

Asymmetric Demand Response when Prices Increase and Decrease: The Case of Child Healthcare*

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Abstract

This study tests whether demand responds symmetrically to price increases and decreases—a seemingly obvious proposition under conventional demand theory that has not been rigorously tested. Exploiting the rapid expansion in Japanese municipal subsidies for child healthcare in a difference-in-differences framework, we find evidence against conventional demand theory: when coinsurance, our price measure, increases from 0% to 30%, the demand response is more than twice that to a price decrease from 30% to 0%. This result indicates that while economists and policymakers pay little attention, price change direction matters and should be incorporated into welfare analysis.

Keywords: Asymmetric Demand Response, Patient Cost-Sharing, Child Healthcare, Conventional Demand Theory

JEL codes: I18, I13, I11, J13

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1. Introduction

According to conventional demand theory, a movement along the demand curve between two prices will have the same impact on the quantity demanded regardless of the movement's direction. That is, the absolute value of the change in demand should be the same regardless of whether the price increases from $P1$ to $P2$ or decreases from $P2$ to $P1$. This study's aim is to examine this seemingly obvious proposition, which, in our view, lacks rigorous testing.

We believe this is an important question to study. Such asymmetry—if it exists—provides a cautionary note against applying price sensitivity estimates derived from a price change in one direction (e.g., a price increase/decrease) to a price change in the opposite direction (e.g., a price decrease/increase), as welfare calculations can be substantially biased in the presence of such asymmetric responses. However, economists and policymakers rarely consider the direction of a price change when they report estimates or use estimates from existing studies. This omission may be due to a lack of data and evidence, as it is quite rare in a single market to observe exogenous price changes in opposite directions. Thus, few studies credibly show that demand responses differ depending on the direction of a price change.

We test asymmetric demand responses in the context of demand for child healthcare using individual-level claims data from Japan. In the last decade, municipalities in Japan have rapidly expanded child healthcare subsidies; these typically reduce patient cost-sharing, our price measure, from 30% coinsurance to 0% (free care). Children also face price increases from 0% to 30% when they reach the subsidy's age limit and the coverage expires. Because many municipalities have introduced such subsidies for different age groups at different times, we observe the same price change in opposite directions (either from 0% to 30% or from 30% to 0%) even for children of the same age. These price variations allow us to examine whether

children (and consequently, their parents) react to price increases in much the same way as they do to price decreases.

As noted before, traditional demand theory implies that a movement along the demand curve between two prices will have the same impact on the quantity demanded regardless of the direction of the price change. However, alternative economic theories point to the possibility that this might not be the case. For example, if individuals are loss averse (Tversky and Kahneman, 1991) and feel more loss from a price increase than gain from a price decrease, the change in healthcare spending may be larger in response to a price increase than to a price decrease. Thus, whether the demand responses are symmetric in price direction is ultimately an empirical question.

Exploiting unique price changes in a difference-in-differences framework, we find strong evidence against conventional demand theory. When the price is reduced from 30% to 0%, outpatient spending per month increases by USD 8.9. In contrast, when the price is increased from 0% to 30%, outpatient spending per month decreases by as much as USD 20.0. Thus, the demand response is twice as large when the price increases than when it decreases. The difference between these two estimates is statistically significant at the 1% level, rejecting conventional demand theory. To the best of our knowledge, this is the first study to rigorously test symmetric demand responses when prices increase and decrease.

This result has strong policy implications for optimal health insurance design and policy evaluation in general. If policymakers determine policy based on a parameter estimated using a price change in the opposite direction, they may overestimate or underestimate the demand response by more than a factor of two.

To further understand what drives the asymmetric demand response, we categorize demand

by service type and find that most of this response is driven by medication: outpatient spending per month increases by only USD 5.7 for price decreases, while it decreases as much as USD 10.2 for price increases.

Finally, as a separate note, we observe substantial intertemporal substitution before and after a price change. This pattern reveals that some children (and hence, parents) anticipate the upcoming price change and behave strategically by delaying or rushing visits. We observe larger anticipatory effects when the price increases (rushing) than when the price decreases (delaying). In addition, our results indicate that individuals intertemporally substitute consumption only imperfectly.

Marketing studies have examined asymmetric demand responses using scanner or sales data (e.g., Kalwani *et al.*, 1990; Krishnamurthi *et al.*, 1992; Putler, 1992; Kalyanaram and Winer, 1995; Bell and Lattin, 2000; Han *et al.*, 2001; Mazumdar *et al.*, 2005). In general, these studies find that consumers are more sensitive to price increases (losses) than price decreases (gains). However, our study has several advantages. First, because patients face only two prices (either 0% or 30%) that stay the same without a policy change, the reference price in our case is clearly defined; past studies arbitrarily use a past price as the reference price (e.g., Hardie *et al.*, 1993). Second, the magnitude of the price change in our study is the same in both directions ($\Delta = 30\%$), which is particularly helpful for directly testing conventional demand theory's prediction. Third, because the prices vary between two price points (i.e., 0% and 30%), we can rule out non-linearity of the demand function as the cause of asymmetry. In contrast, previous studies often use the same starting price to show that demand responds more to price increases than price decreases, but the results may be driven by the non-linearity of demand rather than asymmetric demand responses. Fourth, we can distinguish short- and long-term demand responses. In

contrast, past studies could examine only short-term demand fluctuations because prices in a retail context frequently go up and down.

This study contributes to the literature on behavioral health economics (see Chandra *et al.*, 2019 and Rice, 2013 for reviews) by presenting clear additional evidence against the standard neoclassical model of healthcare demand. We do so by exploiting the clean price variation in our context, where 30% coinsurance is added or removed. Moreover, we identify both short-run and long-run effects, which helps clarify behavioral decision-making in healthcare. Recent healthcare studies investigate whether individuals indeed follow classical demand assumptions in consumer choice of insurance (inertia) (e.g., Abaluck and Gruber, 2011), treatment choices (behavioral hazard) (e.g., Baicker *et al.*, 2015), and price responses in a dynamic setting (myopia) (e.g., Einav *et al.*, 2015; Aron-Dine *et al.*, 2015; Brot-Goldberg *et al.*, 2017; Dalton *et al.*, 2020). We add to this literature by showing that, inconsistent with classical theory's prediction, demand responses to price changes are not symmetric.

