthesis. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

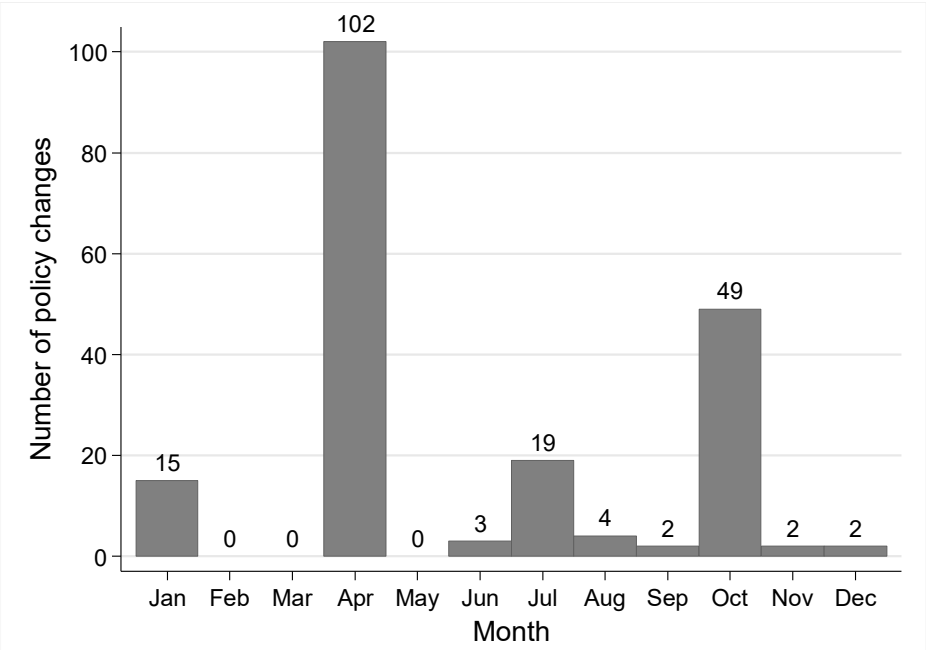
Online Appendix
(Not for Publication)

Figure A1: The timing of the policy changes

A. By year-month



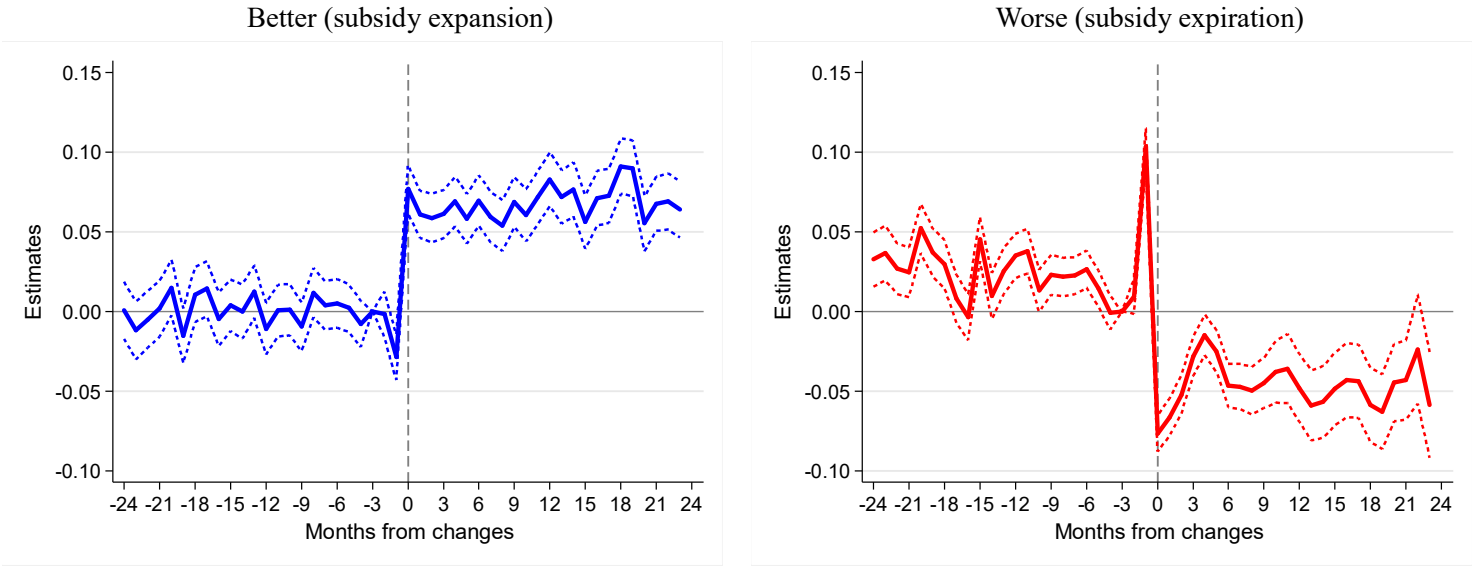
B. By month



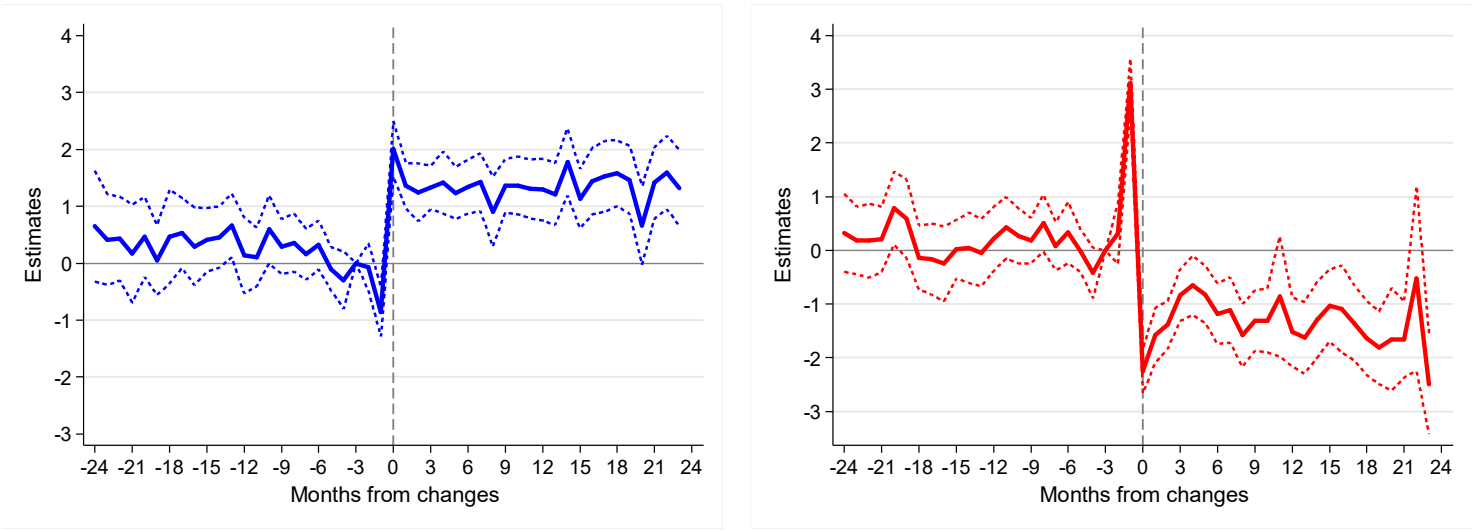
Notes: The total number of municipalities is 165. The data spans from April 2005 to March 2015 (10 years). There are total of 198 subsidy expansions in subsidy for child health care.

Figure A2: Event study (longer horizon)

A. Outpatient visit dummy



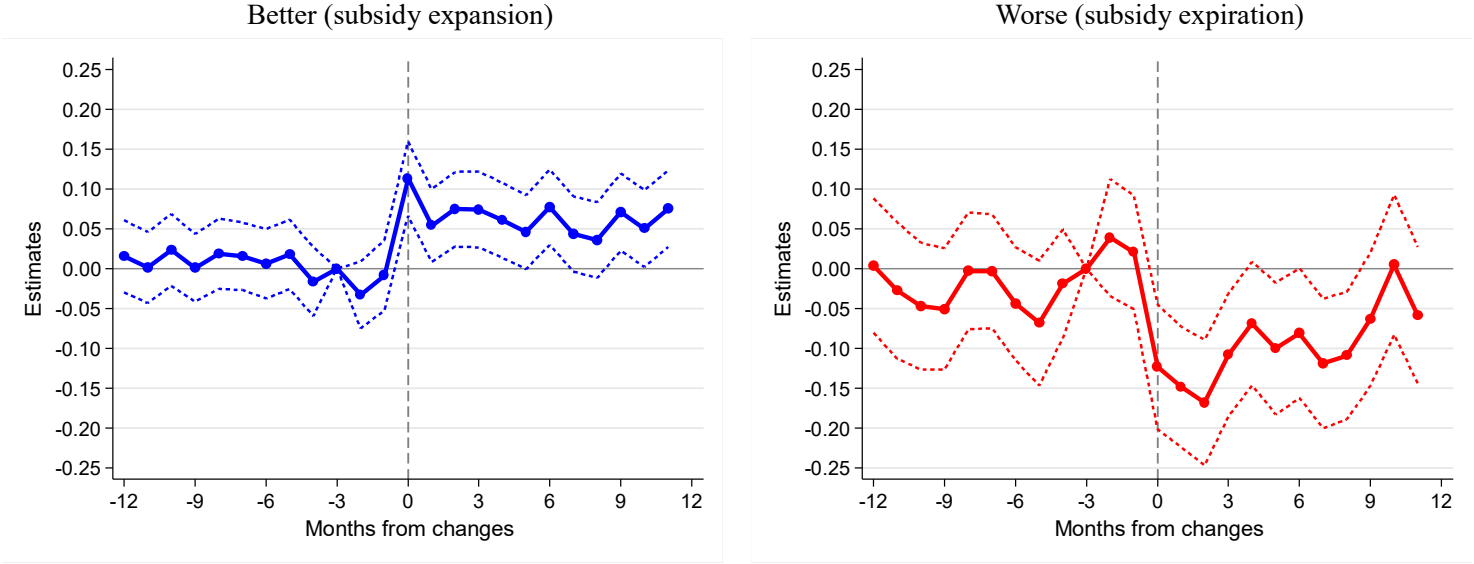
B. Outpatient spending (in 1K JPY)



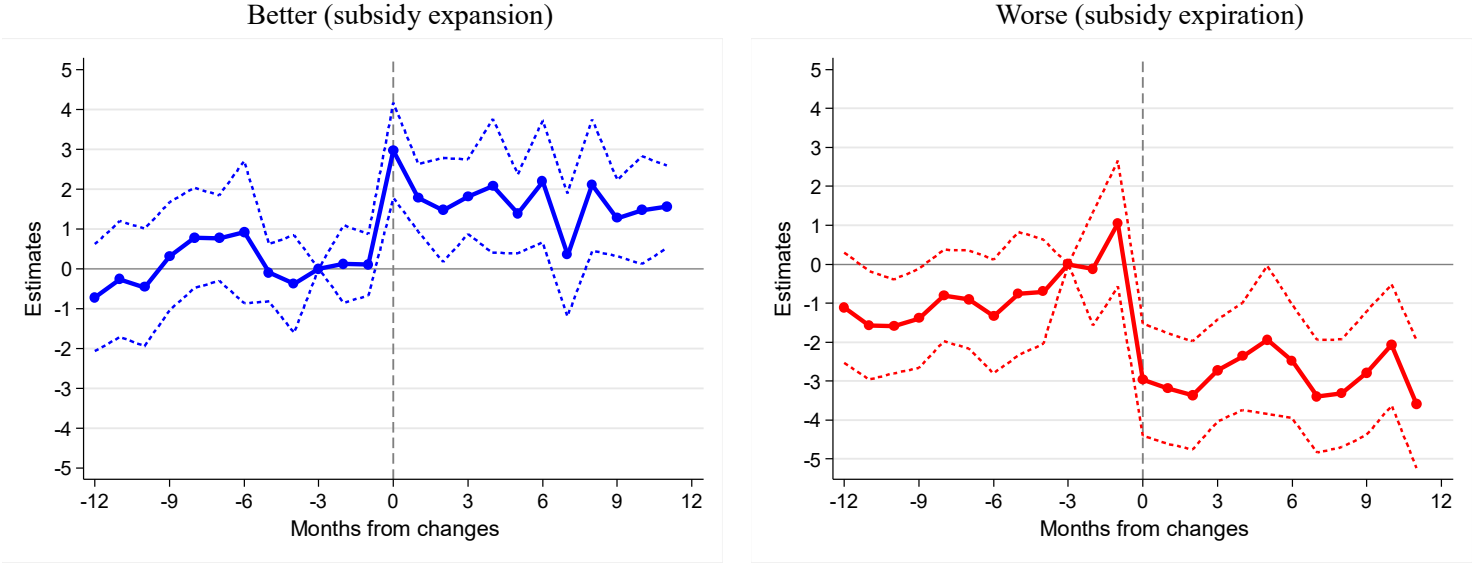
Notes: An outpatient visit dummy takes one if there is at least one outpatient visit per month, and outpatient spending is the monthly spending on outpatient care measured in thousand JPY (roughly USD10). "Better" indicates the subsidy expansion which lowers the price of health care from 30% to 0%, and "Worse" indicates subsidy expiration that raises the price from 0% to 30%. The solid lines plot the estimates from a variant of estimation equation [4] where the subsidized dummy is replaced by a series of dummy for each month ranging from 12 months prior to the change in subsidy status to 24 months after the change in subsidy status (T=-24 to +23, where T=0 is the change). The dotted lines are the 95th confidence interval derived from standard errors clustered at municipality level. The reference month is 3 months before the subsidy changes (T=-3). The observations within two months from the subsidy changes of the opposite direction are excluded to account for intertemporal substitution. Note that the scales of *y*-axis are set the same within the panels so that two figures for opposite directions of subsidy changes are visually comparable.

