Procuring Medical Devices: The Price Effect of Mergers among Orthopedic Prostheses Producers

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Abstract

This paper quantifies the price effects of a merger between two major producers of orthopedic prostheses. It shows that, in the public procurement markets where these products are purchased, the effect of the merger hinges on the characteristics of both the procurement design and the organizational structure of the buyers. Using data from all public procurement events in Italy between 2012 and 2019, and exploiting a difference-in-differences model where pacemakers play the role of the control group, we find that the merger led to a 7.6% increase in prices and that this effect is concentrated in the first three years post-merger. Further insights are: (i) a heterogeneous impact among gender and age groups such that most of the burden is on female patients aged 65 and above; (ii) short term quality does not change, but patenting activity declines; (iii) there is no evidence of the merger triggering ex post coordinated effects in the form of bidding and entry patterns compatible with firm collusion.

JEL classification: I18, J18, C21

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Contents

1 Introduction **1**

2 The Institutional Setting and the Merger **5**

2.1 The Merger and Its Review 5

2.2 Public Procurement of Medical Devices in Italy 6

3 Data **8**

3.1 Dependent Variables 10

3.2 Control variables 11

4 Empirical Strategy **13**

5 Results **14**

5.1 LPA sample 15

5.2 Full sample (LPA + CPB) 19

5.3 Product-specific estimates 21

5.4 Robustness checks 22

6 Insights **23**

6.1 Heterogeneous Effects by Age and Gender 23

6.2 Quality Impacts in the Short and Long Run 24

6.3 Coordinated Effects 26

7 Conclusion **27**

1 Introduction

Merger review is a pillar of competition law and practice. Currently, an active debate is ongoing both in the US and in Europe about whether the enforcement of merger policy has been adequate and what are the effects of this type of policy for both consumer welfare and the competitiveness of entire sectors and countries. Ex-post assessments of merger decisions like the one conducted in this study contribute to this debate by serving two main purposes that Whinston (2008) describes as guiding the formation of priors about which future mergers are more likely to be anti-competitive and helping to refine prospective methods to conduct merger evaluation.

The specific contribution of this study is to conduct a thorough ex-post evaluation of a merger affecting public procurement. While ex-post assessments have been conducted in various sectors ranging from airlines to banking, hospitals, consumer goods, telecoms, and digital platforms (see the reviews in Duso (2012) and Argentesi et al. (2021)), they are fairly rare in public procurement. This is surprising, as governments allocate approximately one-third of their total general spending to public procurement. Indeed, the focus of this study is health procurement, which represents the second-largest public spending area among OECD countries, accounting for over 9% of GDP in 2019 (OECD, 2021). This figure is also likely to increase in the future due to population aging, making it crucial to understand the drivers and consequences of industry consolidation for healthcare procurement.

One instance of public procurement for which evaluations of the impacts of industry consolidation are available is that of US military procurement. Carril and Duggan (2020) has analyzed the sharp rise in concentration among defense contractors in the 1990s and has shown how this led the US Department of Defense (DOD) to modify its contracting practices, and how this prevented industry consolidation from driving up procurement costs. This underscores how features of the procurement process are key to adequately assessing merger impacts. However, if both suppliers merge and buyers change their behavior, the ensuing price effect that will be observed ex-post will reflect their combined change.

For this reason, the current study is based on an empirical design aimed at isolating the effects of suppliers' consolidation by holding fixed the behavior of public buyers. The analysis exploits the variation in industry concentration triggered by a large, "marginal merger" of two US-based, global producers - the Zimmer/Biomet merger of 2015 - to study how it impacted procurement costs for Italian public buyers.[1] The Italian setting is an ideal case study for two reasons. First, within the public procurement sector, medical devices account for a large portion of public health expenditure, with orthopedic prostheses being Italy's most significant item.[2] As reported by the Italian Ministry of Health

[1] Ashenfelter et al. (2013) defines "marginal mergers" as those mergers on the edge between approval and rejection due to their perceived potential of being anti-competitive.

[2] At the European level, medical device expenses reached 0.6% of GDP in 2018 (MedTech Europe, 2020). Over the past decade, the European medical device market has grown by an average of 4.2% per year, reaching almost €110 billion in size. In the coming years, this industry is projected to continue growing at a sustained rate of more than 5%. Italy is Europe's fourth-largest market, responsible for approximately 10% of total sales, behind Germany, France, and the UK

(2018), in 2017, the National Health System (NHS) spent €427 million to satisfy the national demand for orthopedic implants, 27% more than in 2013 and almost €100 million more than the expenditure for cardiac devices, the second item in the ranking. Consequently, the impact on Italian public accounts is significant. This situation reflects various trends. In particular, the number of patients undergoing these procedures has steadily increased over the last decade, driven by factors such as population aging and growing obesity that are affecting most developed countries.[3] Recent projections (Romanini et al., 2019) forecast an increase of 45% in the incidence rate of total knee arthroplasty (the second most common orthopedic procedure) by 2050 compared to 2017.

Secondly, we have access to a unique dataset that combines three primary data sources. We have access to contract-level data covering public procurement events spanning nearly a decade around the year of the merger. This allows us to measure procurement costs and observe key aspects of procurement design and buyer organization. We also observe the whole public expenditure flows toward each producer/product from the NHS which are fundamental to identify a reasonable control group, represented in our setting by the pacemaker market. Finally, we also have data on ancillary but crucial elements such as the demographics of the patients undergoing the surgery where the prostheses are implanted, the patents (requested and approved) for each firm, and the product category.

Our main identification strategy utilizes a difference-in-differences model that is estimated using contract-level data for both prostheses (treated group) and pacemakers (control group). We present results where the outcome is either the contract price or the "winning discount" (a discount over the reserve price posted in the call for tenders). In both cases, we find large, significant effects of the merger indicating greater costs for public buyers: our preferred model specification indicates an increase of 15% when the outcome is the price and a drop of 7.6% when it is the winning discount. We argue that the latter is the most adequate variable to capture the specificity of how competition works in the context of the public procurement setting that we study. Back-of-the-envelope calculations indicate that, if extended to the 2015-2019 period, the merger has cost the Italian NHS about €190 million. We also illustrate the importance of controlling in the analysis for features of this setting in the form of the design of the procurement process and the organizational nature of the buyer.

A series of additional results and robustness checks enrich the analysis of the price effects. In particular, we look for heterogeneity across treated products by distinguishing the markets for different prosthesis devices, also separating the ones for which the antitrust authority had requested divestitures of product lines as the condition to clear the merger. We also look for heterogeneous effects over time. The most remarkable result of this part of the analysis is clear evidence of the merger producing its most significant price effects in the first three years since the merger: the estimated effect in these years is about three times larger than the one estimated in the fourth and fifth year after the merger (which is still marginally positive).

[3]For hip replacement, the most common surgery in this category, the number of people hospitalized each year to receive these implants has grown by approximately 2.5% per year, reaching more than 100,000 individuals in 2018. For arthroplasties linked to partial or total knee and shoulder replacement, the average growth rate over this period was even higher, 4% and 11% respectively (AGENAS, 2018).

We then conclude with a series of insights based on our rich data. Although this portion of the study is not based on a rigorous causal identification strategy, it complements the price analysis with relevant descriptive evidence. First of all, in light of the interest in the evaluation of ESG outcomes, our data allow us to estimate which demographic groups would be more impacted by the price changes. Although in Italy the NHS covers (most of) the cost, this exercise shows that due to the heterogeneous impacts of price effects across products and the differential incidence of products across genders and age groups, older female patients would bear most of the extra cost induced by the merger. The second insight regards the potential impacts on the quality of the products, both in the short and in the long run. In the short run, we partnered with the National Arthroplasties Registry to study any changes in revision interventions for patients who had received Zimmer Biomet prostheses in primary (elective) interventions, but we did not detect any. For the long run, instead, we look at R&D expenditures and patents. We find stagnant R&D expenditures by the merging parties post-merger and a corresponding significant decline in patent applications from the second year since the merger. An analogous decline in patents, although with not identical timings, affects essentially all the large producers of prostheses. Finally, the third insight regards the potential for coordinated effects post-merger. It is an established fact in most economic models of collusion that greater industry concentration is a facilitating factor for the emergence or the strengthening of collusion Whinston (2008). This is also the very reason why, at the ex-ante stage of a merger review, the risk of collusion post-merger (i.e., joint dominance or coordinated effects) is assessed. We explore this issue through a basic analysis of bidding and entry patterns to evaluate whether the data indicates departures from competitive behavior, but find no evidence of coordinated effects materializing post merger.

To conclude, this paper contributes to three main streams of the literature. The first regards the ex-post assessment of completed mergers. As already mentioned, our main contribution is to center the analysis on public procurement and, hence, to complement the work of Carril and Duggan (2020) on US military procurement. Moreover, although our use of a difference-in-differences (DID) method is relatively standard,[4] we provide a credible implementation of this method by both exploiting a merger that is exogenous,[5] and identifying a control group that satisfies the required assumptions of this approach.[6]

[4]See, for example, Ashenfelter and Hosken (2010) and Ashenfelter et al. (2013). Due to its transparency, it is also widely used in policy work (see, for example, European Commission-DG Competition (2015) and Ilzkovitz and Dierx (2015)).

[5]In recent years, interest in industry concentration and its effects has grown (see Benkard et al. (2021) for a recent review of the literature). However, a primary challenge in understanding these effects is the non-random variation in market structure. In our case, we can confidently state that the Zimmer-Biomet merger was fully exogenous to the Italian procurement market, as it was not motivated by the specific features of the Italian prosthetic market. Indeed, in 2014, the year before the merger, France, Germany, Italy, Spain, Switzerland, and the United Kingdom collectively accounted for merely 17% of Zimmer's total global sales – Zimmer being notably the largest of the two merging entities (Zimmer Inc., 2015).

[6]The main challenge that we face is indeed defining a control group that is comparable to the treated one and not directly affected by the merger concurrently. This requirement prevents us from using data from products substitutable with those of the merging parties as controls since prices should respond to the merger at equilibrium (Deneckere and Davidson, 1985). Given that the geographical market for orthopedic prostheses is national, leveraging spatial variation is not feasible. Our contribution to this problem is to propose a comparison group containing different kinds of medical devices in the same national market.

Concerning the second contribution, our results underscore that while public debates and academic research have often concentrated on issues such as corruption, cartels, and incomplete contracts, the role of supplier market power in public procurement markets is highly relevant. Closely related to our study, Bucciol et al. (2020) explored buyer characteristics' role in the Italian procurement market for medical devices, where public administrations acquire goods and services on behalf of healthcare providers via auctions. Using unit prices for different medical devices, they estimated a structural model revealing that much of the variation in public sector procurement costs stems from purchasing administrations' "competence," which is correlated with institutional characteristics and size (measured by procured turnover). We will incorporate their findings into our identification strategy by controlling for buyer competence through a set of covariates analogous to what they used.[7] Additionally, our findings emphasize the need for antitrust authorities to closely examine mergers involving public procurement markets.

The third stream of the relevant literature is regarding competition in the medical device industry. In this regard, Grennan (2013) conducted an intriguing analysis of how market dynamics affect these items' prices by examining price discrimination and bargaining abilities in a business-to-business market where healthcare providers purchase medical devices directly from manufacturers. Our work, instead, revolves around the functioning of competition in public procurement markets.

Finally, we can look back at the two purposes that Whinston (2008) stressed as the merits of ex-post assessments of merger decisions. In light of our findings on price increases, it appears that the antitrust authorities of Europe, Japan, and the US – which all decided to investigate this merger – were right about its potential anticompetitive effects. The forced divestitures of product lines that they mandated, however, do not appear to have sufficed to keep price increases at bay. Furthermore, the descriptive evidence of lower patenting activity is indicative of a potential worsening of a non-price margin of competition. On the other hand, no short-term worsening of product quality or increase in collusion emerged from our analysis. Regarding the latter, it is also interesting to point out a third merit of ex-post merger reviews that have not been stressed in previous works: by screening for collusion in markets previously affected by a merger, they can help direct the investigative activities of antitrust authorities who are constantly looking at possible *ex officio* investigations for breaches of competition.