Finally, this study also contributes to the small but growing body of literature that examines intertemporal substitution in healthcare (Cabral, 2017; Lin and Sack, 2019). Since these studies exploit the non-linear structure of health insurance (either the deductible or coverage maximum), they can only examine intertemporal substitution for price changes in one direction. In contrast, we examine intertemporal substitution for price changes in both directions.

2. Classical Demand Theory

As noted in the Introduction, classical demand theory implies that price changes of the same size will have the same impact on demand (with opposite signs) regardless of their direction. Figure 1 illustrates the textbook case of a consumer's decision, where the consumer

chooses the amounts of two goods, healthcare service Q_h and a composite good Q_c , given their prices (P_h and P_c) under a budget constraint. The initial prices and quantities of the two goods are given by (P_h^0, Q_h^0) and (P_c^0, Q_c^0) , respectively. If the price of healthcare service increases from P_h^0 to P_h^1 , its quantity will decrease from Q_h^0 to Q_h^1 based on the income and substitution effects. Now, suppose that the change in the price of healthcare service is reversed from P_h^1 to P_h^0 . Based on classical demand theory, the quantity of healthcare service will return to the original quantity, Q_h^0 , from Q_h^1 . That is, the absolute value of the impact of the price change on demand should be the same regardless of the direction of the price change.

3. Background

3.1. The Japanese health insurance system

We briefly summarize the Japanese health insurance system related to our study (see Ikegami and Campbell, 1995 and Kondo and Shigeoka, 2013 for details). Residents in Japan are covered by the national health insurance scheme. Because enrollment is mandatory, there is no issue in this market regarding selection into health insurance. Medical providers are paid by fee-for-service for outpatient services, and all receive the same fee for the same service based on the national schedule set by the government. Patients pay coinsurance, which is set nationally at 30%, except for those above age 70 and below age 6. As we discuss in the next section, many municipalities provide subsidies for child healthcare that cover patients' out-of-pocket costs, which often reduce children's cost-sharing to zero. There is a stop-loss after a child spends approximately USD 800 per month out-of-pocket for those in the regular income category, but less than 0.1% of the person-months in our data exceed the stop-loss. This is because costly hospitalization is rare among children in this age group. Private health insurance that covers

patients' out-of-pocket costs is virtually non-existent in Japan (OECD, 2004). As a result, municipal subsidies affect the price of children's healthcare.

3.2. Municipal subsidies and price variations

Over the last decade, municipalities in Japan have drastically expanded subsidies for child healthcare, which typically reduce children's out-of-pocket costs from 30% to zero. Figure A1 plots the share of municipalities in our insurance claims data (described later) by maximum age for outpatient care subsidy eligibility in the period April 2005–March 2015, illustrating the rapid expansion. The figure clearly shows that subsidies have expanded rapidly to older individuals in the last decade. For example, none of the municipalities provided a subsidy up to 15 years of the age in April 2005, the beginning of the sample period. However, this number reached nearly 80% by the end of our sample period a decade later. We should also clarify that, because municipal subsidies expire at a certain age (most often at ages 6, 9, 12, and 15), we observe equally many price increases in the data.

These municipal subsidies provide ideal price variations for testing the implications of conventional demand theory. First, since each municipality determines whether and when to provide a subsidy and the ages it covers, prices faced by children substantially vary by municipality, time, and the child's age. Second, as shown in Figure A2, prices change in both directions, which allows us to separately identify demand responses to price increases and decreases. Moreover, the figure shows that both types of price changes occur throughout the sample period, which mitigates the concern that the estimates are driven by a particular shock such as a financial crisis. Typically, prices “decrease” from 30% to 0% when the municipality “expands” the subsidy coverage to older ages, and prices “increase” from 0% to 30% when the

user reaches the subsidy's age limit and the coverage "expires." Among a total of 2,604 changes in subsidy status in the municipality-age-time cell of our insurance claims data, 1,858 changes are subsidy expansions (price "decreases"), whereas 746 changes are subsidy expirations (price "increases"). Third, the magnitude of the price changes is the same in both directions, which is particularly helpful for directly testing conventional demand theory's prediction, as discussed in Section 2.

4. Data

4.1. Data description

We use two main data sets in this study.¹ The first is information on municipal subsidies. For each municipality, we used a variety of sources, including municipality web pages, local newspapers, and municipal ordinances, to hand-collect subsidy details, including the amount (e.g., free care), maximum age for which the subsidy is provided, whether the subsidy is applied at the point of service or refunded later, and whether there is an income eligibility requirement. The data cover the period from April 2005–March 2015 at the monthly level and include all municipalities in Japan's six largest prefectures, a total of 294 municipalities.² In this study, we focus on 165 municipalities that have either 0% or 30% coinsurance rates.³

¹ Iizuka and Shigeoka (2018, 2020) use the same data.

² In total, there were 47 prefectures and 1,719 municipalities in Japan as of January 2015.

³ We focus on the most common form of child healthcare subsidy, which reduces patient cost-sharing from 30% to 0%. Iizuka and Shigeoka (2018, 2020) utilize other types of price variations, including small copayments (e.g., USD 2/visit and USD 5/visit) and 10%, 15%, and 20%

The second data set includes individual outpatient spending drawn from monthly insurance claims data provided by JMDC Inc. JMDC Inc. collects and analyzes administrative insurance claims data on behalf of large insurers. These data have been used in previous studies, including Iizuka (2012), Fukushima *et al.* (2016), Iizuka and Shigeoka (2018, 2020), and Iizuka *et al.* (2021).

JMDC data consist of administrative enrollment and claims data. For each person, enrollment data consist of patient ID, gender, age, and municipality of residence. The age and municipality of residence in each month are crucial in this study because the level of cost-sharing is uniquely determined by municipality, age, and time. The claims data report monthly outpatient spending, including months of no utilization.⁴ Specifically, the claims data contain the year-month of the visit and line-by-line medical services received, including diagnoses (ICD10), types of services, quantity of each service, and fees charged for each service based on the national fee schedule. The unit of claims data in Japan is monthly, as medical institutions are reimbursed on a monthly basis. A unique patient ID links the enrollment and claims data. One drawback—albeit common for insurance claims data—is that other than the gender and age of children, the data do not include individual characteristics such as parental education, household income, and family structure (e.g., number of children or siblings).

coinsurance rates. Importantly, municipalities use only one type of cost-sharing at a time, and this type applies to all outpatient services in that municipality. Thus, no municipality charges a copayment for one service and coinsurance for another or vice versa. Also, no municipality charges different levels of copayments or coinsurance for different services.