Figure A3-1: Event study at selected ages (Age 9)

A. Outpatient visit dummy



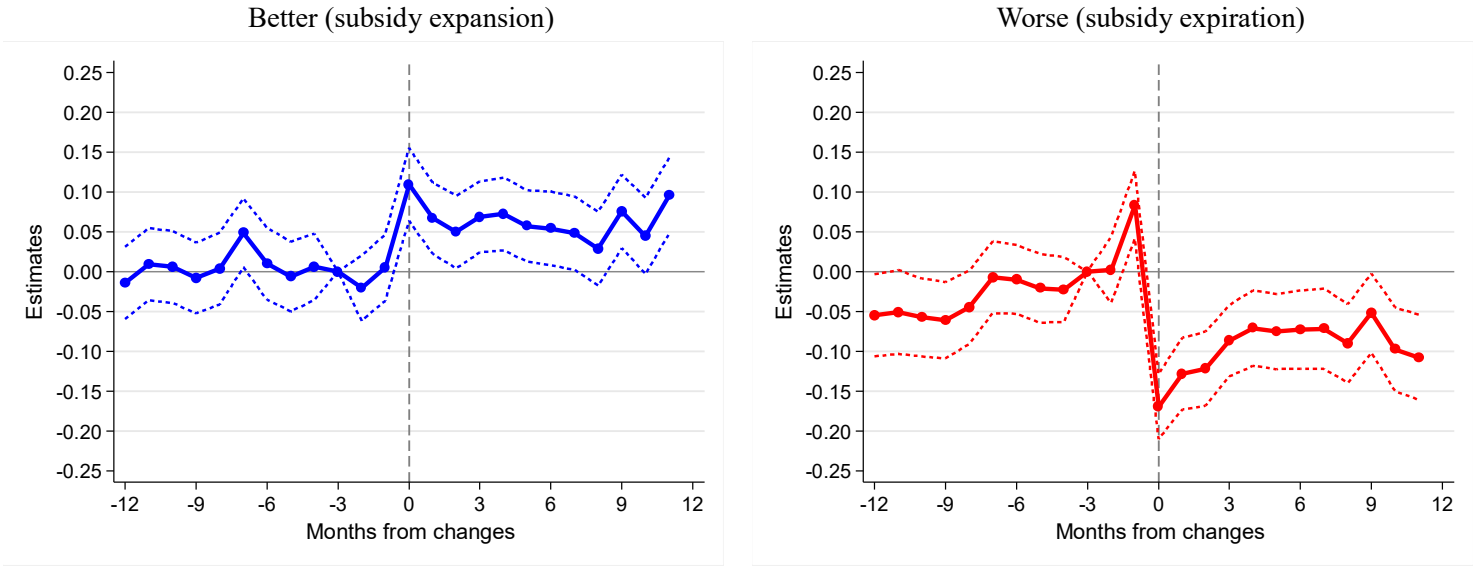
B. Outpatient spending (in 1K JPY)



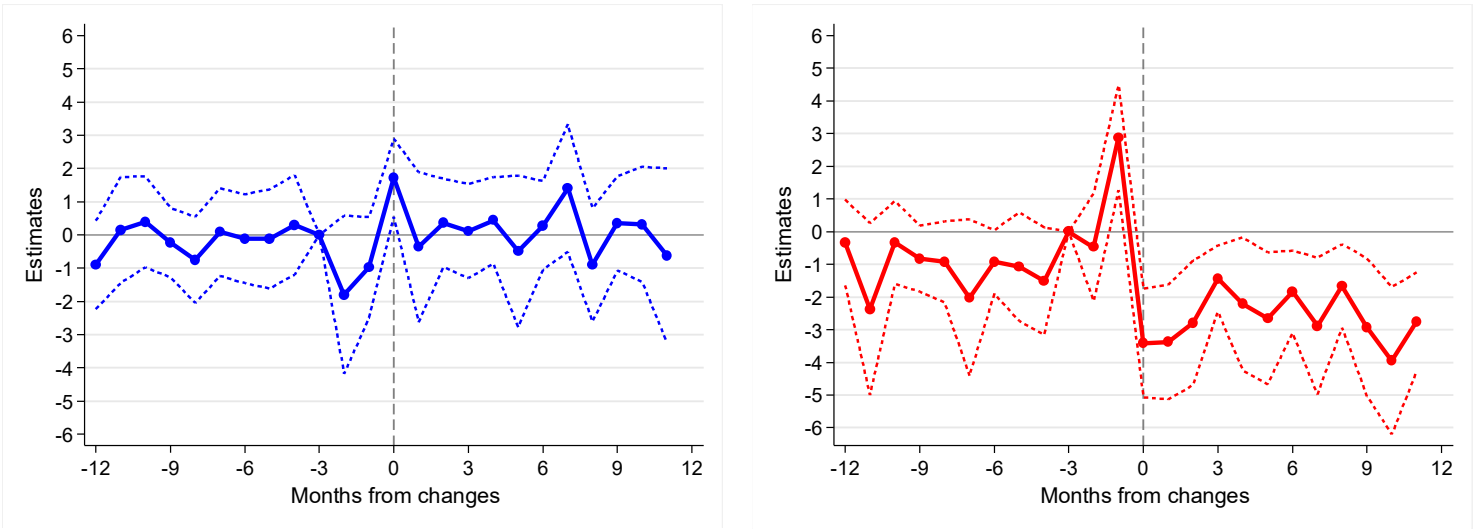
Notes: An outpatient visit dummy takes one if there is at least one outpatient visit per month, and outpatient spending is the monthly spending on outpatient care measured in thousand JPY (roughly USD10). "Better" indicates the subsidy expansion which lowers the price of health care from 30% to 0%, and "Worse" indicates subsidy expiration that raises the price from 0% to 30%. The solid lines plot the estimates from a variant of estimation equation [4] where the subsidized dummy is replaced by a series of dummy for each month ranging from 12 months prior to the change in subsidy status to 12 months after the change in subsidy status (T=-12 to +11, where T=0 is the change) at age between 9 and 0 months and 9 and 11 months. The dotted lines are the 95th confidence interval derived from standard errors clustered at municipality level. The reference month is 3 months before the subsidy changes (T=-3). The observations within two months from the subsidy changes of the opposite direction are excluded to account for intertemporal substitution. Note that the scales of *y*-axis are set the same within the panels so that two figures for opposite directions of subsidy changes are visually comparable.

Figure A3-2: Event study at selected ages (Age 12)

A. Outpatient visit dummy



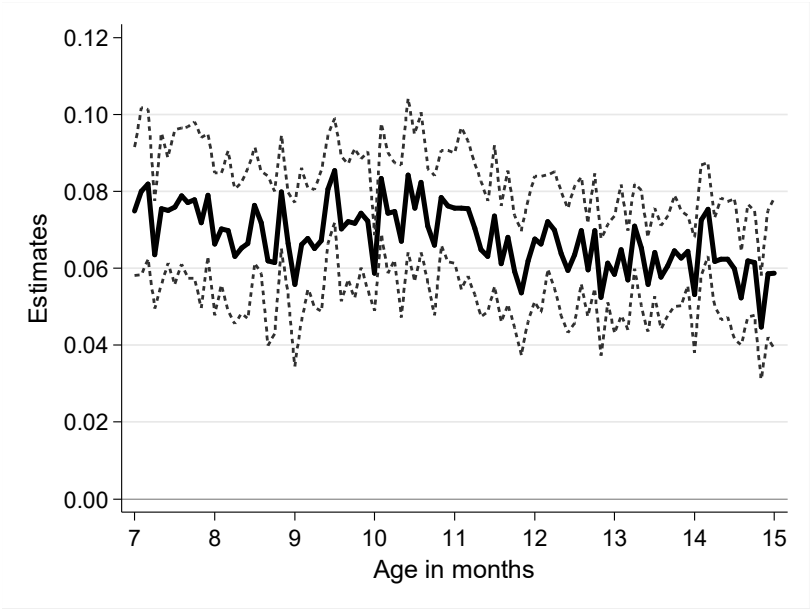
B. Outpatient spending (in 1K JPY)



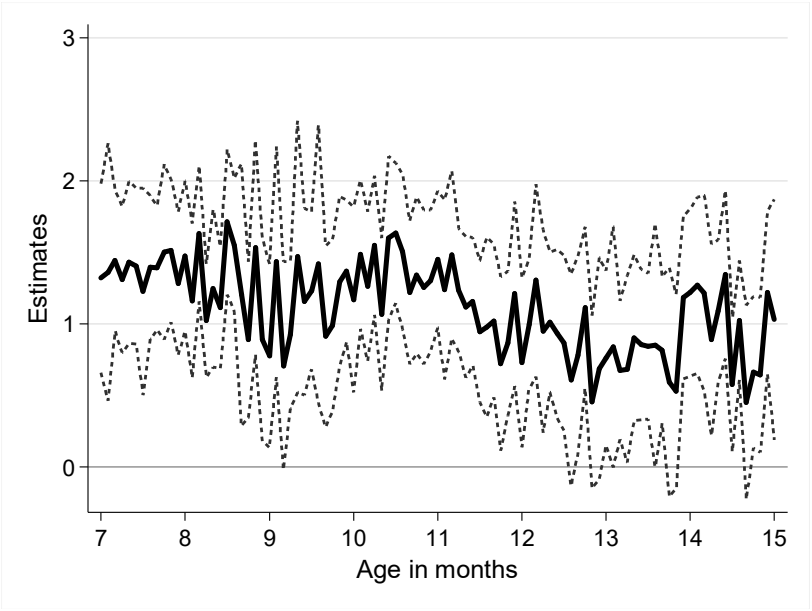
Notes: An outpatient visit dummy takes one if there is at least one outpatient visit per month, and outpatient spending is the monthly spending on outpatient care measured in thousand JPY (roughly USD10). "Better" indicates the subsidy expansion which lowers the price of health care from 30% to 0%, and "Worse" indicates subsidy expiration that raises the price from 0% to 30%. The solid lines plot the estimates from a variant of estimation equation [4] where the subsidized dummy is replaced by a series of dummy for each month ranging from 12 months prior to the change in subsidy status to 12 months after the change in subsidy status (T=-12 to +11, where T=0 is the change) at age between 12 and 0 months and 12 and 11 months. The dotted lines are the 95th confidence interval derived from standard errors clustered at municipality level. The reference month is 3 months before the subsidy changes (T=-3). The observations within two months from the subsidy changes of the opposite direction are excluded to account for intertemporal substitution. Note that the scales of *y*-axis are set the same within the panels so that two figures for opposite directions of subsidy changes are visually comparable.

