

# Ratchet Effects and Strategic Bargaining in Medical Device Procurement\*

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## Abstract

This paper examines how a ratchet-based reimbursement system for medical devices distorts pricing incentives in hospital–supplier negotiations. Administratively set payments that reference lagged transaction prices are a widely used form of regulation in healthcare markets globally, making current prices strategically relevant for future reimbursement levels. Under the specific system studied, government reimbursement prices are periodically updated using wholesale transaction prices observed during pre-announced sampling windows. Because current prices influence future reimbursement levels, hospitals and device sellers – despite normally conflicting interests –share an incentive to raise wholesale prices during these periods.

Using a Nash-in-Nash bilateral bargaining model and transaction-level cost data, we find that hospitals generally possess greater bargaining power. Counterfactual simulations show that although the ratchet rule could, in principle, generate sizable price distortions, its observed impact is modest. This attenuation reflects institutional features such as a long sampling window and the aggregation of products into broad functional categories, which limit the scope for strategic price inflation.

*Keywords:* Nash-in-Nash bargaining; Medical device; Reimbursement prices; Competitive externalities

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# 1 Introduction

Governments around the world face mounting pressure to control healthcare expenditures in order to sustain public finances. Despite ongoing cost-containment efforts, public funds still account for nearly three-quarters of health spending across OECD countries (Organisation for Economic Co-operation and Development, 2018). One of the most pressing challenges is the rapid and persistent increase in spending on pharmaceuticals and medical devices. To respond, many governments impose pricing regulations – either directly or indirectly. However, an obstacle in these regulatory efforts is asymmetric information: While prices are often set in profit-driven markets, regulators lack reliable knowledge of firms’ underlying costs. As a result, pricing decisions frequently rely on historical transaction data rather than cost information, which opens the door to strategic behavior by regulated firms.

One widely used form of regulation in healthcare markets globally is the use of reimbursement pricing, whereby the government sets the amount that healthcare providers are paid for specific treatments or devices, rather than allowing market prices to determine payments. A prominent mechanism within this framework is the ratchet rule, under which future reimbursement prices are adjusted based on past observed transaction prices. This approach is intended to anchor public spending to market behavior, while preserving incentives for efficiency. However, theoretical studies (e.g., Weitzman, 1980; Freixas et al., 1985; Laffont and Tirole, 1993; Armstrong and Sappington, 2007) consistently show that regulated firms leveraging their informational advantage over the regulator may strategically manipulate prices during benchmark periods in order to influence future reimbursement levels. Despite the prominence of such mechanisms internationally – from Medicare reimbursement adjustments in the United States to reference pricing across European health systems – empirical evidence on the ratchet rule remains scarce, largely due to the difficulty of observing both firm behavior and regulatory responses at a sufficiently granular level.

This paper examines how ratchet-based regulation influences market outcomes, using the Japanese cardiac pacemaker market as an ideal empirical testing ground. Japan offers a particularly suitable setting for isolating this global phenomenon for three reasons. First, all pacemakers are imported, and no domestic production exists. This structure enables direct observation of device sellers’ import costs – data that are rarely available in prior empirical work, yet are crucial for identifying the underlying bargaining parameters. Second, reimbursement prices are set by the government through a clearly specified ratchet formula that maps past wholesale transaction prices into future reimbursement levels. This transparent and mechanical linkage between past and future prices offers well-defined institutional environment that facilitates causal identification of the ratchet mechanism. Third, and related to the first point, the analysis draws on a uniquely rich dataset: twelve years of transaction-level records that include import costs, wholesale prices, and detailed product- and hospital-level information. This granularity enables a structural examination of demand and bilateral bargaining that is rarely possible in the analysis of ratchet effects.

Figure 1 illustrates the distribution structure of cardiac pacemakers in Japan, all of which were imported from abroad and ultimately delivered to patients through surgical implantation in hospitals during the study

period. At a given time, a device seller – a domestic subsidiary of a foreign manufacturer – imports model  $j$  from its parent manufacturer and supplies it to hospital  $h$  at the wholesale price  $p_{jh}$ .<sup>1</sup> Each foreign producer appoints a domestic subsidiary as its exclusive distributor (called device seller), thereby eliminating intra-brand competition for the model. Although device sellers typically handle multiple products, each specific product  $j$  is exclusively marketed by a single seller.<sup>2</sup>

Hospital  $h$  then implants the device and is reimbursed at a fixed reimbursement price  $\bar{p}_f$ , which is jointly financed by insurers, the government, and the patient. Here  $f$  denotes a functional category defined by the government, grouping model  $j$  with other functionally similar devices. All devices within the same category receive the identical reimbursement price. Importantly,  $\bar{p}_f$  is applied uniformly across all hospitals nationwide.

If the wholesale price  $p_{jh}$  exceeds the reimbursement price  $\bar{p}_f$ , the hospital must absorb the resulting loss, as Japan’s universal healthcare system prohibits charging patients above the regulated reimbursement level. This contrasts with systems in countries such as France and Germany, where a national reimbursement price is also set but providers may be permitted to charge patients above that level, with the difference paid out-of-pocket.

This institutional design creates opposing incentives in wholesale price negotiations: Hospitals are motivated to minimize  $p_{jh}$  in order to secure a margin between the reimbursement price and the wholesale price, whereas device sellers seek to maximize  $p_{jh}$  to expand its own margin between  $p_{jh}$  and its import cost. As a result, the wholesale market operates as a zero-sum bargaining environment, in which the division of surplus depends critically on the relative bargaining power of hospitals and sellers.

A distinctive feature of the Japanese pricing system is the periodic alignment of incentives between hospitals and device sellers, which occurs during the biennial revision of the reimbursement price  $\bar{p}_f$ . Every two years, the government updates  $\bar{p}_f$  using a ratchet rule based on observed wholesale prices. Specifically, during a designated five-month sampling window in odd-numbered years, the government collects transaction-level data on  $p_{jh}$ , the wholesale prices paid by hospitals to device sellers. The sales-weighted average of these prices is then used to revise the reimbursement price for the following period. This mechanism allows the regulated reimbursement price  $\bar{p}_f$  to reflect trends in the unregulated wholesale price  $p_{jh}$ , albeit with a one-year lag.

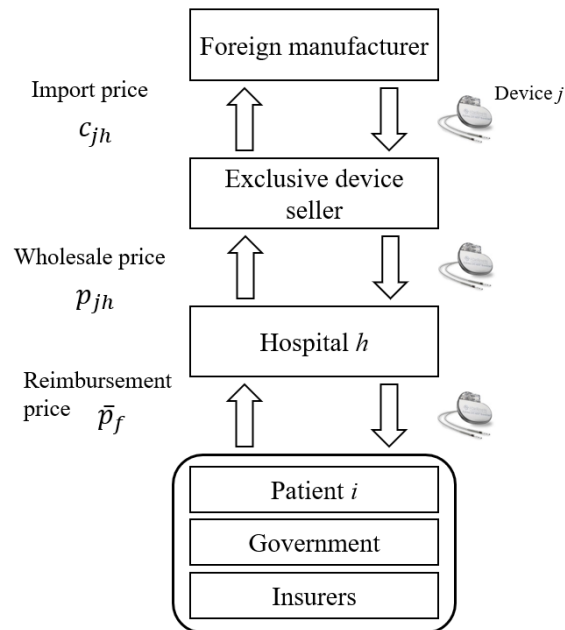
Since the timing of the sampling window is publicly known in advance, both hospitals and device sellers have an incentive to strategically adjust their behavior during this period. By jointly inflating  $p_{jh}$  within the sampling window, device sellers can raise short-term revenues, while hospitals benefit from a higher reimbursement rate in the future. Thus, while hospitals and sellers are typically on opposing sides of the price negotiation, the ratchet mechanism temporarily aligns their incentives – potentially weakening price competition in the wholesale market during the data-collection period.

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<sup>1</sup>We drop the time subscript unless needed for clarity. Because each model  $j$  is sold exclusively by a single seller, we also omit the seller subscript here.

<sup>2</sup>We use the terms “model” and “product” interchangeably throughout the paper.

Figure 1: Distribution Structure of Cardiac Pacemakers in Japan



*Notes:* This figure illustrates the distribution structure of cardiac pacemakers  $j$  in Japan. All pacemaker manufacturers are foreign firms, each of which appoints a domestic subsidiary as its exclusive distributor (device seller). The device seller imports the pacemaker from the foreign manufacturer at an import cost  $c_{jh}$  and sells it to hospital  $h$  at a wholesale price  $p_{jh}$ . Hospital  $h$  implants patient  $i$  the device  $j$  through surgical procedure and is subsequently reimbursed at the regulated reimbursement price  $\bar{p}_f$ , funded jointly by public insurers, the government, and patients.

Another institutional feature of Japan’s reimbursement system is that prices are not set on a device-specific basis. Instead, the government groups pacemakers into functional categories, and all products within a given category – irrespective of brand or device-specific features – are assigned the same reimbursement price  $\bar{p}_f$ . This categorization introduces competitive externalities: When many products are classified under the same functional category, each seller’s ability to influence the average wholesale price – and thereby the reimbursement benchmark – is diluted. Even if one seller raises  $p_{jh}$ , the marginal impact on  $\bar{p}_f$  is small when competitors keep prices low. This paper examines the extent of these externalities and how they interact with firms’ strategic behavior under ratchet-based regulation.

To quantify the effects of this system, we use proprietary transaction-level data obtained from device sellers, covering all cardiac pacemaker sales between hospitals and device sellers from May 2003 to April 2014. The dataset records import costs, wholesale prices, and reimbursement prices for each hospital-seller transaction, as illustrated in Figure 1. It represents approximately 60% of the Japanese pacemaker market overall, and over 80% of the Tokyo metropolitan area. Crucially, the data also allow us to identify multi-product device sellers operating within and across functional categories.

We begin by comparing wholesale price dynamics under two distinct regulatory regimes: (1) government’s data-collection periods, when reimbursement prices are revised using observed wholesale prices, and (2) no-data-collection periods, when no revision occurs and the parties bargain without forward-looking incentives. A difference-in-differences analysis, supported by placebo tests, shows that wholesale prices are on average 1.4% higher during data-collection periods. This effect declines with the number of competing products within a functional category, consistent with the presence of competitive externalities.

To further investigate the strategic pricing behavior, we estimate a structural Nash-in-Nash bargaining model in which hospitals and device sellers negotiate over transaction prices. During data-collection periods, both parties have dynamic incentives to influence future reimbursement rates, and we specify a multi-period bargaining game. In contrast, negotiations in no-data-collection periods are modeled as a one-shot game. A distinctive advantage of our setting is that we directly observe unit-level markups from transactions between hospitals and device sellers. This feature allows us to identify bargaining parameters, without imposing strong parametric assumptions on revenue or cost structures.

Two key findings emerge from the structural estimation. First, the empirical evidence supports the Nash-in-Nash bargaining framework over a benchmark differentiated-product oligopoly model that assumes hospitals are passive price takers. The bargaining model closely reproduces observed pricing patterns, whereas the Bertrand-type model systematically over-predicts wholesale prices. This highlights the central role of negotiated interactions between hospitals and device sellers in governing transaction outcomes in Japan’s pacemaker market.

Second, the estimates reveal that hospitals possess persistent and stable bargaining power relative to device sellers across regulatory regimes, suggesting that variations in pricing dynamics are not driven by shifts in bargaining strength but rather by forward-looking strategic behavior in response to the reimbursement

system’s ratchet incentives.

Building on these estimates, we conduct counterfactual simulations to quantify the magnitude of such ratchet effects – the extent to which hospitals and sellers jointly raise wholesale prices during the data-collection period to influence future reimbursement levels. When both parties are assumed to behave myopically, simulated prices align closely with observed non-data-collection levels. Comparing these outcomes shows that strategic behavior increases wholesale prices by only a modest amount – less than one percent on average. This surprisingly small magnitude indicates that, although the ratchet mechanism provides theoretical incentives for hospitals and sellers to inflate prices, such effects are largely mitigated in practice by the institutional features of Japan’s reimbursement system.

Our simulations indicate that if reimbursement prices were determined separately for each product, ratchet distortions could reach approximately five percent. In practice, however, Japan’s policy of setting reimbursement prices by functional category, which groups multiple substitutable products together, introduces competitive externalities that dilute the incentive for any single hospital-seller pair to inflate prices. Moreover, the government’s use of a five-month data-collection window further attenuates manipulation: Shortening this period to one month would amplify wholesale prices by up to 25 percent. Alternative counterfactual sampling mechanisms are examined in our simulation analysis.

Together, these results underscore a broader policy insight – competition can serve as natural safeguards against ratchet distortions. The Japanese reimbursement system thus provides an example of how institutional design choices can harness competition to preserve price stability even under asymmetric information.

**Literature Review** This paper contributes to three related literatures. First, it contributes to the literature on dynamic incentive problems under benchmark-based regulation, in which past outcomes are used to update future targets or administered payments. A large theoretical literature shows that when regulated parties possess informational advantages, ratchet rules can induce forward-looking distortions in current behavior to influence future regulatory benchmarks (e.g., Weitzman, 1980; Freixas et al., 1985; Laffont and Tirole, 1993; Armstrong and Sappington, 2007). Closely related is work on benchmarking and yardstick competition, where regulators discipline prices or performance by referencing observed outcomes in comparable markets or firms (e.g., Shleifer, 1985). Empirically, ratchet responses have been documented in several policy environments, including Medicaid drug pricing (Duggan and Scott Morton, 2006), energy-efficiency regulation (Ito and Sallee, 2018; Amano and Ohashi, 2018), and trade policy (Ohashi, 2002). Within health care, related research shows that administratively set payments often reference lagged transaction prices, making current prices strategically relevant for future reimbursement levels (e.g., Ridley and Lee, 2020; Acquatella et al., 2023).

This paper complements that evidence by structurally quantifying ratchet-induced incentives in a medical-device market where reimbursement prices are updated using wholesale transaction data collected during pre-announced sampling windows. The transparency of this sampling design creates a particularly clear

mechanism through which current negotiated prices affect future reimbursement benchmarks, allowing us to directly identify and measure the strategic response implied by the ratchet rule.