Specifically, after a thorough analysis detailed below, pacemakers and implantable defibrillators emerged as the most similar products to orthopedic supplies.

[7] Other related studies, such as Rizzo et al. (2006), explore the relationship between procurement prices and supplier concentration. Utilizing data on medical device tenders in Italy from 1995–2005, market concentration is represented by the total number of registered suppliers in various classes of medical devices and the actual number of producers participating in a subset of auctions. Their findings suggest that a higher number of firms participating in procurement auctions generally correlates with lower award prices. Vellez (2012) improved upon these estimates by accounting for additional contract-level and procurement agency-level covariates and implementing an instrumental variable strategy to address endogeneity in firms' participation. While our research question is similar to that of these two studies, our study benefits from more granular data and a causal identification strategy.

2 The Institutional Setting and the Merger

2.1 The Merger and Its Review

In April 2014, Zimmer agreed to acquire Biomet for $13.4 billion, aiming to strengthen its position in the manufacturing and development of orthopedic prostheses and related products. Both companies were based in the United States but active globally. At the time of the merger, Zimmer was a global leader with a turnover of €3.5 billion, and Biomet was a close competitor with a smaller turnover of €2.3 billion. This operation was part of an unprecedented wave of consolidations happening within the prostheses sector. Other major events are the acquisition of DePuy Synthes Inc. by Johnson & Johnson (J&J) in 2012 and that of Wright by Stryker Corp. in 2020. Our analysis focuses specifically on the Zimmer/Biomet merger, and its time frame excludes these two other merger episodes.

In addition to a handful of large, global players, the supply side is composed of a myriad of small and medium enterprises. The fact that the orthopedic prostheses technology is rather mature and relevant patents have already expired allows these smaller firms to represent an effective competitive constraint against the largest ones. This is the main factor explaining why the mergers were authorized to go through. To give a concrete example, the joint replacement implant market was worth US$21 billion in sales in 2023 worldwide, with Europe accounting for 19.8%, and was characterized by high concentration with Zimmer Biomet, Stryker, DePuy Synthes, and Smith and Nephew controlling 71.2% of the market globally. In particular, Zimmer Biomet was the largest player accounting for 25.7% of the market (or sales worth US$5.53 billion), followed by Stryker (21.3%), DePuy Synthes (16.6%) and Smith and Nephew (7.6%).[8]

When Zimmer and Biomet notified the competition authorities of Europe, Japan, and the US of their proposed merger, all three began an in-depth investigation into the potential anticompetitive effects. In the EU, the proposed merger was announced in June 2014 and approved in March 2015 by the European Commission (EC), subject to conditions.[9] During this period, the EC conducted an assessment of the risk of both price and non-price effects. It identified that competition markets were separated across EU countries due to the different regulations and health care systems and also separated into 13 different product markets.[10] The main concerns about the reduction in competition in most EU countries associated with the merger regarded two product markets where the proposed transaction would have led to the creation or strengthening of their dominant positions: partial knee implants and elbow implants.[11] In these markets, the combined market shares were estimated to be over [60-70]%, and as high as [90-100]% in some spe-

[8] These figures are taken from the 2024 industry report of Orthoworld available at this link: https://www.orthoworld.com/joint-replacement/.

[9] The text of the decision is available at this link: https://ec.europa.eu/competition/mergers/cases/decisions/m7265_4754_3.pdf.

[10] These were: elbow implants, hip implants, shoulder implants, bone cement, bone cement accessories, surgical tools (especially "pulsed lavage"), spine devices, trauma devices, dental implants, and knee implants (further divided into four subcategories: patellofemoral knee implants, unicondylar knee implants, primary knee implants, and revision knee implants).

[11] Other affected markets were specific to two Nordic countries: total knee implants and the potential primary knee market (Sweden) and primary and revision knee market (Denmark).

cific countries. The merger would have resulted in very few remaining competitors and essentially no competitive constraints due to buyers' limited product switching and the high regulatory barriers to entry. The conditions posed to approve the merger involved the divestment of product lines for unicondylar knee and elbow prostheses. Zimmer sold the *Zuk* knee implant, and Biomet sold the *Discovery* elbow implant.[12] All divested product lines were purchased by Lima Corporate for a total of €39 million.[13]

Finally, the merger review also involved elements beyond unilateral price effects. Both non-price elements related to product quality and innovation, as well as the risk of coordinated effects, are discussed in the EU decision. But all these elements were not deemed to pose a sufficient risk to justify forbidding the merger, or requesting additional remedies. Interestingly, the decision reports that one rival firm, Aesculap, heavily emphasized risks related to Zimmer's patenting strategy. It argued that Zimmer actively enforced such a strategy to shield its market position and reduce competition, especially in the market for hinged knee implants. By acquiring Biomet's patent portfolio, Zimmer may thus have attempted to become the monopolist of modern hinged knee implants in the near future.[14]

2.2 Public Procurement of Medical Devices in Italy

The Italian National Healthcare System (NHS) is a tax-funded system that, since 1980, provides free healthcare for every citizen, regardless of income. The Regions are in charge of managing healthcare at the local level. Local Health Authorities (LHAs) and other entities with independent legal status provide health services, controlling one or more hospitals whose accounts are included in the LHAs' balance sheets. Besides LHAs, there are "Local Purchasing Authorities" (LPAs)—independent entities involved in supplying health services with their own management, balance sheets, and procurement processes.[15]

These LPAs can launch calls for tenders to purchase health supplies.[16] However, this decentralized system entails potential inefficiency, as the small size of the LPAs does not allow exploitation of, for example, economies of scale and scope. To address this issue, regional and national governments have encouraged initiatives for procurement centralization since the early 2000s. One notable development was the introduction of "Piani di Rientro" by Law 311/2004 - national programs aimed at restoring budget balance in

[12] Biomet also divested the *Vanguard Total Knee System* in Sweden and Denmark.

[13] The case was handled in a similar way by the US Federal Trade Commission and by the Japan Fair Trade Commission. In the latter case, the *Zuk* and *Discovery* lines were divested and purchased by Lima Corporate. In the US, the Federal Trade Commission had similar concerns but also included bone cement among the product lines in need of divestitures so that in addition to the sale of *Zuk* to Smith&Nephews and *Discovery* to DJO Global, Biomet sold to the latter buyer also its *Cobalt* bone cement product line.

[14] A relevant institutional feature that should not be overlooked is that, back in 2015, merger reviews used to devote limited attention to innovation theories of harm. The current situation is radically different, and the new approach to non-price competition has been recently detailed in European Commission (2024).

[15] LPAs include Hospital Enterprises (*Azienda Ospedaliera*), hospitals turned into independent units; the Institutes for Treatment and Research (*Istituto di Ricovero e Cura a Carattere Scientifico*), hospitals focused on specific treatments and on research; and University Hospital Enterprises (*Azienda Ospedaliera Universitaria*), which combine the activities of a hospital with the training of young physicians. For all these institutions, extra information on balance sheets, personnel, and organization is available.

[16] From now on, when mentioning LPAs, we will consider both LHA and LPA.

targeted regions with specific provisions on centralization. Additionally, EU Directive 18/2004 (implemented by Legislative Decree 163/2006) required regions to adopt "Central Purchasing Bodies" (CPBs) for procurement on behalf of all local public administrations, including LPAs. However, regional responses varied significantly, and LPAs still played a crucial role in acquiring health-related goods. In 2015, public procurement centralization was further enhanced by the requirement that certain items' acquisition occurred through CPBs.[17] The majority of the items involved were medical devices, including hip prostheses, pacemakers, and defibrillators, which were chosen due to their high budgetary impact and low complexity.[18] Thanks to the level of detail of our data, we will be able to control for these legislative changes in our analysis.

In addition to the organizational elements described above, another relevant group of features determining the institutional environment regards the design of the procurement process laid down in the public procurement law. The law prescribes how the public buyers shall post calls for tenders and select the winners based on a combination of specific awarding procedures and criteria harmonized at the EU level.

The awarding procedure is the process by which the contracting authority organizes the call for tenders. The main types of procedures are: *i)* open, where all interested suppliers can submit bids; *ii)* restricted, where companies must meet prerequisites before presenting their offers; *iii)* negotiated, where the public administration can directly negotiate contract terms with specific companies; and *iv)* competitive dialogue, where suppliers help define the goods and services to be purchased. The awarding criterion is the method through which the winning bid is selected. It can be either: *i)* lowest price, where the bid offering the highest rebate on reserve price wins; or *ii)* most advantageous economic offer (MEAT), with contracts awarded to bids achieving the highest score based on a weighted average of rebate and goods' quality.

A granular discussion of how procedures and criteria interact to determine different strategic environments for the companies bidding in the auctions is presented in Decarolis and Giorgiantonio (2015). Here, we follow their approach and distinguish three main types of procurement designs according to criterion and procedure combinations: *i)* First Price (FP) auctions, combining lowest price criteria with open or restricted procedures; *ii)* Scoring Rule (SR) auctions, combining MEAT criteria with open or restricted procedures; *i)* Negotiations (N), encompassing all types of negotiated procedures and competitive dialogues regardless of awarding criteria.

Public buyers only have limited flexibility in choosing among the three procurement designs, which are mostly determined by the object of their purchase and its expected

[17] This reform is contained in the Decree of the President of the Council of Ministers (DPCM) 24/12/2015. Its implementation, however, has encountered the opposition of local public buyers. In practice, this implied that LPAs continued their purchasing throughout our whole sample period. Essentially, this implies that in our data, LPA purchases are always observed, while CPB purchases are mostly a phenomenon of the post-2014 years. We observe a total of 14 CPBs representing 14 regions. But before 2015, only two CPBs were active in the purchase of prostheses or pacemakers: ESTAR (Tuscany), which we observed starting in 2013, and ARS/CRA/PAC (Liguria), which we observed starting in 2014.

[18] The full list of items is available at the following web address: `https://www.gazzettaufficiale.it/eli/id/2016/02/09/16A00583/sg`.

cost.[19] Indeed, although the merger might have different impacts depending on both the centralized vs. decentralized organizational structure of the buyer and its procurement design, neither of these two elements is meant to vary in response to an increase in supplier concentration. In the following analysis, we will account for the primary institutional features related to procurement, but we will not examine whether these features change or interact with the merger.[20]

3 Data

The primary data source for this research is the National Database for Public Contracts, managed by the Italian National Anti-Corruption Authority. This dataset encompasses information on all calls for tenders issued by Italian public administrations with a reserve price of over €40,000. Our sample of observation goes from 2012 to 2019. The observation units are lots tendered via auctions or negotiations where one or several lots are procured. The data contains information about the contract object, the procurement design, the reserve price, the winning discount (over the reserve price), and the identity of both the winning bidder and the public buyer.

In addition to the main data source, we use several ancillary sources. We observe: *i)* utilization data from the *Consumption Flows* available on the website of the Italian Ministry of Health at the level of individual products-and-producer; *ii)* individual LHAs balance sheet data; *iii)* primary and secondary surgery intervention data from the National Arthroplasties Registry; *iv)* patent data by producer and product category from Orbis. Additional details on the data are provided in the Appendix.

Our dataset includes lots selected based on Common Procurement Vocabulary (CPV) codes for two main groups of products: orthopedic prostheses (treatment group) and cardiac stimulation devices (control group). In particular, by combining CPV codes with lot descriptions, we assigned each observation to a specific product-market following the market definition in the Zimmer/Biomet EC merger review decision. Seven markets were identified for the treatment group: hip prostheses; unicondylar, primary, and revision knee prostheses; trauma devices; shoulder prostheses; and spine devices. Some categories, such as patellofemoral knee implants and dental prostheses, had limited observations, so they were grouped into a residual eighth market named "Others," which also includes lots with insufficient details to assign them to a specific market **(excluded from the analysis)**.