Figure A4: Basic results (monthly)

A. Outpatient visit dummy



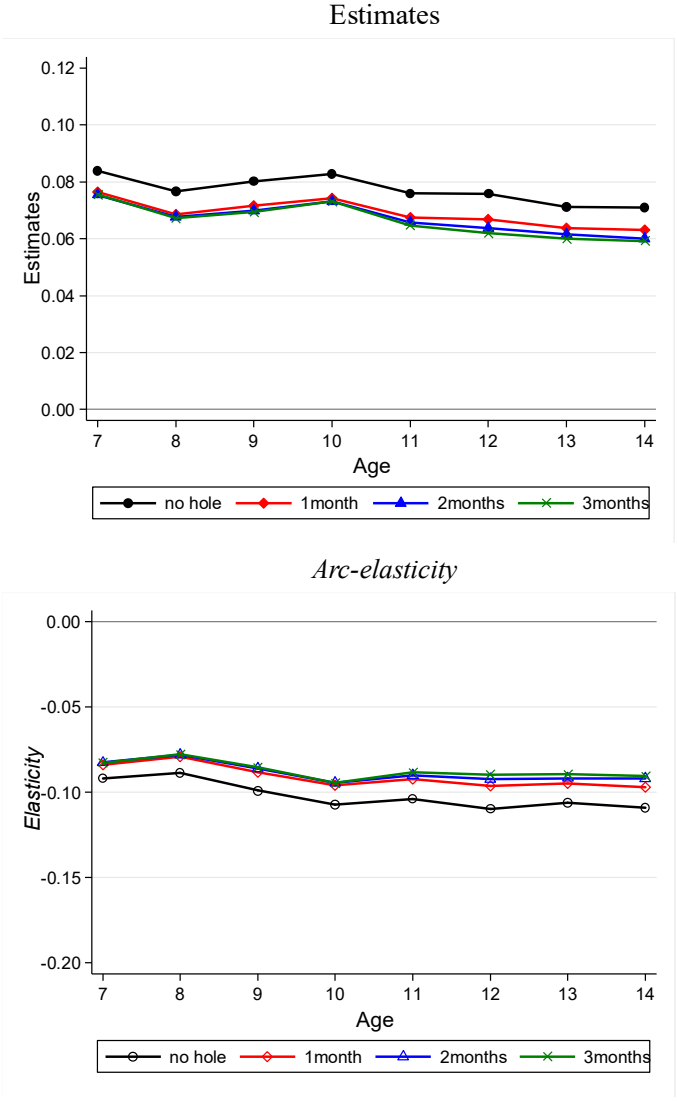
B. Outpatient spending (in 1K JPY)



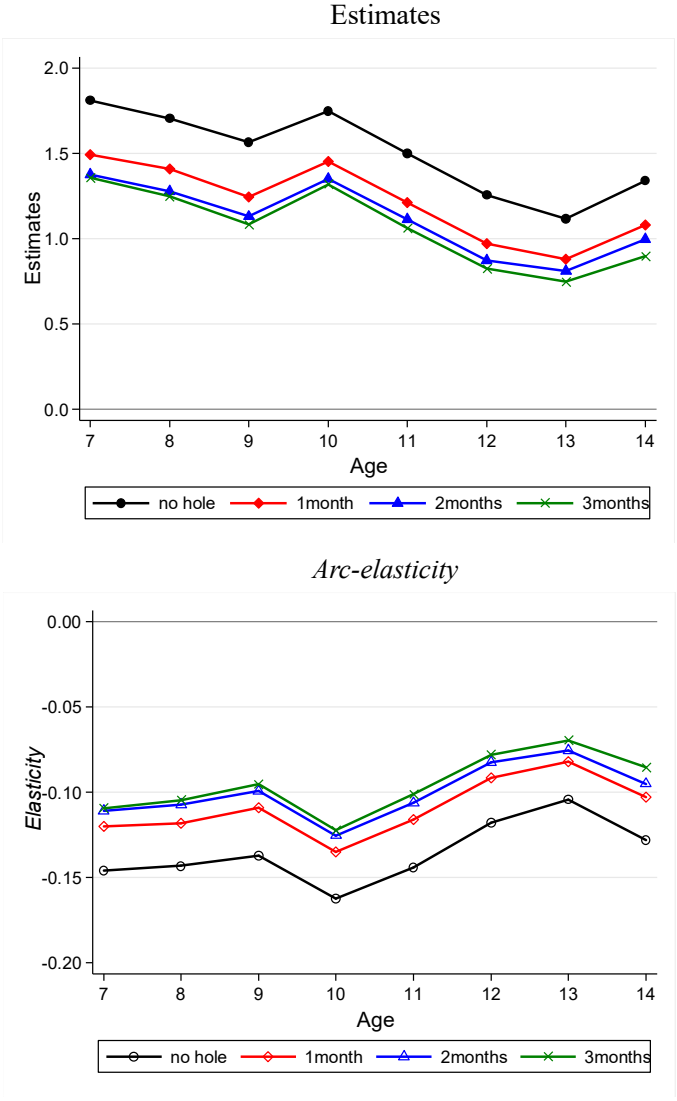
Notes: An outpatient visit dummy takes one if there is at least one outpatient visit per month, and outpatient spending is the monthly spending on outpatient care measured in thousand JPY (roughly USD10). The dotted lines are the 95th confidence intervals and the standard errors clustered at municipality level are used to construct them. The observations within two months from subsidy changes are excluded to account for intertemporal substitution.

Figure A5: Sizes of donut holes and the estimates/elasticity

A. Outpatient visit dummy

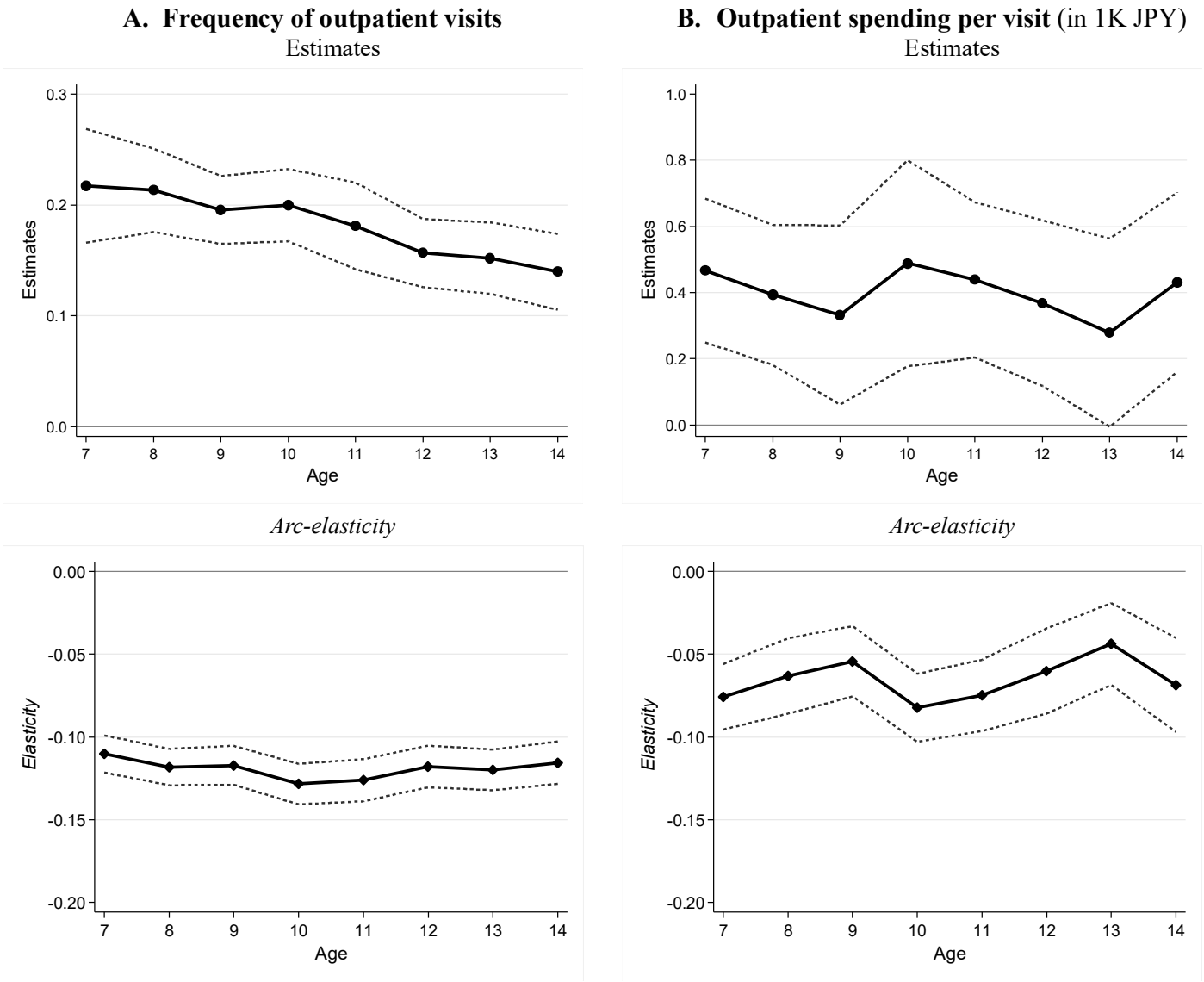


B. Outpatient spending (in 1K JPY)



Notes: An outpatient visit dummy takes one if there is at least one outpatient visit per month, and outpatient spending is the monthly spending on outpatient care measured in thousand JPY (roughly USD10). The lines plot the estimates from the sample where the observations within one, two, and three months from subsidy changes are excluded along with the estimates of no exclusion ("no hole"). See Appendix Table A4 for summary statistics of procedure categories.

Figure A6: Other outcomes

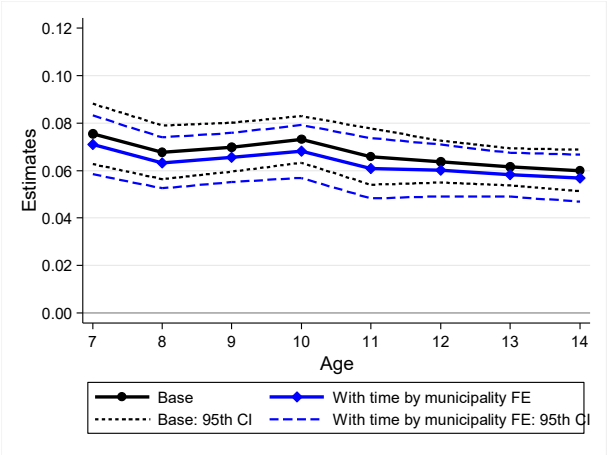


Notes: The frequency of outpatient visits is the number of outpatient visits per month. The outpatient spending per visit is the monthly outpatient spending divided by the number of outpatient visits per month, and is measured in thousand JPY (roughly USD10). The dotted lines are the 95th confidence intervals. The standard errors clustered at municipality level are used for estimates, and the bootstrapped standard errors clustered at municipality with 200 repetitions are used for the arc-elasticity. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. Note that the scale of y-axis on the arc-elasticity is set the same so that they are visually comparable.