A second contribution is to the empirical bargaining literature, surveyed by Lee et al. (2021). Existing applications of Nash-in-Nash bargaining typically estimate bargaining parameters jointly with demand and/or cost primitives and often are often confined to static environments (e.g., Crawford and Yurukoglu, 2012; Gowrisankaran et al., 2015; Grennan, 2013, 2014; Ho and Lee, 2017; Crawford et al., 2018). An identification concern in this literature is that bargaining weights may be confounded with unobserved cost heterogeneity. Our setting mitigates this issue because all pacemakers are imported and we observe transaction-level import costs, allowing us to construct buyer and seller markups directly and to identify bargaining parameters without imposing restrictive assumptions on cost functions. We further demonstrate the importance of cost observability by re-estimating the model under a counterfactual in which marginal-cost data are unavailable, showing that inferred bargaining parameters can shift considerably under conventional cost specifications.

Our framework also extends empirical bargaining models to incorporate dynamics induced by the reimbursement update rule. In our setting, current negotiated prices influence future disagreement payoffs through the reimbursement benchmark. While Dorn (2025) likewise studies forward-looking behavior in a dynamic bargaining environment—specifically, a Nash-in-Kalai model of insurer–hospital negotiations in the United States – the focus and identification environments differ in important ways. Dorn (2025) studies dynamics in the absence of ratchet mechanism, whereas our setting allows the ratchet rule itself to generate forward-looking strategic behavior.

A third contribution connects to research emphasizing that buyer-side institutions and information environments govern negotiated procurement outcomes in health-care supply chains. Work on group purchasing organizations analyzes how pooled purchasing and collective contracting affect negotiated prices (e.g., Hu et al., 2012; Lin and Wang, 2025), while related evidence highlights the role of buyer capability and discretion in medical-device procurement (e.g., Bucciol et al., 2020). Another strand shows how price transparency and information disclosure alter negotiated outcomes by changing beliefs about outside options and the broader price distortion (e.g., Grennan and Swanson, 2020).

This paper complements these contributions by demonstrating that procurement discipline can also be determined by the design of administered pricing rules when regulated payments are benchmarked to observed transaction prices. Though counterfactual simulations, we show that broader product aggregation into functional categories and a longer data-collection window limit the scope for strategic price inflation. We also evaluate predictability as a policy lever: replacing a publicly announced sampling window with randomized (unannounced) sampling reduces the ability of parties to time price increases around the benchmark-setting period.

The paper is organized as follows. Section 2 describes the cardiac pacemakers market. In this section, we provide an overview of the industry, and also describe the details of Japanese medical system, some features of which differ from the U.S. and European countries. Section 3 introduces the data used in this paper

and presents descriptive analyses. Section 4 presents a demand and supply estimation models and Section 5 shows our identification strategy. Section 6 reports estimation results, followed by simulation exercises in Section 7. Section 8 concludes, followed by the appendices.

## 2 Cardiac Pacemaker Market in Japan

This section provides an overview of the Japanese cardiac pacemaker market. Section 2.1 outlines the structure of the markets, which consists of the wholesale and the retail markets. Section 2.2 describes Japan’s healthcare system, which differs significantly from systems such as that of the United States. Japan’s universal healthcare model – because insurers play only a minimal role in price negotiations – offers a relatively clean setting to study the strategic interaction between hospitals and device sellers. Section 2.3 explains the dynamic mechanism through which reimbursement prices are determined. The ratchet-based regulation employed in Japan is intended to control costs, but creates distorted incentives for both hospitals and device sellers. These institutional details discussed in this section form the empirical foundation for the analyses in the subsequent sections.

### 2.1 Cardiac Pacemakers Market

Cardiac pacemakers are battery-operated medical devices that help regulate abnormal heart rhythms. In patients with arrhythmia, the heart fails to pump blood effectively, leading to symptoms such as fainting, fatigue, or—in severe cases—sudden death. Pacemakers are generally classified into two categories: implantable and external. This study focuses on implantable pacemakers, which are surgically placed in the chest or abdomen, with electrical leads threaded through blood vessels to deliver signals to the heart. In contrast, external pacemakers are used temporarily in hospital settings and account for a small share of the market. During the study period, implantable pacemakers accounted for over 90% of total pacemaker sales in Japan.

The market for implantable pacemakers in Japan is composed of two distinct layers. The wholesale market involves transactions between hospitals and device sellers. All pacemakers sold in Japan are foreign made, and each foreign manufacturer appoints a single domestic subsidiary as its exclusive sales agent, resulting in no resale markets or competition among distributors for the same product. The retail market refers to the clinical provision of pacemakers to patients, which occurs through surgical implantation in hospitals. While the wholesale market is unregulated and governed by private price setting behavior, the retail market is subject to strict regulation, as we discuss in Sections 2.2 and 2.3.

Our dataset contains transaction-level information on every pacemaker model traded in the Japanese market between May 2003 to April 2014. For each transaction, we observe three key variables: (i) the import cost at which a device seller procures pacemaker  $j$  from the foreign manufacturer,  $c_{jh}$ ; (ii) the wholesale price at which the device seller sells it to hospital  $h$ ,  $p_{jh}$ ; and (iii) the exact timing of delivery.

A distinctive feature of the dataset is that it allows us to trace the entire transaction chain – from import by the device seller, to wholesale delivery to hospitals, and ultimately to the hospital’s reimbursement from insurers, patients, and the government at the regulated price,  $\bar{p}_f$ . This structure enables us to compute markups separately for device sellers ( $p_{jh} - c_{jh}$ ) and hospitals ( $\bar{p}_f - p_{jh}$ ) at the level of each individual pacemaker transaction. In turn, this permits the estimation of bargaining parameters without conflating them with unobserved cost heterogeneity.<sup>3</sup>

## 2.2 Japan’s Healthcare System

Japan operates under a universal healthcare system, in which all citizens are required to enroll in health insurance. Assignment to specific insurers is automatic and determined by an individual’s age, place of residence, and employment status. While insurance premiums may differ by provider, individuals cannot choose or switch insurers based on their preferences.<sup>4</sup>

One of the notable features of Japan’s healthcare system is that patients are free to seek care from any hospital or physician, regardless of their assigned insurer. Reimbursement rates for medical procedures and devices are set nationally by the Ministry of Health, Labor and Welfare (MHLW), and apply uniformly across all healthcare providers. Hospitals thus receive the same payment for a given treatment, irrespective of the patient’s insurer. Insurers in Japan act primarily as payment intermediaries, lacking authority over physician behavior, provider networks, or reimbursement negotiations.

Patients typically pay approximately 30% of the regulated reimbursement price out-of-pocket, while the remaining 70% is covered by insurers and government subsidies. For high-cost procedures exceeding one million Japanese Yen (JPY), the portion above the threshold is financed by public funds. We will return to this reimbursement structure in our modeling of demand-side behavior. It is important to note that physicians in Japan are salaried employees of hospitals, and there are no direct payments from insurers or the government to individual physicians. Consequently, physicians’ treatment decisions are best understood as reflecting both hospital financial incentives and patient welfare – an assumption that underpins our demand model in Section 4.

Because the reimbursement price for pacemakers is fixed and nationally standardized, hospitals’ financial outcomes depend on the relationship between the wholesale price and the reimbursement level. When the wholesale price is lower than the reimbursement amount, hospitals earn a positive margin; when it is higher, they must bear the loss. Under Japan’s universal health insurance system, hospitals are legally prohibited from charging patients more than the regulated reimbursement price, so they cannot pass such losses onto patients.

This institutional arrangement gives hospitals strong incentives to negotiate lower wholesale prices in

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<sup>3</sup>In Section 6.2.2, we further examine how the absence of observed cost data – as is typical in much of the literature – can bias estimates of bargaining parameters when costs may be misspecified.

<sup>4</sup>For a detailed description of Japan’s medical device reimbursement listing and pricing process, see Tamura et al. (2018).

order to preserve their margins. Building on this feature, Section 4 develops a Nash-in-Nash bargaining model to characterize how wholesale prices are determined through negotiations between device sellers and hospitals. As demonstrated in Section 6, incorporating buyer (hospital) bargaining power is crucial: models that account for hospital bargaining power provide a significantly better fit to the observed data than models that assume hospitals lack bargaining leverage (such as, product-differentiated Bertrand competition).

In the next subsection, we turn to another key factor in determining wholesale prices: the reimbursement price itself. We explain how reimbursement levels are set endogenously under Japan’s ratchet-based regulatory system, which creates forward-looking incentives for both hospitals and device sellers.

### 2.3 Ratchet-based Regulation on Reimbursement

The mechanism by which reimbursement levels are set plays a critical role in the structure of bargaining between device sellers and hospitals, since it directly affects the incentives embedded in wholesale price negotiations.

Medical devices in Japan are typically covered under two reimbursement schemes (see Ministry of Health, Labour and Welfare, 2024). The first is special treatment material (STM) reimbursement, which provides direct reimbursement for the device itself, based on its assigned functional category. The second is technical fee reimbursement, which covers the procedure associated with the device and is paid in addition to STM reimbursement.<sup>5</sup> Cardiac pacemakers fall under the STM reimbursement scheme. A key broad difference between Japanese and US systems is that Japan reimburses both the device and the associated procedure separately, whereas the U.S. relies on bundled payments under Diagnosis-Related Groups (DRGs) and the Prospective Payment System (PPS).

For STM products, initial reimbursement levels are determined by regulatory authorities upon approval of safety and effectiveness. The price of a new device is set by comparison to existing functional substitutes – that is, products already available on the market that perform a similar therapeutic function. If two devices, say models  $j$  and  $j'$ , are judged by the regulator to be functional substitutes, they are assigned the same reimbursement price. By contrast, if a newly introduced device is deemed to provide substantially different or higher functionality, the regulator establishes a new functional category and assigns an initial reimbursement level to that category.<sup>6</sup>

The reimbursement price is revised by the regulator in April of every even-numbered year. The regulator collects data on the wholesale prices,  $p_{jhs}$ , of pacemaker  $j$  sold to hospital  $h$  at date  $s$  during the data-collection period from May through September of the preceding year  $y$  of the revision. We denote the data-collection period,  $T_y$ . The following formula is used for the biennial revision on the reimbursement prices for every odd-numbered year,  $y$ :

<sup>5</sup>The only devices that do not receive STM reimbursement are capital equipment and commodities used during medical procedures.

<sup>6</sup>To ensure transparency and accountability, the MHLW delegates classification and pricing decisions to the Central Social Insurance Medical Council, an independent advisory panel.

$$\bar{p}_{f,y+1} = \frac{\sum_{s \in T_y} \sum_{h \in H_s} \sum_{j \in J_{fhs}} p_{jhs} q_{jhs}}{\sum_{s \in T_y} \sum_{h \in H_s} \sum_{j \in J_{fhs}} q_{jhs}} + 0.04 \cdot \bar{p}_{fy}, \quad (1)$$

and

$$\bar{p}_{f,y+2} = \bar{p}_{f,y+1}. \quad (2)$$

Note that  $q_{jhs}$  is the number of units of pacemaker  $j$  sold to hospital  $h$  at date  $s$ . Also note that  $H_s$  is a set of hospitals that purchase pacemakers at date  $s$ , and  $J_{fhs}$  is the set of pacemakers in functional category  $f$  sold to hospital  $h$  at date  $s$ . The first term of Eq.(1) is the sales-weighted average of the wholesale prices of all pacemakers under category  $f$  sampled in  $T_y$ . If this sales-weighted average is set more than 4 percent below the reimbursement price at year  $y$ , the reimbursement price in the following year falls. For every even-numbered year, the reimbursement price remains the same as the previous year’s, as shown in Eq.(2).

The price setting rule presented in Eqs.(1) and (2) is considered as a variant of ratchet-based regulation. Every other year, the regulator updates the reimbursement price using the recent wholesale prices, according to Eq.(1). Notice that this regulation may leave an opportunity for both device sellers and hospitals to “game” the market: An increase in  $p_{jhs}$ , where  $s$  belongs to  $T_y$ , would raise  $\bar{p}_{f,y+1}$ , thus benefiting both the hospital and the device seller, at the cost of insurers and patients. The reimbursement rule would thus create an incentive common for both hospital and device seller to edge up the wholesale prices in the data-collection period, while their interests conflict each other during the other times.

In addition, reimbursement prices are determined at the functional category level rather than on an individual device basis. This means that all products within the same category are assigned the same reimbursement price. As the number of products in a category increases, competitive externalities become more pronounced: Each product’s wholesale price contributes only marginally to the category-wide average that determines the reimbursement price.

In the next section, we examine the extent to which these two features – the ratchet-based regulation and competitive externalities – influence the Japanese pacemaker market.

### 3 Data Description

This section introduces the data and empirical patterns that motivate our structural model developed later in the paper. Section 3.1 describes the dataset used in the analysis. A distinctive feature of this dataset is that it allows us to directly observe both seller (device seller) and buyer (hospital) markups for each transaction. In Section 3.2, we examine the relationship between these two markups. We find a moderately negative correlation between seller and buyer markups, consistent with their opposing profit incentives. However, the relative markup shares exhibit substantial dispersion across transactions, much of which can be attributed to heterogeneity across hospitals rather than across time and products. Section 3.3 presents a reduced-form analysis that provides evidence consistent with the presence of ratchet effects in Japan’s

reimbursement system. The empirical regularities documented in this section highlights the need for a bargaining framework capable of capturing the strategic interactions between hospitals and device sellers.

### 3.1 Data

The primary panel dataset used in this paper is at transaction level for each product-hospital pair of cardiac pacemakers, ranging from May 2003 to April 2014. The data identify ten multi-product device sellers and contain 22,862 transactions, representing approximately 60% of the overall domestic market in Japan and more than 80% of the Tokyo metropolitan area. For the purpose of our empirical analyses, we aggregate the data to the monthly ( $t$ ) level, leading to 11,096 transactions across 265 products and 141 hospitals. The dataset is further supplemented with hospital and product characteristics. Additional details – including an assessment of the representativeness of the data – are provided in Appendix A.

