Online Appendix

Is Zero a Special Price? Evidence from Child Healthcare

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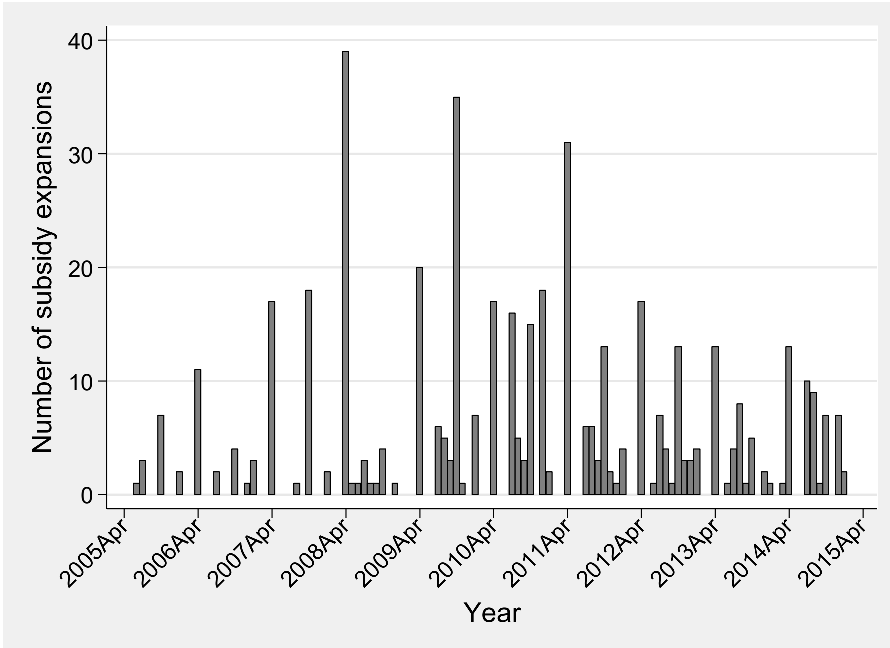
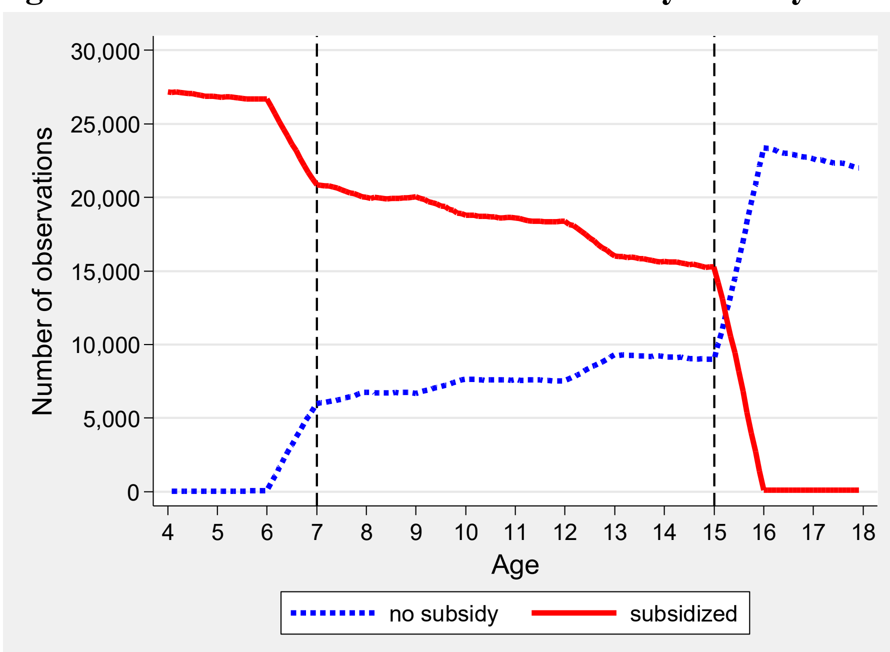
Appendix A: Additional figures and tables

Figure A-1: Timing of the subsidy expansions



Notes: The total number of municipalities is 294. The data spans from April 2005 to March 2015 (10 years). There are total of 480 expansions of a child healthcare subsidy.

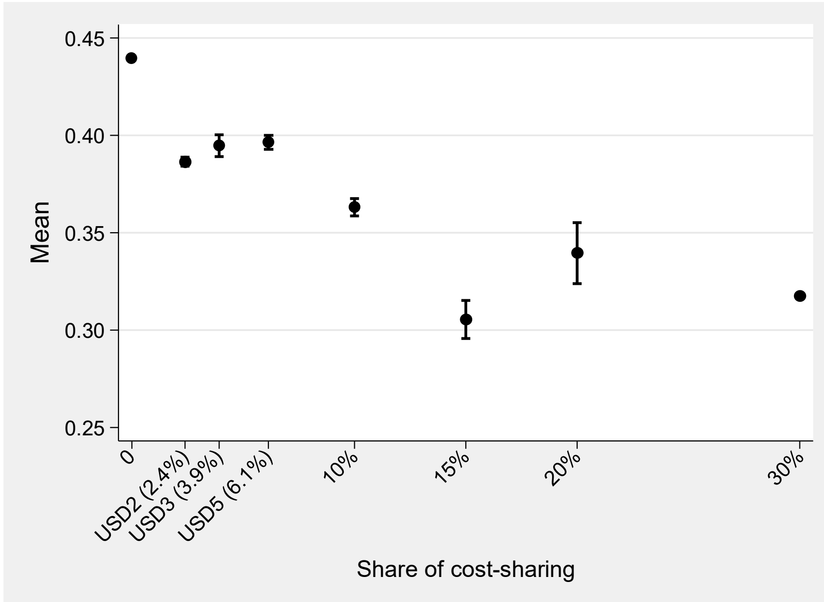
Figure A-2: The number of observations by subsidy status



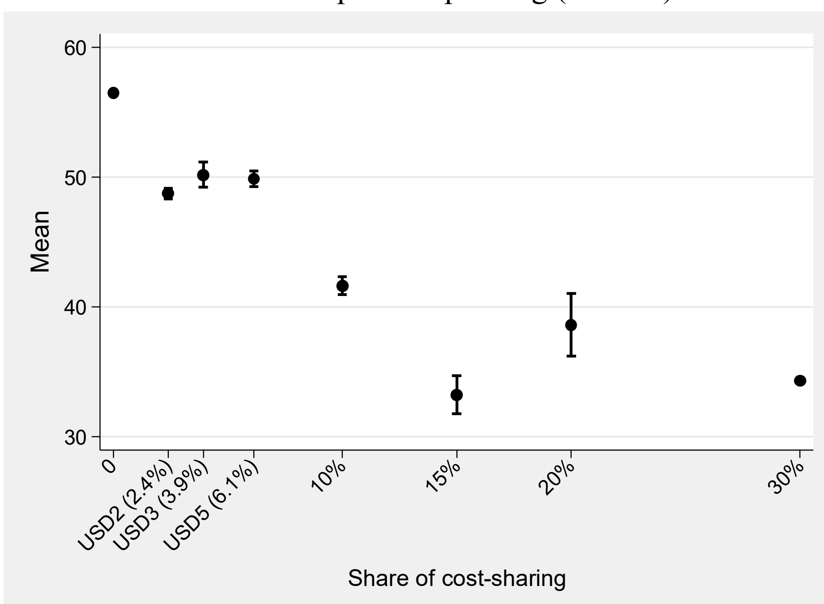
Notes: The two vertical dotted lines indicate that we focus on the ages of children within these intervals as we do not have many observations without subsidy below age 7 years and with subsidy (any forms and levels) above age 15 years. This is because the majority of municipalities (81.3%) already provided the subsidy until the age of 6 years (start of primary school) at the beginning of our sample period (April 2005), and most municipalities do not provide subsidy beyond age 15 years (end of junior high school) at the end of our sample period (March 2015).