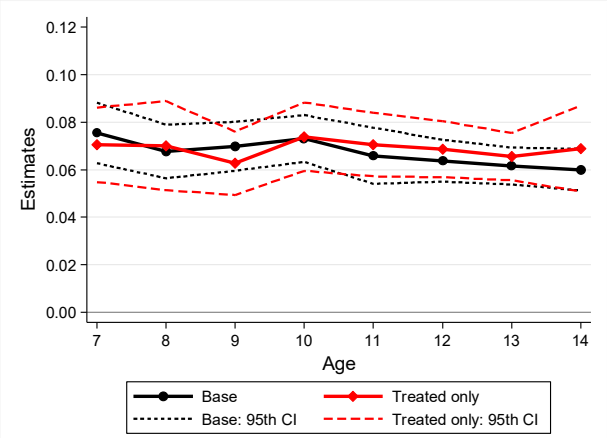
Figure A7: Robustness checks (Estimates only)

A. Outpatient visit dummy

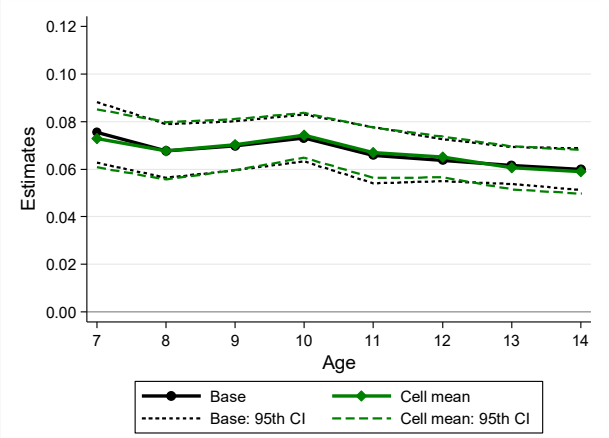
(i) Base vs. With time by municipality FE



(ii) Base vs. Treated only

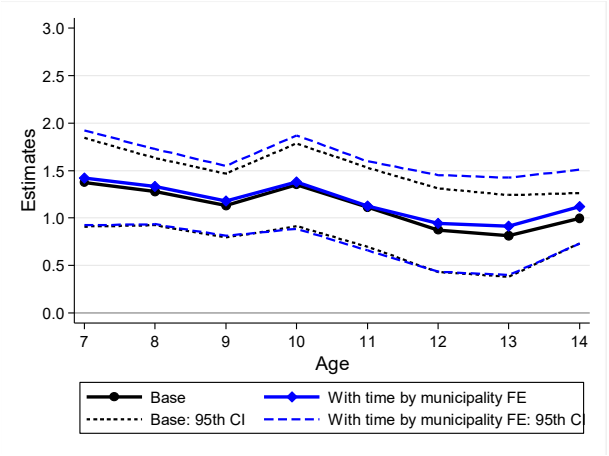


(iii) Base vs. cell means

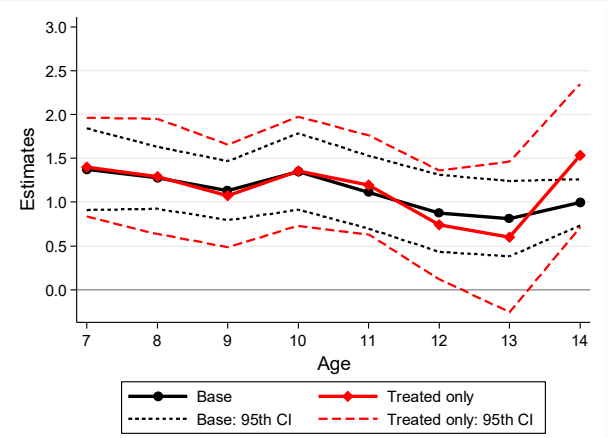


B. Outpatient spending (in 1K JPY)

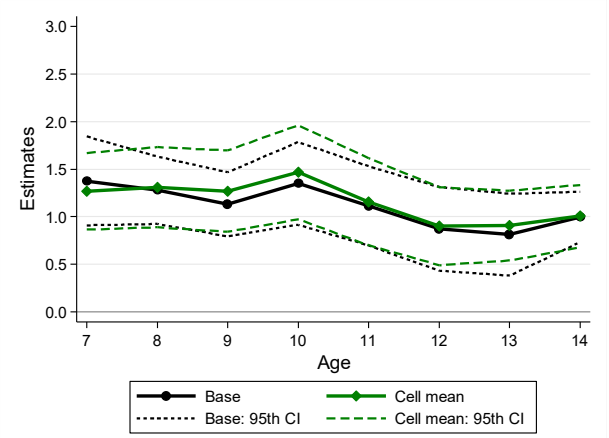
(i) Base vs. With time by municipality FE



(ii) Base vs. Treated only



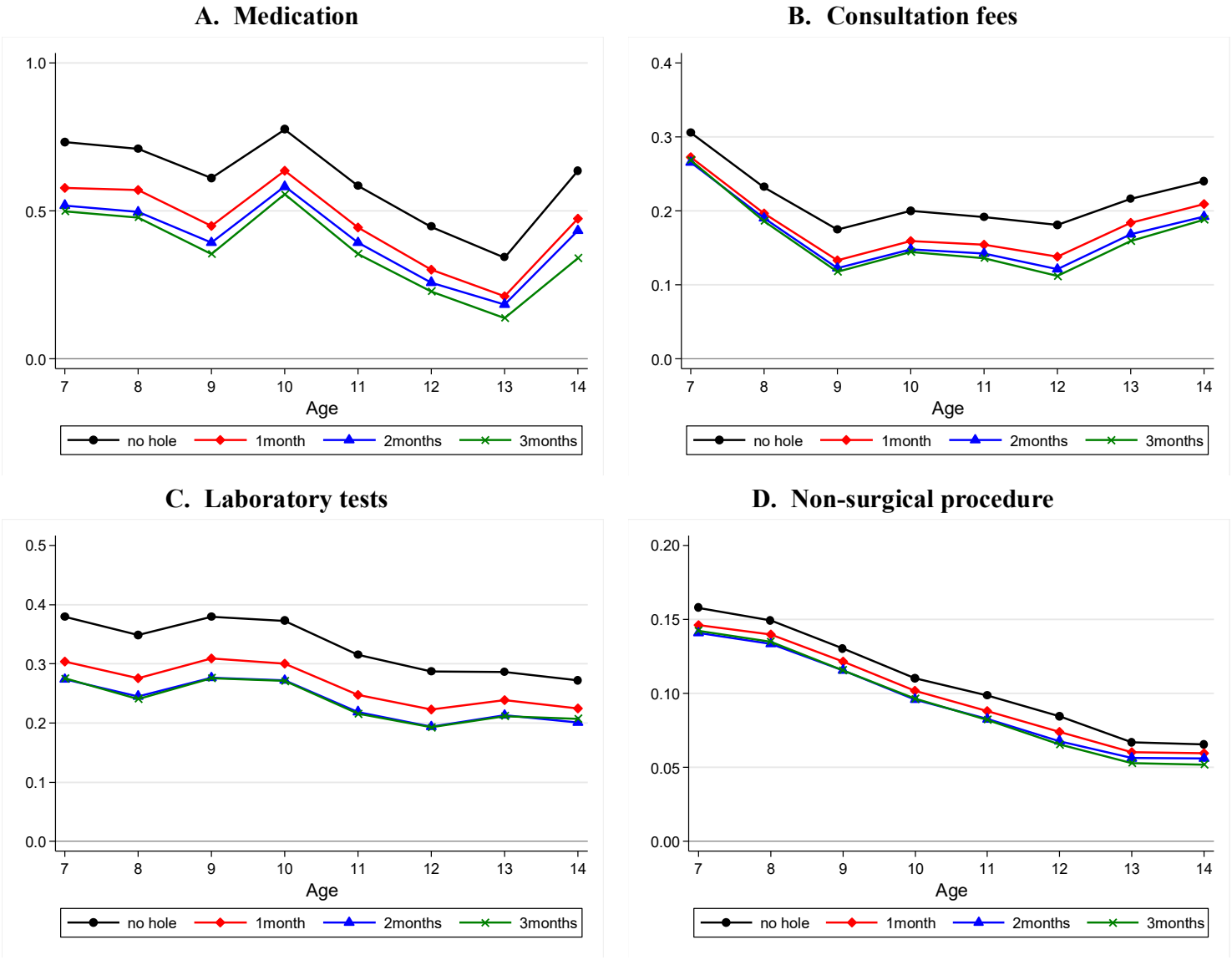
(iii) Base vs. cell means



Notes: An outpatient visit dummy takes one if there is at least one outpatient visit per month, and outpatient spending is the monthly spending on outpatient care measured in thousand JPY (roughly USD10). The dotted lines are the 95th confidence intervals derived from standard errors clustered at municipality level except for 2) where standard errors clustered at individual level. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. Along with our baseline estimates, (i) reports the estimates which include time by municipality FE, (ii) reports the estimates from the sample limited to those individuals which experienced at least one change in subsidy status, and (iii) reports the estimates from cell means where the cell is defined by age×time×municipality and the number of observations in each cell is used as a weight.

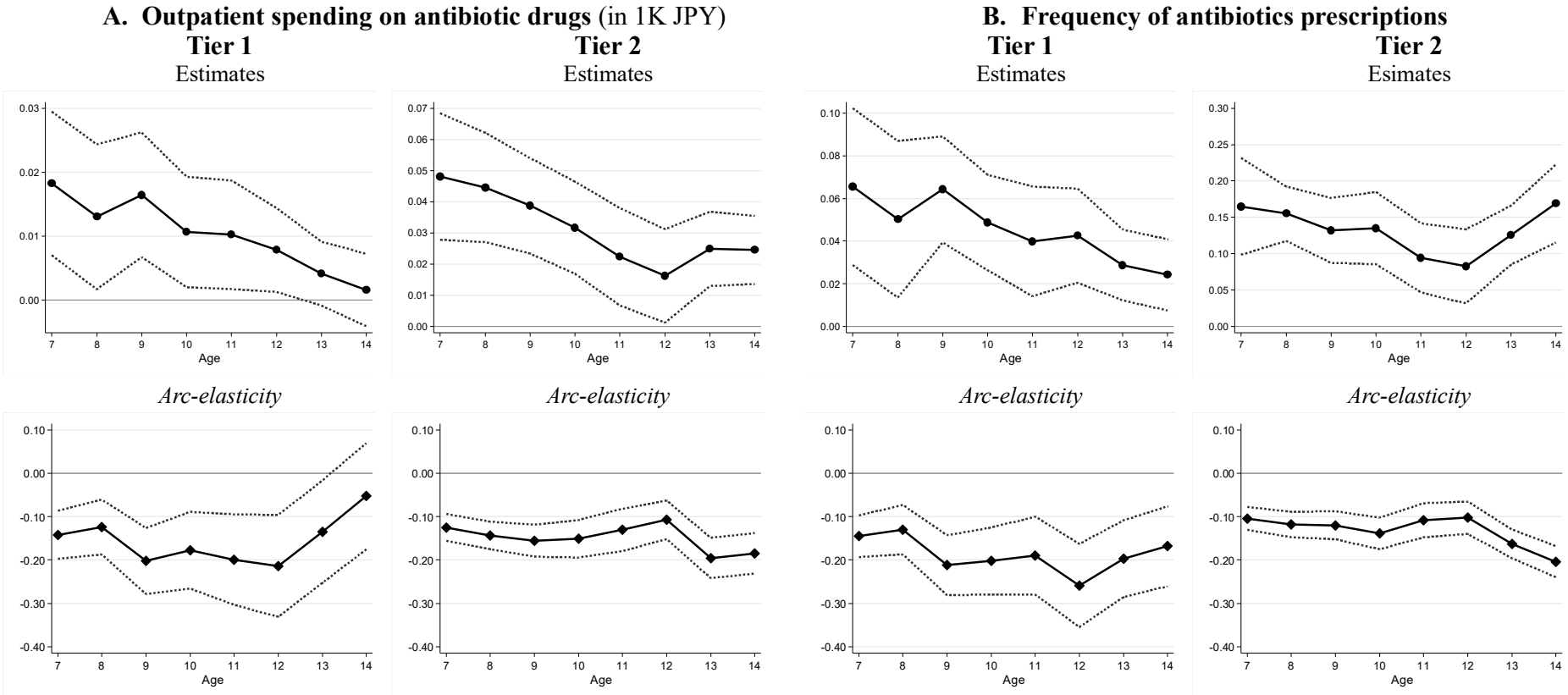
Figure A8: Sizes of donut holes and the estimates by procedure categories

Outcome: Outpatient spending (in 1K JPY)



Notes: The outpatient spending is the monthly spending on outpatient care measured in thousand JPY (roughly USD10). The lines plot the estimates from the sample where the observations within one, two, and three months from subsidy changes are excluded along with the estimates of no exclusion ("no hole"). See Appendix Table A4 for summary statistics of procedure categories.