⁴ The data do not, however, include dental claims or inpatient food and housing costs, which are relatively small.

Our data cover a period of 10 years between April 2005 and March 2015 (120 months). We limit our sample to 6–15-year-olds since we have few observations without subsidy below age 6 or with subsidy above age 15. This is because most municipalities already provide a subsidy up to 6 years of age (start of primary school) at the beginning of our sample period, and most municipalities do not provide a subsidy beyond the age of 15 years (end of junior high school) at the end of our sample period (see Figure A1).

4.2. Summary statistics

Table A1 presents the summary statistics of selected variables in the main sample at the individual and person-month levels in Panels A and B, respectively. At the individual level (Panel A), there is a total of 59,775 individuals. At least one subsidy change is experienced by 16.6% of them: 15.5% experience at least one subsidy expansion (from 30% to 0%) and 5.2% experience at least one expiration (from 0% to 30%). Panel B of Table A1 reports some key variables at the unit level of analysis (person-month); there is a total of 2,027,910 person-months over the sample period of 120 months. The proportion of children who see a doctor at least once a month is 40.7%. Children spend USD 60.8 per month, including zero-spending, and USD 149.9 per month conditional on at least one visit. Out-of-pocket payment per visit *without* subsidy is USD 22.3, which gauges the magnitude of the financial burden on individuals if no subsidy is available.

4.3. Event study

We first graphically explore the pattern of demand responses using an event study. For price increases and price decreases, we separately normalize the spending data around the change

in subsidy status. Then, using individuals who experience price increases and those who experience no price change, we run a simple individual-level fixed effects model that includes interaction terms between subsidy status and a series of dummies for each month, ranging from 12 months prior to the price increase to 12 months after the change ($T = -12$ to $+11$, where $T=0$ is the month of the price increase).⁵ We then plot the estimates of the interaction terms in a figure. The regression model additionally controls for age and time fixed effects (both in months). We follow the same process for price decreases.

Figure 2 presents the results of the event study for outpatient spending separately for price decreases (subsidy expansion) and price increases (subsidy expiration). The reference month is three months before the change in subsidy status ($T = -3$). The scales of the y-axis are set the same so that the two figures for opposite price change directions are visually comparable.

We summarize three important facts illustrated by these figures. First, there are long-lasting demand responses to price changes in both directions, and the estimates take opposite signs for opposite directions. The long-term estimate for price decreases (increases) is roughly USD 10 (USD 20). This simple figure alone indicates that the long-term demand response is larger for price increases than price decreases.

Second, there are short-run demand responses in both price change directions, as indicated by a surge (in the case of price increases) and a drop (when prices decrease) in outpatient spending just before $T=0$. Interestingly, we also observe offsetting spending immediately after $T=0$. These patterns reveal that some children (and hence, parents) anticipate upcoming price

⁵ We exclude observations if there is another price change within two months of the observation. For example, if there is another price change at $T=10$ for an individual, we include data only up to $T=7$ for that individual.

changes and behave strategically by delaying or rushing visits. As we include age and time fixed effects (both in months), this difference is not driven by a particular age or year-month effect, such as expiration of a subsidy after graduation from junior high school.

Finally, the short-run demand response immediately before a price change appears substantially larger than that immediately after a price change, as if demand overshoots before a price change. This “overshooting” is especially larger for price increases (graph on the right); the surge before the price increase at $T=0$ is much larger than the drop just after the price increase. This may imply that children purchased healthcare services more during the pre-price change period than they could intertemporally substitute between the pre and post periods.

5. Empirical Framework

5.1. Stylized demand responses and hypotheses to be tested

The event study presented in Section 4.3 indicates that 1) price changes in both directions have long-lasting effects on demand, 2) there is a short-term demand response immediately before a price change, and 3) the short-term response is greater before than after the price change. The goal of our empirical model is to estimate parameters relevant to these observations in a parsimonious way. Figure 3 presents a stylized model of demand responses that incorporates all these features. The figure on the left corresponds to price decreases, while that on the right is for price increases.

We first focus on long-term responses, our main variable of interest. The event study indicates that a price reduction from 30% to 0% clearly increases demand after the price change, and the impact is long-lasting. In the figure on the left, we call this effect a “long-term response (①)” and parameterize it as β^{dec} . Similarly, the long-term effect of price increases (①’) in the

figure on the right is expressed as β^{inc} . Conventional demand theory predicts that β^{dec} and β^{inc} have the same magnitude because a movement along the demand curve between two prices will have the same impact on quantity demanded regardless of the direction of the price change.

Hypothesis 1 (symmetry in long-term responses): $|\beta^{dec}| = |\beta^{inc}|$

If null hypothesis 1 is rejected, we conclude that conventional demand theory does not hold, at least in our setting. This first hypothesis is the main interest of this study.

Next, we turn to short-term responses. We first discuss the figure on the left for price decreases. The event study indicated that there are short-term demand responses immediately before the price change at $T = -1$ and immediately after the price change at $T = 0$. We term the former as the “anticipatory effect (②),” represented by γ_{-1}^{dec} , and the latter as the “offset effect (③),” with the parameter γ_0^{dec} . The anticipation effect, γ_{-1}^{dec} , may arise if people reduce spending on healthcare in anticipation of lower future prices. Such a temporary demand reduction may also result in the offset effect, γ_0^{dec} , if individuals can delay purchases until the price is reduced at $T = 0$. If both anticipation and offset effects are present, we can see that individuals intertemporally substitute consumption.

The short-term demand response for price increases can be similarly characterized with analogous parameters (see the figure on the right in Figure 3). In this case, the anticipation effect, γ_{-1}^{inc} , may imply that individuals stock up on healthcare in anticipation of higher future prices. This effect may be offset by γ_0^{inc} after the price increase if people cut back because they have fewer unmet needs.

We test whether anticipatory and offset effects exist in both price directions.

Hypothesis 2 (non-existence of anticipatory effect and offset effect):

$$\gamma_{-1}^{dec} = 0, \gamma_0^{dec} = 0, \gamma_{-1}^{inc} = 0, \gamma_0^{inc} = 0.$$

Finally, we can examine whether the impact of the anticipatory effect (②) is completely canceled by the offset effect (③). This is equivalent to examining whether “overshooting (④),” which is the difference between the anticipation effect and the offset effect, that is $(|\gamma_{-1}^{dec}| - |\gamma_0^{dec}|)$, equals zero. If “overshooting” exists, it implies that when prices decrease, children spend less during the pre-price change period than they intertemporally substitute. Similarly, we can define overshooting for the price increase (④’) by $(|\gamma_{-1}^{inc}| - |\gamma_0^{inc}|)$. We examine whether such overshooting exists in both price directions and if there is asymmetry in overshooting.