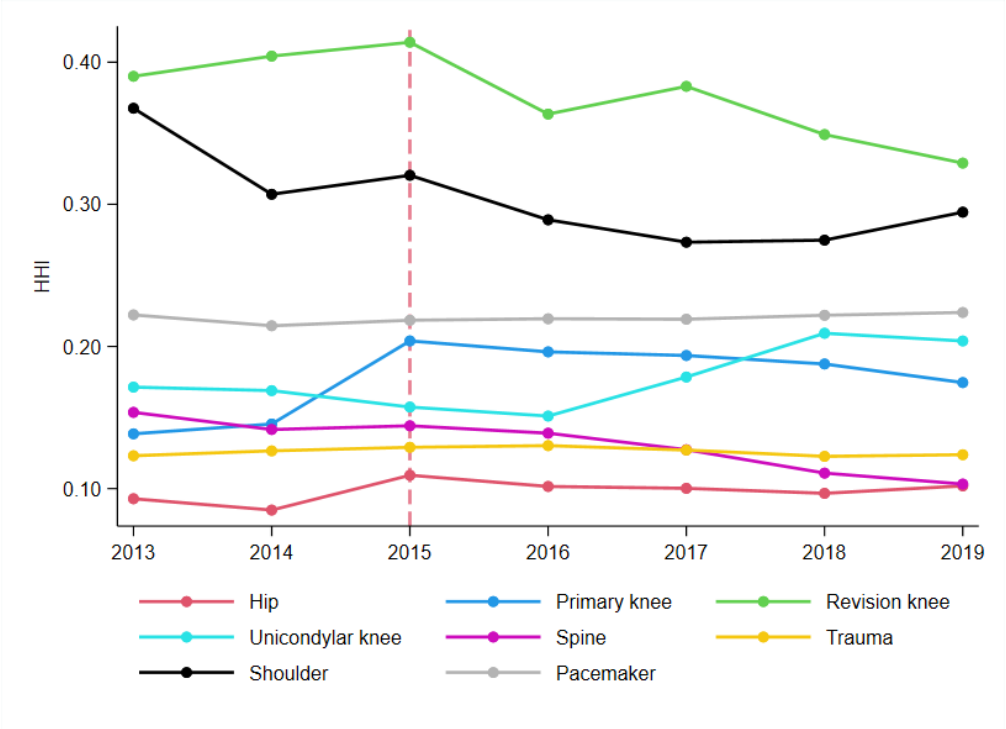
For the control group, we combined pacemaker and implantable defibrillator lots due to their frequent joint purchases and similarities from the contracting authority's perspective. Additionally, both markets share similar structures, where the same five companies constitute approximately 95% of total sales for each product (see Appendix A). Consequently, we treat pacemakers and implantable defibrillators as a single entity known as the pacemaker market. The use of this set of products as our control group is based on

[19] Indeed, as already mentioned in the Introduction, according to a survey conducted by the World Bank (Bosio et al., 2022) Italy ranks third worldwide in terms of the extent of its procurement regulations.

[20] In a series of analyses not reported in the paper, we verified that in our data the merger is not associated with changes in either the organization of public buyers or their choice of procurement designs.

multiple elements. First of all, as discussed in industry reports, pacemakers are the only medical device with a stable concentration trend from 2014 to 2017 (Cergas, 2017). This is indeed clearly visible in our data on the *Consumptions Flows* in Figure 1, where we report the Herfindahl-Hirschman Index (HHI) of both the treated products and the pacemakers. Additionally, the technological complexity of pacemakers is comparable to that of treated product markets, as underscored by their inclusion in the regulatory reform of 2015 on procurement centralization, which included them along with a few other types of medical devices, including hip prostheses. This was motivated by perceived similarities in terms of maturity, standardization, and budgetary impact.

Figure 1: HHI of specific prostheses markets



Note: HHI built on the basis of expenditures data from the *Consumption Flows* available on the website of the Italian Ministry of Health. Further details are presented in the Appendix. The red vertical dashed line indicates the year of the merger.

The EC investigation described above concluded that in Italy, the merger would have "significantly impeded competition" in the unicondylar knee prosthesis market, absent remedies (European Commission, 2015). As shown in Figure 1, transferring ZUK from Zimmer to Lima Corporate is crucial to controlling the HHI growth of the unicondylar knee market; otherwise, Zimmer and Biomet would hold a combined market share of 50%. Among the remaining markets, the primary knee market experiences the greatest HHI increase after the merger.

3.1 Dependent Variables

We will present our estimates using either the contract price or the winning discount from the procurement process as dependent variables. These two variables are closely linked: the price is equal to the reserve price (i.e., the maximum price) set in the call for tenders minus the discount offered by the winning bidder. We refer to this variable as the "Net Price". In our analysis, we use its logarithmic form to smooth out a distribution that ranges from as low as €40,000 to nearly €10 million. Working with the (log of) the net price is customary for ex-post merger evaluations as the price increase is a key element of the analysis. The winning discount is an important variable to consider in this analysis, given the institutional features of the procurement process.[21] In Italy, firms primarily compete by offering discounts rather than bidding prices. Therefore, examining these discounts helps us better understand the variations in competition. Furthermore, despite having detailed data, we are unable to control exactly for granular contract features. Substantial variability in the net price remains linked to unobservable factors. However, this is less relevant for the discount since prices are normalized by the auction reserve price, which captures many drivers of heterogeneity across contracts.[22]

To use the discount as our dependent variable, it is crucial that the reserve price setting process remains independent of market structure.[23] This is indeed the case in our setting. Procurement regulations outline various tools for purchasing authorities to determine the reserve price, including reference prices from national regulators, market surveys, and regional price lists. However, there remains a certain degree of discretion.[24]

In practice, reserve prices are set by purchasing administrations that typically follow a hierarchical process while consulting various sources.[25] First, they examine previous auction results for identical items, which aligns with Article 35(12) of D.Lgs. 50/2016 for regular purchases. If this information is unavailable (e.g., when buying an item for the first time), contracting authorities evaluate bids for similar items from different entities. Lacking this information, public procurers consult suppliers' price lists directly. Based on these findings, purchasing administrations make minor adjustments to reserve prices, aiming to approximate the true value of items for producers and gradually decreasing

[21] The winning discount equals 100 times 1 minus the ratio between the net price of the winning offer and the contract reserve price.

[22] Importantly, unlike in infrastructure procurement where price renegotiations can take place multiple times until completion (often resulting in price increases), in the medical device sector, price renegotiations do not occur. Therefore, the discount acts as a good estimate for the final procurement price.

[23] Consider a scenario where two LPAs purchase the same item at identical prices, but one sets a higher reserve price than the other. This would make it difficult to directly compare the resulting winning rebates.

[24] The legal framework can be summarized as follows: Before the 2016 reform of public procurement laws, Article 89 of D.Lgs. 163/06 provided purchasing authorities with tools to establish reserve prices based on reference prices set by the regulator, generic market surveys, or their own price lists. An attempt to create a reference price scheme for medical devices by D.L. 98/2011 failed when Lazio's Regional Administrative Court deemed it unlawful in 2012. The sector regulator created a new reference price list in 2014, covering only a small portion of medical devices. Subsequently, Article 89 was replaced by Article 35 D.Lgs. 50/2016 during the reform of the Code of Public Contracts in 2016. The new provisions were rather generic and addressed reserve price computation only in certain cases.

[25] We thank the researchers of the "Observatory on Management of Public Procurement and Contracts in Health Care" (MASAN) of CERGAS – SDA Bocconi for pointing us to such a mechanism.

bidding firms' profits.

At the same time, a reserve price that is set too low may make the auction unappealing and jeopardize the timely supply of medical devices. To minimize this risk, it is crucial to consider granting a fair amount of profit when setting the reserve price. Additionally, factors like quality and innovation prevent the reserve price from falling close to the marginal cost of production for even the most efficient firms.[26] This trade-off leads to a decrease in average winning rebates over time, which aligns with observed data trends. However, comparing the rebate before and after a merger can be misleading when assessing the treatment effect. A DiD design like the one described below naturally addresses this issue. For this identification strategy to be valid, we must assume that purchasing administrations set the reserve price similarly for both treatment and control groups, all else being equal. This assumption seems plausible since orthopedic prostheses and pacemaker markets are often viewed as comparable in terms of procurement processes, and both markets have a long history of being frequently purchased by local public administrations.

3.2 Control variables

A series of factors must be considered when assessing the relationship between concentration and rebates. One potentially relevant factor is the frequency with which an LPA purchases a particular medical device. Greater purchase frequency might lead to higher expertise in setting reserve prices and designing procedures, which could result in lower rebates over time. To account for this, we created the variable *maturity*, indicating the number of auctions an LPA issued for a specific product since 2007 (when data first became available).

Another crucial factor in determining medical device prices could be the general competence of the public procurer. Bucciol et al. (2020) showed that fixed effects for LPAs have a significant role to play in explaining price variations for medical devices that Italy's National Health Service purchases. Furthermore, these correlations align with variables indicating public procurers' competence.

[26] In Appendix B, we provide some examples that validate the description offered here on how the reserve price is set.

Table 1: Descriptive Statistics of the Two Samples

LPA Sample					
Variable	Obs	Mean	Std. Dev.	Min	Max
Net Price	5,632	341,639	604,339	40,000	8,382,000
Ln(Net Price)	5,632	12.06	1.051	10.597	15.942
Reserve Price	5,632	452,437	830,562	40,000	9,954,000
Ln(Reserve Price)	5,632	12.256	1.126	10.597	16.113
Discount	5,632	.139	.209	0	.872
Ln(Maturity)	5,632	1.836	1.092	0	4.344
Ln(Personnel)	5,632	18.971	.86	11.469	20.523
Non-health Personnel Ratio	5,632	.186	.043	.071	.388
Medical Device Ratio	5,632	.362	.106	.027	.759
Treated	5,632	.716	.451	0	1
First Price	5,632	.1	.3	0	1
Negotiation	5,632	.503	.5	0	1
Scoring Rule	5,632	.336	.472	0	1
Budg. Plan	5,632	.297	.457	0	1

LPA+CPB Sample					
Variable	Obs	Mean	Std. Dev.	Min	Max
Net Price	6,660	425,829	785,880	40,000	9,811,900
Ln(Net Price)	6,660	12.175	1.135	10.597	16.099
Reserve Price	6,660	570,341	1,057,271	40,000	9,954,000
Ln(Reserve Price)	6,660	12.396	1.207	10.597	16.113
Discount	6,660	.158	.214	0	.879
Ln(Maturity)	6,660	1.733	1.088	0	4.344
Treated	6,660	.724	.447	0	1
First Price	6,660	.088	.283	0	1
Negotiation	6,660	.438	.496	0	1
Scoring Rule	6,660	.422	.494	0	1
Budg. Plan	6,660	.267	.442	0	1
CPB	6,660	.154	.361	0	1

Note: On the top panel, the LPA sample includes all lots awarded between 2012 and 2019 by all public buyers, excluding CPBs; on the bottom panel, the LPA+CPB sample contains the same lots as the LPA sample as well as those of CPBs. The (lot) rebate is the winning rebate, expressed as a percentage of the reserve price. Log Reserve Price is the log of the reserve price, measured in euros. Log Maturity records the log of the number of auctions that an LPA issued on that same category of prostheses since 2007. Log Tot Personnel is the log of total personnel cost. Non-Health Personnel ratio is the fraction of non-health personnel over total personnel costs. The medical device ratio is the fraction of medical device purchases over the total healthcare material purchases. The cost measures used in these last three variables are all expressed in euros. The set of dummy variables in the lower part of both panels is equal to one if the lot is for a treated product market (Treated) or is awarded: via price-only auctions (First Price), via a negotiated procedure (Negotiation), via a scoring rule auction (Scoring Rule), by an administration located in a region subject to a budgetary plan to curb healthcare expenditures (Budg. Plan), by a CBP.

To incorporate detailed data on LPA, we can use LPA balance sheets available on the Italian Ministry of Health's website. However, balance sheet data are not available for CPBs. Moreover, these data would require a different interpretation between LPAs and CPBs since the latter are public agencies exclusively devoted to procurement (i.e., they do not provide any health service). Therefore, in our analysis, we consider two samples: the *LPA sample*, where CPBs are excluded (5,632 observations), and a larger sample that also includes CPBs (6,660 observations). We consider the former as our baseline sample, as the availability of balance sheet data enhances the possibility of controlling for potential confounders. Moreover, since CPBs are usually able to obtain higher rebates compared to LPAs (Ferraresi et al., 2020), by analyzing the two samples separately, we can highlight the potentially heterogeneous effects of industry concentration across different types of buyers.