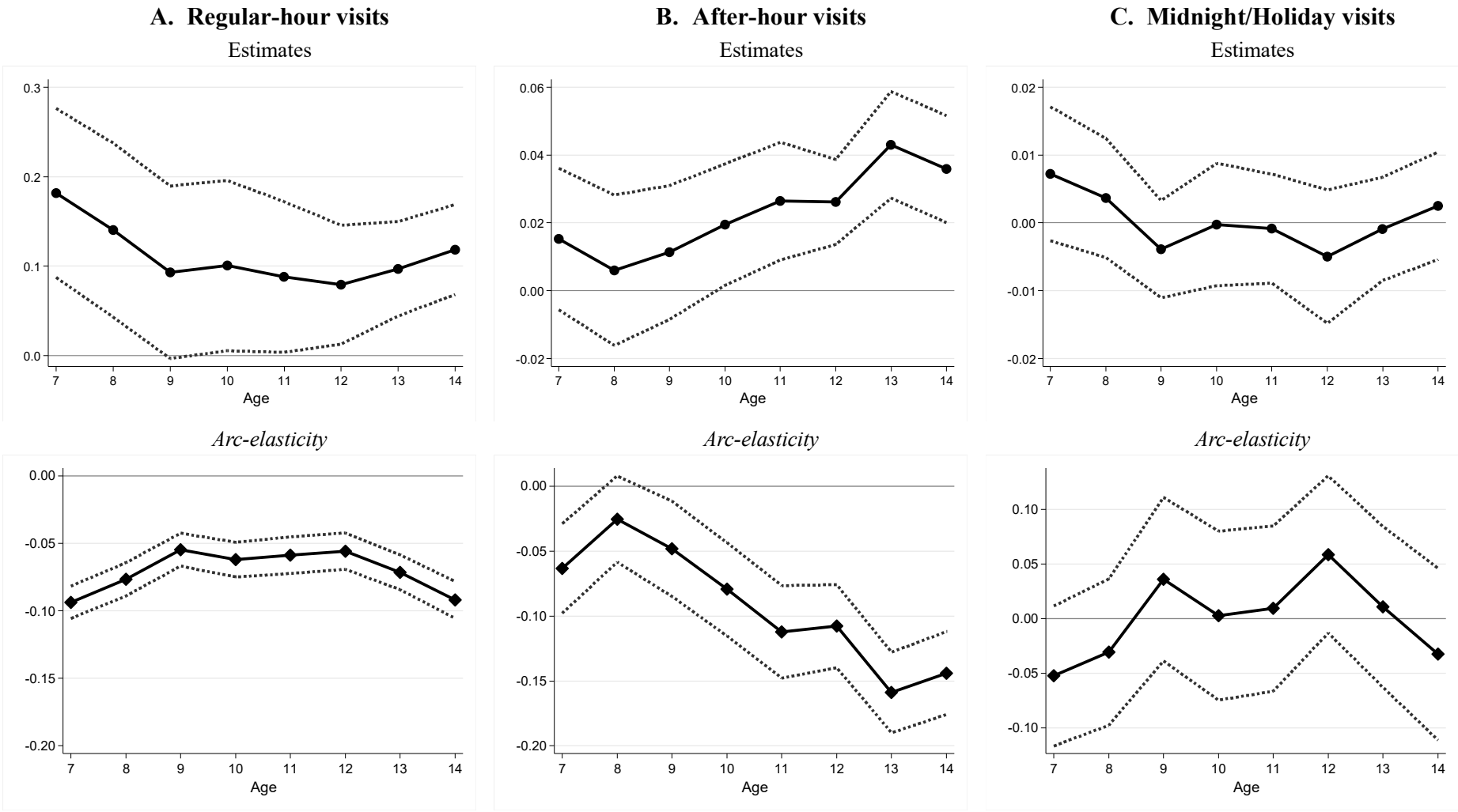
Figure A9: Antibiotics use for Tier 1 and Tier 2



Notes: The outpatient spending on antibiotic drugs is the monthly spending on antibiotics measured in thousand JPY (roughly USD10), and the frequency of antibiotics prescriptions is the number of prescriptions for the antibiotic per month. See Appendix Table A9 for the list of ICD10 codes for each Tier and Appendix Table A10 for the summary statistics. The dotted lines are the 95th confidence intervals. The standard errors clustered at municipality level are used for estimates, and the bootstrapped standard errors clustered at municipality with 200 repetitions are used for the arc-elasticity. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. Note that the scale of *y*-axis on the arc-elasticity is set the same so that they are visually comparable.

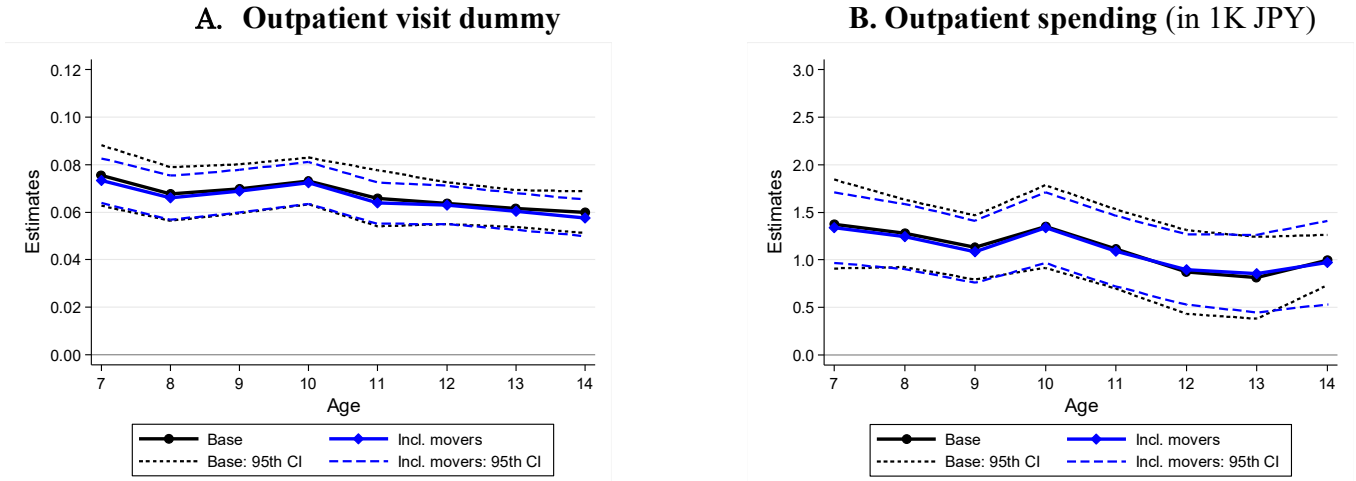
Figure A10: Urgent visits

Outcome: Outpatient spending (in 1K JPY)



Notes: The outpatient spending is the monthly spending on outpatient care measured in thousand JPY (roughly USD10). The dotted lines are the 95th confidence intervals. The standard errors clustered at municipality level are used for estimates, and the bootstrapped standard errors clustered at municipality with 200 repetitions are used for the arc-elasticity. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. See Appendix Table A12 which provides the list of billing codes for these urgent visits and corresponding fees that are additionally charged on top of fees for regular-hour visits. Note that the scale of y-axis on the arc-elasticity is set the same so that they are visually comparable.

Figure A11: Base vs. including movers



Notes: An outpatient visit dummy takes one if there is at least one outpatient visit per month, and outpatient spending is the monthly spending on outpatient care measured in thousand JPY (roughly USD10). The dotted lines are the 95th confidence intervals derived from standard errors clustered at individual level. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. Along with our baseline estimates, we reports estimates from the sample that include inter-municipality movers (4.8%).

Table A1: Other outcomes

	A. Frequency of outpatient visits				B. Outpatient spending per visit (in 1K JPY)			
	(1)		(2)		(3)		(4)	
	Estimate	(SE)	*Arc-elasticity*	[SE]	Estimate	(SE)	*Arc-elasticity*	[SE]
Subsidized ×								
Age7	0.217***	(0.026)	-0.110***	[0.006]	0.467***	(0.110)	-0.076***	[0.010]
Age8	0.213***	(0.019)	-0.118***	[0.006]	0.393***	(0.107)	-0.063***	[0.012]
Age9	0.196***	(0.016)	-0.117***	[0.006]	0.332**	(0.137)	-0.054***	[0.011]
Age10	0.200***	(0.016)	-0.128***	[0.006]	0.488***	(0.158)	-0.082***	[0.010]
Age11	0.181***	(0.020)	-0.126***	[0.006]	0.438***	(0.119)	-0.075***	[0.011]
Age12	0.157***	(0.016)	-0.118***	[0.006]	0.368***	(0.127)	-0.06***	[0.013]
Age13	0.152***	(0.016)	-0.120***	[0.006]	0.279*	(0.144)	-0.044***	[0.013]
Age14	0.140***	(0.017)	-0.116***	[0.007]	0.431***	(0.137)	-0.069***	[0.014]
In-kind	0.072	(0.051)			0.141	(0.190)		
Income restriction	-0.083***	(0.026)			-0.141	(0.208)		
R-squared	0.28				0.44			
N	2,205,647				2,205,647			
N of Individual	63,530				63,530			
Mean wo subsidy	0.62				2.59			

Notes: The frequency of outpatient visits is the number of outpatient visits per month. The outpatient spending per visit is the monthly outpatient spending divided by the number of outpatient visits per month, and is measured in thousand JPY (roughly USD10). All the regressions include age (in months) FE, time (in month) FE, and individual FE. In-kind is a dummy that takes one if the municipality offers the subsidy in the form of in-kind instead of refund, and income restriction is a dummy that takes one if the municipality imposes income restriction for subsidy eligibility. For the estimates, the standard errors clustered at the municipality level are reported in parenthesis. For the arc-elasticity, the bootstrapped standard errors with 200 repetitions clustered at municipality level are reported in brackets. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table A2-1: The size of donut-holes and corresponding estimates/elasticity

Outcome: Outpatient visit dummy

	No exclusion		±1month excluded		±2months excluded		±3months excluded		No exclusion	±1month excluded	±2months excluded	±3months excluded
	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	*Arc-elasticity*			
	(1)		(2)		(3)		(4)		(5)	(6)	(7)	(8)
Subsidized ×												
Age7	0.084***	(0.005)	0.077***	(0.006)	0.075***	(0.006)	0.076***	(0.007)	*-0.106*	*-0.097*	*-0.095*	*-0.095*
Age8	0.077***	(0.004)	0.069***	(0.005)	0.068***	(0.006)	0.067***	(0.007)	*-0.098*	*-0.088*	*-0.086*	*-0.086*
Age9	0.080***	(0.004)	0.072***	(0.005)	0.070***	(0.005)	0.069***	(0.006)	*-0.105*	*-0.093*	*-0.091*	*-0.090*
Age10	0.083***	(0.005)	0.074***	(0.005)	0.073***	(0.005)	0.073***	(0.005)	*-0.109*	*-0.097*	*-0.095*	*-0.095*
Age11	0.076***	(0.005)	0.067***	(0.006)	0.066***	(0.006)	0.065***	(0.006)	*-0.101*	*-0.089*	*-0.086*	*-0.085*
Age12	0.076***	(0.004)	0.067***	(0.004)	0.064***	(0.004)	0.062***	(0.005)	*-0.100*	*-0.087*	*-0.083*	*-0.081*
Age13	0.071***	(0.004)	0.064***	(0.004)	0.062***	(0.004)	0.060***	(0.004)	*-0.092*	*-0.082*	*-0.078*	*-0.076*
Age14	0.071***	(0.004)	0.063***	(0.004)	0.060***	(0.004)	0.059***	(0.005)	*-0.090*	*-0.079*	*-0.074*	*-0.073*
In-kind	0.041***	(0.013)	0.042***	(0.013)	0.047***	(0.014)	0.051***	(0.014)				
Income restriction	-0.021***	(0.008)	-0.018**	(0.008)	-0.020**	(0.009)	-0.017	(0.011)				
R-squared	0.23		0.23		0.23		0.23					
N	2,304,040		2,253,851		2,205,647		2,158,881					
N of Individual	63,590		63,570		63,530		63,362					

Notes: An outpatient visit dummy takes one if there is at least one outpatient visit per month. All the regressions include age (in months) FE, time (in month) FE, and individual FE. In-kind is a dummy that takes one if the municipality offers the subsidy in the form of in-kind instead of refund, and income restriction is a dummy that takes one if the municipality imposes income restriction for subsidy eligibility. The standard errors clustered at the municipality level are reported in parenthesis. Column (1) does not exclude any observations, while Columns (2)-(4) exclude the observations within one, two, and three months from subsidy changes to account for intertemporal substitution. Columns (5)-(9) report the arc-elasticity that corresponds to estimates from Columns (1)-(4). Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table A2-2: The size of donut-holes and corresponding estimates/elasticity

Outcome: Outpatient spending (in 1K JPY)