The summary statistics are presented in Table 1. The upper panel shows prices and markups for device sellers and hospitals. Two observations are notable. First, wholesale prices,  $p_{jht}$ , exhibit nontrivial variation over the study period. Using the coefficient of variation (CV) – defined as the standard deviation divided by the mean – the average CV for  $p_{jht}$  exceeds 0.21. The variation is notable even when calculated separately for each product and month. This observation in wholesale prices has direct implications for the distribution of markups among buyers and sellers, as detailed in Section 3.2.

Second, wholesale prices are, on average, 1.92% higher during the data-collection periods compared to non-data-collection periods. This finding is consistent with the ratchet-based reimbursement regulation discussed in Section 2.3, under which hospitals and device sellers have incentives to raise wholesale prices during the periods when reimbursement benchmark is determined. Although import costs are also higher during data-collection periods, the magnitude of the increase is smaller than that of wholesale prices, implying that device sellers’ markups are correspondingly larger during these periods. Importantly, we find in the lower panel of Table 1 no systematic differences in observable product and hospital characteristics between data-collection and non-data collection periods, suggesting that the observed price differences may not be driven by compositional changes of hospital and products in the data. In what follows, we further analyze two key aspects of the wholesale price dynamics discussed above.

### 3.2 Seller and Buyer Markups

We now calculate the respective markups earned by device sellers and hospitals for cardiac pacemakers during the study period. For each product  $j$  transacted at time  $t$  in year  $y$ , the hospital’s markup is defined as  $\bar{p}_{fy} - p_{jht}$ . The device seller’s markup is  $p_{jht} - c_{jht}$ .

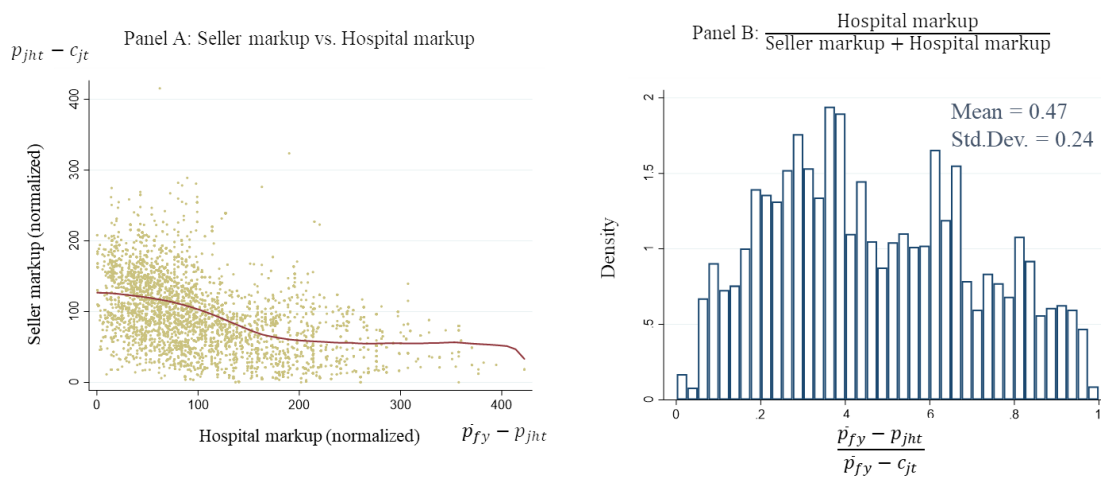
Panel A of Figure 2 plots these two markups against one another, normalized to have a mean of 100. The fitted line slopes downward, consistent with the idea that sellers and hospitals have conflicting profit motives. At the same time, the dispersion around the line is substantial, suggesting wide heterogeneity in

Table 1: Summary Statistics

	Total	Data-collection periods	Non-data- collection periods	Difference (%)
Average values (in JPY):				
Wholesale price	1,008,921 (216,956)	1,023,658 (231,380)	1,004,406 (212,151)	1.92*** (0.49)
Reimbursement price	1,187,097 (211,872)	1,203,282 (225,810)	1,182,138 (207,176)	1.79*** (0.41)
Import cost	820,770 (177,572)	831,139 (185,358)	817,593 (175,006)	1.66*** (0.49)
Seller markup	188,151 (94,301)	192,520 (97,905)	186,813 (93,133)	3.05*** (1.15)
Hospital markup	178,176 (120,713)	179,624 (114,424)	177,733 (122,578)	1.06*** (1.54)
Product characteristics:				
Battery lifetime (year)	8.36 (2.02)	8.33 (2.01)	8.37 (2.02)	-0.49 (0.59)
Size (mm <sup>3</sup> )	14,453 (2,478)	14,424 (2,429)	14,462 (2,493)	-0.27 (0.41)
Hospital characteristics:				
Num. beds	647.63 (360.21)	649.95 (363.11)	646.91 (359.34)	0.47 (1.27)
Num. inpatients per year	529.40 (308.32)	528.51 (305.99)	529.68 (309.04)	-0.22 (1.32)
Num. device sellers	10	10	10	-
Num. hospitals	141	111	136	-
Num. months	132	30	102	-
Num. observations	10,792	2,531	8,261	-

*Notes:* Standard deviations are reported in parentheses for the first three columns. The last column reports the mean differences in each variable between the data-collection and non-data-collection periods, with standard errors in parentheses. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure 2: Sellers and Buyers Markups



Notes: Panel A plots the hospital markups,  $\bar{p}_{fy} - p_{jht}$ , against the device sellers' markups,  $p_{jht} - c_{jt}$ , with each markup normalized to have a mean of 100. Panel B presents the distribution of the hospital's share of the total transaction surplus, calculated as  $(\bar{p}_{fy} - p_{jht})/(\bar{p}_{fy} - c_{jt})$ .

the division of profits across transactions.

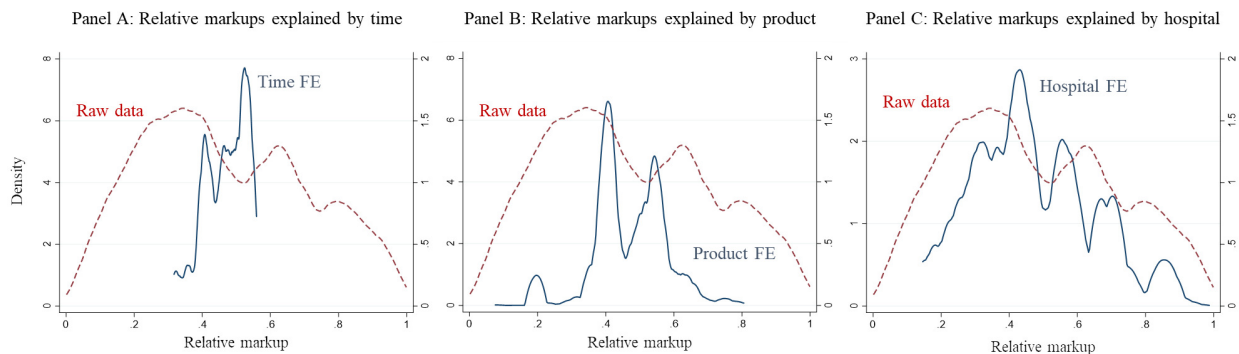
This heterogeneity is further illustrated in Panel B, which shows the share of the hospital's markup relative to the total markup,  $\bar{p}_{fy} - c_{jht}$ . The ratio ranges between 0 and 1, with an average 0.47, indicating that, on average, hospitals and device sellers split total profits roughly equally. Nonetheless, the distribution is wide, reflecting substantial asymmetry in how transaction surplus is divided between hospitals and sellers.

The observed variation in markups arises not only across products and over time but also across hospitals. To assess how each dimension contributes to the overall dispersion in markups, we regress relative markups on sets of dummy variables for time (year-month combinations), products, and hospitals. Figure 3 decomposes the relative markups from Figure 2 (B) into components attributable to these three dimensions. The distributions shown in the panels indicate that the largest share of variation in relative markups stems from differences across hospitals, whereas product- and time-related factors explain relatively little. Taken together, this evidence suggests that much of the observed heterogeneity in relative markups reflects differences in hospital-level bargaining outcomes. These results underscore the importance of explicitly modeling negotiations between individual hospitals and device sellers, as developed in Section 4.2.

### 3.3 Evidence on Strategic Incentives under Ratchet-based Regulation

Table 1 in Section 3.1 showed that wholesale prices during the data-collection periods are systematically higher than those observed in non-data-collection periods, consistent with the strategic behavior predicted under Japan's ratchet-based reimbursement regulation. To assess the robustness of this finding, we conduct a set of reduced-form analyses.

Figure 3: Decomposition of Relative Markups



Notes: Relative markups from Figure 2(B) are decomposed into components explained by year-month (Panel A), product (Panel B), and hospital (Panel C) dummies.

Specifically, we regress the wholesale price  $p_{jht}$  on product- and hospital-specific fixed effects, together with a treatment dummy variable that equals one when month  $t$  falls within the government’s data collection window  $T_y$ , and zero otherwise. The estimation results are reported in Table 2. Across the first two specifications (2-1) and (2-2), the coefficients on the treatment dummy remain positive and statistically significant even after controlling for a rich set of fixed effects. On average, wholesale prices are approximately USD 100 – roughly 1.4 percent – higher during the data-collection period compared with other months.

To verify that this effect is not driven by differential time trends between treated and control months, we perform a placebo test. We redefine the data-collection window to coincide with the same five months (May-September) in *even-numbered* years, denoted by  $T_y^c$ , and re-estimate the regressions using this counterfactual treatment period. As shown in Table 3, the coefficients on the placebo dummy are statistically insignificant and, in some cases, negative. This result reinforces the interpretation that the observed price increases are specific to the actual data-collection periods rather than a by-product of secular price trends.

The magnitude of the ratchet effect may vary depending on the degree of competition within a functional category. As discussed in Section 2.3, stronger competitive externalities reduce the incentive for any individual buyer-seller pair to raise wholesale prices during the data-collection window, because the effect of a single price increase on the future reimbursement benchmark becomes diluted. To test this hypothesis, we extend the baseline regression by including the number of competing pacemaker models within each functional category as an explanatory variable, and interact this measure with the treatment dummy.

The results, reported in (2-3) and (2-4) of Table 2, show that the interaction term is negative and statistically significant: The price differential between data-collection and non-data-collection periods diminishes as the number of competing models increases. This finding supports the view that stronger competition constraints the joint incentive of hospitals and device sellers to manipulate prices in anticipation of future reimbursement updates.

Figure 4 illustrates a simple descriptive evidence. It compares wholesale prices between data-collection

Table 2: Estimation Results on the Wholesale Prices

The dependent variable:	(2-1)	(2-2)	(2-3)	(2-4)
Wholesale prices (JPY)				
(A) Treatment dummy	11177.82*** (2304.60)	14543.46*** (1411.32)	8082.52 (5413.45)	21806.16*** (3139.10)
(B) Num. competing pacemakers			2648.44*** (142.83)	3301.70*** (82.91)
(A) × (B)			-1290.43*** (348.91)	-2370.28*** (202.37)
Time trend	No	Yes	No	Yes
Product dummy	Yes	Yes	Yes	Yes
Hospital dummy	Yes	Yes	Yes	Yes
R-squared	0.805	0.927	0.811	0.937
F value	107.00***	327.90***	110.83***	380.07***
Observation	10,792	10,792	10,792	10,792

*Notes:* The dependent variable is the wholesale prices (in JPY). The explanatory variables are the treatment variable, which takes the value of 1 when the month belongs to the data-collection period, and 0 otherwise; the number of competing pacemakers to product  $j$ ; the interaction of the first two explanatory variables; the monthly time trend, and the dummy variables specific to products and hospitals. Standard error is inside parentheses. \*\*\*, \*\*, and \* indicate  $p < 0.01$ ,  $p < 0.05$ , and  $p < 0.1$ , respectively.

Table 3: Placebo Test Results

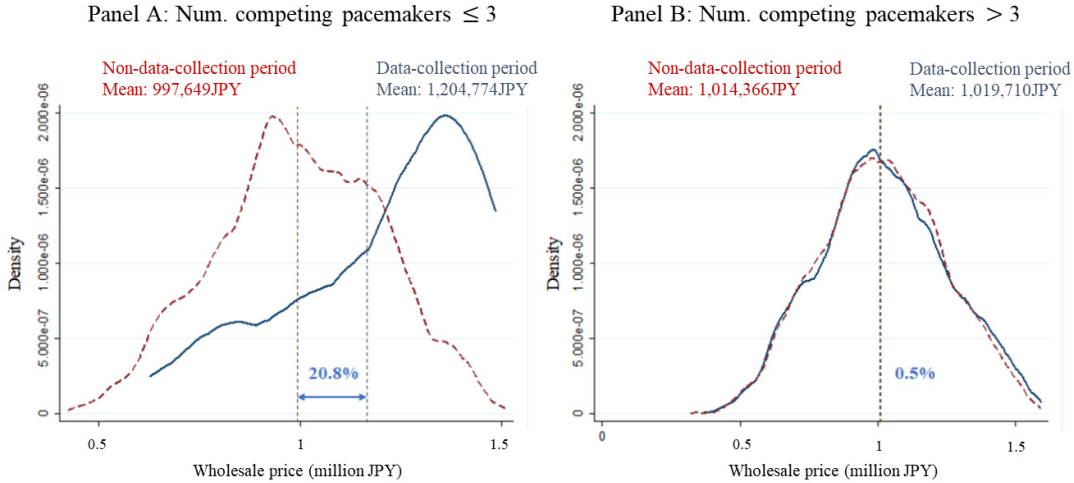
The dependent variable: Wholesale prices (JPY)	(3-1)	(3-2)
Placebo period dummy	1818.93 (2747.80)	-14252.18*** (1643.19)
Time trend	No	Yes
Product dummy	Yes	Yes
Hospital dummy	Yes	Yes
R-squared	0.818	0.936
F value	62.59***	201.94***
Observation	4,792	4,792

*Notes:* The dependent variable is the wholesale prices (in JPY). The explanatory variables are the placebo period variable, which takes the value of 1 when the month belongs to May-September in even-numbered years, and 0 otherwise; the monthly time trend, and the dummy variables specific to products and hospitals. All samples are from even-numbered years. Standard errors are inside parentheses. \*\*\* indicates  $p < 0.01$ .

and non-data-collection periods for functional categories with differing numbers of products. We divide categories into two groups: those with three or fewer products and those with more than three. The average wholesale price difference between data-collection and non-data-collection periods is approximately 20.8 percent for the former, but only 0.5 percent for the latter. This pattern aligns with theoretical predictions: in more competitive environments, the marginal impact of strategic price increases on the reimbursement benchmark is smaller, weakening incentives for price manipulation.