Figure A-3: Raw means

A. Outpatient dummy



B. Outpatient spending (in USD)

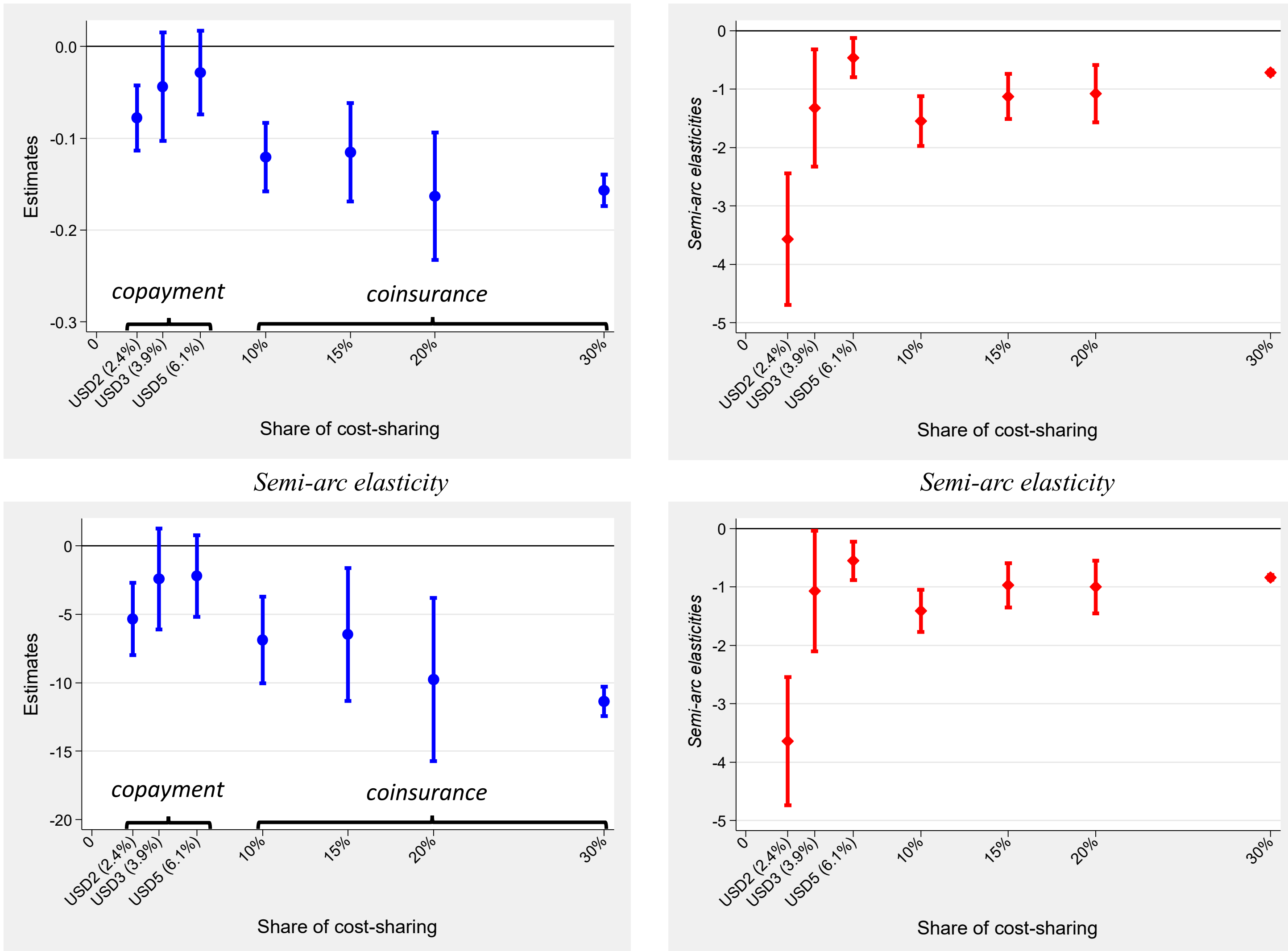


Notes: Simple means at each level of patient cost-sharing are plotted. Panel A is an outpatient dummy which takes 1 if there is at least one outpatient visit per month, and panel B is an outpatient spending which is the monthly spending on outpatient care measured in USD (100 JPY/USD). The upper and lower bars indicate the 95th confidence intervals. Note that this figure does not control for any compositional effects of age and time. The approximate coinsurance rates implied by the copayments are 2.4% (USD 2 per visit), 3.9% (USD 3 per visit), and 6.1% (USD 5 per visit). We derived these rates by dividing the average out-of-pocket payment (average number of visits per month times the copayment) by the total average monthly outpatient spending.

Figure A-4: Effect of different cost-sharing (other outcomes)

A. Frequency of outpatient visits — Estimate

B. Outpatient spending — Estimate



Notes: Panel A is the frequency of outpatient visits which is the number of outpatient visits per month, and panel B is an outpatient spending which is the monthly spending on outpatient care measured in USD (100 JPY/USD). The upper half plots β_C from equation [1], and the lower half plots the corresponding semi-arc elasticity. The control group is children with free care (C= 0). The mean for the control group is 0.877 in Panel A and 56.2 in Panel B. The upper and lower bars indicate the 95th confidence intervals where 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-arc elasticity. The observations within 2 months from the price changes are excluded from the sample to account for anticipatory utilization. The approximate coinsurance rates implied by the copayments are 2.4% (USD 2/visit), 3.9% (USD 3/visit), and 6.1% (USD 5/visit). We derived these rates by dividing the average out-of-pocket payment (average number of visits per month times the copayment) by the total average monthly outpatient spending. For Panel A, the elasticity difference between ε_2 and ε_3 is 2.25, and the elasticity difference between ε_2 and ε_5 is 3.11 (both *p-values*<0.01). Similarly, for Panel B, the elasticity difference between ε_2 and ε_3 is 2.57, and the elasticity difference between ε_2 and ε_5 is 3.09 (both *p-values*<0.01).

Table A-1: Transition matrix of price changes

A. Number of price changes at the municipality-time-age cell level

Cost-sharing before price change	Current cost-sharing: 0%	10%	15%	20%	30%	USD 2/visit	USD 3/visit	USD 5/visit	Total
0%		159	51	1	3,323	527	1	0	4,062
10%	124		0	0	116	0	0	0	240
15%	17	0		0	33	0	0	0	50
20%	49	0	0		39	473	0	12	573
30%	2,678	248	37	0		325	257	1,014	4,559
USD 2/visit	27	0	0	0	787		124	0	938
USD 3/visit	0	0	0	0	161	14		0	175
USD 5/visit	0	0	0	0	669	0	0		669
									11,266

B. Number of children affected by the price change

Cost-sharing before price change	Current cost-sharing: 0%	10%	15%	20%	30%	USD 2/visit	USD 3/visit	USD 5/visit	Total
0%		440	218	1	14,447	1,035	1	0	16,142
10%	421		0	0	245	0	0	0	666
15%	32	0		0	144	0	0	0	176
20%	64	0	0		49	970	0	13	1,096
30%	11,546	708	104	0		453	477	2,478	15,766
USD 2/visit	30	0	0	0	1,376		278	0	1,684
USD 3/visit	0	0	0	0	311	14		0	325
USD 5/visit	0	0	0	0	1,499	0	0		1,499
									37,354

Notes: This table shows the transition matrix of price changes occurring in our claims data. "Number of price changes at the municipality-time-age cell level" shows the frequency of each price change at the municipality-time-age cell level where both age and time are measured in months. For example, if a price change from 0 to 30% occurs in municipality *m* at time *t* (in months) and affects two age groups (*a*), say ages 6 years and 2 months and 6 years and 3 months, this will increase the N in the middle column by 2. In other words, the "municipality-time-age cell" counts the number of treatments that help identify the price parameter. "Number of children affected by the price change" is obtained by weighting the "municipality-time-age cell" by the number of children in each cell.

Table A-2: Estimates and Elasticities

Outcome:	Outpatient dummy	
	Estimate	Semi-arc elasticity
	(1)	(2)
USD 2/visit	-0.031	-2.648
	(0.007)	[0.429]
USD 3/visit	-0.026	-1.485
	(0.011)	[0.407]
USD 5/visit	-0.026	-0.829
	(0.008)	[0.132]
10%	-0.040	-0.992
	(0.006)	[0.159]
15%	-0.037	-0.668
	(0.014)	[0.154]
20%	-0.055	-0.684
	(0.013)	[0.186]
30%	-0.064	-0.562
	(0.003)	[0.015]
R-squared	0.23	
N	2,992,982	
Mean at *C*=0	0.439	

Notes: This table corresponds to Figure 5 in the main text. An outpatient dummy takes the value of 1 if an individual makes at least one outpatient visit per month and 0 otherwise. Column (1) reports β_C from equation [1], and column (2) reports the corresponding semi-arc elasticity. The control group is children with free care ($C = 0$). The standard errors clustered at the municipality level are reported in parentheses for the estimates in column (1), and the bootstrapped standard errors clustered at municipality with 200 repetitions are reported in brackets for the semi-arc elasticity in column (2). The observations within 2 months from the price changes are excluded from the sample to account for anticipatory utilization.