	No exclusion		±1month excluded		±2months excluded		±3months excluded		No exclusion	±1month excluded	±2months excluded	±3months excluded
	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	*Arc-elasticity*			
	(1)		(2)		(3)		(4)		(5)	(6)	(7)	(8)
Subsidized ×												
Age7	1.812***	(0.192)	1.493***	(0.221)	1.376***	(0.236)	1.357***	(0.270)	*-0.158*	*-0.131*	*-0.121*	*-0.117*
Age8	1.705***	(0.164)	1.410***	(0.175)	1.278***	(0.179)	1.249***	(0.199)	*-0.153*	*-0.126*	*-0.115*	*-0.110*
Age9	1.565***	(0.155)	1.243***	(0.163)	1.131***	(0.171)	1.083***	(0.196)	*-0.142*	*-0.112*	*-0.102*	*-0.097*
Age10	1.749***	(0.200)	1.453***	(0.217)	1.350***	(0.221)	1.319***	(0.246)	*-0.160*	*-0.131*	*-0.121*	*-0.118*
Age11	1.502***	(0.192)	1.214***	(0.208)	1.113***	(0.211)	1.062***	(0.229)	*-0.137*	*-0.108*	*-0.099*	*-0.094*
Age12	1.255***	(0.186)	0.970***	(0.201)	0.872***	(0.223)	0.824***	(0.253)	*-0.109*	*-0.083*	*-0.074*	*-0.070*
Age13	1.117***	(0.192)	0.881***	(0.205)	0.811***	(0.218)	0.748***	(0.240)	*-0.094*	*-0.072*	*-0.066*	*-0.061*
Age14	1.341***	(0.112)	1.080***	(0.117)	0.998***	(0.134)	0.899***	(0.166)	*-0.113*	*-0.088*	*-0.080*	*-0.073*
In-kind	-0.385	(0.661)	0.422	(0.354)	0.440	(0.388)	0.470	(0.435)				
Income restriction	-0.564*	(0.317)	-0.553	(0.356)	-0.561	(0.372)	-0.626	(0.401)				
R-squared	0.51		0.51		0.51		0.51					
N	2,303,335		2,253,851		2,205,647		2,158,881					
N of Individual	63,590		63,570		63,530		63,362					

Notes: The outpatient spending is the monthly spending on outpatient care measured in thousand JPY (roughly USD10). All the regressions include age (in months) FE, time (in month) FE, and individual FE. In-kind is a dummy that takes one if the municipality offers the subsidy in the form of in-kind instead of refund, and income restriction is a dummy that takes one if the municipality imposes income restriction for subsidy eligibility. The standard errors clustered at the municipality level are reported in parenthesis. Column (1) does not exclude any observations, while Columns (2)-(4) exclude the observations within one, two, and three months from subsidy changes to account for intertemporal substitution. Columns (5)-(9) report the arc-elasticity that corresponds to estimates from Columns (1)-(4). Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table A3-1: Robustness checks for outpatient visits

Outcome: Outpatient visit dummy

	Baseline (Col. 1 Table 2)		With municipality-time trend		With municipality-time FE		Among only treated		Cell		Including movers	
	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)
	(1)		(2)		(3)		(4)		(5)		(6)	
Subsidized ×												
Age7	0.075***	(0.006)	0.070***	(0.006)	0.071***	(0.006)	0.070***	(0.008)	0.073***	(0.006)	0.073***	(0.005)
Age8	0.068***	(0.006)	0.064***	(0.005)	0.063***	(0.005)	0.070***	(0.009)	0.068***	(0.006)	0.066***	(0.005)
Age9	0.070***	(0.005)	0.066***	(0.005)	0.065***	(0.005)	0.063***	(0.007)	0.070***	(0.005)	0.069***	(0.005)
Age10	0.073***	(0.005)	0.070***	(0.005)	0.068***	(0.006)	0.074***	(0.007)	0.074***	(0.005)	0.072***	(0.005)
Age11	0.066***	(0.006)	0.063***	(0.006)	0.061***	(0.006)	0.071***	(0.007)	0.067***	(0.005)	0.064***	(0.004)
Age12	0.064***	(0.004)	0.062***	(0.005)	0.060***	(0.006)	0.069***	(0.006)	0.065***	(0.004)	0.063***	(0.004)
Age13	0.062***	(0.004)	0.061***	(0.004)	0.058***	(0.005)	0.065***	(0.005)	0.061***	(0.005)	0.060***	(0.004)
Age14	0.060***	(0.004)	0.060***	(0.005)	0.057***	(0.005)	0.069***	(0.009)	0.059***	(0.005)	0.058***	(0.004)
In-kind	0.047***	(0.014)	0.054***	(0.019)	0.017	(0.031)	0.040**	(0.019)	0.054***	(0.016)	0.050***	(0.018)
Income restriction	-0.020**	(0.009)	-0.015*	(0.008)	-0.014	(0.009)	-0.017*	(0.009)	-0.017**	(0.008)	-0.020***	(0.008)
R-squared	0.23		0.23		0.24		0.19		0.30		0.23	
N	2,205,647		2,205,647		2,204,496		862,211		465,241		2,326,758	
N of Individual	63,530		63,530		63,502		13,892		-		66,576	
Age FE	X		X		X		X		X		X	
Time FE	X		X		X		X		X		X	
Individual FE	X		X		X		X		X		X	
Municipality-Time trend			X									
Municipality-Time FE					X							

Notes: An outpatient visit dummy takes one if there is at least one outpatient visit per month. For ease of comparison, Column (1) replicates the estimates from Column (1) in Table 2. Columns (2) and (3) add municipality-specific trend and municipality-time (in months) FE, respectively. Column (4) reports the estimates from the sample limited to those individuals which experienced at least one change in subsidy status. Column (5) reports the estimates from cell means where the cell is defined by age×time×municipality and the number of observations in each cell is used as a weight. Column (6) reports estimates from the sample that include inter-municipality movers (4.6%). The standard errors clustered at the municipality level are reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table A3-2: Robustness checks for outpatient visits

Outcome: Outpatient spending (in 1K JPY)

	Baseline (Col. 3 Table 2)		With municipality-time trend		With municipality-time FE		Among only treated		Cell		Including movers	
	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)
	(1)		(2)		(3)		(4)		(5)		(6)	
Subsidized ×												
Age7	1.376***	(0.236)	1.452***	(0.216)	1.422***	(0.253)	1.401***	(0.285)	1.267***	(0.204)	1.337***	(0.189)
Age8	1.278***	(0.179)	1.366***	(0.172)	1.331***	(0.201)	1.293***	(0.333)	1.310***	(0.213)	1.245***	(0.174)
Age9	1.131***	(0.171)	1.215***	(0.147)	1.180***	(0.186)	1.073***	(0.297)	1.269***	(0.216)	1.085***	(0.167)
Age10	1.350***	(0.221)	1.430***	(0.189)	1.378***	(0.249)	1.353***	(0.315)	1.468***	(0.251)	1.339***	(0.190)
Age11	1.113***	(0.211)	1.184***	(0.191)	1.128***	(0.237)	1.196***	(0.287)	1.157***	(0.231)	1.091***	(0.190)
Age12	0.872***	(0.223)	0.943***	(0.212)	0.944***	(0.257)	0.741**	(0.314)	0.900***	(0.208)	0.898***	(0.189)
Age13	0.811***	(0.218)	0.889***	(0.196)	0.912***	(0.260)	0.602	(0.435)	0.907***	(0.186)	0.855***	(0.208)
Age14	0.998***	(0.134)	1.069***	(0.124)	1.120***	(0.197)	1.531***	(0.414)	1.006***	(0.167)	0.971***	(0.224)
In-kind	0.440	(0.388)	0.815***	(0.305)	0.405	(0.792)	0.097	(0.336)	0.399	(0.363)	0.537*	(0.326)
Income restriction	-0.561	(0.372)	-0.519*	(0.269)	-0.366	(0.288)	-0.501	(0.439)	-0.297	(0.617)	-0.701**	(0.296)
R-squared	0.51		0.51		0.51		0.54		0.56		0.51	
N	2,205,647		2,205,647		2,204,496		862,211		465,241		2,326,758	
N of Individual	63,530		63,530		63,502		13,892		-		66,576	
Age FE	X		X		X		X		X		X	
Time FE	X		X		X		X		X		X	
Individual FE	X		X		X		X		X		X	
Municipality-Time trend			X									
Municipality-Time FE					X							

Notes: The outpatient spending is the monthly spending on outpatient care measured in thousand JPY (roughly USD10). For ease of comparison, Column (1) replicates the estimates from Column (1) in Table 2. Columns (2) and (3) add municipality-specific trend and municipality-time (in months) FE, respectively. Column (4) reports the estimates from the sample limited to those individuals which experienced at least one change in subsidy status. Column (5) reports the estimates from cell means where the cell is defined by age×time×municipality and the number of observations in each cell is used as a weight. Column (6) reports estimates from the sample that include inter-municipality movers (4.6%). The standard errors clustered at the municipality level are reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table A4: Summary statistics of procedure categories

Procedure categories	Outpatient visit dummy			Outpatient spending (in 1K JPY)		
	Unconditional	Conditional on visit	Share	Unconditional	Conditional on visit	Share
	(1)	(2)	(3)	(4)	(5)	(6)
Medication	0.35	0.85	31.2%	2.84	7.00	48.8%
Consultation fees	0.38	0.94	34.6%	1.38	3.39	23.6%
Laboratory tests	0.19	0.47	17.5%	1.01	2.49	17.3%
Non-surgical procedure	0.16	0.40	14.6%	0.34	0.83	5.8%
Others	0.02	0.05	1.7%	0.19	0.47	3.3%
Surgical procedure	0.01	0.01	0.5%	0.07	0.17	1.2%

Notes: "Unconditional" includes observations (year-month) with no outpatient visits, and "Conditional on visit" limits to observations with outpatient visit. The unit of spending is measured in thousand JPY (roughly USD10).

Table A5-1: Asymmetric responses by procedure

Outcome: Outpatient visit dummy

	A. Medication		B. Consultation Fees		C. Laboratory tests		D. Non-surgical procedure	
	Estimate	*Semi point-elasticity*	Estimate	*Semi point-elasticity*	Estimate	*Semi point-elasticity*	Estimate	*Semi point-elasticity*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Subsidized ×								
Age7 × Better	0.055***	-0.515***	0.058***	-0.587***	0.035***	-0.715***	0.034***	-0.662***
	(0.009)	[0.064]	(0.010)	[0.065]	(0.006)	[0.109]	(0.007)	[0.095]
Age8 × Better	0.069***	-0.697***	0.074***	-0.774***	0.039***	-0.822***	0.037***	-0.789***
	(0.007)	[0.054]	(0.010)	[0.056]	(0.006)	[0.11]	(0.007)	[0.083]
Age9 × Better	0.060***	-0.661***	0.061***	-0.704***	0.030***	-0.65***	0.028***	-0.683***
	(0.005)	[0.055]	(0.007)	[0.06]	(0.005)	[0.103]	(0.004)	[0.092]
Age10× Better	0.065***	-0.764***	0.069***	-0.828***	0.030***	-0.704***	0.036***	-0.916***
	(0.006)	[0.049]	(0.008)	[0.051]	(0.006)	[0.084]	(0.005)	[0.08]
Age11× Better	0.071***	-0.893***	0.071***	-0.886***	0.037***	-0.858***	0.033***	-0.909***
	(0.006)	[0.048]	(0.008)	[0.045]	(0.004)	[0.081]	(0.005)	[0.074]
Age12× Better	0.071***	-0.966***	0.067***	-0.879***	0.035***	-0.785***	0.032***	-0.991***
	(0.005)	[0.049]	(0.007)	[0.049]	(0.004)	[0.074]	(0.004)	[0.083]
Age13× Better	0.069***	-0.992***	0.062***	-0.839***	0.034***	-0.767***	0.035***	-1.211***
	(0.004)	[0.05]	(0.007)	[0.051]	(0.003)	[0.07]	(0.004)	[0.088]
Age14× Better	0.070***	-1.034***	0.062***	-0.861***	0.034***	-0.811***	0.033***	-1.191***
	(0.004)	[0.055]	(0.007)	[0.047]	(0.003)	[0.075]	(0.004)	[0.094]
Subsidized ×								
Age7 × Worse	-0.068***	-0.515***	-0.061***	-0.412***	-0.027***	-0.408***	-0.045***	-0.67***
	(0.008)	[0.035]	(0.009)	[0.034]	(0.004)	[0.056]	(0.005)	[0.057]
Age8 × Worse	-0.073***	-0.584***	-0.064***	-0.458***	-0.035***	-0.532***	-0.041***	-0.663***
	(0.009)	[0.043]	(0.010)	[0.039]	(0.005)	[0.076]	(0.007)	[0.069]
Age9 × Worse	-0.066***	-0.563***	-0.057***	-0.426***	-0.027***	-0.404***	-0.027***	-0.47***
	(0.009)	[0.047]	(0.010)	[0.049]	(0.006)	[0.078]	(0.006)	[0.083]
Age10× Worse	-0.061***	-0.54***	-0.053***	-0.412***	-0.022***	-0.331***	-0.032***	-0.604***
	(0.007)	[0.047]	(0.009)	[0.044]	(0.005)	[0.072]	(0.006)	[0.075]
Age11× Worse	-0.066***	-0.631***	-0.054***	-0.448***	-0.030***	-0.485***	-0.030***	-0.623***
	(0.006)	[0.047]	(0.008)	[0.043]	(0.005)	[0.081]	(0.006)	[0.081]
Age12× Worse	-0.065***	-0.667***	-0.050***	-0.437***	-0.025***	-0.411***	-0.034***	-0.796***
	(0.006)	[0.054]	(0.009)	[0.043]	(0.005)	[0.073]	(0.006)	[0.086]
Age13× Worse	-0.060***	-0.649***	-0.045***	-0.409***	-0.025***	-0.407***	-0.040***	-1.014***
	(0.004)	[0.053]	(0.006)	[0.045]	(0.004)	[0.069]	(0.005)	[0.097]
Age14× Worse	-0.061***	-0.676***	-0.044***	-0.414***	-0.026***	-0.447***	-0.031***	-0.874***
	(0.004)	[0.047]	(0.006)	[0.048]	(0.004)	[0.072]	(0.005)	[0.098]
R-squared	0.23		0.24		0.14		0.23	
N	2,144,756		2,144,756		2,144,756		2,144,756	
N of Individual	62,609		62,609		62,609		62,609	
Mean wo subsidy	0.27		0.27		0.15		0.12	