Including CPB purchases may complicate the interpretation of estimates due to their interplay with an earlier-mentioned reform concerning the centralization of hip prosthesis and pacemaker procurement. This reform was implemented in 2016, right after the merger. Despite this law, LPAs continued to issue auctions for these medical devices well beyond 2016. The reason is that many CPBs were unprepared for this change (Osservatorio Conti Pubblici Italiani, 2018) and needed more time to fully comply with the new obligation. Simultaneously, some "forerunner" CPBs were already active in procuring these items even before 2016. Consequently, CPB observations span much of the sample period, allowing us to evaluate the mergers' effects on those estimates involving lots awarded by both LPAs and CPBs.

Additional controls included in the analysis are three dummies for the procurement design. As discussed above, these are indicators for the first price, scoring rule, and negotiations. The dataset contains a small share of instances – 5% – for which special types of procurement procedures are used: we keep these cases in the dataset and use them as the excluded category in the regression analysis. Furthermore, the analysis also uses an indicator variable for whether the lot was awarded in a region subject to a budgetary plan to curb expenditures ("Piano di Rientro," labeled as *Budg. Plan*). Lastly, since larger lots may be associated with higher discounts, we control for the logarithm of the reserve price. Descriptive statistics for samples with and without CPBs are presented in Table 1.

4 Empirical Strategy

We employ an empirical strategy that utilizes a Difference-in-Differences (DiD) approach through the following linear, two-way fixed effect model:

$$y_{i,t} = \beta_0 + \beta_1 Treat_{i,t} + \beta_2 Treat_{i,t} \text{ x } Post_t + \beta_3 Z_{i,t} + \nu_t + \eta_r + \xi_p + \epsilon_{i,t} \quad (1)$$

where subscript i indicates the lot, t the year, $Treat_{i,t}$ is a dummy that takes value 1 if the observation belongs to the treatment group, $Post_t$ is another dummy equal to one for lots issued from 2015 onward, $Z_{i,t}$ is the matrix of controls described in the previous section and ν_t, η_r and ξ_p are year, region and product market fixed effects. Finally, $\epsilon_{i,t}$ is the idiosyncratic error term.

Relative to this baseline model specification, we consider including different sets of controls and fixed effects. In particular, we present a series of estimates that are obtained by gradually expanding the controls for the procurement design and the buyer organizational structure. We also present results that are specific to the treated product market.[27]

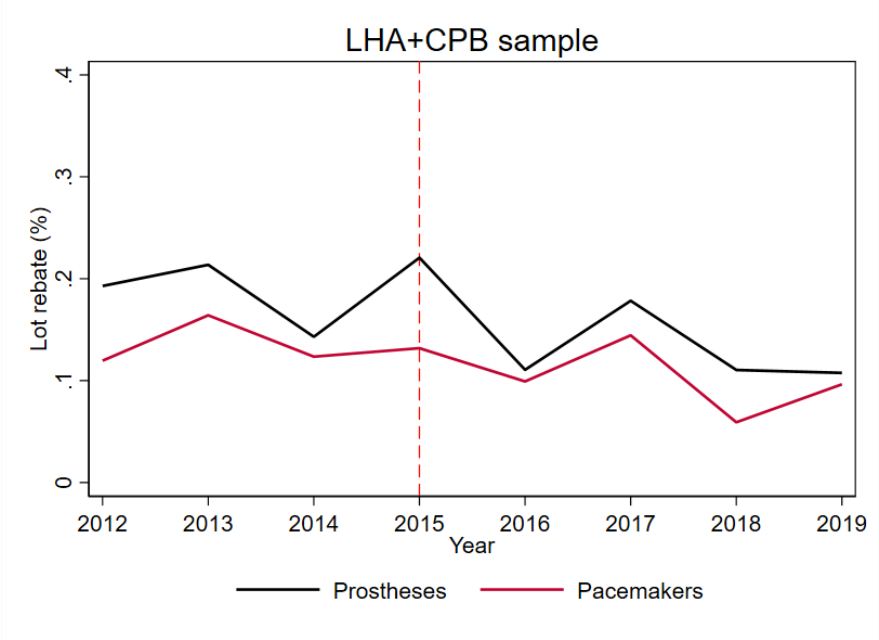


Figure 2: Average rebates over time across treatment and control groups

From an empirical point of view, among the several challenges embedded in a DiD analysis, the key challenge for our identification strategy is represented by the selection of an adequate control group. Ideally, this should be a similar product market, hit by the same supply and demand shocks as the treatment group, but different enough to not be affected directly by the treatment. In section 2.1, we highlighted how pervasive the phenomenon of consolidation is across medical device manufacturers. Thus, it is not easy to find a medical device market where no mergers between rivals occurred within the time frame of our analysis. We discussed several motives for using peacemakers as the control group earlier. Figure 2 reinforces this selection by showing similar pre-treatment trends in average rebates between these two markets.

5 Results

We begin the presentation of the results from the evidence obtained from the sample of tenders within LPAs both for the net price and the winning discount. Next, we broaden our analysis to include an extended sample of LPAs and CPBs. Furthermore, we explore

[27] In Appendix C, we also present additional results that expand on the set of fixed effects by including interactions between region and CPB, and alternative regression models using probit, Beta, and zero-inflated Beta regression (see Appendix C).

potential heterogeneity across prosthetic markets. Finally, we conclude with a review of robustness checks and extensions.

5.1 LPA sample

Table 2 displays the estimates of equation (1) for the LPA sample using the (log) net price as the outcome variable. All orthopedic prosthesis product markets are included: market fixed effects are included in the models reported in the latter two columns, while a single dummy variable to separate prostheses from pacemakers is included in the first four columns. The model specifications also vary regarding the inclusion of controls for the auction design and the organizational structure of the buyer.

The coefficient of interest is that on the $Treated$x$Post$ variable. Although it is always positive and significant, underscoring that the merger is associated with a price increase, it also displays remarkable variability across models. In line with the earlier discussion, the inclusion of procurement-related variables absorbs substantial price variability, as illustrated by comparing the models with and without these controls. We thus consider the sixth model our preferred one. This is based on both its statistical performance in terms of the adjusted R-squared and its adherence to the need to account for the different drivers of price variability. Under this model, the price increase is the smallest among the six models but still substantial: it corresponds to 15% price surge (which is obtained as $[(exp(\beta_2) - 1) * 100]$) or €51 thousand per lot.

Regarding the sign and magnitude of the other coefficients, they all appear reasonable. All else being equal, prices are lower under the most competitive procurement design (first price auctions) and higher under the least competitive one (negotiations). A higher (log) reserve price is also associated with a higher (log) net price: this association is in part mechanical, but it also captures the fact that lots with higher reserve prices have fewer competitors due to legal constraints tying the minimum firm size (in terms of past revenues or other metrics, depending on the specific tender) to the lot reserve price.[28] Finally, although not statistically significant across all specifications, other factors leading to lower prices include buyer organizational elements such as being subject to a budgetary plan and maturity. These findings are also reasonable as the latter variable represents the buyer's experience in purchasing medical devices, while the former indicates that the buyer is in a region under a budgetary program (*Piano di Rientro*), which requires efforts toward reducing healthcare costs.

In Table 3, we replicate the models described above, but this time we use the winning discount as the outcome variable.[29] in Recall that the winning discount is the rebate ex-

[28]Controlling for the logarithm of the reserve price is crucial, as evidenced by the significant increase in R-squared upon its inclusion. This variable also acts as a proxy for both the economic value and potential complexity of the procurement event. Additionally, it accounts for varying regulatory regimes that are triggered at different reserve price thresholds. Finally, our results remain qualitatively consistent whether we use dummy variables to categorize lots based on these threshold values or employ a continuous measure.

[29]The model specifications shown in Table 3 differ from those used for the Net Price analysis in Table 2. In Table 3 we replaced the continuous variable *Ln*(*Reserveprice*) with five dummy variables representing different procurement thresholds (i.e., reserve price levels above which special procurement regulations apply). This approach is effectively motivated by some key considerations. When performing regressions

Table 2: Baseline Estimates - Net Price (NP) - (LPA sample)

VARIABLES	(1) Ln(Np)	(2) Ln(Np)	(3) Ln(Np)	(4) Ln(Np)	(5) Ln(Np)	(6) Ln(Np)
Treated	-0.331***	-0.256***	-0.104***	-0.104***		
	(0.052)	(0.050)	(0.014)	(0.014)		
Treated x Post	0.338***	0.185***	0.140***	0.140***	0.143***	0.135***
	(0.064)	(0.062)	(0.018)	(0.018)	(0.018)	(0.017)
First Price		0.699***	-0.122***	-0.122***	-0.116***	-0.099***
		(0.079)	(0.028)	(0.029)	(0.029)	(0.030)
Negotiation		-0.079	0.203***	0.203***	0.193***	0.210***
		(0.062)	(0.021)	(0.021)	(0.022)	(0.022)
Scoring Rule		0.566***	-0.041*	-0.041*	-0.045*	-0.015
		(0.064)	(0.022)	(0.023)	(0.023)	(0.022)
Ln(Maturity)			-0.029***	-0.029***	-0.027***	-0.006
			(0.004)	(0.004)	(0.004)	(0.004)
Ln(Reserve Price)			0.940***	0.940***	0.939***	0.940***
			(0.005)	(0.005)	(0.005)	(0.005)
Budg. Plan			-0.048***	-0.048***	-0.044***	
			(0.011)	(0.011)	(0.011)	
Medical Device Ratio				-0.002	0.013	-0.068
				(0.038)	(0.038)	(0.042)
Constant	12.418***	12.124***	0.615***	0.616***	0.563***	0.519***
	(0.059)	(0.067)	(0.061)	(0.061)	(0.059)	(0.062)
Observations	5,632	5,632	5,632	5,632	5,632	5,632
Adjusted R-squared	0.042	0.128	0.920	0.920	0.920	0.923
FE Years	Yes	Yes	Yes	Yes	Yes	Yes
FE Market	No	No	No	No	Yes	Yes
FE Region	No	No	No	No	No	Yes

Note: Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

pressed as a percentage of the reserve price and, hence, negative coefficients in Table 3 represent lower discounts (i.e., higher procurement prices). Across all models, the merger effect is estimated to lower the discount. Focusing on the model in the sixth column, the coefficient indicates a decline of 7.6% of discount on the reserve price, corresponding (at the average lot reserve price) to €26 thousand per lot.

A rough back-of-the-envelope calculation implies that, if extended over the 2015-2019 period, such a lower winning discount cost the Italian NHS €190 million extra relative to what it would have paid absent the merger. This is calculated as follows. Since Italian Ministry of Health (2018) states that in 2017 the NHS spent €427 million on orthopedic devices, with lots awarded at an average rebate of 20% that year, assuming a counterfac-

involving price, it is crucial to factor in the lot size, represented by the reserve price, due to the absence of other characteristic variables. Although including procurement thresholds would be beneficial, they correlate highly with the reserve price, preventing the practical inclusion of both. For the Discount variable, this consideration is inherently accounted for by its construction (see footnote 21), avoiding the need to add the reserve price as a control and instead allowing the inclusion of procurement thresholds. We thank one of the referees for pointing out this aspect.