Hypothesis 3 (non-existence of overshooting): $|\gamma_{-1}^{dec}| - |\gamma_0^{dec}| = 0, |\gamma_{-1}^{inc}| - |\gamma_0^{inc}| = 0$

Hypothesis 4 (symmetry in overshooting): $|\gamma_{-1}^{dec}| - |\gamma_0^{dec}| = |\gamma_{-1}^{inc}| - |\gamma_0^{inc}|$

We reiterate here that our main interest is the long-term response, that is, hypothesis 1.

5.2. Empirical model

We estimate an empirical model that allows us to identify the key parameters discussed in the previous section using longitudinal claims data in a difference-in-differences framework. Specifically, our basic estimation equation is:

$$Y_{it} = \alpha + \beta^{dec} dec_{it} + \beta^{inc} inc_{it} + \sum_{k=-K}^{K-1} \gamma_k^{dec} 1(D^{dec} = k) + \sum_{k=-K}^{K-1} \gamma_k^{inc} 1(D^{inc} = k) + \omega X'_{mt} + \delta_a + \pi_t + \rho_m + \theta_i + \varepsilon_{it} - [1]$$

where Y_{it} is the outpatient spending of child i whose age is a (measured in months) at time t (year-month) and who lives in municipality m . δ_a , π_t , and ρ_m are fixed effects for age, time, and

municipality, respectively.⁶ In addition, θ_i represents individual fixed effects, which captures the child's unobserved time-invariant characteristics and addresses the compositional changes in the unbalanced panel data. We also control for two time-varying municipality variables: X_{mt} , a dummy that equals one if the subsidy is applied at the point of service and zero otherwise, and a second dummy variable that equals one if there is an income restriction on subsidy eligibility and zero otherwise.

The variable dec_{it} is the indicator for a price decrease, which equals zero before i experiences a price reduction and one in all periods after a price decrease, even if the subsidy is expired. We define inc_{it} similarly.⁷ For example, suppose an individual's coinsurance rate is initially 30% at age 6, goes down to 0% at age 10, and increases to 30% at age 12. Then, dec_{it} equals zero before age 10, and one at age 10 and thereafter. The value of inc_{it} is zero before age 12, and one at age 12 and thereafter. Currie *et al.* (2015) employ a similar strategy to examine the asymmetric effects on housing values of opening and closing toxic plants. β^{dec} and β^{inc} capture the long-term effect of price decreases and increases in spending, respectively, as they are illustrated in our stylized model. These parameters are identified from within individual variations before and after a price change, along with a control for the time trend to which individuals in other municipalities without a price change contribute. Note that we estimate one

⁶ Note that we still include δ_a at the monthly level to account for any age in month-specific effects (e.g., graduation from junior high school).

⁷ Note that constructing variables this way makes sense only when the subsidy status changes up to two times per individual. Thus, we remove 921 individuals (1.45%) who experience more than two changes in subsidy status.

coefficient each for price increases (β^{inc}) and price decreases (β^{dec}) instead of estimating age specific values. Although this is a simplification, previous work using the same data (Iizuka and Shigeoka, 2018) shows that the effect of a price change is quite similar across children between ages 6 and 15, which supports our modeling approach.

The indicator variable $1(D^{dec} = k)$ equals one in the k th month from the price decrease and zero otherwise. γ_k^{dec} captures the short-run deviation in spending from the long-run average spending in month k . γ_k^{dec} corresponds to the anticipation effect (②) and offset effect (③) in Figure 3. $1(D^{inc} = k)$ can be defined similarly and γ_k^{inc} is interpreted accordingly.

We first experiment with K equal to one (i.e., allowing the short-run deviation to exist one month before and after the price change) and then expand K to two (months). We find that the anticipation and offset effects become statistically significant only in the month of the price change ($k = 0$) and one month before the price change ($k = -1$), as seen in Figure 2. Thus, we set K equal to one, and the resulting estimation equation is written as:

$$Y_{iamt} = \alpha + \beta^{dec} dec_{iamt} + \beta^{inc} inc_{iamt} + \gamma_{-1}^{dec} 1(D^{dec} = -1) + \gamma_0^{dec} 1(D^{dec} = 0) + \gamma_{-1}^{inc} 1(D^{inc} = -1) + \gamma_0^{inc} 1(D^{inc} = 0) + \omega X'_{mt} + \delta_a + \pi_t + \rho_m + \theta_i + \varepsilon_{iamt} \quad [2]$$

We estimate this equation using ordinary least squares (OLS).⁸ Standard errors are clustered at the municipality level to account for serial correlation in the error terms within municipalities.

The identifying assumption in our difference-in-differences strategy is that there are no unobserved municipality-specific changes that are (1) correlated with subsidy changes in the municipality and (2) correlated with municipality-specific changes in healthcare utilization. For

⁸ Iizuka and Shigeoka (2018, 2020) used OLS and alternative functional forms, including one- and two-part generalized linear models, and find the estimates are almost identical.

example, if municipalities in better financial condition are more likely to implement subsidy expansion whereas income effects simply increase utilization, our estimates may be biased upward.

To address this concern, we adopt two approaches. First, the event study in Section 4.3 already shows that there are no systematic differences in the pre-trend between the treated and control municipalities before price changes except for the anticipation effect. Second, we add time-by-municipality fixed effects (with time measured in months) to examine the robustness of our baseline estimates. 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.⁹

6. Results

6.1. Main results

We report estimation results from equation [2] and the results of the hypotheses tests in Table 1. We first focus on the long-term demand responses (hypothesis 1). Spending increases (①) by USD 8.89 when prices decrease, whereas spending decreases (①') by as much as USD 20.0 when prices increase, more than double the change for a price decrease. These results indicate that children react much more strongly to price increases than price decreases. Note that although a price increase from 0% to 30% starts from a “zero price,” this does not explain the

⁹ Additionally, one may be concerned that sicker children may move to a municipality that offers free care. To alleviate this concern, we estimated a conditional logit model that examines whether children migrate to a municipality that provides free care and found little evidence to support this (see Iizuka and Shigeoka, 2018).

differential demand responses because a price decrease from 30% to 0% also includes a zero price. The difference between the two estimates is USD 11.1 and highly statistically significant at the 1% level. These results are not consistent with conventional demand theory, suggesting that the classical model might not always work in practice as expected.