Table A-3: Estimates and Elasticities (other outcomes)

Outcomes:	**Frequency of outpatient visits**		**Outpatient spending** (in USD)	
	Estimate	Semi-arc elasticity	Estimate	Semi-arc elasticity
	(1)	(2)	(3)	(4)
USD 2/visit	-0.078	-3.571	-5.341	-3.641
	(0.018)	[0.574]	(1.344)	[0.560]
USD 3/visit	-0.044	-1.325	-2.406	-1.075
	(0.030)	[0.512]	(1.875)	[0.527]
USD 5/visit	-0.029	-0.463	-2.215	-0.553
	(0.023)	[0.172]	(1.516)	[0.168]
10%	-0.121	-1.549	-6.878	-1.412
	(0.019)	[0.218]	(1.603)	[0.183]
15%	-0.115	-1.129	-6.477	-0.974
	(0.027)	[0.197]	(2.464)	[0.193]
20%	-0.163	-1.079	-9.758	-1.002
	(0.035)	[0.252]	(3.029)	[0.23]
30%	-0.157	-0.718	-11.372	-0.837
	(0.009)	[0.019]	(0.548)	[0.019]
R-squared	0.27		0.28	
N	2,992,982		2,992,982	
Mean at C=0	0.877		56.273	

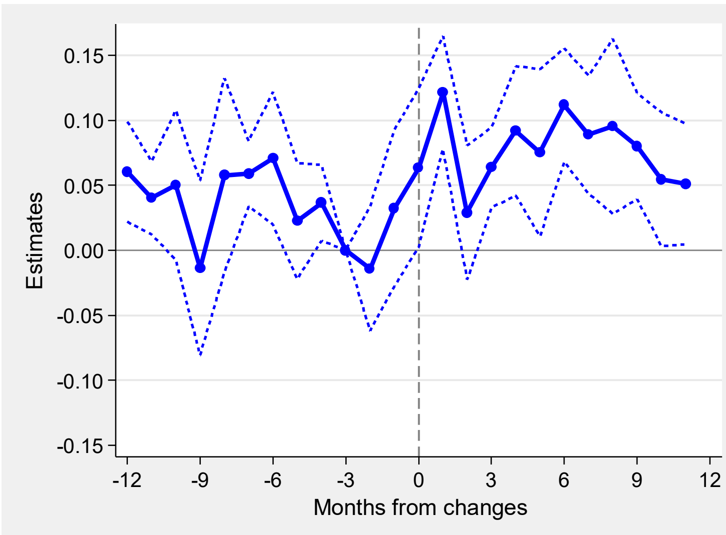
Notes: This table corresponds to Figure A-4. The frequency of outpatient visits is the number of outpatient visits per month, and the outpatient spending is the monthly spending on outpatient care measured in USD (100 JPY/USD). Columns (1) and (3) report β_C from equation [1], and columns (2) and (4) report the corresponding semi-arc elasticity. The control group is children with free care (C= 0). The standard errors clustered at the municipality level are reported in parentheses for the estimates in columns (1) and (3), and the bootstrapped standard errors clustered at the municipality level with 200 repetitions are reported in brackets for the semi-arc elasticity in columns (2) and (4). The observations within 2 months from the price changes are excluded from the sample to account for anticipatory utilization.

Appendix B: Event-study

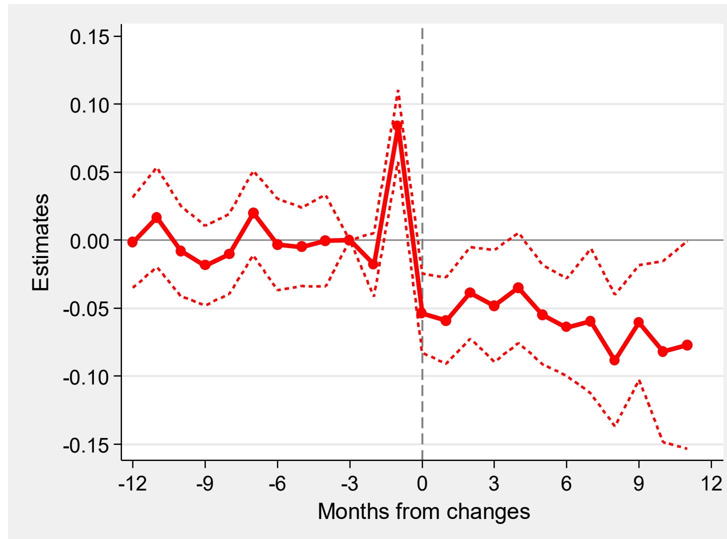
Figure B-1: Event study (USD 2/visit ↔ 30%)