These reduced-form estimates and descriptive evidence are indicative to the presence of distortionary incentives driven by the ratcheting scheme on the reimbursement prices. The findings presented here, however, may be vulnerable to the choice of controls, primarily because pricing behavior (more precisely, bargaining power conferred in the price negotiation discussed in Sections 2.2 and 2.3) may differ between the treated group (those in the data-collection periods) and the control (those in the non-data-collection period). The next section thus introduces a structural model of demand and supply behavior. The structural model enables us to understand a bargaining mechanism under play between buyers and sellers underlying the reduced-form estimates.

Figure 4: Difference in Wholesale Prices



*Notes:* Panel A focuses on functional categories with up to three pacemaker models, while Panel B shows categories with more than three. The “data-collection period” refers to May through September of odd-numbered years; the “non-data-collection period” covers all other months. The solid blue line represents the distribution of wholesale prices during the data-collection period, and the dashed red line represents the distribution during the non-data-collection period. A vertical line marks the mean price in each period.

## 4 Estimation Model

This section introduces the estimation model we use to analyze the pacemaker market in Japan. Based on the data analyses discussed in the previous section, we build a bilateral Nash bargaining model to describe the pacemakers transactions in Japan. To do so, we proceed in two steps. In Section 4.1, we introduce a demand system, derived from a random-coefficient discrete-choice model of patients-physicians decision making. We then turn to a bilateral Nash bargaining model over the wholesale prices between hospitals and device sellers under the ratchet-based regulation in Section 4.2.

### 4.1 Demand

We define a market as the combination of functional category  $f$ , a hospital  $h$  and time (month)  $t$ . We assume no substitution across functional categories, as devices in different categories are regarded as serving distinct functional purposes.

To model choice, we employ a random-coefficient discrete-choice framework following Berry et al. (1995) and Grennan (2013). Specifically, we assume that a patient arrives at a hospital to undergo diagnostic procedure. A physician affiliated with hospital  $h$  then chooses a pacemaker model  $j \in J_{fht}$  for patient  $i$  at time  $t$ , in order to maximize the indirect utility that reflects the joint surplus of physicians and patients, where the treatment decision generates revenue for the hospital while simultaneously accounting for the patient’s financial burden. An interpretation of this model draws on the physician altruism framework

introduced by Arrow (1963) and further developed by Ellis and McGuire (1986) and Blomqvist (1991). In this view, physicians maximize an objective function that incorporates not only hospital income but also patient welfare, thereby blending financial and altruistic motives.

Because patient- and physician-level data are unavailable, we make two simplifying assumptions. First, patient arrivals are treated as exogenous. Second, physicians' decision-making is assumed to be uniform within each hospital, so that choices can be represented at the hospital level. The choice set  $J_{fht}$  includes all pacemaker models available at hospital  $h$  in category  $f$  and period  $t$ , as well as the outside option ( $j = 0$ ) representing treatment alternatives to pacemaker implantation. The indirect utility is given by:

$$u_{ijht} = \delta_{ijht} + \epsilon_{ijht}. \quad (3)$$

where  $\epsilon_{ijht}$  is an idiosyncratic taste shock distributed Type I extreme value, and  $\delta_{ijht}$  is the deterministic component of utility defined as:

$$\begin{aligned} \delta_{ijht} &= \alpha(\bar{p}_{fy} - p_{jht}) + \beta e^t(\bar{p}_{fy}; A_{it}, I_{it}) + \gamma x_{jht} + \xi_{jht} \\ &= \delta_{jht} + \beta e^t(\bar{p}_{fy}; A_{it}, I_{it}), \end{aligned} \quad (4)$$

where

$$\delta_{jht} \equiv \alpha(\bar{p}_{fy} - p_{jht}) + \gamma x_{jht} + \xi_{jht}.$$

The deterministic component comprises several terms. The first,  $\bar{p}_{fy} - p_{jht}$ , represents the markup that hospital  $h$  earns when implanting pacemaker  $j$  at time  $t$ , capturing the hospital's financial benefit from the transaction. The second,  $e^t(\bar{p}_{fy}; A_{it}, I_{it})$ , captures patient  $i$ 's out-of-pocket expenditure at time  $t$ . Typically, patients are required to pay 30% of the reimbursement price,  $\bar{p}_{fy}$ , although for high-cost treatments such as pacemaker implantation of our interest, a different copayment schedule applies, depending on patient characteristics such as age ( $A_{it}$ ) and income ( $I_{it}$ ). Specifically, during the study period, the copayment schedule for pacemakers is given by:

$$\begin{aligned} &e^t(\bar{p}_{fy}; A_{it}, I_{it}) \\ &= \begin{cases} e_{1t} + 0.11 \cdot \bar{p}_{fy} & \text{if } A_{it} < 70 \text{ and } I_{it} > 350,000, \text{ or } A_{it} > 70 \text{ and } I_{it} > 6,000,000\text{JPY} \\ e_{0t} & \text{otherwise} \end{cases} \end{aligned}$$

where

$$\begin{aligned} e_{1t} &= 40,200, \quad e_{0t} = 69,890 & t \in [\text{May 2003, September 2006}]. \\ e_{1t} &= 44,400, \quad e_{0t} = 77,430 & t \in [\text{October 2006, April 2014}]. \end{aligned}$$

This schedule implies that lower-income patients and typical elderly patients (those not receiving exceptionally high income of six million JPY) face an lower bound of  $e_{0t}$  on their out-of-pocket payment. By contrast, other patients are required to pay a base amount  $e_{1t}$ , plus 11% of  $\bar{p}_{fy}$ . After September 2006,

both thresholds  $e_{0t}$  and  $e_{1t}$  were raised, effectively increasing copayments for patients undergoing pacemaker implantation. Table 1 shows that the average reimbursement price for a pacemaker during the study period was about 1.2 million JPY, with the minimum around 0.64 million JPY. Given these levels, patients receiving a pacemaker typically incurred out-of-pocket payments exceeding  $e_{0t}$ .

The vector,  $x_{jht}$ , on the right-hand side of Eq.(4) contains the dummy variables specific to product, hospital, month and year. While we have several dimensions of observed product characteristics, including battery voltages, battery capacity and expected lifetime, these characteristics are subsumed by product-specific dummy variable. Note that persistent unobserved heterogeneity at the product-hospital level is controlled for by the inclusion of this dummy variable. An unobservable time fluctuation in the hospital preference for the product is denoted by  $\xi_{jht}$  with the property that  $E[\xi_{jht}] = 0$ . The distributional assumption on  $\epsilon_{ijht}$  yields the closed-form probability of the choice of device  $j$  as follows:

$$s_{ijht} = \frac{\exp(\delta_{ijht})}{1 + \sum_r \exp(\delta_{irht})},$$

The market share of device  $j$  that purchased by hospital  $h$  is thus obtained by integrating out patients characteristics:

$$s_{jht} = \int \int s_{ijht} dG(A_{it}) dH(I_{it}),$$

where  $dG(A_{it})$  and  $dH(I_{it})$  represent respective empirical distributions of age and income for Japanese population for each year  $y$ .<sup>7</sup>

To approximate the integral, we draw 1000 random observations independently from the respective distributions. For each draw  $d$ , we obtain the values  $A_{it}^d$  and  $I_{it}^d$ , and compute the corresponding choice probability as follows:

$$s_{ijht}^d = \frac{\exp(\delta_{ijht} + \beta e^t(\bar{p}_{fy}; A_{it}^d, I_{it}^d))}{1 + \sum_r \exp(\delta_{rht} + \beta e^t(\bar{p}_{fy}; A_{it}^d, I_{it}^d))}.$$

Then, the approximated market share is given by:

$$\hat{s}_{jht} = \frac{1}{1000} \sum_{d=1}^{1000} s_{ijht}^d.$$

The market share of product  $j$  is defined as the fraction of the potential market size,  $M_{ht}$ , from which hospital  $h$  selects a pacemaker at time  $t$ . Accordingly, the demand for product  $j$  can be expressed as

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<sup>7</sup>The data are taken from *Patient Survey* and *Comprehensive Survey of Living Conditions* of respective years. The data description is detailed in Appendix.A

$q_{jht}(\mathbf{p}_{fht}, \bar{p}_{fy}) \equiv M_{ht} \cdot s_{jht}$ , where  $\mathbf{p}_{fht}$  denotes the price vector, with its  $j$ -th component given by  $p_{jht}$ . We measure the potential market size,  $M_{ht}$ , as the number of patients with heart diseases in hospital  $h$  during period  $t$ .<sup>8</sup>

We normalize the mean utility of the outside option to zero. The estimated demand parameters allow us to compute the welfare measure, following Small and Rosen (1981) for example. In particular, we define hospital surplus as:

$$\pi_{fht}^H(\mathbf{p}_{fht}, \bar{p}_{fy}; J_{fht}) \equiv \frac{M_{ht}}{\alpha} \cdot \int \int \log \left[ 1 + \sum_r \exp(\delta_{irht}) \right] dG(A_{it}) dH(I_{it}).$$

We approximate the integral using the 1000 random draws. The resulting approximation of hospital surplus is:

$$\hat{\pi}_{fht}^H(\mathbf{p}_{fht}, \bar{p}_{fy}; J_{fht}) = \frac{M_{ht}}{\alpha} \cdot \frac{1}{1000} \sum_{d=1}^{1000} \log \left[ 1 + \sum_r \exp(\delta_{rht} + \beta e^t(\bar{p}_{fy}; A_{it}^d, I_{it}^d)) \right].$$

Our estimation strategy follows that of Berry et al. (1995). We employ a two-step GMM (generalized method of moments) procedure using the instruments described in the next section. For the numerical optimization and the construction of standard errors, we adopt the methods in Nevo (2001) and Conlon and Gortmaker (2020). The empirical results are presented in Section 6.

## 4.2 A Bilateral Bargaining Model

This section develops a model of how wholesale prices,  $p_{jht}$ , are determined in transactions between hospitals and device sellers. We model the interaction as a bilateral Nash bargaining problem over wholesale prices. Specifically, hospital  $h$  and multi-product device seller  $m$  simultaneously negotiate wholesale prices for the set of products  $j \in J_{mfht}$ , where  $J_{mfht}$  denotes the collection of devices delivered by seller  $m$ . Each hospital negotiates separately with each seller, and the resulting outcomes reflect the bilateral Nash bargaining solutions. The overall outcomes can thus be interpreted as a Nash equilibrium of these pairwise negotiations, consistent with the framework originally proposed by Horn and Wolinsky (1988).

Following the institutional details outlined in Section 2.3, the model distinguishes between two regimes: data-collection periods and non-data-collection periods. We first describe the non-data-collection regime, which is represented as a one-period bargaining model (Section 4.2.1). We then expand the analysis to incorporate data-collection regimes, modeled as a two-period bargaining environment (Section 4.2.2).

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<sup>8</sup>According to the MHLW, the number of inpatients diagnosed with heart diseases exceeds five percent of the Japanese population, amounting to approximately 1.2 million in 2014. As a robustness check, we also use the number of hospital beds as an alternative measure for  $M_{ht}$ . The resulting estimates differ only marginally from those reported in Section 6.

### 4.2.1 One-period problem

We begin with the non-data-collection period ( $t \notin T_y$ ), where device sellers and hospitals negotiate over the wholesale prices under the fixed reimbursement price. This problem is modeled as a one-period zero-sum game, which is given by the following static bilateral Nash bargaining model:

$$\max_{\{p_{jht}\}_{j \in J_{mfht}}} [v_{mfht}^M(\mathbf{p}_{fht}, \bar{p}_{fy})]^{1-b_{mft}^h} \cdot [v_{mfht}^H(\mathbf{p}_{fht}, \bar{p}_{fy})]^{b_{mft}^h}, \quad (5)$$

where

$$\begin{aligned} v_{mfht}^M(\mathbf{p}_{fht}, \bar{p}_{fy}) &\equiv \pi_{mft}^M(\mathbf{p}_{fht}, \bar{p}_{fy}; J_{fht}) - \pi_{mft}^M(\mathbf{p}_{fht}, \bar{p}_{fy}; J_{mft} \setminus J_{mfht}), \\ v_{mfht}^H(\mathbf{p}_{fht}, \bar{p}_{fy}) &\equiv \pi_{fht}^H(\mathbf{p}_{fht}, \bar{p}_{fy}; J_{fht}) - \pi_{fht}^H(\mathbf{p}_{fht}, \bar{p}_{fy}; J_{fht} \setminus J_{mfht}). \end{aligned}$$

Here,  $b_{mft}^h$  denotes the bargaining weight of hospital  $h$  in its negotiation with seller  $m$  for product  $j$  at time  $t$ . The parameter is allowed to vary across sellers, functional categories, and time. The per-period payoff of a multi-product device seller  $m$  is given by  $\pi_{mft}^M(\mathbf{p}_{fht}, \bar{p}_{fy}; J_{fht}) = \sum_h \sum_j q_{jht}(\mathbf{p}_{fht}, \bar{p}_{fy})(p_{jht} - c_{jht})$ , where  $h \in H_t, j \in J_{mfht}$ . Hospital payoffs,  $\pi_{fht}^H(\mathbf{p}_{fht}, \bar{p}_{fy}; J_{fht})$ , are defined in Section 4.1.

At the disagreement point, device seller  $m$  and hospital  $h$  terminate their trading relationship. The seller's disagreement payoff,  $\pi_{mft}^M(\mathbf{p}_{fht}, \bar{p}_{fy}; J_{mft} \setminus J_{mfht})$ , is defined as the profit seller  $m$  earns from transactions with other hospitals, since no sales occur with hospital  $h$  at this point. Accordingly, the seller's continuation value is

$$v_{mfht}^M(\mathbf{p}_{fht}, \bar{p}_{fy}) = \pi_{mfht}^M(\mathbf{p}_{fht}, \bar{p}_{fy}; J_{fht}) \equiv \sum_j q_{jht}(\mathbf{p}_{fht}, \bar{p}_{fy})(p_{jht} - c_{jht}),$$

where  $q_{jht}$  denotes the quantity of device  $j$  sold by seller  $m$  to hospital  $h$  at time  $t$ . The hospital's disagreement payoff,  $\pi_{fht}^H(\mathbf{p}_{fht}, \bar{p}_{fy}; J_{fht} \setminus J_{mfht})$ , is defined analogously over the restricted set of available devices, excluding those supplied by seller  $m$ .