Notes: The outpatient spending is total monthly spending on outpatient care measured in thousands JPY (roughly 10USD). "Better" indicates the subsidy expansion which lowers the price of health care from 30% to 0%, and "Worse" indicates subsidy expiration that raises the price from 0% to 30%. All the regressions include age (in months) FE, time (in month) FE, individual FE, an in-kind dummy that takes one if the municipality offers the subsidy in the form of in-kind instead of refund, and an income restriction dummy that takes one if the municipality imposes income restriction for subsidy eligibility. For the estimates, the standard errors clustered at the municipality level are reported in parenthesis. For the semi point-elasticity, the bootstrapped standard errors with 200 repetitions clustered at municipality level are reported in brackets. The observations within two months from subsidy changes are excluded. See Appendix Table A4 for summary statistics of procedure categories. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table A5-2: Asymmetric responses by procedure

Outcome: Outpatient spending per month (in 1K JPY)

	A. Medication		B. Consultation Fees		C. Laboratory tests		D. Non-surgical procedure	
	Estimate	*Semi point-elasticity*	Estimate	*Semi point-elasticity*	Estimate	*Semi point-elasticity*	Estimate	*Semi point-elasticity*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Subsidized ×								
Age7 × Better	0.410	-0.636***	0.197***	-0.752***	0.300***	-1.473***	0.113***	-1.263***
	(0.250)	[0.181]	(0.051)	[0.113]	(0.059)	[0.229]	(0.041)	[0.226]
Age8 × Better	0.341	-0.527***	0.260***	-1.039***	0.306***	-1.567***	0.116***	-1.448***
	(0.239)	[0.204]	(0.059)	[0.106]	(0.042)	[0.192]	(0.034)	[0.197]
Age9 × Better	0.353*	-0.599***	0.195***	-0.846***	0.228***	-1.198***	0.077***	-1.077***
	(0.212)	[0.194]	(0.041)	[0.102]	(0.041)	[0.195]	(0.025)	[0.186]
Age10× Better	0.381	-0.693***	0.253***	-1.146***	0.233***	-1.213***	0.116***	-1.72***
	(0.262)	[0.213]	(0.045)	[0.095]	(0.042)	[0.157]	(0.022)	[0.166]
Age11× Better	0.382	-0.637***	0.251***	-1.214***	0.278***	-1.405***	0.096***	-1.47***
	(0.251)	[0.178]	(0.049)	[0.088]	(0.028)	[0.135]	(0.021)	[0.174]
Age12× Better	0.220	-0.332**	0.220***	-1.078***	0.253***	-1.191***	0.097***	-1.637***
	(0.276)	[0.151]	(0.042)	[0.085]	(0.033)	[0.129]	(0.020)	[0.176]
Age13× Better	0.134	-0.182	0.198***	-0.996***	0.259***	-1.197***	0.090***	-1.658***
	(0.327)	[0.138]	(0.043)	[0.083]	(0.032)	[0.12]	(0.016)	[0.178]
Age14× Better	0.110	-0.152	0.196***	-1.019***	0.241***	-1.134***	0.081***	-1.619***
	(0.303)	[0.154]	(0.045)	[0.082]	(0.035)	[0.118]	(0.013)	[0.201]
Subsidized ×								
Age7 × Worse	-0.844***	-0.863***	-0.187***	-0.315***	-0.259***	-0.739***	-0.109***	-0.742***
	(0.254)	[0.105]	(0.039)	[0.037]	(0.048)	[0.089]	(0.033)	[0.1]
Age8 × Worse	-0.801***	-0.816***	-0.185***	-0.336***	-0.293***	-0.855***	-0.098***	-0.705***
	(0.234)	[0.155]	(0.054)	[0.049]	(0.055)	[0.104]	(0.032)	[0.107]
Age9 × Worse	-0.873***	-0.899***	-0.117***	-0.23***	-0.207***	-0.591***	-0.043*	-0.33**
	(0.240)	[0.134]	(0.045)	[0.059]	(0.059)	[0.116]	(0.025)	[0.139]
Age10× Worse	-0.928***	-1.02***	-0.113**	-0.232***	-0.199***	-0.574***	-0.091***	-0.773***
	(0.189)	[0.135]	(0.047)	[0.054]	(0.048)	[0.104]	(0.029)	[0.129]
Age11× Worse	-0.822***	-0.967***	-0.140***	-0.31***	-0.261***	-0.8***	-0.064**	-0.597***
	(0.149)	[0.14]	(0.045)	[0.057]	(0.038)	[0.11]	(0.032)	[0.152]
Age12× Worse	-0.726***	-0.835***	-0.090**	-0.213***	-0.221***	-0.668***	-0.077***	-0.814***
	(0.234)	[0.135]	(0.037)	[0.053]	(0.044)	[0.099]	(0.029)	[0.15]
Age13× Worse	-0.557***	-0.644***	-0.025	-0.061	-0.207***	-0.609***	-0.086***	-1.022***
	(0.188)	[0.144]	(0.035)	[0.058]	(0.041)	[0.1]	(0.025)	[0.169]
Age14× Worse	-0.567***	-0.665***	0.025	0.066	-0.181***	-0.554***	-0.045*	-0.597***
	(0.162)	[0.145]	(0.035)	[0.058]	(0.039)	[0.104]	(0.023)	[0.209]
R-squared	0.53		0.25		0.12		0.17	
N	2,144,756		2,144,756		2,144,756		2,144,756	
N of Individual	62,609		62,609		62,609		62,609	
Mean wo subsidy	2.13		0.72		0.68		0.21	
Share	54.1%		18.4%		17.2%		5.3%	

Notes: The outpatient spending is total monthly spending on outpatient care measured in thousands JPY (roughly 10USD). "Better" indicates the subsidy expansion which lowers the price of health care from 30% to 0%, and "Worse" indicates subsidy expiration that raises the price from 0% to 30%. All the regressions include age (in months) FE, time (in month) FE, individual FE, an in-kind dummy that takes one if the municipality offers the subsidy in the form of in-kind instead of refund, and an income restriction dummy that takes one if the municipality imposes income restriction for subsidy eligibility. For the estimates, the standard errors clustered at the municipality level are reported in parenthesis. For the semi point-elasticity, the bootstrapped standard errors with 200 repetitions clustered at municipality level are reported in brackets. The observations within two months from subsidy changes are excluded. See Appendix Table A4 for summary statistics of procedure categories. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table A6: List of diagnosis group and ICD10

	ICD10	Share
A. Broad Category		
Diseases of the respiratory system		31.4%
Diseases of the skin and subcutaneous tissue		13.2%
Diseases of the eye and adnexa		13.0%
Certain infectious and parasitic diseases		10.0%
Diseases of the ear and mastoid process		6.5%
Injury, poisoning and external causes		6.4%
B. ICD10 4digit (Top 10)		
Allergic rhinitis, unspecified	J304	9.5%
Acute bronchitis, unspecified	J209	4.9%
Asthma, unspecified	J459	4.8%
Acute atopic conjunctivitis	H101	4.1%
Acute sinusitis, unspecified	J019	3.6%
Acute laryngopharyngitis	J060	3.5%
Astigmatism	H522	3.1%
Dermatitis, unspecified	L309	2.5%
Acute pharyngitis, unspecified	J029	2.5%
Diarrhea and gastroenteritis of infectious origin	A09-	2.5%

Table A7: List of Ambulatory Care Sensitive Conditions (ACSC)

Name of diseases	A dummy for disease		Share among ACSC (%)	ICD-10
	Uncond. Mean	Cond. on visit Mean		
Congenital syphilis	0.000	0.000	0.0%	A50.0-A50.9
Immunization preventable conditions	0.002	0.005	1.0%	A35, A36, A37, A80, G00
Grand mal status and other epileptic convulsions	0.005	0.012	2.4%	G40, G41
Convulsions "A" & "B"	0.001	0.004	0.7%	R56
Severe ENT infections	0.114	0.280	56.9%	H66, H67 , J02, J03, J06, J31.2
Bacterial pneumonia	0.003	0.007	1.5%	J13, J14, J15.3, J15.4, J15.7, J15.9, J16.8, J18, J18.1
Asthma	0.063	0.155	31.5%	J45, J46
Tuberculosis	0.000	0.000	0.0%	A15, A16, A17, A18, A19
Cellulitis	0.005	0.013	2.6%	L03 L04 L08.0 L08.8 L08.9 L88 L98.0
Diabetes "A", "B", "C"	0.000	0.001	0.1%	E10.0-E10.8, E11.0-E11.8, E12.0-E12.8, E13.0-E13.8, E14.0-E14.8
Hypoglycemia	0.000	0.001	0.2%	E16.2
Gastroenteritis	0.001	0.001	0.3%	K52.2, K52.8, K52.9
Kidney/urinary infection	0.000	0.001	0.2%	N10, N11, N12, N13.6
Dehydration-volume depletion	0.003	0.008	1.5%	E86
Iron deficiency anemia	0.002	0.005	0.9%	D50.1, D50.8, D50.9
Nutritional deficiencies	0.000	0.001	0.2%	E40, E41, E42, E43, E55.0, E64.3
Failure to thrive	0.000	0.000	0.0%	R629
Any ACSC	0.166	0.407		

Notes: "Unconditional" includes observations (year-month) with no outpatient visits, and "Conditional" limits to observations with outpatient visits. We convert the ICD9-CM listed in Gadomski *et al*. (1998) to ICD10.
Source: Gadomski *et al*. (1998)

Table A8: Mortality

	Estimate	(SE)
	(1)	
Subsidized ×		
Age7	0.034	(0.043)
Age8	0.031	(0.045)
Age9	0.057*	(0.033)
Age10	0.003	(0.041)
Age11	0.044	(0.031)
Age12	-0.033	(0.042)
Age13	-0.017	(0.048)
Age14	0.021	(0.028)
In-kind	-0.026*	(0.014)
Income restriction	-0.038	(0.045)
R-squared	0.06	
N	2,205,647	
N of Individual	64,295	
Mean wo subsidy	0.039	

Notes: A mortality dummy is multiplied by 1000. All the regressions include age (in months) FE, time (in month) FE, individual FE, an in-kind dummy that takes one if the municipality offers the subsidy in the form of in-kind instead of refund, and an income restriction dummy that takes one if the municipality imposes income restriction for subsidy eligibility. The standard errors clustered at the municipality level are reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table A9: List of tiers for antibiotics use

Name of diseases	ICD-10
Tier 1	
Miscellaneous bacterial infections	A15-A28, A30-A32, A35-A37, A39-A44, A48-A59, A63-A71, A74-A75, A77-A79, A82, A96, B07, B15-B19, B25-B27, B30, B34, B50-B60, B64, B85-B91, B94-B97, B99, D86, G00-G02, G05, G14, G92, H70, J36, R11 A881, A983, A984, A985, B081, B084, B085, B088, B330, B332, B333, B334, B338, B451, B471, B479, B600, B608, B834, G030, G031, G038, G039, G040, G042, G048, G049, H950, H951,K908, L081, L946, M023, M352, M600, N341
Pneumonia	J13-J17, B440, J180, J181, J189
Urinary tract infections	N10, N12, N16, N151, N159, N300, N309, N390
Tier 2	
Acne	L70
Gastrointestinal infections	A00-A09, R10, R12-R16, R18, R190, R191, R192, R193, R194, R195, R197, R198, K522, K528
Pharyngitis	J02, J03, A38
Sinusitis	J01, J32
Skin, cutaneous and mucosal infections	A46, B35, B36, H62, H66, H67, L01-L03, L05, L88, E832, H600, H601, H602, H603, H610, H619, K122, L049, L080, L088, L089, L663, L731, L738, L980, L983, M726, P390
Suppurative otitis media	H66, H67
Tier 3	
Asthma, allergy	J30, J44, J45, T784
Bronchitis, bronchiolitis	J20, J21, J40
Influenza	J09, J10, J11
Non-suppurative otitis media	H65, H68, H69
Viral pneumonia	J12
Viral upper respiratory infection	J00, J04, J05, J06, R05
Other respiratory conditions	All remaining respiratory conditions (J00-J99) not coded above and R060-R064, R068-R069, R042, R048, R049, R093
All other codes not listed elsewhere	All other codes not listed elsewhere

Source: From Fleming-Dutra *et al.* (2016) eTable "2. Diagnostic categories by tier with corresponding ICD-9CM code".