A. Outpatient dummy

30% → USD 2/visit

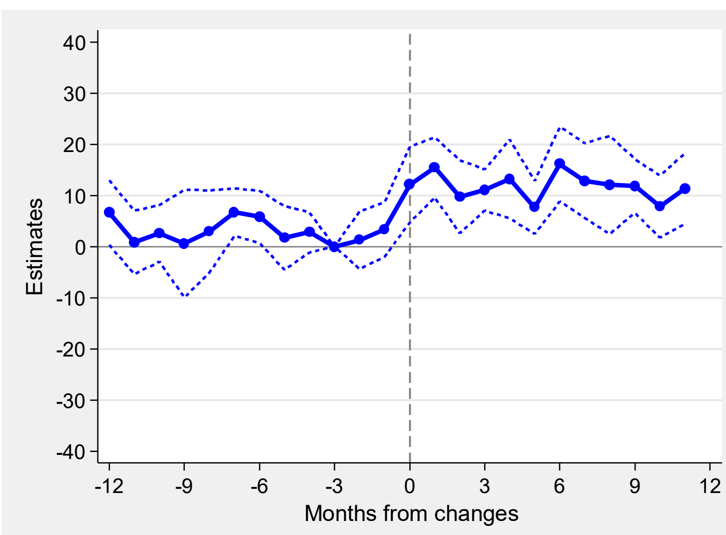


USD 2/visit → 30%

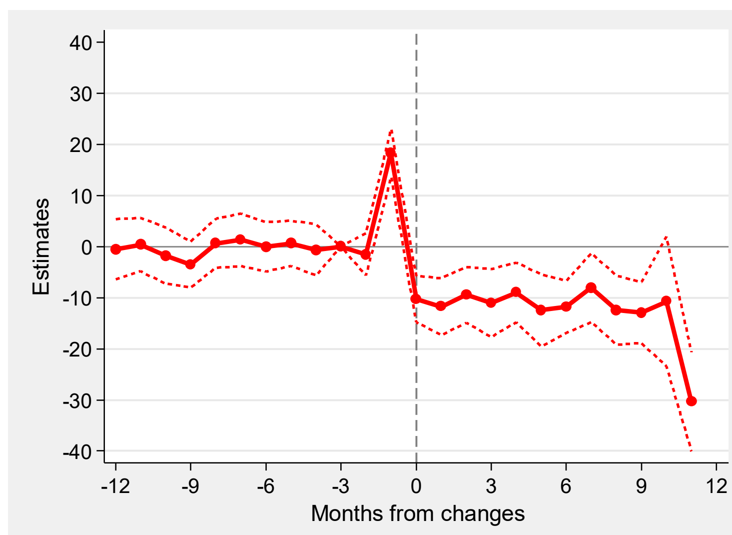


B. Outpatient spending (in USD)

30% → USD 2/visit



USD 2/visit → 30%



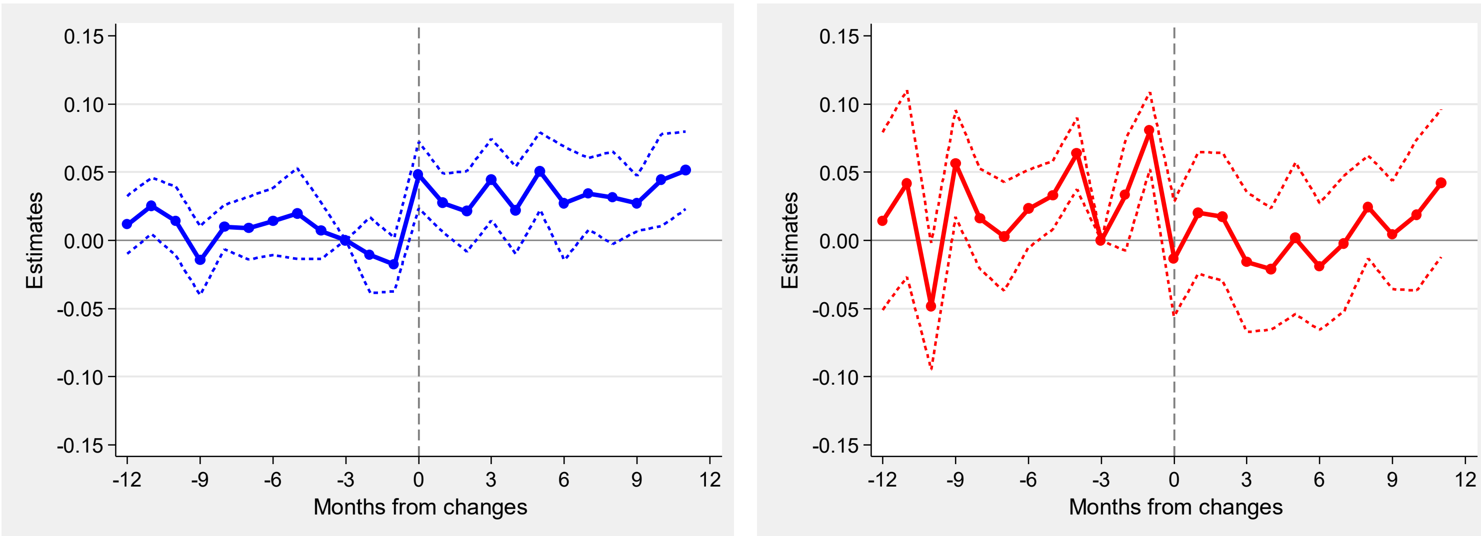
Notes: Panel A is an outpatient dummy which takes the value of 1 if there is at least one outpatient visit per month, and panel B is outpatient spending, which is the monthly spending on outpatient care measured in USD (100 JPY/USD). The solid lines indicate the estimates from a variant of equation [1] where the subsidized dummy is replaced by the interaction of belonging to the treatment group (i.e., experiencing the change in subsidy status) and a series of dummies 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). The dotted lines are the 95th confidence intervals where standard errors clustered at the municipality level are used to construct them. The reference month is 3 months before the change (T= –3). The scales of the y-axis are set the same for the two panels so that the two figures for the opposite directions of the price changes are visually comparable.

Figure B-2: Event study (USD 5/visit ↔ 30%)

A. Outpatient dummy

30% → USD 5/visit

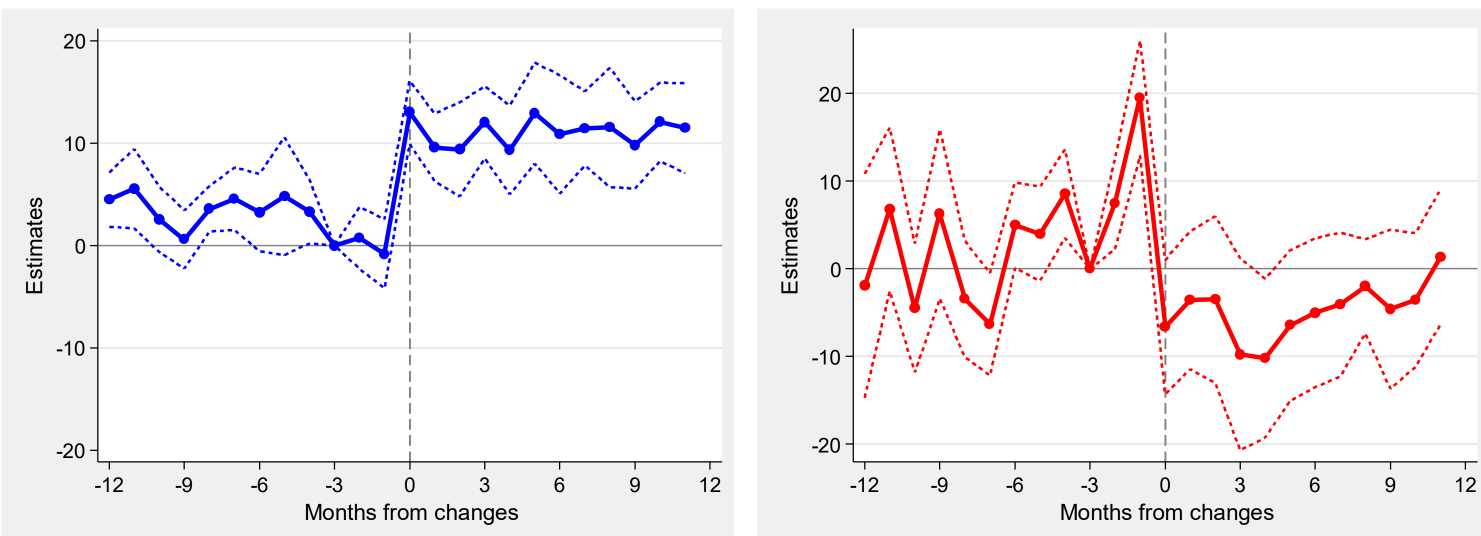
USD 5/visit → 30%



B. Outpatient spending (in USD)

30% → USD 5/visit

USD 5/visit → 30%



Notes: Panel A is an outpatient dummy which takes the value of 1 if there is at least one outpatient visit per month, and panel B is outpatient spending, which is the monthly spending on outpatient care measured in USD (100 JPY/USD). The solid lines indicate the estimates from a variant of equation [1] where the subsidized dummy is replaced by the interaction of belonging to the treatment group (i.e., experiencing the change in subsidy status) and a series of dummies 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). The dotted lines are the 95th confidence intervals where standard errors clustered at the municipality level are used to construct them. The reference month is 3 months before the change ($T = -3$). The scales of the y-axis are set the same for the two panels so that the two figures for the opposite directions of the price changes are visually comparable.

Appendix C: Robustness checks

This study exploits the fact that municipalities introduce different subsidies at different times. On the one hand, the fact that there are local policies that result in many different prices gives us a great advantage. On the other hand, a potential concern about utilizing decentralized municipal policies for identification is that these policies could be endogenous to other conditions or policies in these municipalities, as municipal policies might not be enacted randomly. For example, if municipalities in a better financial situation are more likely to implement the subsidy expansion, whereas income effects simply increase utilization, our estimates may be biased.

We address these endogeneity issues using five approaches. First, as already reported in Subsection 5.1, we employ event study analysis to show that our control group—namely, children in municipalities without changes in subsidy—exhibits a time trend similar to children in municipalities with subsidy changes (except for anticipatory effects). This is reassuring, as it supports the parallel trend assumption crucial for the DID model.

Second, we estimate a model that adds the time-by-municipality fixed effects to equation [1] (where time is measured in months) to account for the time-varying municipality characteristics that are potentially correlated with both the expansion of the subsidy and utilization. We can identify such a model because the subsidy status often varies by age group even for those who live in the same municipality in a period. This specification is most stringent, as these fixed effects capture the average effect of municipality-specific policy changes or events in a particular month, if any, such as income transfers, other subsidies, or business cycles.

Third, we re-estimate the model [1] by excluding individuals who do not experience any price changes (i.e., never-treated children). This identification strategy exploits only the *timing* of the changes in subsidy status, and thus we can mitigate the concern that individuals in the treatment and control groups are different.

Figures C-1 and C-2 report that estimates and corresponding semi-arc elasticities from different specifications to check the robustness of our results, along with our baseline results. These figures show that the estimates and semi-arc elasticities across different specifications are barely changed.