An alternative specification of the the disagreement point assumes that only the negotiation over a particular product  $j$  fails, while the relationship between hospital  $h$  and multi-product seller  $m$  continues for other devices in  $m$ 's portfolio. Under this assumption, the seller's disagreement payoff becomes  $\pi_{mft}^M(\mathbf{p}_{fht}, \bar{p}_{fy}; J_{fht} \setminus j)$ , and the hospital's payoff adjusts accordingly. We confirm that adopting this alternative modeling choice leaves our empirical results virtually unchanged.

### 4.2.2 Two-period model

We now turn to the data-collection period, during which wholesale prices at time  $t \in T_y$  determine the reimbursement price in year  $y + 1$  and  $y + 2$ , according to Eq.(1) in Section 2.3. Because the timing of data collection is publicly known, both device sellers and hospitals have strategic incentives to influence the next-period reimbursement price,  $\bar{p}_{fy}$ , through their negotiated wholesale prices  $p_{jht}$ .

Let  $\Phi$  denote the regime indicator;  $\Phi = 1$  for the data-collection period and  $\Phi = 0$  for the non-data collection period. The two-period bargaining problem can then be formulated as a bilateral Nash bargain model, where the negotiated wholesale prices jointly affect not only the contemporaneous payoffs seller and hospital but also the future payoff through the future reimbursement price schedule.

$$\max_{\{\mathbf{p}_{jht}\}_{j \in J_{mfht}}} \left[ v_{mfht}^M(\mathbf{p}_{fht}, \bar{p}_{fy}) + \Phi_t V_{mfht}^M(\mathbf{p}_{fht}, \bar{p}_{fy}) \right]^{1-b_{mft}^h} \cdot \left[ v_{mfht}^H(\mathbf{p}_{fht}, \bar{p}_{fy}) + \Phi_t V_{mfht}^H(\mathbf{p}_{fht}, \bar{p}_{fy}) \right]^{b_{mft}^h}. \quad (6)$$

When  $\Phi_t = 0$ , Eq.(6) collapses to the static problem introduced in Eq.(5) for the non-data-collection period. By contrast, when  $\Phi = 1$ , additional terms enter the bargaining problem: both seller  $m$  and hospital  $h$  can now benefit from the revised reimbursement price in the subsequent two periods. These intertemporal effects are captured through the subsequent two-period payoffs,  $V_{mfht}^M(\mathbf{p}_{fht}, \bar{p}_{fy})$  and  $V_{mfht}^H(\mathbf{p}_{fht}, \bar{p}_{fy})$ , defined as follows:

$$\begin{aligned} V_{mfht}^M(\mathbf{p}_{fht}, \bar{p}_{fy}) &= \sum_{s=1,2} \sum_{\tau \in \Psi_{y+s}} \delta^s \pi_{mfht}^M(\tilde{\mathbf{p}}_{mfht}, \bar{p}_{y+1}(\mathbf{p}_{fht}); J_{fht}) \\ &= \sum_{s=1,2} \sum_{\tau \in \Psi_{y+s}} \sum_{k \in J_{mfht}} \delta^s q_{jh\tau}(\tilde{\mathbf{p}}_{fl\tau}, \bar{p}_{y+1})(\tilde{p}_{kh\tau} - c_{kh\tau}), \end{aligned} \quad (7)$$

and

$$\begin{aligned} V_{mfht}^H(\mathbf{p}_{fht}, \bar{p}_{fy}) &\equiv \sum_{s=1,2} \sum_{\tau \in \Psi_{y+s}} \delta^s \left[ \pi_{fht}^H(\tilde{\mathbf{p}}_{fht}, \bar{p}_{fy+s}(\mathbf{p}_{fht}); J_{fht}) - \pi_{fht}^H(\tilde{\mathbf{p}}_{fht}, \bar{p}_{fy+s}(\mathbf{p}_{fht}); J_{fht} \setminus J_{mfht}) \right]. \end{aligned} \quad (8)$$

We assume that both hospitals and sellers have perfect foresight with a common discount factor  $\delta = 0.95$ . Let  $\tilde{\mathbf{p}}_{fht} \equiv \{\tilde{p}_{kh\tau}\}_{k \in J_{fht}}$  in Eqs.(7) and (8) denote the vector of future wholesale prices at month  $\tau$ , which depend on the wholesale prices negotiated during the data-collection period. The set of months belonging to fiscal year  $y + s$  is denoted by  $\Psi_{y+s}$ .

Note that Eq.(6) is not expressed as a recursive form; it does not account for how current wholesale prices affect profits in periods  $y + 3$ ,  $y + 4$ , and beyond. A fully recursive formulation would require treating the reimbursement price  $\bar{p}_{fy}$  as a state variable and explicitly specifying how the change in  $\bar{p}_{fy+1}$  and  $\bar{p}_{fy+2}$  – which are triggered by the current wholesale prices – influence subsequent wholesale prices  $p_{jhs}$  for  $s \in [\Psi_{y+3}, \Psi_{y+4}]$ , and in turn, future reimbursement prices  $\bar{p}_{fy+5}$  and  $\bar{p}_{fy+6}$ , and those in later years.

As discussed in Section 7, however, the actual ratchet effect transmitted through wholesale prices is empirically small. Hence, even if we were to extend the model to include effects on reimbursement prices in

and beyond  $y+3$ , the resulting impact would likely be negligible. Accordingly, our analysis can be interpreted as a conservative estimate of the ratchet effect, providing a lower-bound assessment of its influence on the dynamic bargaining behavior.

The first-order necessary condition for Eq.(6) is derived as follows:

$$(1 - b_{mft}^h) \cdot \frac{q_{jht} + \sum_{k \in J_{mft}} \frac{\partial q_{kht}}{\partial p_{jht}} (p_{kht} - c_{kht}) + \Phi_t r_{jht} \frac{\partial V_{mft}^M}{\partial \bar{p}_{fy+1}}}{v_{mft}^M + \Phi_t V_{mft}^M} + b_{mft}^h \cdot \frac{\frac{\partial v_{mft}^H}{\partial p_{jht}} + \Phi_t r_{jht} \frac{\partial V_{mft}^H}{\partial \bar{p}_{fy+1}}}{v_{mft}^H + \Phi_t V_{mft}^H} = 0. \quad (9)$$

This condition indicates that the equilibrium pricing that maximizes the Nash product reflects a weighted sum of the marginal profits earned by the device seller and hospital, with relative bargaining weights serving as the corresponding coefficients. The ratchet effect is captured by the term,  $r_{jht} \equiv \frac{\partial \bar{p}_{y+1}}{\partial p_{jht}}$ , which measures the extent to which the current wholesale price for product  $j$  at time  $t$  influences the reimbursement price in the subsequent revision period ( $y+1$  and  $y+2$ ). Using the pricing relationship defined in Eq.(1), the ratchet term can be expressed as:

$$r_{jht} = \frac{q_{jht}}{\sum_{s \in T_y} \sum_{h \in H_s} \sum_{k \in J_{jhs}} q_{khs}} \quad (10)$$

This term represents the relative contribution of the transaction volume for product  $j$  traded with hospital  $h$  in month  $t \in T_y$  to the total transaction volume of all pacemakers within the same functional category  $f$  during the data-collection period. When  $r_{jht} = 0$ , sellers and hospitals have no shared incentive to raise future reimbursement price, and the Nash bargaining problem collapses to a static one – analogous to the case when  $\Phi_t = 0$ . Eq.(9) can be rewritten as:

$$\begin{aligned} \sum_{k \in J_{mft}} \left\{ \frac{\partial q_{kht}}{\partial p_{jht}} + \frac{b_{mft}^h}{1 - b_{mft}^h} \cdot \frac{\frac{\partial v_{mft}^H}{\partial p_{jht}} + \Phi_t r_{jht} \frac{\partial V_{mft}^H}{\partial \bar{p}_{fy+1}}}{v_{mft}^H + \Phi_t V_{mft}^H} q_{kht} \right\} (p_{kht} - c_{kht}) \\ = -q_{jht} - \Phi_t r_{jht} \frac{\partial V_{mft}^M}{\partial \bar{p}_{fy+1}} - \frac{b_{mft}^h}{1 - b_{mft}^h} \cdot \frac{\frac{\partial v_{mft}^H}{\partial p_{jht}} + \Phi_t r_{jht} \frac{\partial V_{mft}^H}{\partial \bar{p}_{fy+1}}}{v_{mft}^H + \Phi_t V_{mft}^H} \Phi_t V_{mft}^M, \end{aligned}$$

Rearranging the first-order condition yields the following vector form:

$$\begin{aligned} (\mathbf{\Omega} + \mathbf{\Lambda} + \mathbf{\Lambda}_1)(\mathbf{p} - \mathbf{c}) &= -\mathbf{q} - \mathbf{v} \\ \Leftrightarrow \mathbf{p} &= \mathbf{c} - (\mathbf{\Omega} + \mathbf{\Lambda} + \mathbf{\Lambda}_1)^{-1}(\mathbf{q} + \mathbf{v}), \end{aligned} \quad (11)$$

where  $\mathbf{\Omega}$ ,  $\mathbf{\Lambda}$  and  $\mathbf{\Lambda}_1$  are  $J_{mft} \times J_{mft}$  matrices defined as:

$$\begin{aligned}
\mathbf{\Omega}(j, k) &= \frac{\partial q_{kht}}{\partial p_{jht}}, \\
\mathbf{\Lambda}(j, k) &= \frac{b_{mft}^h \frac{\partial v_{mft}^H}{\partial p_{jht}} q_{kht}}{1 - b_{mft}^h v_{mft}^H}, \\
\mathbf{\Lambda}_1(j, k) &= -\frac{b_{mft}^h \frac{\partial v_{mft}^H}{\partial p_{jht}} q_{kht}}{1 - b_{mft}^h v_{mft}^H} + \frac{b_{mft}^h \frac{\partial v_{mft}^H}{\partial p_{jht}} q_{kht}}{1 - b_{mft}^h v_{mft}^H + \Phi_t V_{mft}^H} + \frac{b_{mft}^h \Phi_t r_{jht} \frac{\partial V_{mft}^H}{\partial \bar{p}_{fy+1}} q_{kht}}{1 - b_{mft}^h v_{mft}^H + \Phi_t V_{mft}^H}.
\end{aligned}$$

The vector  $\mathbf{v}$  is  $J_{mft} \times 1$  is given by:

$$\mathbf{v}(j) = \frac{b_{mft}^h \Phi_t \frac{\partial v_{mft}^H}{\partial p_{jht}} V_{mft}^M}{1 - b_{mft}^h v_{mft}^H + \Phi_t V_{mft}^H} + \Phi_t r_{jht} \frac{\partial V_{mft}^M}{\partial \bar{p}_{fy+1}} + \frac{b_{mft}^h \Phi_t r_{jht} \frac{\partial V_{mft}^H}{\partial \bar{p}_{fy+1}} V_{mft}^M}{1 - b_{mft}^h v_{mft}^H + \Phi_t V_{mft}^H}.$$

The matrix  $\mathbf{\Lambda}_1$  in Eq.(11) captures the dynamic component associated with the buyer's (hospital's) bargaining power, while  $\mathbf{v}$  reflects dynamic interactions between both buyers and sellers. Both  $\mathbf{\Lambda}_1$  and  $\mathbf{v}$  include the term  $r_{jht}$ , which measures the extent to which the current wholesale prices  $p_{jht}$  influence the subsequent reimbursement price,  $\bar{p}_{fy+1}$ . The magnitude of  $r_{jht}$  depends on institutional factors such as the duration of the data-collection period and the number of products within a functional category  $f$  – factors that affect the scope for strategic price manipulation, as explored in the simulation analysis in Section 7.

When  $r_{jht} = 0$ , current prices have no effect on future reimbursement levels. In this case, the dynamic bargaining problem collapses to its static counterpart, expressed as:

$$\mathbf{p} = \mathbf{c} - (\mathbf{\Omega} + \mathbf{\Lambda})^{-1} \cdot \mathbf{q}. \tag{12}$$

Similarly, when buyers possess no bargaining power (i.e.,  $b_{mft}^h = 0$  for  $\forall m, f, t$ ), the system further simplifies to the standard static differentiated-product Bertrand competition model:

$$\mathbf{p} = \mathbf{c} - \mathbf{\Omega}^{-1} \cdot \mathbf{q}.$$

These benchmark cases are useful for interpreting the sources of dynamics in our model. The first illustrates how the ratchet mechanism – captured by  $r_{jht}$  – introduces forward-looking incentives that link present pricing to future reimbursement outcomes. The second isolates the role of bargaining power in shaping price determination. In Section 6, we empirically assess the significance of both effects, evaluating whether hospitals' bargaining power and the ratchet parameter  $r_{jht}$  influence observed pricing behavior.

## 5 Identification

This section discusses identification issues in estimating the demand and bilateral bargaining models presented in the previous sections.

A primary identifying assumption in our empirical strategy is that the observed import costs,  $c_{jht}$ , reflect true marginal costs faced by device sellers. In principle, one might be concerned that these import costs could embed post-contractual rebates or other retrospective adjustments made by foreign manufacturers after transactions with hospitals are completed. If such rebates existed, they could generate endogeneity in  $c_{jht}$  by linking it to the outcome of the wholesale price negotiation,  $p_{jht}$ . In this scenario, when hospitals exert stronger bargaining power and negotiate lower wholesale prices, foreign manufacturers might compensate their domestic subsidiaries by adjusting effective import costs downward, thereby maintaining the dealers' profitability. Interviews with representatives from device dealers, however, indicate otherwise. According to them, import costs recorded in our dataset represent the actual purchase prices at the time of procurement, and do not include any ex post rebates or side agreements.