Table 3: Baseline Estimates - Discount - (LPA sample)

VARIABLES	(1) Discount	(2) Discount	(3) Discount	(4) Discount	(5) Discount	(6) Discount
Treated	0.049***	0.074***	0.058***	0.058***		
	(0.009)	(0.008)	(0.008)	(0.008)		
Treated x Post	-0.020*	-0.072***	-0.081***	-0.081***	-0.082***	-0.076***
	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
First Price		0.124***	0.086***	0.086***	0.083***	0.069***
		(0.016)	(0.016)	(0.016)	(0.016)	(0.018)
Negotiation		-0.138***	-0.137***	-0.137***	-0.130***	-0.141***
		(0.013)	(0.012)	(0.012)	(0.013)	(0.012)
Scoring Rule		0.065***	0.037***	0.037***	0.040***	0.024*
		(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Ln(Maturity)			0.023***	0.023***	0.022***	0.007***
			(0.002)	(0.002)	(0.002)	(0.003)
80,0000-208,999			0.051***	0.051***	0.051***	0.048***
			(0.004)	(0.004)	(0.004)	(0.004)
209,000-417,999			0.068***	0.068***	0.068***	0.068***
			(0.007)	(0.007)	(0.007)	(0.007)
418,000-999,999			0.102***	0.102***	0.103***	0.098***
			(0.009)	(0.009)	(0.009)	(0.009)
≥1,000,000			0.108***	0.108***	0.109***	0.106***
			(0.010)	(0.010)	(0.010)	(0.010)
Budg. Plan			0.037***	0.038***	0.034***	
			(0.006)	(0.006)	(0.006)	
Medical Device Ratio				0.002	-0.010	0.048*
				(0.023)	(0.023)	(0.025)
Constant	0.133***	0.128***	0.042***	0.042***	0.069***	0.093***
	(0.008)	(0.013)	(0.013)	(0.015)	(0.015)	(0.020)
Observations	5,632	5,632	5,632	5,632	5,632	5,632
Adjusted R-squared	0.045	0.264	0.306	0.306	0.311	0.340
FE Years	Yes	Yes	Yes	Yes	Yes	Yes
FE Market	No	No	No	No	Yes	Yes
FE Region	No	No	No	No	No	Yes

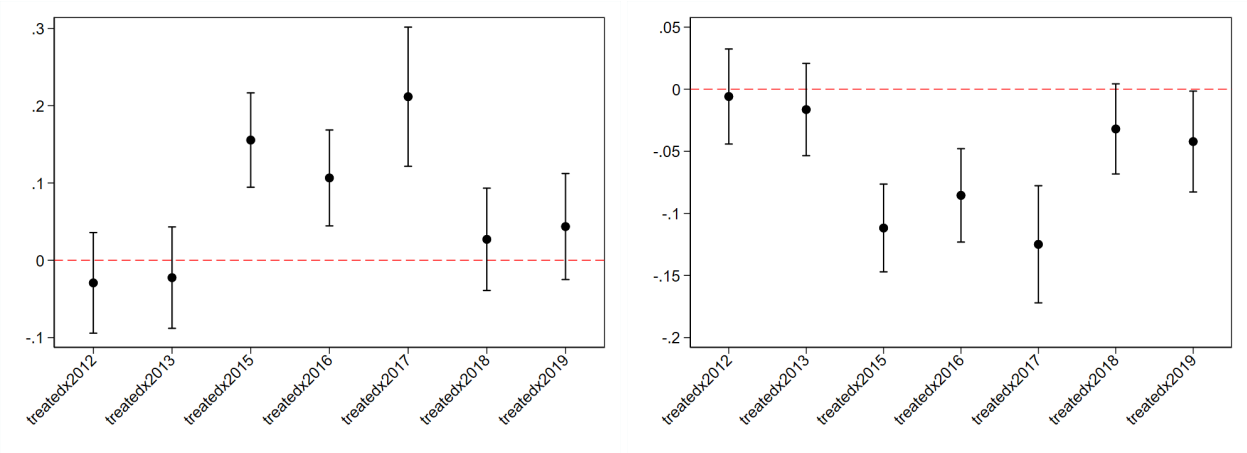
Note: Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

tual rebate of 27% (i.e., the baseline 20% discount increased by a conservative estimate of 7%), we have that, without the merger, the final expenditure would have been around €389 million, or €38 million lower than the actual amount. If we consider the entire period after the merger (2015–2019) and repeat this calculation for each year, the merger's impact on Italy's balance sheet would amount to about €190 million.

We consider the estimate of a discount drop of 7.6% from model six in Table 3 to be our best assessment of the causal impact of the merger on procurement cost. As extensively discussed earlier, although the net price is the typical focus of merger reviews and is the natural outcome of interest, the specificity of the procurement setting implies that the winning discount is the most adequate measure to capture variation in competition. Indeed, the fact that the implied effect is halved when using the winning discount relative to the net price squares well with the difficulty of adequately accounting for all of the procurement lot idiosyncrasies in the analysis using the net prices, a problem that is less severe when using the discount. Indeed, we would expect the two estimates to get closer as more controls are included, and this is precisely what we observe comparing more and less saturated models in Table 2 and Table 3. Regarding all other controls, they have the same sign and roughly the same significance level in Table 2 and Table 3, which is also

reassuring.

Figure 3: Heterogenous Impacts over Time (LPA sample)



(a) Ln(Net Price) **(b)** Discount

Next we turn to exploring the timing of the estimated impacts. Following the now classical, event-study approach of Autor (2003), we estimate the same model of column six in the previous two tables but include leads and lags by interacting the treatment dummy with a series of dummy variables, each taking the value of one starting in subsequent years. We exclude the one for 2014 to have the pre-merger year as a baseline. Figure 3 presents the coefficients of leads and lags estimated for both the net price outcome variable (left panel) and the discount (right panel).[30]

The result is qualitatively identical in both cases: the two coefficients on the two lead periods are not statistically significant, while those post-merger are (almost always) significant and with the expected sign. The most revealing finding from this exercise is that the merger has its strongest impact in the initial three years. Afterward, the effect remains indicative of a price increase, but the magnitude and the statistical significance are substantially attenuated. Indeed, if we look at the discount, the average effect of 7.6% that we illustrated earlier is due to a combination of an initial sharper drop of about 12% followed by a more modest drop of about 3%.

It is worth emphasizing that the pattern just described has been identified in several other studies on mergers. In particular, Focarelli and Panetta (2003) focuses their review of the effects of mergers among banks on the differences between short-run and long-run effects, showing that while the former result in adverse price changes, these are temporary. In the long run, price declines due to the efficiency gains dominating the market power effect. In our setting, in addition to their plausible explanation of efficiencies requiring time to materialize, we also have qualitative evidence indicating a gradual increase in participation in the call for tenders in the later years. Since the merger was indeed allowed

[30]To check if the difference in the magnitude of the estimated effects in the initial three years post-merger and in the subsequent phase are robust, in Table C.1 in Appendix C we show the results from estimating the preferred specification of the baseline model for an increasing number of years post-treatment.

because the authority considered that the barriers to entry were not capable of precluding entry, the fact that higher lower discounts (and, hence, higher profits) attracted entry by more bidders is also reasonable. Clearly, the welfare interpretation of the merger effect under the two scenarios would differ, but it would also remain unclear absent a very thorough investigation of multiple outcomes that we do not aim to conduct in this study. Although, on the surface, creating efficiency might suggest greater welfare benefits than merely welcoming existing players, a thorough evaluation should also consider the advantages that increased entry might offer. This includes enhancing new entrants' incentives to invest and innovate, as well as strengthening the resilience of the hospitals' supply chain through their presence.

5.2 Full sample (LPA + CPB)

The first extension of our baseline findings involves repeating the analysis from the previous section on a different sample that includes both LPAs and CPBs.

Table 4: Net Price (NP) Effects in the Full sample (LPA + CPB)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Ln(Np)	Ln(Np)	Ln(Np)	Ln(Np)	Ln(Np)	Ln(Np)
Treated	-0.346***	-0.216***	-0.109***	-0.105***		
	(0.052)	(0.049)	(0.013)	(0.013)		
Treated x Post	0.085	-0.127**	0.086***	0.086***	0.091***	0.112***
	(0.067)	(0.063)	(0.017)	(0.017)	(0.017)	(0.017)
First Price		0.683***	-0.145***	-0.143***	-0.133***	-0.084***
		(0.079)	(0.028)	(0.028)	(0.028)	(0.030)
Negotiation		-0.171***	0.203***	0.203***	0.199***	0.213***
		(0.062)	(0.021)	(0.021)	(0.022)	(0.021)
Scoring Rule		0.692***	-0.048**	-0.041*	-0.041*	-0.020
		(0.062)	(0.021)	(0.022)	(0.022)	(0.022)
Ln(Maturity)			-0.025***	-0.028***	-0.026***	-0.006
			(0.004)	(0.004)	(0.004)	(0.004)
Ln(Reserve Price)			0.946***	0.948***	0.946***	0.945***
			(0.004)	(0.004)	(0.004)	(0.004)
Budg. Plan			0.001	-0.004	0.001	
			(0.010)	(0.011)	(0.011)	
CPB				-0.034**	-0.033**	
				(0.016)	(0.016)	
Constant	12.435***	12.074***	0.522***	0.499***	0.450***	0.425***
	(0.058)	(0.066)	(0.051)	(0.054)	(0.052)	(0.058)
Observations	6,660	6,660	6,660	6,660	6,660	6,660
Adjusted R-squared	0.025	0.150	0.927	0.927	0.927	0.932
FE Years	Yes	Yes	Yes	Yes	Yes	Yes
FE Market	No	No	No	No	Yes	Yes
FE Region x CPB	No	No	No	No	No	Yes

Note: Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

There are pros and cons to including CPBs. On the pros, it allows us to account for the activities of a growing and increasingly significant type of public buyer. On the cons, we cannot measure several organizational variables for CPBs that are structurally different

from LPAs.[31] Nevertheless, it is interesting to report the findings on the broader sample. As before, we present the estimates for the net price (Table 4) and for the winning discount (Table 5).

Table 5: Discount Effects in the Full sample (LPA + CPB)

VARIABLES	(1) Discount	(2) Discount	(3) Discount	(4) Discount	(5) Discount	(6) Discount
Treated	0.048***	0.076***	0.067***	0.061***		
	(0.008)	(0.008)	(0.008)	(0.008)		
Treated x Post	-0.001	-0.050***	-0.052***	-0.052***	-0.055***	-0.065***
	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
First Price		0.119***	0.097***	0.094***	0.089***	0.057***
		(0.016)	(0.016)	(0.016)	(0.016)	(0.018)
Negotiation		-0.139***	-0.137***	-0.137***	-0.134***	-0.143***
		(0.013)	(0.012)	(0.012)	(0.012)	(0.012)
Scoring Rule		0.071***	0.048***	0.037***	0.037***	0.026**
		(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Ln(Maturity)			0.017***	0.022***	0.020***	0.008***
			(0.002)	(0.002)	(0.002)	(0.003)
80,0000-208,999			0.058***	0.057***	0.058***	0.053***
			(0.004)	(0.004)	(0.004)	(0.004)
209,000-417,999			0.074***	0.074***	0.075***	0.073***
			(0.007)	(0.007)	(0.007)	(0.007)
418,000-999,999			0.107***	0.103***	0.105***	0.098***
			(0.008)	(0.008)	(0.008)	(0.008)
≥1,000,000			0.113***	0.103***	0.106***	0.105***
			(0.008)	(0.009)	(0.009)	(0.009)
Budg. Plan			0.004	0.011*	0.008	
			(0.006)	(0.006)	(0.006)	
CPB				0.049***	0.048***	
				(0.009)	(0.009)	
Constant	0.137***	0.126***	0.049***	0.051***	0.085***	0.114***
	(0.008)	(0.013)	(0.013)	(0.013)	(0.013)	(0.016)
Observations	6,660	6,660	6,660	6,660	6,660	6,660
Adjusted R-squared	0.043	0.264	0.296	0.300	0.304	0.355
FE Years	Yes	Yes	Yes	Yes	Yes	Yes
FE Market	No	No	No	No	Yes	Yes
FE Region x CPB	No	No	No	No	No	Yes

Note: Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

The estimates in both tables indicate qualitatively similar results to our baseline. Specifically, we find that in the larger sample, the effect is somewhat diminished. For example, regarding the winning discount, the estimated effect of the merger in the more credible models, which include at least controls for procurement design, ranges from a drop in the

[31] Indeed, we should also consider that: *1)* Limiting the sample to LPAs improves comparability among observations. *2)* This allows us to account for the potential confounding effect of LPA "competence" in procurement by including balance sheet data, which has been deemed relevant by literature (Bucciol et al., 2020). *3)* The DPCM 24/12/2015 was implemented right after the merger, so excluding auctions awarded through CPBs prevents bias from procurement centralization. However, these issues are less severe in practice: we can partially control CPB effects with a dummy variable; enforcement of the DPCM was not strict, and many CPBs were nonfunctional, while others followed its provisions even before 2016. Additionally, including CPB-awarded lots enlarges the sample and extends the period by one year (2019).

discount of 4.7% to 6.3%. Therefore, while the effects are smaller than the baseline, the implied cost increase is still significant.