As a separate note, we collapse the data at municipality-age-time cells, which is the level of variation, to partially account for zero spending at the individual-month level. Then, we run cell regression analogous to equation [1] in which the number of observations in each cell is used as a weight. Figures C-1 and C-2 show that the estimates and corresponding semi-arc elasticities from the cell-level analysis yields almost identical results to those from underlying individual micro data.

Fourth, we perform a falsification test using the data constructed as below. Here, for ease of presentation, we limit the sample to individuals who experienced only either 0 or 30% throughout the sample period. As discussed in Section 3.2, our analysis focused on children aged 7–14 because those under 7 years are always subsidized and those over 15 years are almost always no longer subsidized (see Appendix Figure A-2). Now, we extend the data to a wider range of children (ages 4–18), where we continue to assign those *outside* the age ranges to the cost-sharing arrangements of the closest age in 7–15 *as if* they were 7 and 15 even though they face cost sharing of 0 and 30%, respectively. Figures C-3—which is an extended version of Figure 3—shows that the raw means of outpatient utilization align well outside of the 7–15 age range, suggesting that children in municipalities without changes in subsidy are not systematically different from children in municipalities with subsidy changes.

We now formally run a falsification test by using the data that extract *only* outside the age ranges of 7–15 from the sample constructed above. Specifically, we run a variant of equation [1] (C= 30% only) where children under age 7 and over age 15 are categorized to "cost sharing" as if they were 7 and 15 respectively. Table C1 presents the results where we combine the sample of children below age 7 and above age 15. The table shows that none of the estimates on 30% coinsurance rate (relative to 0%) are statistically significant nor economically large. Note that while the two lines in Figures C-3 do not completely converge outside of the 7–15 age range, we include individual FE to control for the potential difference in the level of utilization across individuals in this specification. Together with the lack of pre-trends in Figure 4, these exercises reassure that there are unlikely any unobserved municipality-specific changes in child access to health care that changes simultaneously with cost-sharing arrangements, supporting the parallel trend assumption in the DID model.

Finally, although we have very few movers in our data (1.7%), we are still concerned that the estimated effects of the subsidy may be biased if sicker children move to a municipality that offers a more generous subsidy. To alleviate this concern, in Appendix Section F, we estimate a conditional logit model that examines whether children (and their parents) are more likely to migrate to a municipality that provides free care than a municipality with a positive price, and find little evidence of such a migration pattern.[1]

We also run the alternative models for outpatient spending to check the robustness. In particular, we run two non-linear models (one-part and two-part GLM models) to account for highly skewed distribution of outpatient spending with the large mass at zero (e.g., Mullahy 1998; Blough et al. 1999).[2] In the two-part models, we use the logit model for the first part, and the GLM model with a log link and a gamma distribution family for the second part.[3] For one-part GLM, we also choose the log link and gamma distribution. Figure C-4 shows that estimates from these alternative models are qualitatively very similar to the OLS estimates.[4] To ease the computational burden for estimating the bootstrapped standard errors for our elasticity measures, we report the OLS estimates throughout the study.

<u>References:</u>

Aron-Dine, Aviva, Liran Einav, Amy Finkelstein, and Mark Cullen. (2015) "Moral Hazard in Health Insurance: Do Dynamic Incentives Matter?" *Review of Economics and Statistics* 97(4): 725–741.

Blough David K., Carolyn W. Madden, and Mark C. Hornbrook. (1999) "Modeling risk using generalized linear models." *Journal of Health Economics* 18: 153–171.

Brot-Goldberg, Zarek C., Amitabh Chandra, Benjamin R. Handel, and Jonathan T. Kolstad. (2017) "What does a

[1] Including movers in the sample hardly changes the results owing to the small amount of inter-municipality migration. Similarly, almost identical results are obtained when we keep movers and assign the first municipality as an instrument (both results are available upon request).

[2] Another widely used but rather ad-hoc approach is to take the logarithm of spending variable after adding an arbitrary small constant to account for zero spending (e.g., Aron-Dine *et al.* 2015; Brot-Goldberg *et al.* 2017). However, with a large number of zero observations, this model is very sensitive to the choice of small constant added to zero, and thus we do not adopt such an approach here (results are available upon request).

[3] The choices of a link function and a distribution family for a two-part model are conducted as follows. First, the Box–Cox test indicates that the estimated coefficient is close to zero (–0.033), leading to the choice of the log link. Second, a modified Park test, which empirically tests the relationship between the mean and the variance, turns out to be close to two (2.27), suggesting that a gamma family is appropriate. See for example, Buntin and Zaslavsky (2004) and Deb and Norton (2018) for details on these procedures.

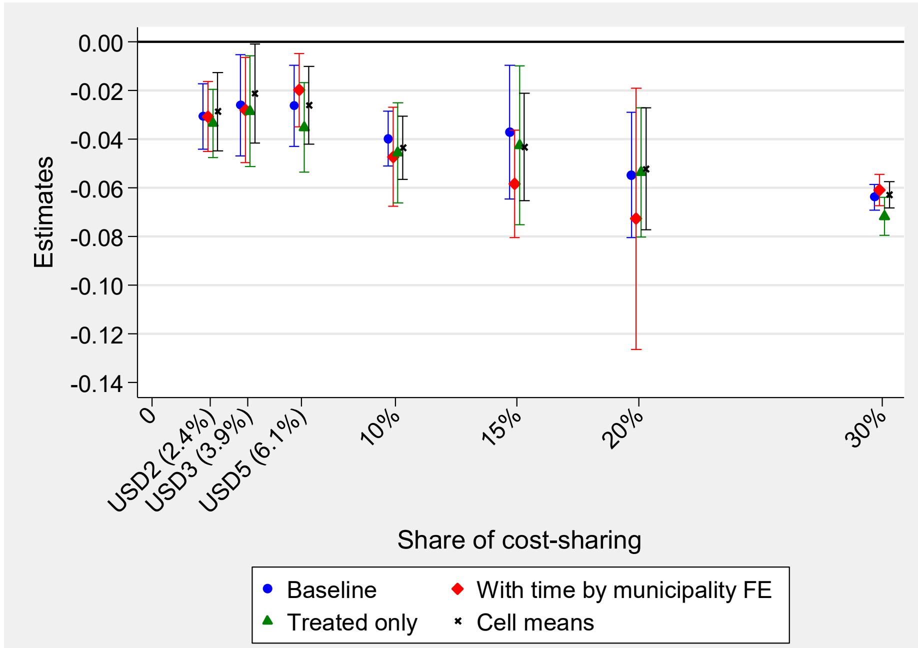
[4] Here, we report the estimates from a variant of the main specification [1] where individual FE is replaced by municipality FEs to ease the computation burden of GLM models. The margin command in Stata14 is used to obtain the treatment effects.

Deductible Do? The Impact of Cost-Sharing on Health Care Prices, Quantities, and Spending Dynamics." *Quarterly Journal of Economics* 132(3): 1261–1318.
Buntin, Melinda Beeuwkes, and Alan M. Zaslavsky. (2004) "Too much ado about two-part models and transformation?: Comparing methods of modeling Medicare expenditures." *Journal of Health Economics* 23(3): 525–542.
Deb, Partha, and Edward C. Norton. (2018) "Modeling Health Care Expenditures and Use." *Annual Review of Public Health* 39: 489–505.
Mullahy, John. (1998) "Much ado about two: reconsidering retransformation and the two-part model in health econometrics" *Journal of Health Economics* 17(3): 247–281.