For our analysis, we therefore treat  $c_{jht}$  as the true marginal costs of device dealers. Even if some unobserved rebate existed, their magnitude or proportion relative to import costs would be empirically difficult to identify from unobserved cost heterogeneity. If such rebates were indeed present, device sellers' profits,  $v_{mfht}^M + \Phi_t V_{mfht}^M$ , would be overstated in our data, meaning that hospitals' bargaining power – as estimated in our model – would actually be stronger than reported. Consequently, this paper's estimates of hospital bargaining power  $b_{mft}^h$ , as well as the implied magnitude of the ratchet effect, should be interpreted as conservative lower bounds.

In estimating the demand system, we employ three sets of instruments. The first is the import cost,  $c_{jht}$ , which we treat as exogenous for the reasons discussed above. The second exploits the geographic distance between each hospital and the nearest wholesaler's office, which may affect supply-side costs, including logistics and service expenditures, and thereby would influence wholesale prices.<sup>9</sup> The third instrument is the reimbursement price,  $\bar{p}_{fy}$ , which is predetermined to negotiations and thus exogenous to the wholesale price set at that time.

On the supply side, the Nash bargaining parameter  $b_{mft}^h$  is identified from the first-order necessary condition of the bargaining problem given in Eq.(6). As discussed in Section 4.2.2, the FONC yields the relative bargaining weight as follows:

$$\frac{b_{mft}^h}{1 - b_{mft}^h} = - \left\{ \frac{\frac{\partial v_{mfht}^H}{\partial p_{jht}} + \Phi_t r_{jht} \frac{\partial V_{mfht}^H}{\partial \bar{p}_{fy+1}}}{v_{mfht}^H + \Phi_t V_{mfht}^H} \right\}^{-1} \left\{ \frac{q_{jht} + \sum_{k \in J_{mfht}} \frac{\partial q_{kht}}{\partial p_{jht}} (p_{kht} - c_{kht}) + \Phi_t r_{jht} \frac{\partial V_{mfht}^M}{\partial \bar{p}_{fy+1}}}{v_{mfht}^M + \Phi_t V_{mfht}^M} \right\}. \quad (13)$$

---

<sup>9</sup>In addition to our baseline instruments, we also tried using an additional set following the standard approach of Berry et al. (1995), which incorporates the number of pacemaker models offered by the same dealer and the number of other models available within the same functional category, hospital, and month. The demand estimates obtained when these BLP-type instruments are added are nearly identical to those derived without them. Therefore, the estimates reported in the main analysis are based on the specification excluding the BLP-type instruments.

The right-hand side of Eq.(13) can be constructed entirely from observed variables and estimated demand parameters. Access to direct cost data,  $c_{jht}$ , plays a crucial role in achieving precise identification of the bargaining parameters. Such cost information allows us to isolate the bargaining component from cost heterogeneity, thereby improving the accuracy of the estimates. In contrast, when marginal costs are unobserved, mis-specifying the cost structure can introduce systematic bias into the estimated bargaining parameters. We revisit this issue in Section 6.2.2, where we evaluate both the direction and magnitude of potential bias by re-estimating the model under the assumption that cost data are unavailable, and discuss an alternative strategy for reliable identification when direct cost observations are not at hand.

## 6 Estimation Results

This section presents the results of estimating the models of demand and bilateral bargaining. We first discuss estimates for demand, then turn to estimated bargaining parameters.

### 6.1 Demand Estimates

In estimating the parameters of the indirect utility function defined in Eq.(4), we treat the wholesale price  $p_{jht}$  as endogenous, as discussed in Section 5. The first-stage results, reported in Appendix A.3, confirm that the instruments are jointly significant: the  $F$ -statistics reject the null hypothesis that all instrument coefficients are equal to zero. These results indicate that the instruments exhibit sufficient explanatory power and may not suffer from weak-instrument concerns.

Table 4 reports the estimated parameters for the utility function. Column (4-1) presents the OLS estimates without instruments, while columns (4-2) and (4-3) incorporate the instrumental variables described above. Without instrumenting for wholesale prices, we find a positive but statistically insignificant coefficient on the hospital's markup,  $(\bar{p}_{fy} - p_{jht})$ , and a negative but imprecisely estimated coefficient on patients' out-of-pocket expenses. Once endogeneity is addressed using the IV specifications, the coefficient on hospital markup becomes positive and statistically significant at the 1 percent level, indicating that higher hospital margins are associated with increased demand for pacemaker implantation. This result is consistent with the interpretation that physicians, acting on behalf of hospitals, internalize part of the revenue effects when recommending device use.

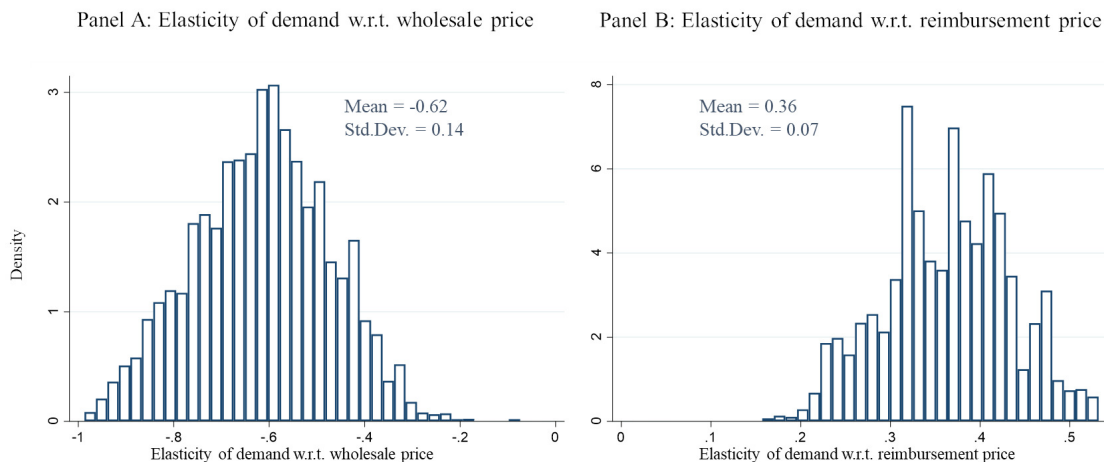
The coefficient on patients' out-of-pocket expenses is negative and statistically significant across all specifications. Its magnitude becomes larger (in absolute value) once the instruments are introduced, suggesting that ignoring endogeneity would bias downward the estimated price sensitivity. Between the two IV specifications, the inclusion of geographic distance in column (4-3) does not materially alter the estimates, and the Sargan test statistic ( $\chi^2 = 0.15$ ) indicates no evidence that the over-identifying restrictions are violated. For this reason, we adopt specification (4-3) as our preferred model in the subsequent analyses.

Table 4: Demand Estimates

	(4-1)	(4-2)	(4-3)
Hospital's markup (in million JPY)	0.20 (0.09)	0.84*** (0.25)	0.89*** (0.26)
Out-of-pocket expense (in million JPY)	-31.66 (28.54)	-75.04** (32.29)	-79.06** (32.44)
Instruments			
Import cost	No	Yes	Yes
Distance from the nearest dealer's warehouse	No	No	Yes
Reimbursement price	Yes	Yes	Yes
R-squared	0.710	0.709	0.704
Sargan chi2	-	-	0.15
Observation	10,792	10,792	10,740

*Notes:* The table reports parameter estimates of the utility function defined in Eq.(4). Explanatory variables include hospital markups and patients' out-of-pocket expenses, along with fixed effects for years, months, products, and hospitals. (4-1) presents the OLS estimates, while the other columns employ instrumental variables discussed in Section 5. (4-3) additionally includes the geographic distance between each hospital and the nearest dealer's warehouse. Standard errors are reported in parentheses; \*\*\*, \*\* denote significance at the 1% and 5% levels, respectively.

Figure 5: Estimated Prices Elasticities of Demand



*Notes:* Panel (A) plots the distribution of estimated demand elasticities with respect to wholesale prices, while Panel (B) shows the distribution of elasticities with respect to reimbursement prices. Each distribution is based on the preferred specification reported in Table 4. Negative values indicate that demand decreases as prices rise, with the dispersion reflecting heterogeneity across hospitals, products, and time.

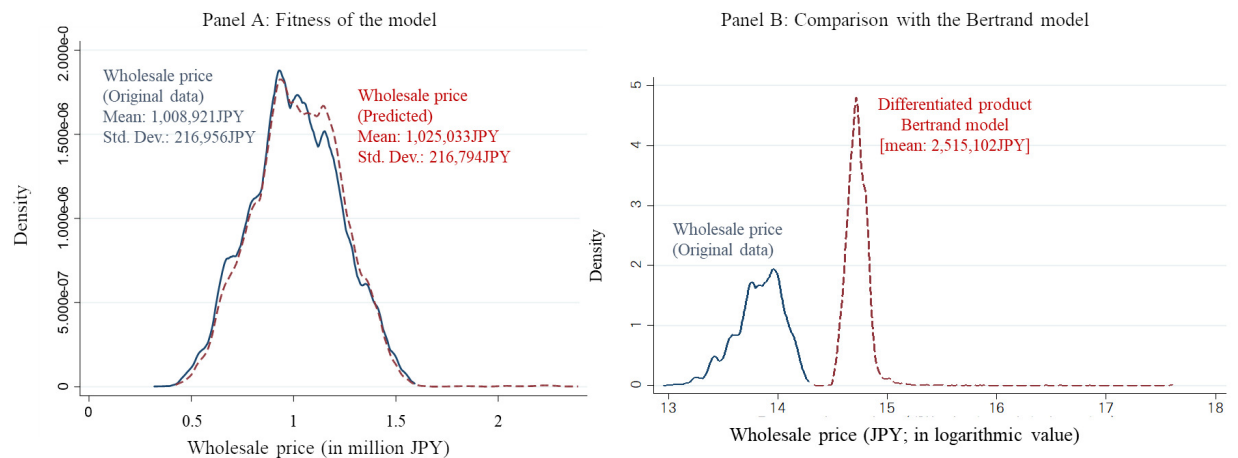
Figure 5 presents the implied distributions of price elasticities with respect to wholesale and reimbursement prices, derived from the estimated parameters of (4-3). Panel (A) shows that the demand elasticity with respect to wholesale prices has a mean of  $-0.62$  and a standard deviation of  $0.14$ . This magnitude implies moderately inelastic demand, consistent with the clinical nature of pacemaker use. For comparison, Grennan (2013), using U.S. coronary stent data, reports own-price elasticities of approximately  $-0.3$  for bare-metal stents and  $-0.5$  for drug-eluting stents—values somewhat lower in magnitude than ours, possibly reflecting greater physician discretion and competitive differentiation in the pacemaker market.

Panel (B) displays the elasticity with respect to reimbursement prices. Reimbursement changes influence demand through two opposing channels: higher reimbursement rates raise hospital markups ( $\bar{p}_{fy} - p_{jht}$ ), stimulating utilization, but simultaneously increase patients’ out-of-pocket expenses  $e^t(\bar{p}_{fy})$ , which dampen demand. Panel (B) indicates that, on average, the positive markup effect outweighs the negative altruistic effect, suggesting that increase in the reimbursement price exerts a net expansionary influence on utilization. This result provides an important behavioral foundation for the ratchet mechanism analyzed in Section 4.2.

## 6.2 Bargaining Parameters Estimates

Using the transaction-level data and the estimated demand parameters, we recover hospital’s normalized bargaining weights,  $b_{mft}^h$ , according to Eq.(13). The availability of direct cost data  $c_{jht}$  allows us to compute these bargaining parameters at the level of each seller-buyer-functional category-period  $(m, h, f, t)$  combination. In total, approximately 9,300 bargaining parameters are identified.

Figure 6: Model Prediction and Data



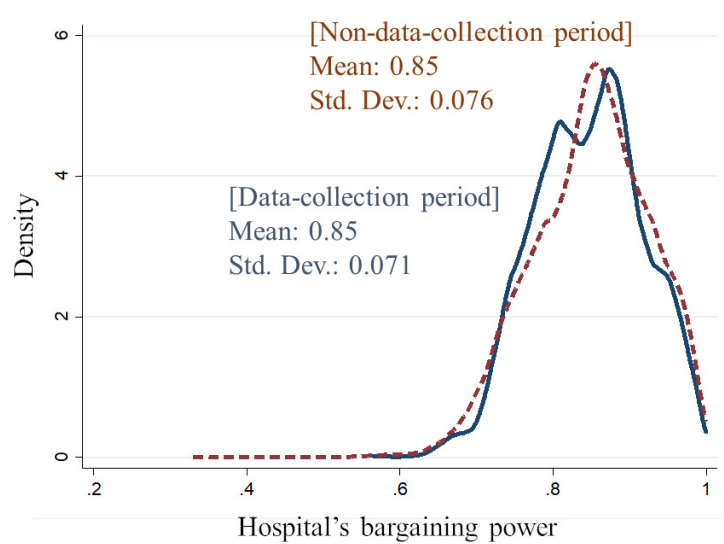
*Notes:* Panel A compares the observed distribution of wholesale prices (blue solid line) with the distribution predicted by the estimated bargaining model (red dashed line). Panel B compares the observed logarithmic wholesale prices with those predicted by a differentiated-product Bertrand competition model that assumes hospitals have no bargaining power. The poor fit of the Bertrand model highlights the empirical importance of hospital bargaining power.

### 6.2.1 Model Fit and Benchmark Comparison

Panel A of Figure 6 shows that the estimated bargaining model closely replicates the observed distribution of wholesale prices, using Eq.(9), suggesting a strong in-sample fit. By contrast, Panel B compares the observed data with predictions from a differentiated-product Bertrand competition model, which assumes that hospitals possess no bargaining power (i.e.,  $b_{mft}^h = 0$ ). The simulated wholesale prices generated by the Bertrand model systematically over-predict those observed in the data. This contrast underscores that treating hospitals as passive price takers – as in the standard Bertrand framework – is inconsistent with actual market behavior. Incorporating bilateral bargaining between hospitals and device sellers, which grants hospitals non-negligible buyer power, is therefore essential to capture observed pricing patterns.