Table A10: Summary statistics of antibiotic use

Name of disease	fraction of the disease	Conditional on having the disease: antibiotics use (dummy)	Conditional on having the disease: spending on antibiotics (in 1K JPY)	Conditional on having the disease: freq. of antibiotics prescriptions	Probability of having the disease & antibiotics use (dummy)	Probability of having the disease & spending on antibiotics (in 1K JPY)	Probability of having the disease & freq. of antibiotics prescriptions
	(1)	(2)	(3)	(4)	(1)×(2)	(1)×(3)	(1)×(4)
Tier1	0.052	0.40	0.75	2.93	0.020	0.038	0.151
Tier2	0.136	0.62	0.91	4.34	0.084	0.123	0.589
Tier3	0.218	0.19	0.24	0.94	0.041	0.053	0.205
Tier1							
Miscellaneous bacterial infections	0.047	0.38	0.67	2.74	0.018	0.031	0.129
Pneumonia	0.003	0.80	2.57	7.18	0.002	0.008	0.021
Urinary tract infections	0.003	0.49	0.96	3.92	0.002	0.003	0.012
Tier2							
Acne	0.010	0.39	0.60	5.48	0.004	0.006	0.053
Gastrointestinal infections	0.026	0.46	0.67	2.76	0.012	0.018	0.073
Pharyngitis	0.036	0.73	1.04	4.43	0.026	0.037	0.157
Sinusitis	0.071	0.72	1.09	5.41	0.051	0.078	0.385
Skin, cutaneous and mucosal infections	0.012	0.52	0.84	3.79	0.006	0.010	0.046
Suppurative otitis media	0.006	0.82	2.07	7.63	0.005	0.013	0.046
Tier3							
Asthma, allergy	0.058	0.27	0.36	1.45	0.015	0.021	0.084
Bronchitis, bronchiolitis	0.035	0.66	0.90	3.38	0.023	0.032	0.118
Influenza	0.019	0.37	0.48	1.80	0.007	0.009	0.034
Non-suppurative otitis media	0.002	0.27	0.38	1.73	0.001	0.001	0.004
Viral pneumonia	0.000	0.33	0.50	2.34	0.000	0.000	0.000
Viral upper respiratory infection	0.033	0.53	0.67	2.65	0.017	0.022	0.087
Other respiratory conditions	0.000	0.26	0.30	1.78	0.000	0.000	0.000
All other codes not listed elsewhere	0.168	0.11	0.14	0.56	0.019	0.024	0.095

Notes: The spending on antibiotics is measured in thousand JPY (roughly USD10). See Appendix Table A9 for the list of ICD10 codes for each Tier.

Table A11-1: Antibiotic use for Tier 1 and Tier 2

Outcome: Outpatient spending on antibiotics (in 1K JPY)

	Tier1				Tier2			
	(1)		(2)		(3)		(4)	
	Estimate	(SE)	*Arc-elasticity*	[SE]	Estimate	(SE)	*Arc-elasticity*	[SE]
Subsidized ×								
Age7	0.018***	(0.006)	-0.142***	[0.028]	0.048***	(0.010)	-0.125***	[0.016]
Age8	0.013**	(0.006)	-0.124***	[0.032]	0.045***	(0.009)	-0.143***	[0.016]
Age9	0.016***	(0.005)	-0.202***	[0.039]	0.039***	(0.008)	-0.155***	[0.019]
Age10	0.011**	(0.004)	-0.177***	[0.045]	0.032***	(0.007)	-0.151***	[0.022]
Age11	0.010**	(0.004)	-0.199***	[0.053]	0.022***	(0.008)	-0.131***	[0.025]
Age12	0.008**	(0.003)	-0.214***	[0.060]	0.016**	(0.008)	-0.107***	[0.023]
Age13	0.004	(0.003)	-0.135**	[0.060]	0.025***	(0.006)	-0.195***	[0.024]
Age14	0.002	(0.003)	-0.053	[0.062]	0.025***	(0.006)	-0.185***	[0.024]
In-kind	0.007	(0.027)			0.026**	(0.012)		
Income restriction	-0.003	(0.005)			-0.020	(0.014)		
R-squared	0.08				0.13			
N	2,205,647				2,205,647			
N of Individual	63,530				63,530			
Mean wo subsidy	0.026				0.090			

Notes: The outpatient spending on antibiotic drugs is the monthly spending on antibiotics measured in thousand JPY (roughly USD10). All the regressions include age (in months) FE, time (in month) FE, and individual FE. In-kind is a dummy that takes one if the municipality offers the subsidy in the form of in-kind instead of refund, and income restriction is a dummy that takes one if the municipality imposes income restriction for subsidy eligibility. For the estimates, the standard errors clustered at the municipality level are reported in parenthesis. For the semi point-elasticity, the bootstrapped standard errors with 200 repetitions clustered at municipality level are reported in brackets. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. See Appendix Table A9 for the list of ICD10 codes for each Tier and Appendix Table A10 for the summary statistics. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table A11-2: Antibiotic use for Tier 1 and Tier 2

Outcome: Frequency of antibiotics prescriptions

	Tier1				Tier2			
	(1)		(2)		(3)		(4)	
	Estimate	(SE)	*Arc-elasticity*	[SE]	Estimate	(SE)	*Arc-elasticity*	[SE]
Subsidized ×								
Age7	0.066***	(0.019)	-0.145***	[0.025]	0.165***	(0.034)	-0.104***	[0.014]
Age8	0.050***	(0.019)	-0.130***	[0.029]	0.155***	(0.019)	-0.118***	[0.015]
Age9	0.064***	(0.013)	-0.212***	[0.035]	0.132***	(0.023)	-0.120***	[0.016]
Age10	0.049***	(0.011)	-0.202***	[0.039]	0.135***	(0.025)	-0.139***	[0.019]
Age11	0.040***	(0.013)	-0.190***	[0.046]	0.094***	(0.024)	-0.108***	[0.020]
Age12	0.043***	(0.011)	-0.259***	[0.049]	0.082***	(0.026)	-0.102***	[0.019]
Age13	0.029***	(0.008)	-0.197***	[0.045]	0.126***	(0.021)	-0.163***	[0.017]
Age14	0.024***	(0.008)	-0.168***	[0.047]	0.169***	(0.027)	-0.204***	[0.018]
In-kind	-0.035	(0.100)			0.161***	(0.052)		
Income restriction	-0.021	(0.015)			-0.116*	(0.059)		
R-squared	0.10				0.17			
N	2,205,647				2,205,647			
N of Individual	63,530				63,530			
Mean wo subsidy	0.096				0.420			

Notes: The frequency of antibiotics prescriptions is the number of prescriptions for the antibiotic per month. All the regressions include age (in months) FE, time (in month) FE, and individual FE. In-kind is a dummy that takes one if the municipality offers the subsidy in the form of in-kind instead of refund, and income restriction is a dummy that takes one if the municipality imposes income restriction for subsidy eligibility. For the estimates, the standard errors clustered at the municipality level are reported in parenthesis. For the semi point-elasticity, the bootstrapped standard errors with 200 repetitions clustered at municipality level are reported in brackets. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. See Appendix Table A9 for the list of ICD10 codes for each Tier and Appendix Table A10 for the summary statistics. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table A12: List of billing codes for urgent visits and corresponding additional fees charged

Billing code #	Type of visit	Timing of visit	Additional fee charged (in 1K JPY)
After-hour visits			
111000570	initial visit	after-hour	0.85
111000870	initial visit	after-hour (*)	2.30
111012470	initial visit	night/early morning	0.50
111700870	initial visit	after-hour (*)	2.30
112001110	revisit	after-hour	0.65
112001410	revisit	after-hour (*)	1.80
112006470	revisit	after-hour	0.65
112006770	revisit	after-hour (*)	1.80
112015570	revisit	night/early morning	0.50
Midnight/Holiday visits			
111000670	initial visit	holiday	2.50
111000770	initial visit	midnight	4.80
112001210	revisit	holiday	1.90
112001310	revisit	midnight	4.20
112006570	revisit	holiday	1.90
112006670	revisit	midnight	4.20

Notes: The fees listed on the far right are the fees charged additionally to the fees for regular-hour visits. The fees for regular-hour visits during the sample period are roughly 0.7 for initial visit, and 0.5 for revisits measured in thousands JPY (roughly USD10). (*) is applied to specific medical institutions. The unit of additional fee is in thousand JPY
Source: From Japan Federation of Democratic Medical Institutions (2015)

Table A13: Urgent visits

Outcome: Outpatient spending (in 1K JPY)

	A. Regular-hour visits				B. After-hour visits				C. Midnight/Holiday visits			
	(1)		(2)		(3)		(4)		(5)		(6)	
	Estimate	(SE)	*Arc-elasticity*	[SE]	Estimate	(SE)	*Arc-elasticity*	[SE]	Estimate	(SE)	*Arc-elasticity*	[SE]
Subsidized ×												
Age7	0.182***	(0.048)	-0.094***	[0.006]	0.015	(0.011)	-0.063***	[0.018]	0.007	(0.005)	-0.053	[0.033]
Age8	0.140***	(0.049)	-0.077***	[0.006]	0.006	(0.011)	-0.025	[0.017]	0.004	(0.004)	-0.031	[0.034]
Age9	0.093*	(0.049)	-0.055***	[0.006]	0.011	(0.010)	-0.048**	[0.019]	-0.004	(0.004)	0.036	[0.038]
Age10	0.101**	(0.048)	-0.062***	[0.007]	0.019**	(0.009)	-0.079***	[0.018]	-0.000	(0.005)	0.003	[0.039]
Age11	0.088**	(0.043)	-0.059***	[0.007]	0.026***	(0.009)	-0.112***	[0.018]	-0.001	(0.004)	0.009	[0.039]
Age12	0.079**	(0.034)	-0.056***	[0.007]	0.026***	(0.006)	-0.108***	[0.016]	-0.005	(0.005)	0.059	[0.037]
Age13	0.097***	(0.027)	-0.071***	[0.007]	0.043***	(0.008)	-0.159***	[0.016]	-0.001	(0.004)	0.011	[0.038]
Age14	0.118***	(0.025)	-0.092***	[0.007]	0.036***	(0.008)	-0.144***	[0.016]	0.003	(0.004)	-0.033	[0.040]
In-kind	0.080	(0.057)			0.052	(0.032)			-0.004	(0.019)		
Income restriction	-0.029	(0.055)			-0.008	(0.020)			-0.002	(0.009)		
R-squared	0.21				0.10				0.04			
N	2,205,647				2,205,647				2,205,647			
N of Individual	63,530				63,530				63,530			
Mean wo subsidy	0.509				0.057				0.032			
Share	85.1%				9.5%				5.4%			

Notes: The outpatient spending is the monthly spending on outpatient care measured in thousand JPY (roughly USD10). All the regressions include age (in months) FE, time (in month) FE, and individual FE. In-kind is a dummy that takes one if the municipality offers the subsidy in the form of in-kind instead of refund, and income restriction is a dummy that takes one if the municipality imposes income restriction for subsidy eligibility. For the estimates, the standard errors clustered at the municipality level are reported in parenthesis. For the semi point-elasticity, the bootstrapped standard errors with 200 repetitions clustered at municipality level are reported in brackets. The observations within two months from subsidy changes are excluded to account for intertemporal substitution. Significance levels: *** p<0.01, ** p<0.05, * p<0.10