Interestingly, lots awarded through a CPB show an increase in the winning discount of a magnitude analogous to that of the merger effect (around 4%) if compared to those awarded by the other types of buyers. Estimating public expenditure as previously discussed, a counterfactual scenario of a 6 percentage point average discount increase for treated observations would result in €161 million total savings for Italy's accounts from 2015 to 2019.

5.3 Product-specific estimates

To investigate the presence of heterogeneity across product markets, we replicated the previous analyses for each specific market of orthopedic prostheses using the LPA sample. Utilizing the model 6 specification from Table 2 and Table 3, we present in Table 6 the estimates of the interaction parameters ($TreatmentxPost$) for the net price (top panel) and the winning discount (bottom panel).

Table 6: Merger Impacts by Product Market (LPA sample)

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(NP)	Ln(NP)	Ln(NP)	Ln(NP)	Ln(NP)	Ln(NP)
VARIABLES	hip	knee	shoulder	spine	trauma	unic. knee
Treated x Post	0.159***	0.260***	0.164**	0.230***	0.133***	0.161
	(0.030)	(0.058)	(0.066)	(0.036)	(0.021)	(0.129)
Constant	0.373	0.249	-0.031	-1.089***	-0.304*	-0.285
	(0.250)	(0.307)	(0.295)	(0.286)	(0.181)	(0.331)
Observations	2,181	1,770	1,708	2,153	3,420	1,634
Adjusted R-squared	0.937	0.936	0.939	0.919	0.924	0.939
FE Years	Yes	Yes	Yes	Yes	Yes	Yes
FE Market	Yes	Yes	Yes	Yes	Yes	Yes
FE Region	Yes	Yes	Yes	Yes	Yes	Yes
Treated obs.	583	172	110	555	1822	36

	(1)	(2)	(3)	(4)	(5)	(6)
	Discount	Discount	Discount	Discount	Discount	Discount
VARIABLES	hip	knee	shoulder	spine	trauma	unic. knee
Treated x Post	-0.096***	-0.171***	-0.099**	-0.121***	-0.073***	-0.103
	(0.018)	(0.034)	(0.041)	(0.021)	(0.012)	(0.075)
Constant	0.201	0.303*	0.466***	0.762***	0.685***	0.656***
	(0.139)	(0.167)	(0.159)	(0.155)	(0.094)	(0.176)
Observations	2,181	1,770	1,708	2,153	3,420	1,634
Adjusted R-squared	0.320	0.340	0.338	0.326	0.346	0.357
FE Years	Yes	Yes	Yes	Yes	Yes	Yes
FE Market	Yes	Yes	Yes	Yes	Yes	Yes
FE Region	Yes	Yes	Yes	Yes	Yes	Yes
Treated obs.	583	172	110	555	1822	36

Note: Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Although all product markets experience price increases associated with the merger, we find evidence of some heterogeneity. Knee and spine prostheses are the ones reg-

istering the highest increases, followed by shoulder and hip, while trauma is the least affected.[32] These results have some associations with the evolution of the HHI described earlier: (primary and unicondylar) knee prostheses registered HHI increases in the period after the merger; the shoulder market witnessed a relatively small growth in the HHI in 2015 and then a slow decline, but starting from a concentration level that was already very high (HHI above 0.30); for the hip market, the change in the HHI was similar to the shoulder one, but the concentration level post-merger kept being relatively low. The only surprising findings are for spine prostheses, which showed barely no change in HHI in 2015 and a steady decline in the following years, and for trauma prostheses, whose HHI remained stable over time. However, it is worth reminding that concentration indexes serves just as an initial indicator of the degree of competition in a market, but they are clearly unable to capture comprehensively all the competitive constraints faced by market participants.[33]. Nonetheless, apart from the spine prostheses, we can conclude that the relative magnitude of the estimated effects for individual product markets matches quite accurately the changes in their concentration levels.

As a final note, the unicondylar knee prostheses sector in column six presents an interesting result. Recall this market was the most directly involved in the remedies. It is, therefore, of special interest to analyze the effect of mergers on this market. Although our sample contains a very limited number of observations (36) for this type of prosthesis purchases, leading to an imprecisely estimated coefficient, its magnitude is indicative of an effect that is smaller than those of the other knee products but still close to the merger average treatment effect. The fact that for such a concentrated market prices do not appear to have significantly increased relative to other treated products is indicative of the positive effects of the merger remedies.[34]

5.4 Robustness checks

In this section, we explore the robustness of our baseline with respect to the non-linearity of the regression model. This involves the use of non-linear regression models for the discount outcome variable. We only briefly report the outcomes of this analysis here, while all of its findings are detailed in Appendix D. The motive for looking at alternative functional forms when modeling the winning discount is twofold. The first motive is that the conditional distribution of the errors of the winning discount is not normal as the discount is expressed in percentage terms, thus being defined only on the interval $[0, 1)$. To deal with this "fractional outcome," we can use a beta distribution for the response variable.[35] The second motive is that the data present is a mass point at zero in the winning

[32] Note that the results for the knee sector in column two pool together all the different knee product markets: unicondylar, revision, and primary implants.

[33] This is clearly demonstrated, for example, by the fact that concentration thresholds used by competition authorities to consider mergers potentially harmful for competition may change over time (as the recent case of the 2023 Merger Guidelines in the US).

[34] The findings are qualitatively similar for the full sample (LPA+CPB) as shown in Appendix D. However, as observed before, all product-specific estimates are attenuated when including the CBPs in the sample.

[35] The literature offers various approaches to deal with this type of "fractional outcome," ranging from simply ignoring this feature to sophisticated methods like those in Papke and Wooldridge (1996) and Ramalho et al. (2011).

discount distribution. This conflicts with the beta distribution not being defined at the boundary values 0 and 1. To cope simultaneously with these two problems, in Appendix C, we report the results following the method by Ospina and Ferrari (2012), which entails adapting the beta distribution to allow for the value 0 (the so-called "Zero Inflated Beta Regression," ZIBR). We also consider a series of alternative models (logit and beta) and sample splits (with and without the cases of zero winning discount). To summarize these results, we consistently find that the merger had a negative and significant impact on the winning discount. The magnitude is attenuated relative to the baseline case presented here, and our favorite ZIBR model specification entails a drop in the winning discount due to the merger of 5.5%.

6 Insights

6.1 Heterogeneous Effects by Age and Gender

To provide a tangible idea of the merger's impact on the NHS (and indirectly patients), we conducted a "back-of-the-envelope calculation" to estimate the prosthesis price increase per patient and the distribution of additional costs over different demographic groups in a typical year.[36]

Table 7: Heterogenous impacts in terms of hypothetical merger extra costs by age class and gender

	Male		Female	
Age	**Mln €**	**%**	**Mln €**	**%**
<45	0.3	1%	0.1	1%
45–54	0.7	3%	0.5	3%
55–64	1.5	7%	1.8	9%
65–74	2.4	12%	4.3	22%
75–84	1.9	10%	4.3	22%
≥85	0.5	2%	1.4	7%
Tot	7.2	37%	12.5	63%

Data on patient demographics were obtained from the Italian NHS RIAP report.[37] RIAP data covers the 2007-2021 period and collects data on hip, knee, and shoulder pros-

[36] It is important to note that the extra cost estimates concerning patients are speculative since the Italian NHS covers the full cost increase without any co-payment required from patients. However, the burden will eventually shift to patients through increased taxation to fund the additional costs. The results are intended to illustrate how the additional costs would be distributed in the absence of the NHS.

[37] The Italian arthroplasty registry (Registro Italiano di ArtroProtesi – RIAP) is a project funded by the Italian Ministry of Health – Directorate General of Medical Devices and Pharmaceutical Service, and coordinated by the Italian National Institute of Health. It started in 2006 with the aim of organizing the national registry, a systematic data collection of all the joint replacements (hip, knee, shoulder, and ankle) performed at the national level.

thesis implants, as well as the patients' demographics. RIAP data is collected from regions, Local Health Authorities (LHAs), and hospitals that adhere to the project. From 2007 to 2021, 16 regions, 3 LHAs, and 3 hospitals have collaborated with RIAP, although not every participant did so continuously. Hip and knee prosthesis data have been available since 2007, while data on shoulder prostheses have been available from 2017 onwards. Overall, RIAP collected data on about 25% of the total medical procedures of interest in the observed period, 85.9% of which were deemed suitable for analysis, for a total of 584,116 interventions (RIAP, 2022).

The calculation of the additional cost incurred by the NHS in a typical year pertains solely to hip, knee, and shoulder prostheses, as RIAP data is restricted to these categories. This calculation was carried out in three stages. First, we retrospectively estimated the reference prices for auctions in 2014—the year before the merger—by combining the average discounts obtained through auctions with their final prices. Next, we applied our estimation of "lost discounts"—the decrease in discounts following the merger—to these reference prices to quantify the post-merger additional cost faced by the NHS for each prosthesis type. Finally, assuming that the RIAP patient sample is representative of the general population receiving implants, we used RIAP data to allocate the extra cost across patient demographics. Our findings indicate that over 50% of the additional cost has been attributed to prostheses for women over 65 years old.

The additional cost per patient following the merger was also calculated by dividing the total extra cost per prosthesis type (hip, knee, and shoulder) by the estimated number of patients. The total number of patients was estimated considering that RIAP recorded 25% of the total prosthesis implants and that only 85.9% of its data were reported in the report. The estimated extra cost per patient is €107 on average. Specifically, the extra cost per patient is €108 for hip prosthesis implants, €106 for knee prosthesis implants, and €88 for shoulder prosthesis implants.

6.2 Quality Impacts in the Short and Long Run

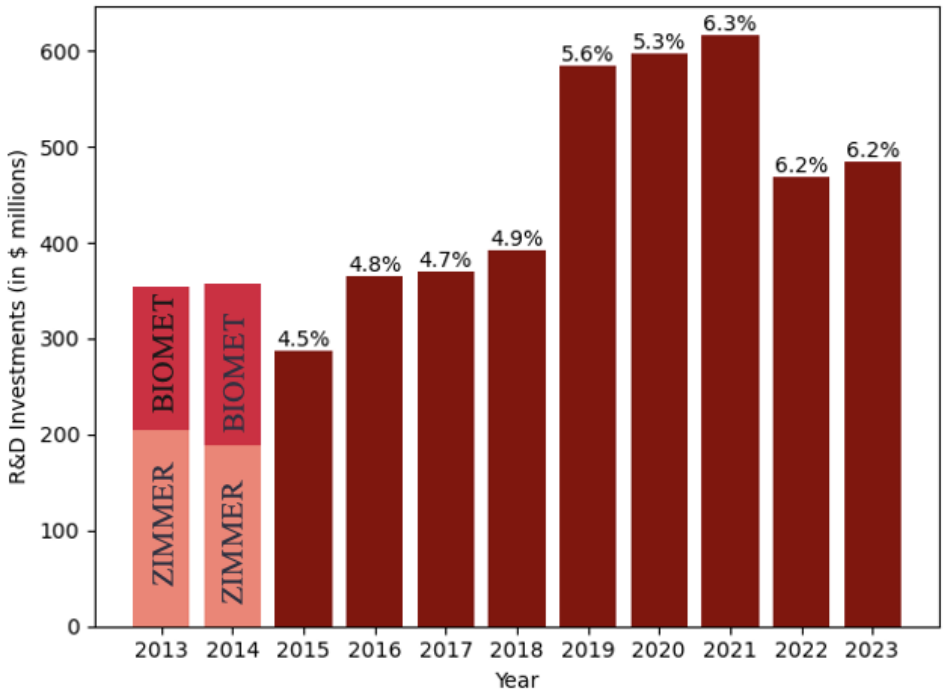
Quality impacts are examined using different data sets for both the short and long term. For the short term, we utilize the RIAP data described in the previous section, while for the long term, we analyze company R&D expenses and patent activity.