Next, we examine how estimated bargaining parameters differ between the data-collection and non-data-collection periods. Figure 7 plots the distributions of  $b_{mft}^h$  for the two regimes ( $\Phi_t = 1$  and  $\Phi_t = 0$ ). The two distributions are nearly identical, indicating that hospitals' relative bargaining positions do not vary systematically between the regimes. The mean bargaining weight is approximately 0.85, suggesting that hospitals, on average, wield greater bargaining power than device sellers, consistent with the finding from the comparison with the Bertrand model in Figure 6. This finding implies that higher wholesale prices in the data-collection period as presented in Section 3.3 arises not from changes in relative bargaining positions between device sellers and hospitals, but may come from forward-looking ratchet behavior under the reimbursement rule.

Figure 7: Estimated Bargaining Power Parameters



*Notes:* The blue solid line represents the distribution of estimated bargaining parameters during the data-collection period ( $\Phi_t = 1$ ), and the red dashed line represents that during the non-data-collection period ( $\Phi_t = 0$ ). The similarity of the two distributions indicates that hospital bargaining power remains stable across regulatory regimes.

## 6.2.2 Estimation of Bargaining Parameters Without Marginal-cost Data

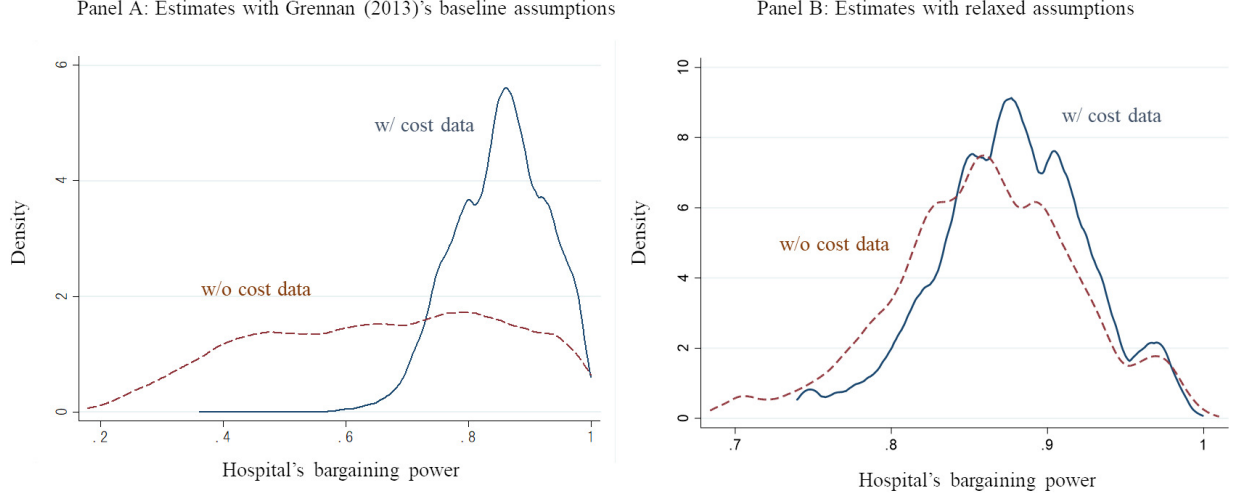
As emphasized by Lee et al. (2021), separately identifying bargaining parameters from the structural components of the payoff function is inherently difficult. In empirical work, they are typically estimated jointly, creating the possibility that mis-specification of payoff primitives may distort the inferred bargaining weights. This subsection examines how such confounding arises and evaluates whether more flexible model specifications can reduce the resulting biases.

To do so, we construct a counterfactual estimation environment in which marginal-cost data are unavailable – an assumption that aligns with much of the existing empirical literature. By comparing the bargaining parameters estimated under this constraint with those obtained using observed cost data, we quantify the extent and direction of bias that arises when marginal costs must be inferred rather than observed.

Following Grennan (2013), we impose functional restrictions on costs and bargaining terms. As discussed in Section 5, downward bias in estimated marginal costs tends to inflate seller profits and, consequently, understate hospitals' relative bargaining power.

To facilitate comparability with prior work, we begin by adopting the baseline specification of Grennan (2013), estimating bargaining parameters under the assumption that marginal costs are constant across hospitals and time. In this framework, marginal costs are captured by product-specific fixed effects,  $\gamma_j$ , and bargaining weights are parameterized by:

Figure 8: Estimated Hospital Bargaining Power: With and Without Cost Data



*Notes:* Panel A compares the distributions of bargaining power parameters estimated with and without observed cost data. The blue solid line shows estimates using observed marginal cost data, while the red dashed line shows estimates obtained without cost data under the assumptions  $c_{jht} = \gamma_j$  and  $\frac{b_{jt}^h}{1-b_{jt}^h} = \lambda_{jh}\nu_{jht}$ . Panel B presents analogous results under the relaxed assumptions  $c_{jht} = \gamma_{jy}$  and  $\nu_{jht} = \rho\nu_{jht-1} + \varepsilon_{jht}$ .

$$c_{jht} = \gamma_j, \quad \frac{b_{jt}^h}{1-b_{jt}^h} = \lambda_{jh}\nu_{jht},$$

where  $\nu_{jht}$  represents unobserved heterogeneity in bargaining weights that satisfies the orthogonality condition  $E[\log \nu_{jht} | z_{jht}] = 0$ , and  $\lambda_{jh}$  is a hospital-product-specific parameter to be estimated. Estimation is based on the orthogonality condition, and instruments here are the same as those for our demand estimation.

Panel A of Figure 8 compares the distributions of bargaining weights estimated with and without marginal cost data. To avoid the comparison is influenced by ratchet incentives, we use data from the non-data-collection period. According to the figure, when cost data are omitted, the estimated bargaining weights exhibit both a lower mean and greater dispersion, consistent with attenuation bias from cost mis-specification. These results reinforce that direct cost information plays an important role in accurately identifying bargaining power.

To examine whether more flexible cost and bargaining structures improve estimation performance, we relax the baseline assumptions as follows:

$$c_{jht} \equiv \gamma_{jy}, \quad \frac{b_{jt}^h}{1-b_{jt}^h} \equiv \lambda_{jh}\nu_{jht}.$$

and allow for temporal dependence in the bargaining unobservable:

$$\nu_{jht} = \rho\nu_{jht-1} + \varepsilon_{jht}.$$

This specification permits marginal costs to vary also by year and introduces serial correlation in bargaining shocks, capturing potential persistence in hospital-seller relationships.

Panel B of Figure 8 presents the resulting distribution of estimated bargaining weights. The relaxed specification considerably improves model fit: The estimated distribution aligns more closely with that obtained using actual cost data, both in mean and dispersion. This exercise demonstrates that adopting richer cost and bargaining structures can partially correct for biases arising from missing cost information.

In summary, the analysis confirms that omitting cost data introduces systematic downward bias in the estimated bargaining weights, overstating sellers' relative power. Nevertheless, allowing for moderate flexibility in the cost function and dynamic correlation among bargaining shocks significantly reduces this bias. These findings highlight the empirical importance of cost observability and provide guidance for future research using incomplete transaction data.

## 7 Simulating Policy Implications of Ratchet-Based Regulation

Building on the demand and bargaining estimates presented in Section 6, this section quantifies the policy implications of Japan's ratchet-based reimbursement system for medical devices. Specifically, we examine how the reimbursement rule – whereby future reimbursement prices are updated based on past transaction data – affects the pricing behavior of hospitals and device sellers.

Section 7.1 evaluates the extent to which wholesale prices increase during data-collection periods as a result of forward-looking strategic behavior by both buyers (hospitals) and sellers (device dealers). This exercise isolates the ratchet effect, capturing how expectations about future reimbursement revisions distort current pricing incentives.

Section 7.2 investigates competitive externalities arising from the reimbursement design. Since reimbursement prices are set at the functional-category level rather than by individual product, firms' incentives to raise prices depend on the number of competitors within the same category. We assess how market structure shapes the magnitude of ratchet-induced price distortions.

The section also explores counterfactual policy scenarios to assess how alternative reimbursement designs would alter the ratchet effect. In particular, we examine how adjustments to the sampling protocol – such as shortening the data-collection period or adopting a randomized sampling scheme in place of a fixed, publicly known window – and changes in the degree of product aggregation used in the reimbursement price setting would affect the scope for strategic price manipulation.

The analyses in this section rely on simulation exercises that combine the estimated demand system and the Nash-in-Nash bilateral bargaining framework. This approach enables us to quantify not only how the ratchet rule distorts observed pricing outcomes but also how regulatory design choices can either amplify or mitigate such distortions.

## 7.1 Quantifying the Ratchet Effects

This section quantifies the ratchet effect embedded in Japan’s medical device reimbursement system – that is, the mechanism through which hospitals and device sellers jointly manipulate wholesale prices during the designated data-collection period to influence future reimbursement levels. Under the current regulatory framework, the reimbursement price for each functional category is revised every two years, based on the sales-weighted average of wholesale transaction prices collected over a five-month window (from May to September). During this window, both hospitals and device sellers have an incentive to raise wholesale prices strategically, anticipating that higher reported prices will translate into more favorable reimbursement rates in the next revision. Outside this period, however, such incentives vanish, and the interaction between buyers and sellers becomes a zero-sum bargaining game where higher prices for one side imply lower margins for the other.

To quantify the magnitude of this ratchet effect, we simulate a counterfactual scenario in which buyers and sellers behave myopically – that is, without anticipating future reimbursement adjustments. We compute counterfactual wholesale prices by setting  $\Phi_t = 0$ , equivalent to the static model given in Eq.(12), for each functional category  $f$ . This exercise isolates the portion of observed price variation that can be attributed purely to forward-looking strategic incentives.

During our study period, reimbursement prices were revised five times. Table 5 reports the simulation results for the final revision cycle in 2012, showing how wholesale prices would have differed in the absence of such strategic behavior. The estimates indicate that, during the data-collection period, wholesale prices were on average 0.49% higher than those predicted under the counterfactual non-strategic scenario. This strategic increase subsequently raised reimbursement prices in the following year by approximately 0.47%.

Importantly, this pattern is not limited to the 2011 – 2012 cycle. When we replicate the same exercise across all five reimbursement updates in the study period, the average strategic increase in wholesale prices remains modest –about 0.89%. Hence, while the ratchet mechanism generates measurable forward-looking behavior, its quantitative impact on market prices and reimbursement adjustments is relatively limited.

The modest quantitative effects stem from the structure of the ratchet mechanism itself. As defined in Eq.(10), the parameter  $r_{jht}$  determines the extent to which each transaction affects the next-period reimbursement price through the dynamic components  $\mathbf{A}_1$  and  $\mathbf{v}$  discussed in Section 4. To illustrate, suppose that, in the data-collection period, the number of hospitals and traded products remains constant – i.e.,  $H_s = H$  and  $J_{jhs} = J_f$  – and that each product in the same functional category  $f$  sells an equal quantity  $q$ . Then Eq.(10) simplifies to:

$$r_{jht} = \frac{q_{jht}}{\sum_{s \in \Gamma_y} \sum_{h \in H_s} \sum_{k \in J_{jhs}} q_{khs}} = \frac{1}{|T_y| \cdot |H| \cdot |J_f| \cdot |R|}, \quad (14)$$

where  $|H|$  is the number of hospitals transacting in device  $j$ ,  $|J_f|$  the number of products in category  $f$ ,  $|T_y|$

Table 5: Simulated Impact of Strategic Pricing under the Reimbursement System

	Strategic incentives (Data)		No strategic incentives (Simulated values)		Differences (%)	
	Data-collection period	Non-data- collection period	Data-collection period	Non-data- collection period	Data-collection period	Non-data- collection period
Year: 2011						
Reimbursement price	1,086,585	1,078,243	1,086,585	1,078,243		
Wholesale price	916,408	906,924	911,937	906,924	0.49	0.00
Year: 2012						
Reimbursement price	959,722		955,251		0.47	

*Notes:* The table reports simulation results for the reimbursement revision cycles of 2011–2012. The “Strategic incentives” columns correspond to the observed data in which hospitals and sellers behave forward-looking under  $\Phi_t = 1$ . The “No strategic incentives” columns represent counterfactual outcomes simulated under the static model ( $\Phi_t = 0$ ). The data-collection period covers May–September of odd-numbered years; the non-data-collection period refers to the remaining months. Results for earlier revision cycles (2003 – 2010) are qualitatively similar and available upon request. Values are in JPY.

the number of months in the data-collection period, and  $|R|$  the average number of monthly transactions per hospital. Using the empirical values reported in Section 3.1 ( $|H| = 141$ ,  $|J_f| = 8$ ,  $|T_y| = 5$ , and  $|R| = 2.55$ ), the implied average  $r_{jht}$  roughly approximates to our estimated value of 0.89.

In the next subsection, we explore counterfactual scenarios to assess how changes in institutional design would alter the strength of the ratchet effect.

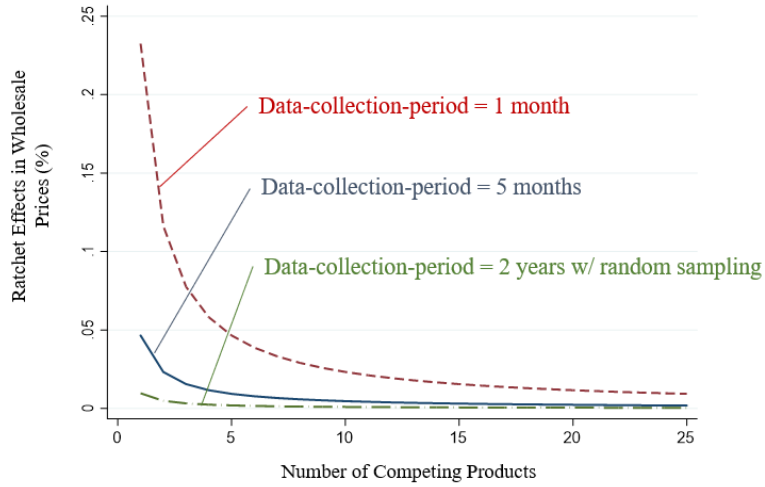
## 7.2 Competitive Externalities and Alternative Sampling Designs

This section consists of two parts. Section 7.2.1 quantifies competitive externalities in the presence of ratchet-based reimbursement regulation by examining how the strength of the ratchet effect varies with changes in market structure – proxied by the number of products within the each functional category. Section 7.2 then considers alternative reimbursement designs and evaluates how modifications to the data-collection process could mitigate these distortionary incentives.