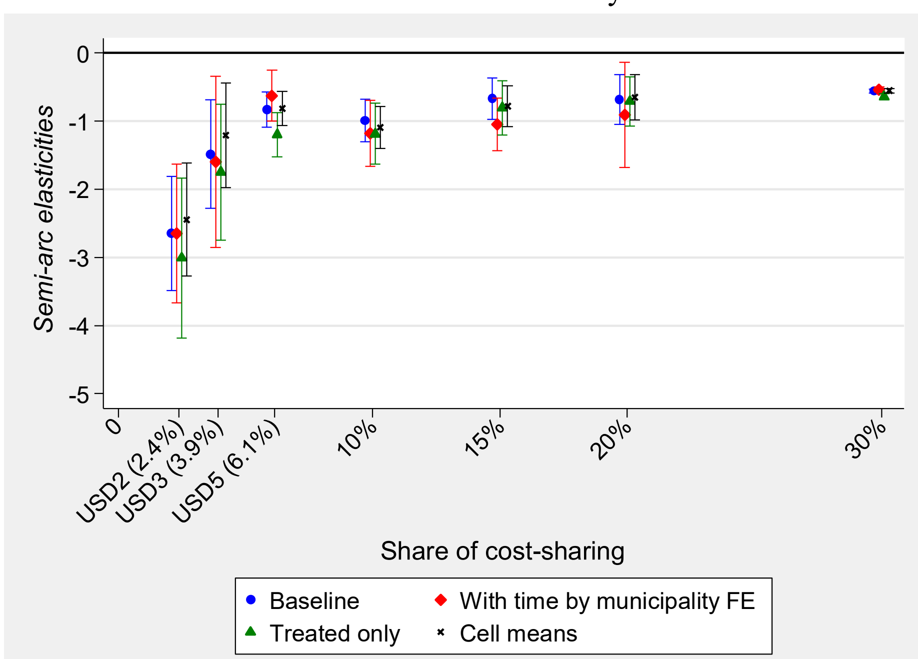
Figure C-1: Robustness checks

Outcome: Outpatient dummy

Estimate



Semi-arc elasticity

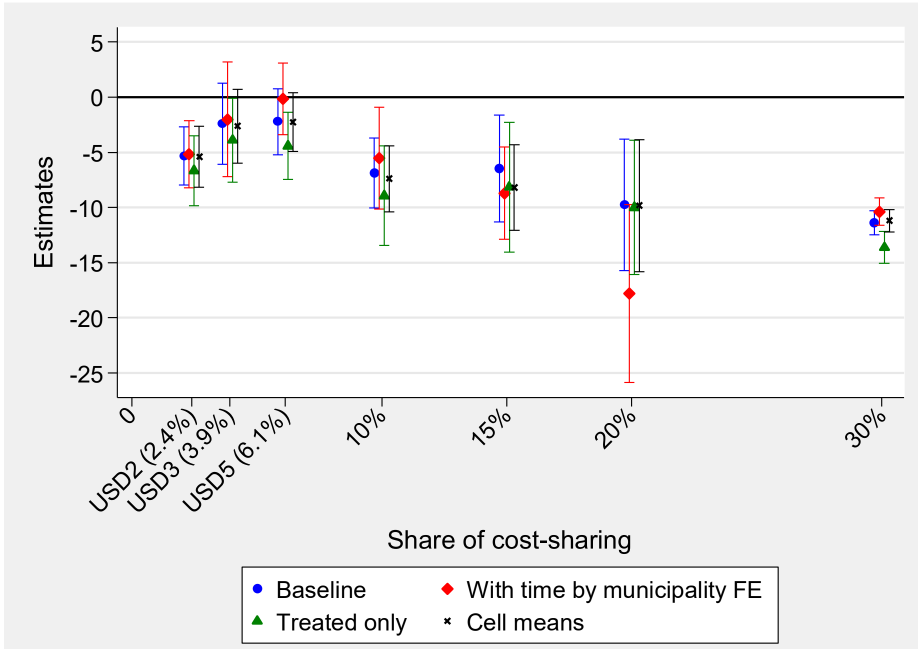


Notes: The outcome is an outpatient dummy which takes a value of 1 if there is at least one outpatient visit per month. The upper half plots β_C from equation [1], and the lower half plots the corresponding semi-arc elasticity. The control group is children with free care (C=0). The observations within 2 months from the price changes are excluded from the sample to account for anticipatory utilization. "Baseline" is identical to the estimates reported in Figure 5. "With time by municipality FE" adds time-by-municipality FE (where time is measured in months) to baseline specification. "Treated only" restricts the sample to only children who experienced at least one change in subsidy status. "Cell means" are estimates from the municipality-age-time cell sample. The approximate coinsurance rates implied by the copayments are 2.4% (USD 2 per visit), 3.9% (USD 3 per visit), and 6.1% (USD 5 per visit). We derived these rates by dividing the average out-of-pocket payment (average number of visits per month times the copayment) by the total average monthly outpatient spending.

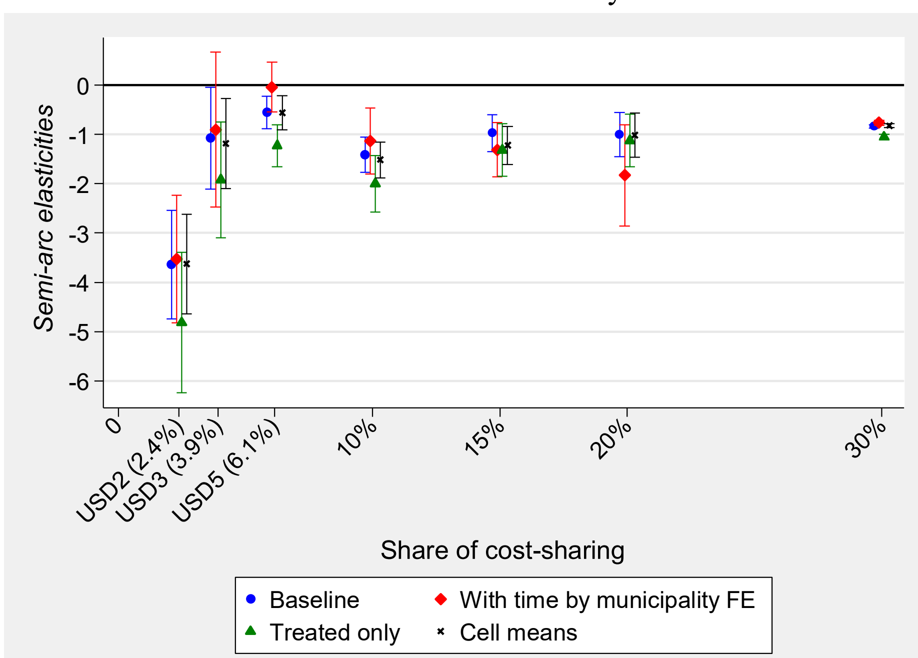
Figure C-2: Robustness checks

Outcome: Outpatient spending (in USD)