This result has strong policy implications. If policymakers determine policy based on a parameter estimated using a price change in the opposite direction, they may overestimate or underestimate the demand response by more than a factor of two. Although previous studies pay little attention to a price change's direction, the direction of a price change does matter.

We next examine the short-term demand responses. First, there is substantial intertemporal substitution in both price directions, as we find both the anticipation and offset effects are statistically significant (hypothesis 2). Interestingly, the magnitude of the anticipation effect is larger than that of the offset effect regardless of the price direction (hypothesis 3), which results in significant overshooting in both directions. These results indicate that individuals intertemporally substitute consumption only imperfectly. We also find that asymmetry exists in overshooting (hypothesis 4): overshooting for a price increase (USD 21.25) is much larger than that for a price decrease (USD 9.41), and the difference is statistically significant at the 1% level.

For robustness, we estimate a model that adds time-by-municipality fixed effects to equation [2] and find qualitatively similar results (Table A2). Furthermore, we implement Sun and Abraham's (2020) interaction-weighted estimator, which addresses the potential bias that staggered treatment timing and treatment effect heterogeneity may create. Reassuringly, the results change little (Figure B1).

6.2. Asymmetry or heterogeneity?

One may be concerned that the estimated effects could represent heterogeneity in price

responsiveness rather than asymmetric demand responses. Since our source of identification is the variation in time, age, and municipality, our results may reflect the heterogeneity in these three dimensions.

In terms of time, if price increases and decreases occur in different years, estimated effects may represent the difference in timing as opposed to asymmetry in responses. We believe this is not a major problem because both price decreases and increases are spread out over the period (Figure A2), which mitigates the concern that timing differences drive our results.

Another potential source of heterogeneity is age. That is, if price increases and decreases occur at different ages, our results could reflect the heterogeneity in price responsiveness by age. To address this issue, columns 1 and 2 in Table 2 report the estimates for each age. This specification extends our basic equation [2] by interacting the dummies for price increase and decrease with a dummy for each age, allowing for age-specific coefficients. Column 3 shows that the difference between price increases and decreases is always statistically significant, indicating that asymmetry exists in all age ranges (7–14). Figure A3 graphically illustrates this result.

The final dimension is municipality. If price increases and decreases occur in different municipalities, our results may reflect heterogeneity in municipalities. To mitigate this concern, we limit the sample to the municipalities that experience both price increases and decreases during our sample period. As reported in Table A3, the estimates from the limited sample (column 2) are almost identical to those from our main sample (column 1).

6.3 Asymmetry by service type

To further understand what drives the asymmetric demand responses, we examine

heterogeneity by service type. We divide spending into six service types: medication (54.1%)¹⁰, consultation fees (23.6%), laboratory tests (17.4%), non-surgical procedures (5.8%), surgical procedures (3.2%), and all else (1.2%). Table A4 reports the results for the four largest categories, which equal 95.6% of total spending. The corresponding values are presented in Figure A5. Note again that the same cost-sharing applies to all outpatient services.

Panel A of Table A4 presents the long-term demand response by service type. It shows that medication contributes most to the long-term asymmetry observed at the aggregate level: whereas outpatient spending increases by only USD 5.67 for price decreases, it decreases as much as USD 10.2 for price increases. The difference is statistically significant at the 1% level. We note that although we find a negative sign for consultation, the magnitude is relatively small.

Panel B of Table A4 presents the short-term demand response by service type. First, we find anticipation effects in both directions (rows 1 and 3) for all service types. In particular, we find large anticipation effects for price increases (row 3) in medication (USD 12.56)—implying the stockpiling of storable goods—and in laboratory testing (USD 7.82). By contrast, the magnitude of the offset effect (rows 2 and 4) is relatively small in all service types and in both price change directions. While we observe little overshooting for price decreases (row 5), we find substantial overshooting for price increases (row 6) for medication (USD 10.67) and laboratory testing (USD 6.25). As a result, asymmetry in overshooting is observed only for medication and laboratory testing (row 7).

The large overshooting in medication may indicate that future price increases induce

¹⁰ Medication includes fees for prescribing and dispensing medications. We exclude outliers from the sample (i.e., growth hormone injections) as they are extremely expensive (on average USD 3,334) relative to other medications and substantially increase the variance.

consumers to purchase additional medications (such as additional days of prescriptions or different types of medications) that may not necessarily be intertemporally substituted.¹¹

7. Conclusion

This study tests whether the demand response differs when prices increase and decrease in the context of child healthcare. Exploiting the rapid expansion in municipal subsidies for child healthcare in Japan, we find that when coinsurance increases from 0% to 30%, the demand response is more than twice that to a price decrease from 30% to 0%. This result suggests the price change direction does matter and, thus, should be incorporated in welfare analysis. Moreover, our results provide additional evidence against the standard neoclassical model of healthcare demand.

This study focuses on documenting asymmetric demand responses because the unique price variation we examine is most suited for testing classic demand theory's prediction. Future research should explore alternative mechanisms, such as loss aversion and asymmetric adjustment costs, that may explain asymmetric demand responses. Additionally, testing whether similar asymmetric demand responses exist for other goods is an interesting avenue for future research.

¹¹ We abstract from whether this effect is induced by the patient or physician. See Iizuka (2007, 2012) for attempts to separate these two effects.