### 7.2.1 Competitive Externalities

Figure 9 illustrates how the magnitude of the ratchet effect responds to exogenous variation in the number of products per functional category. The solid blue line depicts the simulated ratchet effects under different levels of market competition. The benchmark case, corresponding to the observed average number of products per functional category ( $|J_f| = 8$ ), yields a ratchet effect of the level consistent with the baseline results reported in Section 7.1.

Figure 9: Simulated Ratchet Effects and Market Competition



*Notes:* The figure plots the simulated magnitude of the ratchet effects under three institutional settings. The solid blue line represents the current reimbursement mechanism (five-month data-collection period). The red dashed line shows the counterfactual case where the period is shortened to one month. The green dash-dot line illustrates the proposed randomized sampling rule, which draws transactions from the preceding two years with a sampling probability equivalent to the five-month window. The vertical axis shows the size of the ratchet effect (in percent), and the horizontal axis shows the number of competing products per functional category.

The figure reveals that as the number of competing products decreases, the ratchet effect increases at an accelerating rate. This pattern is consistent with the analytical mechanism described in Eqs.(10) and (14), in which the ratchet parameter  $r_{jht}$  – capturing how much each transaction contributes to the future reimbursement price – is inversely proportional to the number of products within a category. In more concentrated markets, each seller-hospital transaction therefore exerts greater influence on the reimbursement benchmark, amplifying the incentive to strategically inflate wholesale prices during the data-collection period.

Under the case of monopoly ( $|J_f| = 1$ ), our simulation suggests that wholesale prices rise by approximately 5 percent relative to the non-strategic benchmark. In contrast, as market structure is more competitive, these strategic effects become increasingly muted, converging toward zero when the category contains a sufficiently large number of competing products.

This exercise highlights an important policy implication: by maintaining a minimum level of product diversity within each functional category, the regulator effectively mitigates the strategic upward pressure on wholesale prices during the data-collection period.

### 7.2.2 Alternative Sampling Mechanisms:

**Shorter Sampling Duration:** The ratchet effects documented in the earlier subsection arise primarily from Japan’s reimbursement rule, under which the data-collection period is both limited in duration and publicly announced in advance. This institutional design creates an opportunity for hospitals and device sellers to strategically adjust wholesale prices during the sampling window in anticipation of future reimbursement revisions.

As shown in Section 7.1, however, the magnitude of these ratchet effects is modest – an average increase of only 0.89 percent in wholesale prices during the data-collection period relative to the counterfactual without strategic incentives. This suggests that, while the ratchet mechanism exists, its aggregate impact is quantitatively small. Consequently, one might ask whether administrative costs could be reduced by shortening the data-collection period without materially amplifying strategic distortions.

To explore this, we simulate a counterfactual scenario in which the sampling window,  $|T_y|$ , is shortened from five months to one month. The results, depicted by the red dashed line in Figure 9, show that the shorter data-collection period would significantly magnify the ratchet effects: when  $|J_y| = 8$  (the observed average number of products per functional category), wholesale prices rise by nearly 4 percent, while under monopoly ( $|J_y| = 1$ ), they increase by as much as 23 percent. This steep price increase occurs because a shorter sampling window increases the weight of each transaction in determining the subsequent reimbursement price, thereby strengthening forward-looking incentives for price inflation.

**Random Sampling Mechanism:** Beyond adjusting the sampling duration, another potential reform concerns the predictability of the data-collection period itself. Currently, the schedule is publicly disclosed in advance, primarily to facilitate efficient data submission by hospitals and sellers. Yet, this transparency also enables market participants to coordinate their pricing behavior strategically, reinforcing ratchet effects.

To address this, we propose an alternative reimbursement mechanism that preserves administrative feasibility while weakening strategic incentives. Specifically, we extend the sampling frame to include transactions from the preceding two years but randomly select a subset of observations equivalent in size to those collected under the current five-month window. Formally, the modified Nash-in-Nash problem becomes:

$$\max_{\{p_{jht}\}_{j \in J_{mft}}} \left[ v_{mft}^M(\mathbf{p}_{fht}, \bar{p}_{fy}) + \rho_t V_{mft}^M(\mathbf{p}_{fht}, \bar{p}_{fy}) \right]^{1-b_{mft}^h} \cdot \left[ v_{mft}^H(\mathbf{p}_{fht}, \bar{p}_{fy}) + \rho_t V_{mft}^H(\mathbf{p}_{fht}, \bar{p}_{fy}) \right]^{b_{mft}^h} .$$

Relative to Eq.(6), the only modification is the substitution of the data-collection period indicator,  $\Omega_t$ , with  $\rho_t$  which represents the ratio of transactions included in the traditional data-collection window (May-September of odd years) to the total number of transactions in category  $f$  over the preceding two-year period. The green dashed line in Figure 9 plots the simulation results under this randomized sampling design.

Compared to the current reimbursement rule, the proposed mechanism mostly suppresses ratchet effects across all market structures, and importantly, the magnitude of this mitigation remains largely invariant to the number of competing products. By randomizing the inclusion of transactions, the mechanism breaks the link between contemporaneous pricing decisions and future reimbursement outcomes, thereby restoring incentives for cost-efficient pricing without imposing excessive administrative burdens.

## 8 Concluding Remarks

The ratchet effect refers to a strategic response by regulated agents who recognize that their current actions influence future policy benchmarks. Anticipating that regulators will use historical outcomes to set future targets or prices, firms or institutions deliberately adjust their behavior in the present to steer subsequent regulatory decisions in their favor. This dynamic has been documented across a wide range of policy domains.

This paper examines Japan’s medical device reimbursement system, using cardiac pacemakers as a case study, and evaluates how its institutional design affects pricing behavior. In Japan, reimbursement refers to the price that medical institutions – typically hospitals – are paid by public insurance for medical devices and services. The government collects transaction-level wholesale price data between hospitals and device dealers during a publicly announced data-collection period, which serves as the basis for setting future reimbursement prices. While this practice increases transparency, it also creates a collective incentive for hospitals and device sellers – parties that are normally on opposing sides of price negotiations – to raise wholesale prices during the data-collection period, anticipating that higher prices will raise the future reimbursement benchmark.

Our analysis shows that if reimbursement prices were determined separately for each product, this ratchet mechanism could distort prices by as much as 5 percent. In practice, however, Japan aggregates multiple products into functional categories, introducing competitive externalities that dilute each firm–hospital pair’s incentive to inflate prices. As a result, the overall distortion remains modest – below 1 percent.

Moreover, the relatively long five-month data-collection window further reduces the impact of any individual transaction on future reimbursement levels. Our simulation exercise showed that if the window shrinks to one month, the wholesale price would go up by close to 25 percent. These institutional features demonstrate how embedding competitive elements into administratively regulated pricing systems can curb theoretically predicted ratchet effects. Japan’s reimbursement system thus provides a concrete example of how regulatory design – balancing transparency, data-based decision-making, and competitive discipline – can sustain both price stability and informational efficiency in settings characterized by asymmetric cost information.

## A Data Appendix

This appendix provides description and validation of the data used in the empirical analysis. The first subsection outlines the construction of the dataset, documenting its various sources, coverage, and the procedures used to integrate information on transaction prices, product attributes, and hospital characteristics. The second subsection assesses the representativeness of the dataset by comparing reimbursement prices reconstructed from the sample with official reimbursement data. The final subsection presents the first-stage regression estimates of demand instruments.

### A.1 Data Sources and Construction

The primary dataset used in this study comprises proprietary transaction-level records provided by medical device dealers. These data include both import costs and wholesale prices for each pacemaker model sold in Japan. The dataset allows us to trace the complete transaction chain – from foreign manufacturers to domestic hospitals – thereby enabling direct calculation of markups for both sellers and buyers.

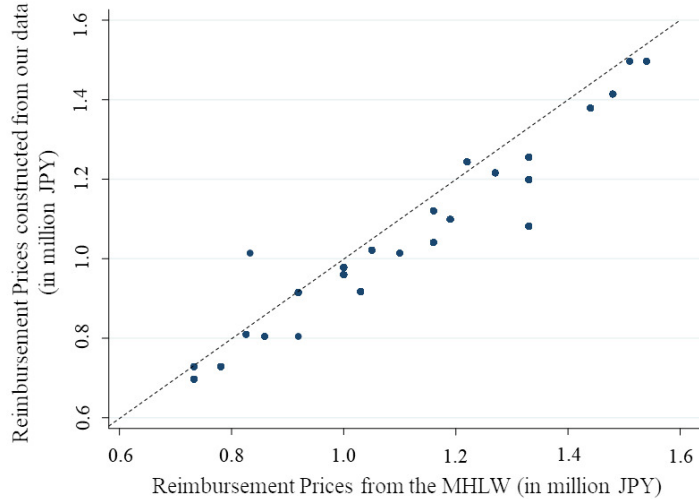
To complement these transaction records, we incorporate additional sources of information. Hospital characteristics are obtained from *Kanto Hospital Information* (Japan Medical Press, 2004–2014), which provides detailed attributes such as ownership type, hospital size, and medical specialization. Product characteristics are drawn from Nitta and Ishikawa (2014), which document the technical specifications and functional categories of cardiac pacemakers. Data on reimbursement prices are obtained from the Japan Association for the Advancement of Medical Equipment (JAAME), which maintains official records of government-determined reimbursement schedule.

In estimating the demand for pacemakers, we incorporate empirical distributions of patients’ age and income to account for heterogeneity in copayment rates. To capture the age distribution of patients, we use data from the *Patient Survey*, conducted by the MHLW. Because the survey is administered every three years, we use the waves from 2002, 2005, 2008, and 2012, aligning each study period  $t$  with the most recent available survey year. From these data, we extract discrete age distributions by disease classification, focusing on *arrhythmias and conduction disorders*, which directly correspond to pacemaker implantation. Since Japan’s copayment schedule applies different rates above and below the age threshold of 70, as discussed in Section 4.1, we use the proportion of patients aged 70 and above to construct the simulated market shares in the demand estimation.

For the income distribution of patients, we employ the *Comprehensive Survey of Living Conditions*, conducted annually by the MHLW. We use data from 2003 through 2014 to obtain discrete distributions of household income brackets. Because the copayment schedule defines income thresholds at 0.5 million and 6 million JPY, we use the corresponding proportions of households above these income levels when generating simulated shares for demand estimation.

Strictly speaking, the survey does not report the exact income bracket at 0.5 million JPY. Therefore,

Figure A.1: Assessment of Data Representativeness by Comparing Reimbursement Prices



*Notes:* The figure presents a scatter plot comparing reimbursement prices calculated from our wholesale price data with those reported in the official records, with the dashed line representing the 45-degree line.

we use the nearest available category – households with annual income below 0.35 million JPY – as a close approximation. Given the very small share of households who implemented cardiac pacemakers in this lower-income range, this adjustment is unlikely to materially affect our simulation results.

## A.2 Data Representativeness

As described in Section 3.1, our dataset covers approximately 60% of Japan’s domestic cardiac pacemaker market and more than 80% of transactions in the Tokyo metropolitan area. This subsection evaluates the representativeness of our data, assessing whether the observed transactions accurately reflect national market conditions.

To this end, we compare the reimbursement prices reconstructed from our sample with the official reimbursement prices published by the MHLW. As explained in Section 2.3, reimbursement prices for each functional category are determined by the regulator based on the sales-weighted average of wholesale prices collected during the data-collection period in the preceding year. Accordingly, these official reimbursement prices can be regarded as population-level benchmarks, representing the aggregate outcome of nationwide transactions.

Using our dataset, we replicate the regulatory pricing procedure following Eqs.(1) and (2), thereby reconstructing reimbursement prices implied by our sample. Comparing these reconstructed values with the official figures provides a direct measure of how well our dataset captures the underlying national price formation process.

Figure A.1 presents this comparison. The strong positive correlation with the correlation coefficient being 0.96 between the reconstructed and official reimbursement prices indicate that data reproduce national-level pricing patterns with a high degree of fidelity. On average, the reimbursement prices derived from our sample are approximately 3% lower than the official values. Even if this difference were interpreted as a systematic downward bias rather than a sampling deviation, its impact on our subsequent analysis would be minimal. For example, a simple back-of-the-envelope calculation shows that, even under a monopolistic scenario, a deviation of 3% would correspond to only about a 1% change in the implied wholesale price during the data-collection period – an effect too small to materially affect our conclusions.

### A.3 First-stage Regression Estimates of Demand Instruments

Table A.1 reports the first-stage regressions that examine the relationship between wholesale price – treated as endogenous in the demand estimation – and the sets of instrumental-variable candidates introduced in Section 5.

Table A.1: First-Stage Regression Results of Demand Instruments

	(A.1-1)	(A.1-2)
Reimbursement price	0.22*** (0.03)	0.22*** (0.03)
Import cost	0.39*** (0.01)	0.39*** (0.01)
Distance from the nearest wholesaler's office		0.01*** (0.00)
R-squared	0.953	0.953
F value ( $H_0$ : all coefficients of IVs are zero)	496.41***	531.86***
Observation	10,792	10,740

*Notes:* The dependent variable is the wholesale prices (in million JPY). Explanatory variables include the instrumental variables discussed in Section 5: the reimbursement price and import cost (both in million JPY), and the distance between the hospital and the nearest device dealer's office (in kilometers). Specification (A.1-2) additionally includes the distance variable, whereas (A.1-1) does not. All specifications include years, months, products and hospital fixed effects. Standard errors are reported in parentheses. \*\*\* indicates the 1% significance level.

The estimation results show that both reimbursement prices and import costs have significantly positive effects on wholesale prices, consistent with the theoretical prediction from Eq.(5). In specification (2), the coefficient on the distance between the hospital and the nearest dealer's warehouse is also positive and statistically significantly different from zero, indicating that higher logistical and coordination costs are

passed through to wholesale prices.

The null hypothesis that all instrument coefficients are jointly equal to zero is rejected at the 1 percent level across all specifications. The high first-stage  $F$ -statistics (above 490) indicate strong relevance of the instruments, alleviating concerns about weak identification.

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