Estimate



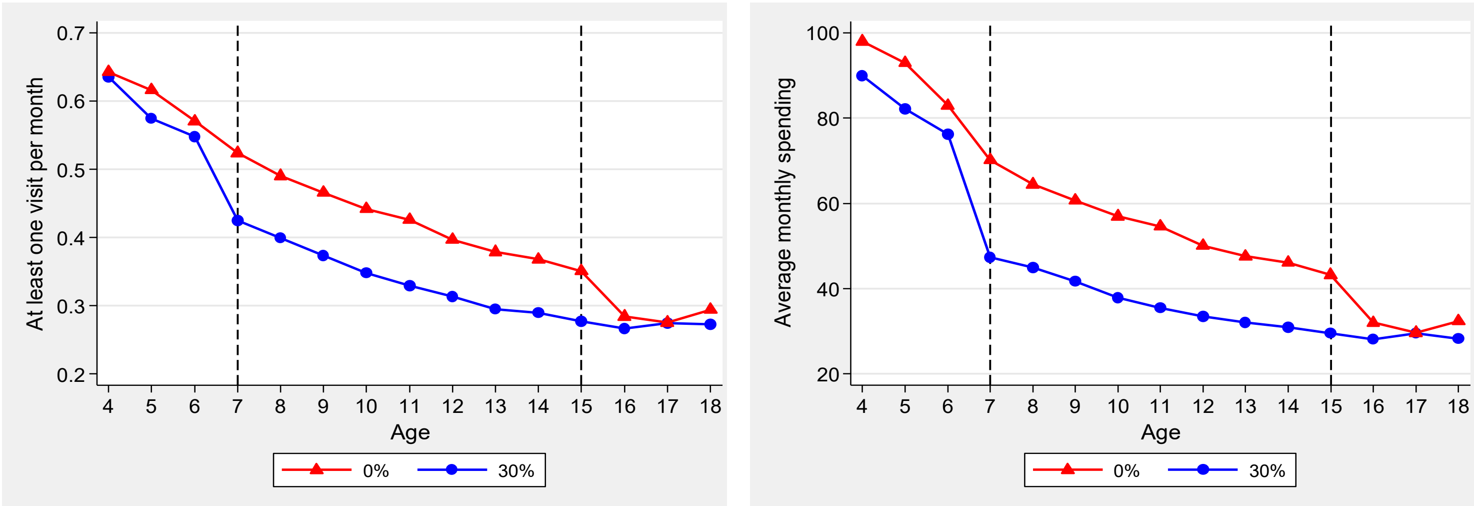
Semi-arc elasticity



Notes: The outcome is outpatient spending, which is the monthly spending on outpatient care measured in USD (100 JPY/USD). The upper half plots β_C from equation [1], and the lower half plots the corresponding semi-arc elasticity. The control group is children with free care (C=0). The observations within 2 months from the price changes are excluded from the sample to account for anticipatory utilization. “Baseline” is identical to the estimates reported in Figure 5. “With time by municipality FE” adds time-by-municipality FE (where time is measured in months) to baseline specification. “Treated only” restricts the sample to only children who experienced at least one change in subsidy status. “Cell means” are estimates from the municipality-age-time cell sample. The approximate coinsurance rates implied by the copayments are 2.4% (USD 2 per visit), 3.9% (USD 3 per visit), and 6.1% (USD 5 per visit). We derived these rates by dividing the average out-of-pocket payment (average number of visits per month times the copayment) by the total average monthly outpatient spending.

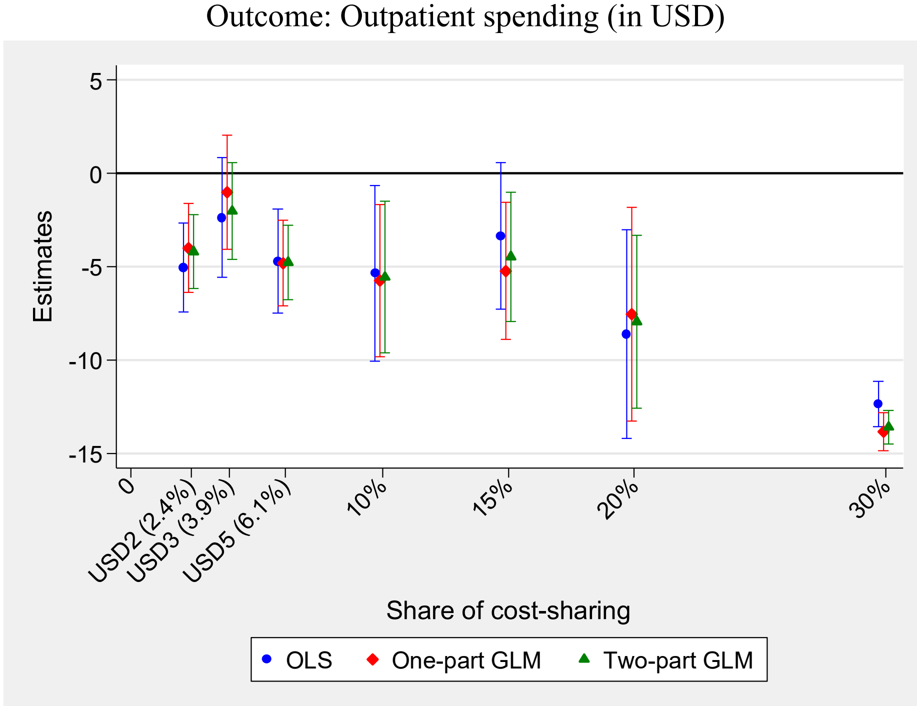
Figure C-3: Counterfactual utilization with and without subsidy

A. Outpatient dummy **B. Outpatient spending** (in USD)



Notes: We first limit the sample to individuals who experienced only either 0 or 30% throughout the sample period. We then extend the data to a wider range of children (ages 4–18), where we continue to assign those outside the age ranges of 7–15 to the cost-sharing arrangements of the closest age in 7–15 *as if* they were 7 and 15 even though they face cost sharing of 0 and 30%, respectively. Both figures plot the raw means of outpatient utilization of individuals at each age of children. Panel A is an outpatient dummy that takes the value of 1 if there is at least one outpatient visit per month. Panel B is outpatient spending, which is the monthly spending on outpatient care measured in USD (100 JPY/USD).

Figure C-4: Non-linear models for outpatient spending (Estimates only)



Notes: An outpatient spending is the monthly spending on outpatient care measured in USD (100 JPY/USD). The observations within 2 months from the price changes are excluded from the sample to account for anticipatory utilization. The graph plots the estimates β_C for each cost-sharing C with three separate models (OLS, one-part GLM, and two-part GLM). For two-part GLM, we use the logit model for the first part, and the GLM model with a log link and a gamma distribution family for the second part. For one-part GLM, we also choose the log link and gamma distribution. Here, we report the estimates from a variant of the equation [1] where individual FE is replaced by municipality FEs to ease the computational burden of GLM models. The control group is children with free care (C=0). The margin command in Stata14 is used to obtain the treatment effects. The approximate coinsurance rates implied by the copayments are 2.4% (USD 2 per visit), 3.9% (USD 3 per visit), and 6.1% (USD 5 per visit). We derived these rates by dividing the average out-of-pocket payment (average number of visits per month times the copayment) by the total average monthly outpatient spending.

Table C-1: Estimates from a falsification test

	Outpatient dummy	**Outpatient spending (in USD)**
	(1)	(2)
30%	-0.044	-5.355
	(0.027)	(4.633)
R-squared	0.33	0.39
N	872,766	872,766

Notes: Column (1) is an outpatient dummy which takes the value of 1 if there is at least one outpatient visit per month, and column (2) is outpatient spending, which is the monthly spending on outpatient care measured in USD (100 JPY/USD). The data is constructed as follows. We first limit the sample to individuals who experienced only either 0 or 30% throughout the sample period. We then extend the data to a wider range of children (ages 4–18), where we continue to assign those outside the age ranges of 7–15 to the cost-sharing arrangements of the closest age in 7–15 *as if* they were 7 and 15 even though they face cost sharing of 0 and 30%, respectively. Then, we extract data *only* outside the age ranges of 7–15. We combine the sample of children below age 7 and above age 15. The table reports β_{30} from a variant of equation [1] (only C= 30%) where the control group is children with free care (C = 0). The standard errors clustered at the municipality level are reported in parentheses. The observations within 2 months from the price changes are excluded from the sample to account for anticipatory utilization.

Appendix D: Preventive care

Table D-1: List of preventive care

Categories	Uncond. mean when C=0 (N=1,796,022) Mean (×100)	Cond. mean on visit when C=0 (N=788,879) Mean (×100)	ICD-10
Healthy Weight and Weight Gain in Pregnancy: Behavioral Counseling Interventions	0.000	0.000	O26.0
Hepatitis B Virus Infection in Adolescents and Adults: Screening	0.006	0.015	B16
Sexually Transmitted Infections: Behavioral Counseling	0.005	0.010	A50-A64
Tobacco Use in Children and Adolescents: Primary Care Interventions	0.000	0.000	F17
Asymptomatic Bacteriuria in Adults: Screening	0.000	0.000	O23.4
Hepatitis B Virus Infection in Pregnant Women: Screening	0.000	0.000	O98.4
HIV Infection: Screening, Prevention of HIV Infection: Preexposure Prophylaxis	0.000	0.000	B20-B24
Syphilis Infection in Pregnant Women: Screening	0.000	0.000	O23.5
Skin Cancer Prevention: Behavioral Counseling	0.002	0.005	C43-C44
Obesity in Children and Adolescents: Screening	0.043	0.098	E66
Syphilis Infection in Nonpregnant Adults and Adolescents: Screening	0.000	0.000	A51
Depression in Children and Adolescents: Screening	0.076	0.174	F32
Chlamydia and Gonorrhea: Screening	0.001	0.002	A54-A56
Gestational Diabetes Mellitus: Screening	0.000	0.000	O24
Rh(D) Incompatibility: Screening	0.000	0.000	P55.0
Screen adults' misuse and provide brief counseling to reduce alcohol use	0.000	0.001	F10
Biennial mammography for women aged 50–74 y; screening before age 50 y an individual decision	0.000	0.001	C50
Screen women aged >65 y and younger women whose fracture risk is equal to or greater than that of white women aged 65 y with no additional risk factors	0.013	0.029	M80-M82
Vision in Children: Screening	0.290	0.659	H53.0
ADHD	0.265	0.602	F90

Notes: "Unconditional" includes observations (person-month) with no outpatient visits in a month, and "Conditional" limits to observations with at least one outpatient visit per month.