References

- Abaluck, Jason, and Jonathan Gruber.** (2011) “Choice Inconsistencies among the Elderly: Evidence from Plan Choice in the Medicare Part D Program.” *American Economic Review* 101 (4): 1180–1210.
- Aron-Dine, Aviva, Liran Einav, Amy Finkelstein, and Mark Cullen.** (2015) “Moral Hazard in Health Insurance: Do Dynamic Incentives Matter?” *The Review of Economics and Statistics* 97(4): 725–741.
- Baicker, Katherine, Sendhil Mullainathan, and Joshua Schwartzstein.** (2015) “Behavioral Hazard in Health Insurance.” *The Quarterly Journal of Economics* 130(4): 1623–1667.
- Bell, David R., and James M. Lattin.** (2000) “Looking for loss aversion in scanner panel data: the confounding effect of price response heterogeneity.” *Marketing Science* 19: 185–200.
- Brot-Goldberg, Zarek C., Amitabh Chandra, Benjamin R. Handel, and Jonathan T. Kolstad.** (2017) “What does a deductible do? The impact of cost-sharing on health care prices, Quantities, and Spending Dynamics.” *Quarterly Journal of Economics* 132(3): 1261–1318.
- Cabral, Marika.** (2017) “Claim timing and ex post adverse selection.” *Review of Economic Studies* 84: 1–44.
- Chandra, Amitabh, Benjamin Handel, and Joshua Schwartzstein.** (2019) “Behavioral economics and health-care markets.” In *Handbook of Behavioral Economics: Foundations and Applications 2*, edited by B. Douglas Bernheim, Stefano DellaVigna, and David Laibson. Amsterdam: Elsevier/North-Holland.
- Currie, Janet, Lucas Davis, Michael Greenstone, and Reed Walker.** (2015) “Environmental health risks and housing values: Evidence from 1,600 toxic plant openings and closings.”

American Economic Review 105(2): 678–709.

Dalton, Christina M, Gautam Gowrisankaran, and Robert J Town. (2020) “Salience, Myopia, and Complex Dynamic Incentives: Evidence from Medicare Part D.” *The Review of Economic Studies* 87(2): 822–869.

Einav, Liran, Amy Finkelstein, and Paul Schrimpf. (2015) “The response of drug expenditure to nonlinear contract design: Evidence from Medicare Part D.” *The Quarterly Journal of Economics* 130(2): 841–899.

Fukushima, Kazuya, Sou Mizuoka, Shunsuke Yamamoto, and Toshiaki Iizuka. (2016) “Patient cost sharing and medical expenditures for the Elderly.” *Journal of Health Economics* 45: 115–130.

Han, Sangman, Sunil Gupta, and Donald R. Lehmann. (2001) “Consumer price sensitivity and price thresholds.” *Journal of Retailing* 77(4): 435–456.

Hardie, Bruce G. S., Eric J. Johnson, and Peter S. Fader. (1993) “Modeling loss aversion and reference dependence effects on brand choice.” *Marketing Science* 12(4): 378–394.

Iizuka, Toshiaki. (2007) “Experts’ agency problems: Evidence from the prescription drug market in Japan.” *RAND Journal of Economics* 38(3): 844–862.

Iizuka, Toshiaki. (2012) “Physician agency and adoption of generic pharmaceuticals.” *American Economic Review* 102(6): 2826–2858.

Iizuka, Toshiaki, and Hitoshi Shigeoka. (2018) “Free for children? Patient cost-sharing and healthcare utilization.” *NBER Working Paper No. 25306*.

Iizuka, Toshiaki, and Hitoshi Shigeoka. (2020) “Is zero a special price? Evidence from child healthcare.” *Unpublished manuscript*.

Iizuka, Toshiaki, Katsuhiko Nishiyama, Brian Chen, and Karen Eggleston. (2021). “False

alarm? Estimating the marginal value of health signals.” *Journal of Public Economics* 195, 104368.

Ikegami, Naoki, and John C. Campbell. (1995) “Medical care in Japan.” *New England Journal of Medicine* 333: 1295–1299.

Kahneman, Daniel, and Amos Tversky. (1979) “Prospect theory: An analysis of decision under risk.” *Econometrica* 47(2): 263–292.

Kalwani, Manohar U., Chi Kin Yim, Heikki J. Rinne, and Yoshi Sugita. (1990) “A price expectations model of customer brand choice.” *Journal of Marketing Research* 27(3): 251–262.

Kalyanaram, Gurumurthy, and Russell S. Winer (1995) “Empirical generalizations from reference price research.” *Marketing Science* 14(3): G161–G169.

Kondo, Ayako, and Hitoshi Shigeoka. (2013) “Effects of universal health insurance on health care utilization and supply-side responses: Evidence from Japan.” *Journal of Public Economics* 99: 1–23.

Krishnamurthi, Lakshman, Tridib Mazumdar, and S. P. Raj. (1992) “Asymmetric response to price in consumer brand choice and purchase quantity decisions.” *Journal of Consumer Research* 19(3): 387–400.

Lin, Haizhen, and Daniel W. Sack. (2019) “Intertemporal substitution in health care demand: Evidence from the RAND Health Insurance Experiment” *Journal of Public Economics* 175: 29–43.

Mazumdar, Tridib, S.P. Raj, and Indrajit Sinha (2005) “Reference price research: Review and propositions.” *Journal of Marketing* 69(4): 84–102.

OECD (2004) *Private Health Insurance in OECD Countries*, The OECD Health Project, OECD

Publishing, Paris. <https://doi.org/10.1787/9789264007451-en>. (Last accessed on June 9, 2021).

Putler, Daniel S. (1992) “Incorporating reference price effects into a theory of consumer choice.” *Marketing Science* 11(3): 287–309.

Rice, Thomas. (2013) “The behavioral economics of health and health care.” *Annual Review of Public Health* 34(1): 431–447.

Sun, Liyang, and Sarah Abraham. (2020) “Estimating dynamic treatment effects in event studies with heterogeneous treatment effects.” *Journal of Econometrics*, forthcoming.

Tversky, Amos, and Daniel Kahneman. (1991) “Loss aversion in riskless choice: A reference-dependent model.” *The Quarterly Journal of Economics* 106(4): 1039–1061.

Table 1: Main results

	Estimates	Test	
<u>Long-term effects</u>			
① β^{dec}	8.885*** (2.254)	$ \beta^{inc} - \beta^{dec} $	11.161*** (2.618)
①' β^{inc}	-20.046*** (2.356)		
<u>Short-term effects</u>			
② γ_{-1}^{dec} (anticipation)	-15.192*** (2.759)	④ $ \gamma_{-1}^{dec} - \gamma_0^{dec} $ (overshooting)	9.414*** (2.722)
③ γ_0^{dec} (offset)	5.777** (2.566)	④' $ \gamma_{-1}^{inc} - \gamma_0^{inc} $ (overshooting)	21.248*** (5.150)
②' γ_{-1}^{inc} (anticipation)	28.219*** (4.460)	$\{ \gamma_{-1}^{inc} - \gamma_0^{inc} \} -$ $\{ \gamma_{-1}^{dec} - \gamma_0^{dec} \}$	11.833** (5.933)
③' γ_0^{inc} (offset)	-6.971*** (2.490)		
R-squared	0.52		
N	2,027,910		
N of Individual	59,775		

Notes: The estimates from equation [2] are reported. The outcome is the monthly spending on outpatient care measured in USD (JPY 100/USD). “Price decrease (*dec*)” indicates subsidy expansions that lower the price of healthcare from 30% to 0%, and “Price increase (*inc*)” indicates subsidy expirations that raise the price from 0% to 30%. All regressions include age (in months) FE, time (in months) FE, and individual FE. We also control for a dummy that equals one the subsidy is applied at the point of service rather than refunded later and zero otherwise, and a second dummy variable that equals one if there is an income restriction on subsidy eligibility and zero otherwise. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

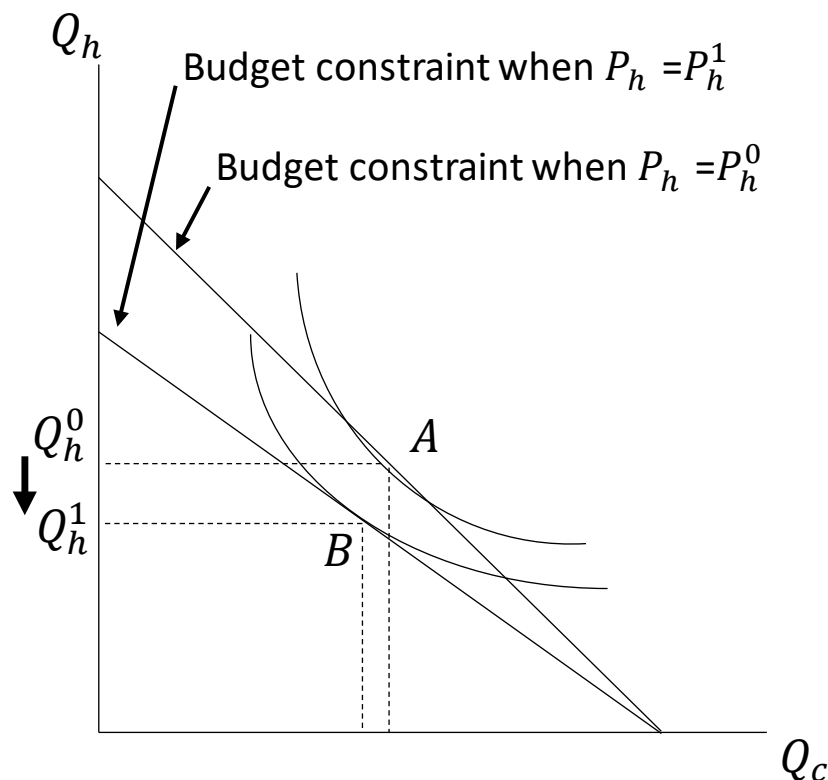
Table 2: Estimates by age

	Estimates		Difference
	Price decreases	Price increases	$ (2) - (1) $
	(1)	(2)	(3)
$\text{Age7} \times (\beta^{dec} \text{ or } \beta^{inc})$	9.988*** (3.015)	-21.759*** (3.178)	11.771*** (3.650)
$\text{Age8} \times (\beta^{dec} \text{ or } \beta^{inc})$	9.881*** (2.693)	-21.460*** (3.521)	11.58*** (3.872)
$\text{Age9} \times (\beta^{dec} \text{ or } \beta^{inc})$	10.398*** (2.630)	-23.242*** (3.154)	12.845*** (3.439)
$\text{Age10} \times (\beta^{dec} \text{ or } \beta^{inc})$	9.863*** (2.964)	-22.350*** (2.810)	12.487*** (3.711)
$\text{Age11} \times (\beta^{dec} \text{ or } \beta^{inc})$	10.210*** (2.713)	-20.899*** (2.504)	10.689*** (2.794)
$\text{Age12} \times (\beta^{dec} \text{ or } \beta^{inc})$	8.248*** (2.702)	-20.025*** (2.674)	11.777*** (3.654)
$\text{Age13} \times (\beta^{dec} \text{ or } \beta^{inc})$	7.136** (3.068)	-17.792*** (2.647)	10.656*** (3.928)
$\text{Age14} \times (\beta^{dec} \text{ or } \beta^{inc})$	6.452** (3.171)	-17.093*** (3.101)	10.641*** (3.323)
R-squared	0.52		
N	2,024,666		
N of Individual	59,775		

Notes: The estimates from a specification, which extends our basic equation [2] by interacting the dummies for price increase and decrease with a dummy for each age, are reported. Note that the estimates in columns (1) and (2) come from a single equation. The outcome is the monthly spending on outpatient care measured in USD (JPY 100/USD). “Price decrease (*dec*)” indicates subsidy expansions that lower the price of healthcare from 30% to 0%, and “Price increase (*inc*)” indicates subsidy expirations that raise the price from 0% to 30%. All regressions include age (in months) FE, time (in months) FE, and individual FE. We also control for a dummy that equals one the subsidy is applied at the point of service rather than refunded later and zero otherwise, and a second dummy variable that equals one if there is an income restriction on subsidy eligibility and zero otherwise. Significance levels: *** $p < 0.01$,