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Appendix E: Antibiotics Use

Table E-1: 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”.

References:

Fleming-Dutra *et al.* (2016) “Prevalence of inappropriate antibiotic prescriptions among US ambulatory care visits, 2010-2011.” *JAMA* 315(17): 1864–1873. https://jamanetwork.com/journals/jama/fullarticle/2518263

Table E-2: Summary statistics of antibiotic use

Name of disease	Share of the diagnosis	Uncond.			Cond. on having the diagnosis		
		Antibiotics use (dummy)	Spending on antibiotics (in USD)	Freq. of antibiotics prescriptions	Antibiotics use (dummy)	Spending on antibiotics (in USD)	Freq. of antibiotics prescriptions
	(1)	(2)	(3)	(4)	(5) = (2)/(1)	(6) = (3)/(1)	(7) = (4)/(1)
Tier1	0.050	0.019	3.314	0.134	0.38	66.04	2.67
Tier2	0.130	0.079	11.242	0.537	0.61	86.40	4.13
Tier3	0.215	0.040	4.941	0.195	0.18	23.01	0.91
Tier1							
Miscellaneous bacterial infections	0.046	0.017	0.271	0.115	0.36	5.86	2.50
Pneumonia	0.003	0.002	0.062	0.017	0.79	23.14	6.27
Urinary tract infections	0.003	0.001	0.022	0.009	0.48	8.24	3.46
Tier2							
Acne	0.008	0.003	0.048	0.044	0.38	5.60	5.15
Gastrointestinal infections	0.026	0.012	0.162	0.068	0.46	6.35	2.64
Pharyngitis	0.034	0.025	0.338	0.144	0.72	9.96	4.23
Sinusitis	0.068	0.047	0.700	0.347	0.70	10.32	5.12
Skin, cutaneous, and mucosal infections	0.012	0.006	0.094	0.042	0.51	7.91	3.54
Suppurative otitis media	0.006	0.005	0.112	0.041	0.81	18.86	6.86
Tier3							
Asthma, allergy	0.058	0.015	0.199	0.081	0.26	3.46	1.40
Bronchitis, bronchiolitis	0.034	0.022	0.294	0.112	0.64	8.61	3.27
Influenza	0.019	0.007	0.085	0.032	0.35	4.43	1.68
Non-suppurative otitis media	0.002	0.001	0.008	0.004	0.26	3.58	1.64
Viral pneumonia	0.000	0.000	0.000	0.000	0.25	3.75	1.75
Viral upper respiratory infection	0.033	0.017	0.209	0.084	0.51	6.37	2.55
Other respiratory conditions	0.000	0.000	0.001	0.000	0.29	3.57	1.62
All other codes not listed elsewhere	0.164	0.018	0.219	0.089	0.11	1.34	0.54

Notes: The spending on antibiotics is measured in USD (100 JPY/USD). See Appendix Table E-1 for the list of ICD10 codes for each Tier.

Appendix F: Inter-municipality migration

In the main text, we focus on the children who do not move across municipalities, as there are only 1,579 such children or 1.7% of the total (91,863). The migration rate in our sample is lower than actual migration, as intra-municipality migration is not considered as migration, as the subsidy level is the same. However, if a family with very sick children is more likely to move to a more generous municipality, our estimates—which may fail to control for the time-varying unobserved health conditions—can be biased. We think that this is very unlikely for two of reasons. First, the migration rate is a declining function of age of children and is already low by age 7 years as parents tend to move before their children enter primary school. Second, many municipality characteristics other than the generosity of subsidy for child healthcare may affect the migration decision, such as quality of school, availability of daycare, and other childrearing support in the districts. Nonetheless, we include those who moved across municipalities into the sample and re-estimate the equation [1]. Owing to the small amount of inter-municipality migration, the estimates with and without movers are almost identical. Similarly, almost identical results are obtained when we keep movers and assign the first municipality as an instrument (both results are available upon request).

A more direct way to test *selective* migration is to examine 1) whether children who move are more likely to choose more generous municipality, and 2) particularly whether sicker children are more likely to move to more generous municipality. To investigate such possibilities, we estimate a location choice model, limiting our sample to a month when children move across municipalities. For the first question, we estimate the following conditional logit model:

$$Pr(Y_{it} = m) = F(\textstyle\sum_C \beta_C\{\mathbf{1}(Price = C)_{amt}\} + \varphi_m + \varepsilon_{it}) \quad \text{–[F1]}$$

where $Pr(Y_{it} = m)$ is the locational choice of municipality m among M municipalities by a child i whose age is a at time t. The price dummy variable $\mathbf{1}(Price = C)_{amt}$ takes the value 1 if the cost-sharing of outpatient care is C at age a at time t in municipality $m \in M$. We also control for municipality of choice fixed effects φ_m to control for time-invariant municipality characteristics that may attract (the families of) children. Our coefficients of interest are series of β_C where $\beta_C < 0$ indicates that children are *less* likely to choose the municipality with cost-sharing at C ($C>0$) at her/his age a in time t compared to the municipality with free care ($C=0$). The standard errors are clustered at the individual level.

For the second question, we further interact the series of price dummies with the proxy for health status—the average outpatient spending for the 6 months just before the month of move (denoted by $prior\ spending_{it-1}$ below) [5]:

$$\Pr(Y_{it} = m) = F(\textstyle\sum_C \beta_C\{\mathbf{1}(Price = C)_{amt}\} + \sum_C \gamma_C\{\mathbf{1}(Price = C)_{amt} \times prior\ spending_{it-1}\} + \varphi_m + \varepsilon_{it}) \quad \text{–[F2]}$$

where $\gamma_C < 0$ indicates that sickly children are *less* likely to choose the municipality with cost-sharing at C ($C>0$) than a municipality with free care ($C=0$). Note that in both regressions, only the children who moved are included in the sample from across the 294 municipalities.

Column (1) in table F-1 show the estimates β_C from estimating equation [F1]. Even though a few estimates are

[5] We experiment the length of prior months to calculate the average prior spending from *X* months (*X*= 3, 6, 9 and 12) but the estimates are very similar. The benefit of taking longer span to compute the average spending is that we may be able to capture the health status with more accuracy while the cost is that we lose individual who move within the first *X* months from the start of the data.

barely statistically significant at the 10 percent level, these estimates are positive (instead of negative) and the rest are not statistically significant at the conventional level. Thus, these results at least do not support that children move to the municipality with free care.

Column (2) in Table F-1 show the estimates β_C and γ_C from estimating equation [F2]. Here, none of β_C are statistically significant at the conventional levels. Furthermore, γ_C are close to zero, and far from statistically significant, suggesting that sickly children are no more likely to choose the municipality with free care than healthy children. Taken together, we do not find any evidence of selective inter-municipality migration, at least in the current setting.

Table F-1: Selective migration

	(1)	(2)
USD 2/visit	-0.257	-0.272
	(0.242)	(0.244)
USD 3/visit	-0.074	-0.013
	(0.305)	(0.337)
USD 5/visit	0.006	0.153
	(0.185)	(0.214)
10%	0.668	0.626
	(0.385)	(0.393)
15%	0.088	0.090
	(0.485)	(0.488)
30%	0.219	0.177
	(0.125)	(0.128)
USD 2/visit × Prior spending		-0.029
		(0.021)
USD 3/visit × Prior spending		0.007
		(0.006)
USD 5/visit × Prior spending		0.000
		(0.011)
10% × Prior spending		0.006
		(0.004)
15% × Prior spending		-0.332
		(0.326)
30% × Prior spending		-0.025
		(0.183)
N	466,373	466,373
N of moves	1,811	1,811
N of individuals	1,579	1,579

Notes: There are 1,579 individuals with 1,811 total moves. The control group is the municipality with free care (*C*=0). The estimates on β_{20} and γ_{20} are excluded as there is no movement to the municipality with *C*=20% in our sample.