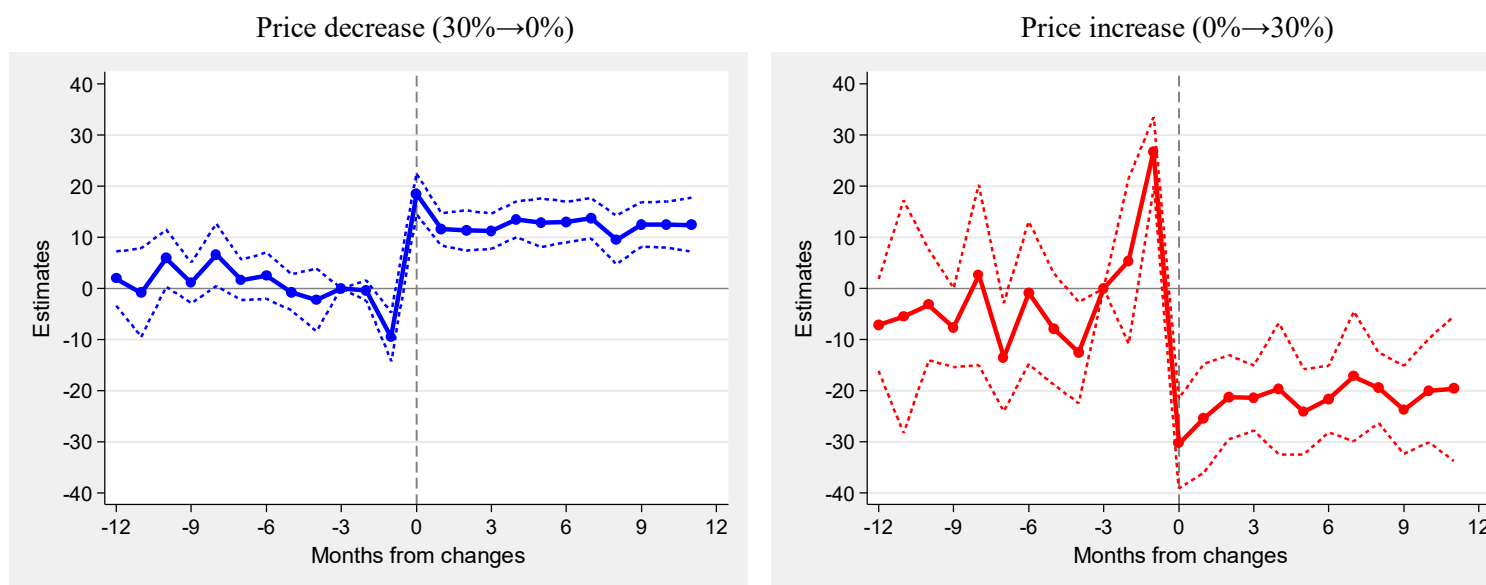
** $p < 0.05$, * $p < 0.10$

Figure 1: Theoretical Underpinning



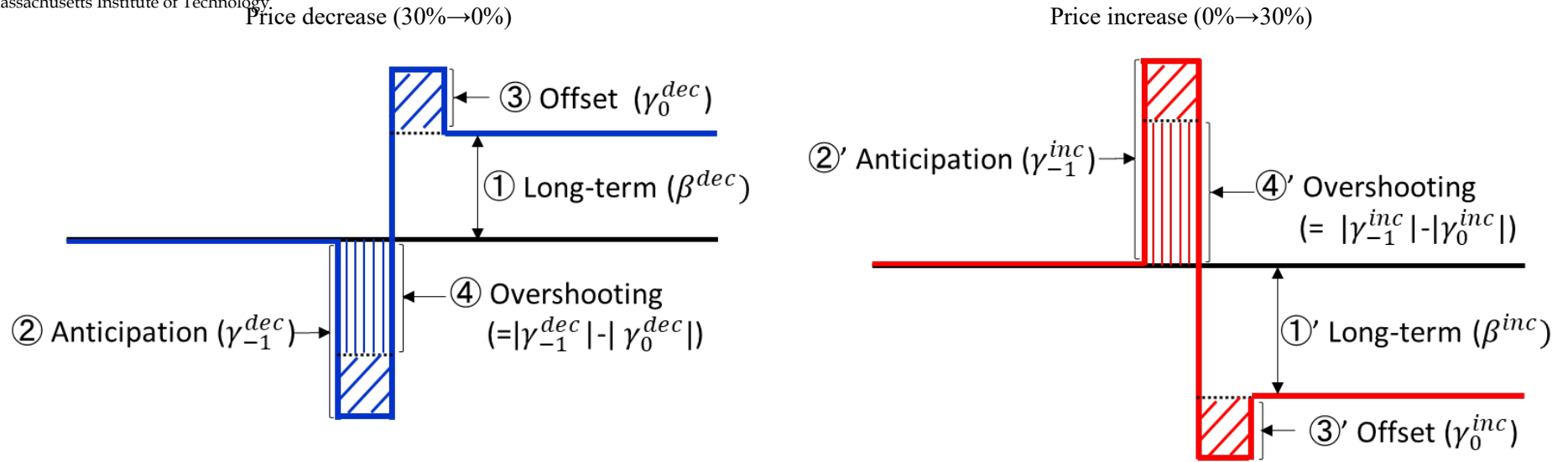
Notes: The figure illustrates the textbook case of a consumer's decision, where the consumer chooses the amounts of two goods, healthcare service Q_h and a composite good Q_c , given their prices (P_h and P_c) under a budget constraint. The initial prices and quantities of the two goods are given by (P_h^0, Q_h^0) and (P_c^0, Q_c^0) , respectively. If the price of healthcare service increases from P_h^0 to P_h^1 , its quantity will decrease from Q_h^0 to Q_h^1 based on the income and substitution effects. Now, suppose that the change in the price of healthcare service is reversed from P_h^1 to P_h^0 . Based on classical demand theory, the quantity of healthcare service will return to the original quantity, Q_h^0 , from Q_h^1 . That is, the absolute value of the impact of the price change on demand should be the same regardless of the direction of the price change.

Figure 2: Event study



Notes: The outcome is the monthly spending on outpatient care measured in USD (JPY 100/USD). “Price decrease” indicates subsidy expansions that lower the price of healthcare from 30% to 0%, and “Price increase” indicates subsidy expirations that raise the price from 0% to 30%. The solid lines plot the estimates from a variant of estimation equation [2], 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, which are constructed using standard errors clustered at the municipality level. The reference month is three months before the change ($T = -3$). The scales of the y-axis are set the same so that the two figures for opposite price change directions are visually comparable.

Figure 3: Stylized Demand Responses



Notes: The figures present a stylized model of demand responses. The figure on the left corresponds to price decreases (from 30% to 0%), while that on the right is for price increases (from 0% to 30%). “Long-term responses (① and ①’)” reflect the long-term demand changes as the price changes, which are parameterized as β^{dec} on the left, and β^{inc} on the right. “Anticipatory effects (② and ②’)” reflect the short-term demand change immediately before the price change at $T = -1$, which are parameterized as γ_{-1}^{dec} on the left, and γ_{-1}^{inc} on the right. “Offset effects (③ and ③’)” reflect the short-term demand change immediately after the price change at $T = 0$, which are parameterized as γ_0^{dec} on the left, and γ_0^{inc} on the right. Finally, “overshooting (④ and ④’)” is the difference between the anticipation effect and the offset effect, i.e., $(|\gamma_{-1}^{dec}| - |\gamma_0^{dec}|)$ on the left, and $(|\gamma_{-1}^{inc}| - |\gamma_0^{inc}|)$ on the right.