In the short run, we will use the RIAP data to assess the increased failures of the prostheses produced by Zimmer Biomet. In principle, the RIAP data should allow for a thorough analysis of this kind as they can be used to measure changes in the incidence of revision interventions for patients who had received Zimmer Biomet prostheses in primary (elective) interventions.[38] Due to data privacy concerns, we examined only a subset of regions (Campania, Puglia, and the Autonomous Province of Trento) where it was possible to ensure patient traceability throughout 2017.

Using these data, a series of econometric models were estimated to identify whether Zimmer Biomet products installed in 2017 in primary (elective) interventions led to a

[38] Despite initiating a research collaboration with RIAP to explore these specific aspects, the variations in patient privacy protection across regions and over time rendered this analysis only partially informative.

Figure 4: Zimmer Biomet R&D Investments in Absolute and Relative Terms Over Time



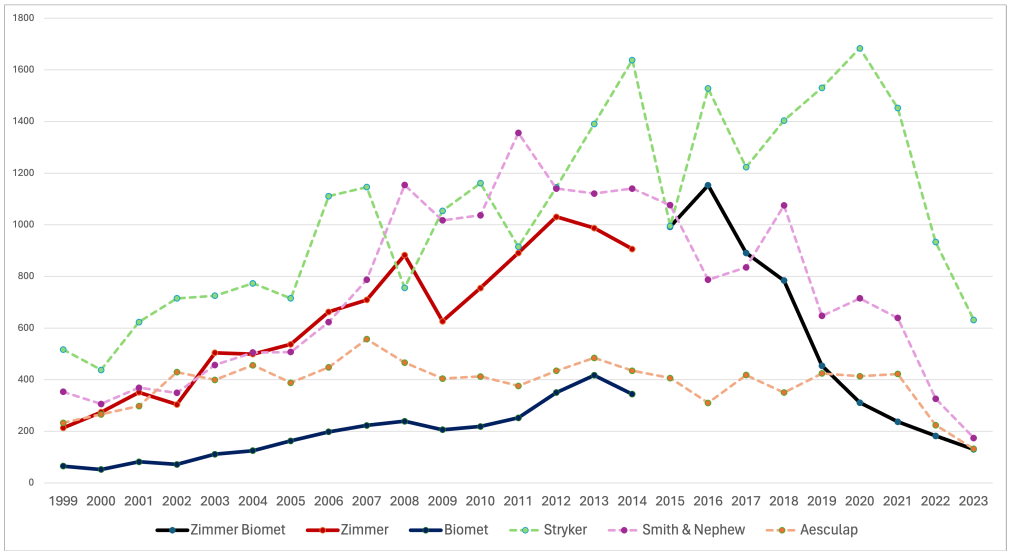
higher incidence of revision interventions. None of the models revealed any indication of more revisions associated with Zimmer Biomet products than with other producers.[39]

Concerning long-term quality effects, we first analyze firm-level research and development (R&D) expenditures using data from Zimmer Biomet's financial reports. Figure 4 shows distinct post-merger phases: expenses remained stable for the first four years, then increased significantly starting in 2019 as R&D expenses grew in absolute terms and relative to net sales. Despite the downturn caused by the COVID-19 pandemic in 2020, R&D spending increased further in 2021, reaching a record 600 million US dollars.

The assessment changes when we shift the focus from R&D expenses to patent activity. Possibly reflecting the first four years post-merger of stagnant R&D or adjustments in the patenting strategy, we observed a significant drop in patent applications after 2016. In Figure 5, we present the annual patent applications of Zimmer Biomet and its competitors before and after the transaction. Before the merger, Zimmer and Biomet exhibited consistent growth in patent activity. However, after the merger, Zimmer Biomet experienced a sharp decline, dropping from 807 patents filed in 2016 to 130 in 2023. This downward trend was also observed among Zimmer Biomet's close competitors, Stryker and Smith & Nephew, albeit with more variability. In general, these findings suggest that

[39] A notable limitation of this analysis is the short duration of the time window considered. The UK Orthopaedic Data Evaluation Panel (ODEP) recommends a minimum of three years to evaluate prosthetic products properly.

Figure 5: Patenting Activity of Zimmer Biomet and Competitors before and after the Merger



Note: This graph is based on patenting activity data from the Orbis database (2024) and includes all product segments of the companies, not only the markets affected by the transaction. For this reason, we have excluded two major competitors, Johnson&Johnson and Medtronic, as it is not feasible to isolate their orthopedic segments (e.g., DePuy Synthes for Johnson&Johnson) from their entire business portfolio. Due to the substantial volume of patents filed by these two multinational companies every year, their inclusion would overwhelm the graph and detract from our sector-specific analysis.

the entire market has experienced a decrease in patent activity in recent years.[40]

6.3 Coordinated Effects

In merger evaluations, antitrust authorities typically devote part of their assessment to analyzing the risk of shifting from competition to collusion due to a merger.[41] Alternatively, if collusion already is at play, the merger could strengthen it. Depending on the jurisdiction, this type of merger effect on the firms' conduct is referred to as joint dominance or coordinated effects. It is, therefore, particularly fitting that, in the context of an ex-post-merger review, the analysis looks for indications of potential collusion.

In our case, this is even more relevant than in conventional markets because pub-

[40] Indeed, the Orbis data indicate a broad decline in patent applications also in the pharmaceutical sector starting around 2014. In Appendix A, we present a detailed analysis by exploring the six classes of patents to which the products of Zimmer Biomet belong, and, despite small differences, we confirm a systematic drop across all patent classes.

[41] In the language of the EU Merger Guidelines (22(b)): "...horizontal mergers may significantly impede effective competition by changing the nature of competition in such a way that firms that previously were not coordinating their behavior, are now significantly more likely to coordinate and raise prices or otherwise harm effective competition. A merger may also make coordination easier, more stable or more effective for firms which were coordinating before the merger."

lic procurement auctions are well known to tick all the boxes for the structural factors that facilitate collusion, from demand predictability to stability of the bidders and transparency of the winner selection procedures (Porter and Zona, 1993). Moreover, in our setting, the largest players are also characterized by a significant extent of common ownership, which is another factor that has been claimed to favor collusive behavior (Azar et al., 2018).[42] Finally, even the presence of a remedy involving the divestment to a competitor may favor collusion (Compte et al. (2002)).

A vast and growing body of literature focuses on detecting cartels in auctions using statistical methods, such as screens (see Kawai and Nakabayashi (2022) for a recent review). However, this approach has two significant limitations. First, screening is intended only to signal a potential competition violation, not to provide conclusive evidence. Second, most advanced tests require detailed data tracking firm entry, bidding, and subcontracting across multiple procurement auctions (Conley and Decarolis, 2016). Affected by the first limitation and lacking the data to address the second, our analysis must be considered a very basic attempt at examining collusion, and by no means do its results imply the existence (or absence) of collusive agreements. With this caveat, we proceed by explaining the two tests, the detailed results of which are in Appendix E.

The first test looks at entry: in this case, we adapt our DiD framework and test whether the merger increased the frequency of single-participant auctions. On the contrary, we find that this type of auction, where there is no competition, became less common post-merger in the treated units. The second test looks at bidding: in the pre-merger data, we estimated the impact of changing the number of bidders on the winning discount, and then we assessed whether the confidence interval of this estimate contains the value that we indicated earlier as our baseline causal effect of the merger. Using 7.6 percent as our baseline causal effect, we systematically find it to be within the confidence interval of our test; thus, the evidence does not support the hypothesis of collusion post-merger. In the appendix, we explore variations of both the entry and bidding tests: in all cases, we fail to find evidence of post-merger collusion.

7 Conclusion

This study examines the ex-post effects of a significant concentration episode among the suppliers of orthopedic prosthetics. This is a key sector for healthcare procurement in most developed countries. In the case of Italy, it represents the highest public expenditure on medical devices. The exogenous nature of the merger relative to the Italian public procurement market as well as the availability of detailed, contract-level data for the latter allowed us to estimate the price effects of the merger which we find to be substantial.

Furthermore, this study explores a series of additional results, including heterogeneous impacts across *i)* product markets both for those markets subject to remedies and for those not; *ii)* years since the merger; and *iii)* patients belonging to different demographic groups. To enhance a more comprehensive assessment of the multifaceted effects of the merger in terms of products' quality, the analysis in this study also involves mea-

[42] See Appendix A and, in particular, the discussion of Figure A.6 for additional details.

sures of prostheses failure risk, patenting, and R&D activities. Finally, to address potential changes in firms' conduct triggered by the merger, it presents a tentative assessment of whether changes in entry and bidding post-merger are suggestive of greater collusion risk.

Overall, the findings highlight that the harmful effect of the merger for consumers might not be limited to higher prices but might also involve reduced innovation and that the burden of this worse outcome would fall disproportionately on a subgroup of patients (older female patients). Among the policy implications of this study, it is therefore paramount to stress the relevance of continued merger review enforcement, especially in cases like that of the Zimmer/Biomet merger, which generated the top global producer of orthopedic prostheses. A second implication is the need for improved coordination between antitrust policies and public procurement, especially given how merger effects will likely play out differently depending on the features of the procurement system.[43] Finally, although our assessment of coordinated effects is far from being exhaustive, it nevertheless reveals the usefulness of combining different tools of competition policy: markets with larger mergers represent the ideal setting in which to conduct *ex officio* investigations for post-merger collusion. Miller and Weinberg (2017) indicate the relevance of this type of approach for consumer products, but the applicability of this idea goes beyond those types of markets and applies well in procurement settings like the one in this study.

[43] In addition to the previous points, it is important to note that the tools used by authorities to evaluate merger effects in procurement markets are less sophisticated than those used in conventional product markets. This discrepancy is partly due to the nature of public procurement, where purchases are lumpy and defining markets and market shares is challenging. In footnote 6 on page 5 of the final ruling regarding the Zimmer-Biomet merger, the EC deemed bidding data (information on procurement auctions, often publicly available) as "unsuitable for conducting a meaningful analysis" (European Commission, 2015). A rigorous quantitative analysis of substitution patterns was unattainable in this case. As a result, the EC relied on expert opinions and market participant input to establish the market definition. The Small but Significant and Non-transitory Increase in Prices (SSNIP) test was also conducted through inquiries directed at market participants (refer to page 17 of the ruling). To address this challenge, the EC evaluated the merger's impact under various product market definitions. Concerning market shares, the EC's only option for approximating them was by requesting volume and sales data directly from producers and third-party collectors.

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Procuring Medical Devices: The Price Effect of Mergers among Orthopedic Prostheses Producers Web Appendix

Appendix

A. Additional Details on the Data

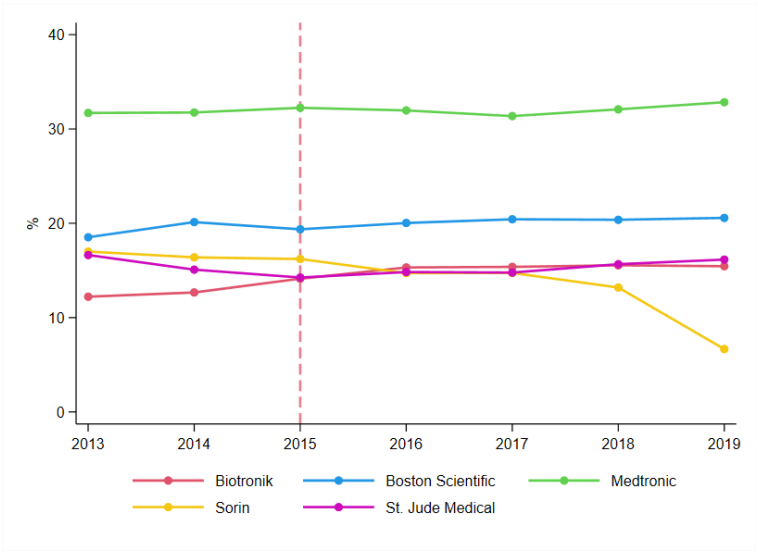
The data used in this study are the combination of multiple data sources listed below and for which we report additional details in this section of the appendix:

- Procurement data from ANAC: https://dati.anticorruzione.it/opendata
- Consumption flow data: https://www.salute.gov.it/portale/dispositiviMedici/dettaglioContenutiDispositiviMedici.jsp
- LHS balance sheet data: https://www.salute.gov.it/portale/temi/p2_6.jsp?lingua=italiano&id=1314&area=programmazioneSanitariaLea&menu=dati
- Patient demographics from the yearly report of RIAP published on November 7, 2023: https://riap.iss.it/riap/it/it/download/11564/?tmstv=1715687797
- Orbis patent data: https://www.moodys.com/web/en/us/capabilities/company-reference-da orbis.html
- R&D data from the financial statements of Zimmer (Zimmer Biomet post merger): https://investor.zimmerbiomet.com/financial-information/quarterly-results/ 2024; and of Biomet (for 2013 and 2014): https://investor.zimmerbiomet.com/~/media/Files/Z/ZimmerBiomet-IR/press-release/09-07-2014-biometannouncesfourthqua pdf
- Ownership data from: https://finance.yahoo.com/ and https://www.marketscreener.com/

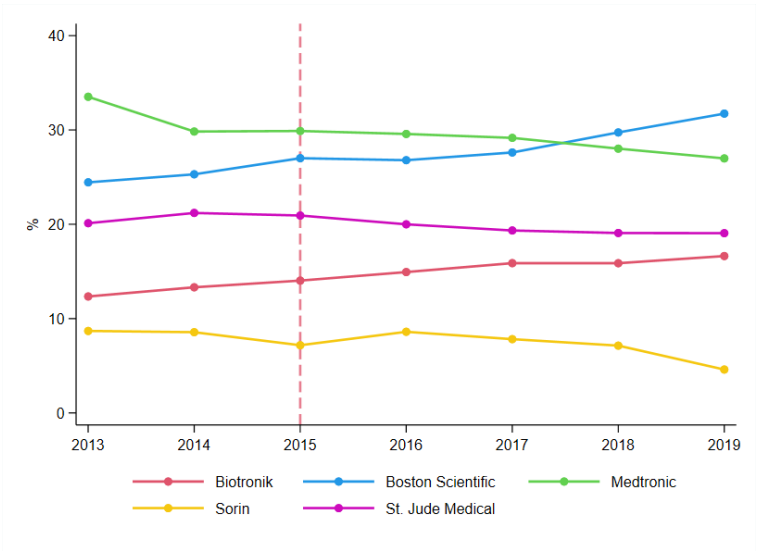
Consumption Data Flows

The data used to calculate the HHI is obtained from the Italian Ministry of Health's Consumption Flows Data. Table A.1 presents a breakdown of expenditures statistics by year and market.

Figure A.1: Market shares of the first 5 companies.



(a) Pacemakers



(b) Implantable Defibrillators

Note: Source: *Consumption Flows of medical devices* (Italian Ministry of Health, 2017). Pacemakers are identified through the CND code J0105, while implantable defibrillators are identified through the code J010.

Table A.1: Consumption Flows Data

Market	Year	Yearly expenditures	Average amount	Rank of Zimmer	Rank of Biomet	HHI
Hip	2013	119.566.711	3688	1	5	0,09289
Hip	2014	132.917.502	5837	1	4	0,08492
Hip	2015	130.796.963	5923	1	1	0,10941
Hip	2016	134.086.978	6650	1	1	0,10153
Hip	2017	130.085.693	6607	1	1	0,10022
Hip	2018	128.800.603	5665	1	1	0,09671
Hip	2019	123.695.013	5060	1	1	0,10191
Primary Knee	2013	41.979.232	5668	1	3	0,13856
Primary Knee	2014	46.003.917	7556	1	3	0,14549
Primary Knee	2015	46.481.850	8363	1	1	0,20392
Primary Knee	2016	48.291.921	7023	1	1	0,19624
Primary Knee	2017	47.258.090	7254	1	1	0,19368
Primary Knee	2018	46.218.826	5889	1	1	0,18769
Primary Knee	2019	42.563.881	5101	1	1	0,17462
Revision Knee	2013	6.971.889	2971	1	5	0,39010
Revision Knee	2014	8.099.745	4405	1	5	0,40431
Revision Knee	2015	8.347.357	3182	1	1	0,41406
Revision Knee	2016	8.641.467	3856	1	1	0,36354
Revision Knee	2017	9.116.796	3353	1	1	0,38304
Revision Knee	2018	10.161.840	3230	1	1	0,34913
Revision Knee	2019	10.197.838	3798	1	1	0,32906
Unicondylar Knee	2013	2.617.740	3812	2	1	0,17141
Unicondylar Knee	2014	2.715.344	3611	1	2	0,16896
Unicondylar Knee	2015	2.530.541	2763	1	1	0,15738
Unicondylar Knee	2016	2.688.238	3999	1	1	0,15107
Unicondylar Knee	2017	2.885.744	3323	1	1	0,17854
Unicondylar Knee	2018	2.789.008	2780	1	1	0,20931
Unicondylar Knee	2019	3.056.866	2935	1	1	0,20391
Shoulder	2013	8.354.152	2267	2	5	0,36762
Shoulder	2014	10.238.431	2881	2	5	0,30711
Shoulder	2015	11.006.446	2524	2	2	0,32044
Shoulder	2016	11.598.026	2573	2	2	0,28914
Shoulder	2017	12.417.244	2867	2	2	0,27339
Shoulder	2018	12.593.177	2419	2	2	0,27481
Shoulder	2019	13.376.473	2275	2	2	0,29449
Spine	2013	39.706.017	7071	3	16	0,15368
Spine	2014	44.046.190	10683	3	17	0,14157
Spine	2015	45.696.914	10837	3	3	0,14420
Spine	2016	46.193.357	10635	5	5	0,13900
Spine	2017	48.778.444	10745	6	6	0,12740
Spine	2018	53.423.188	8745	6	6	0,11094
Spine	2019	54.460.283	8669	7	7	0,10323
Trauma	2013	108.662.161	2481	3	12	0,12313
Trauma	2014	131.014.759	3518	3	11	0,12659
Trauma	2015	138.738.193	3492	3	3	0,12909
Trauma	2016	146.566.471	3237	3	3	0,13025
Trauma	2017	149.335.326	2870	3	3	0,12714
Trauma	2018	158.880.043	2879	3	3	0,12270
Trauma	2019	165.356.739	3175	3	3	0,12387

Note: Source: Consumption Flows of medical devices (Italian Ministry of Health, 2023). The table shows some summary statistics on the Consumption Flows data, which report the yearly expenditure of each LHA by medical device. Medical devices have been grouped in product markets according to the CND classification, explained in the notes of Figure 1. Column [3] shows the total annual purchased amount across all LHA; column [4] shows the average purchased amount by LHA for medical devices belonging to a given product market; column [5] and [6] indicates the rank of Zimmer and Biomet in a given year and product market on the basis of the value of medical devices sold to all the LHA; column [6] shows the HHI index by year and product market as plotted in Figure 1.

This information is also used for the control analysis, as shown in Figure A.1, which illustrates the composition of leading producers in the pacemaker market. The CND codes (*Classificazione Nazionale dei Dispositivi Medici*) corresponding to the markets of implants represented are: P0908 for hip, P0901 for shoulder, P090903 for primary knee, P090904

for unicondylar knee, P090905 for revision knee, P0907 for spine, P0912 for trauma, J0105 and J010 for pacemakers and defibrillators (averaged and labeled as "pacemaker" in the plot).

Patent Data

In this section, we delve into a sector-level analysis to comprehend how patents have evolved in the treated markets over the recent period. To delineate the different prosthesis sectors under examination (i.e., knee, elbow, spine, hip, and shoulders) we used the International Patent Classification ('IPC') system. This system, maintained by the World Intellectual Property Organization (WIPO), stands as one of the most precise classification systems available. The IPC follows a hierarchical structure, subdivided into sections, classes, subclasses, groups, and subgroups. We identified the following specific subgroups of prostheses: (i) *A61F2/38 Knee – Elbow*; (ii) *A61F2/58 Elbow – Wrists*; (iii) *A61F2/64 Knee Joints*; (iv) *A61F2/32 Hip*; (v) *A61F2/40 Shoulders*; (vi) *A61F2/44 Spine*. Figure A.2 illustrates the scheme of the IPC classification for our treated subgroups

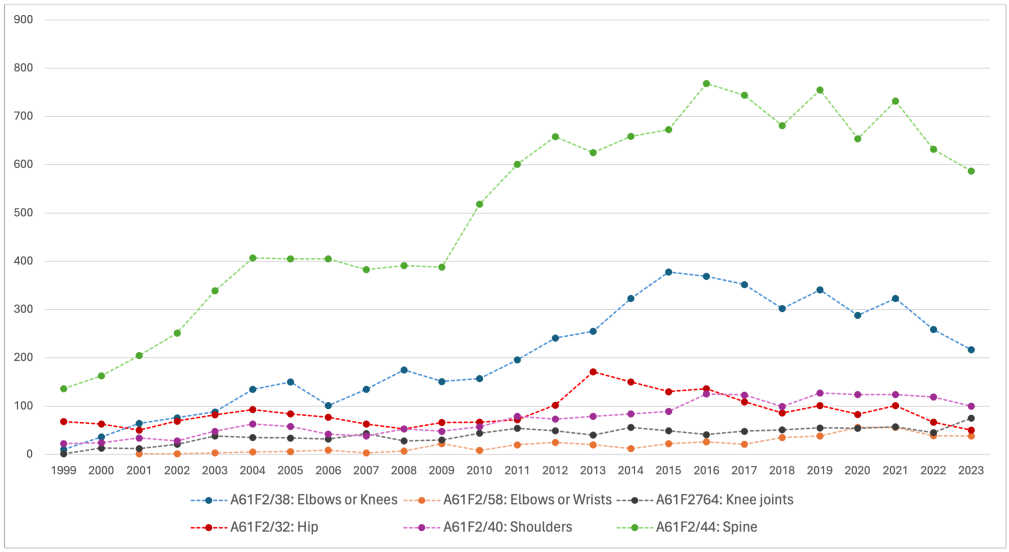
Figure A.2: IPC classification for Treated Markets

Level	Symbol	Description
Section	A	Human necessities
Class	A61	Medical or Veterinary Science, Hygiene
Subclass	A21F	Filters implantable into blood vessels; prostheses; devices providing patency to, or preventing collapsing of, tubular body structures, e.g., stents; orthopaedic, nursing or contraceptive devices; fomentation; treatment or protection of eyes or ears; bandages, dressings or absorbent pads; first-aid kits."
Group	A21F2	Filters implantable into blood vessels; Prostheses, i.e. artificial substitutes or replacements for parts of the body; Appliances for connecting them with the body; Devices providing patency to, or preventing collapsing of, tubular structures of the body, e.g. stents (as cosmetic articles, see the relevant subclasses, e.g. wigs, hair pieces, A41G 3/00, A41G 5/00, artificial nails A45D 31/00; dental prostheses A61C 13/00; materials for prostheses A61L 27/00; artificial hearts A61M 1/10; artificial kidneys A61M 1/14)
Subgroups		
	A61F2/38	Knee - Elbow
	A61F2/58	Elbow - Wrists
	A61F2/64	Knee Joints
	A61F2/32	Hip
	A61F2/40	Shoulders
	A61F2/44	Spine

The classification, and consequently the sector analysis, is relatively straightforward for the Hip, Shoulder, and Spine prosthesis markets — with one product segment corresponding to one patent class. However, some overlap is observed in the remaining two markets: Elbow appears in two classes (*A61F2/38* and *A61F2*/58), as does Knee (*A61F2/38*, *A61F2/64*). It is not feasible to differentiate patents that pertain to one specific sub-market (e.g., separate knee from elbow) from those of the other.

Figure A.3 illustrates the count of patents obtained under the IPC classification within the different product classes. Spine products have the highest number of granted patents, almost three times larger than the second-highest patent class of elbow and knee products. Nevertheless, these markets witnessed a decline in granted patents post-2015 and 2016. By 2023, the number of granted patents in spine and knee/elbow products had reverted to the levels of 2011. Instead, while featuring substantially lower patent numbers, other markets (e.g., shoulder and hip) have more or less followed a stable trend.

Figure A.3: Granted Patents for Treated Markets Overtime based on IPC Classes



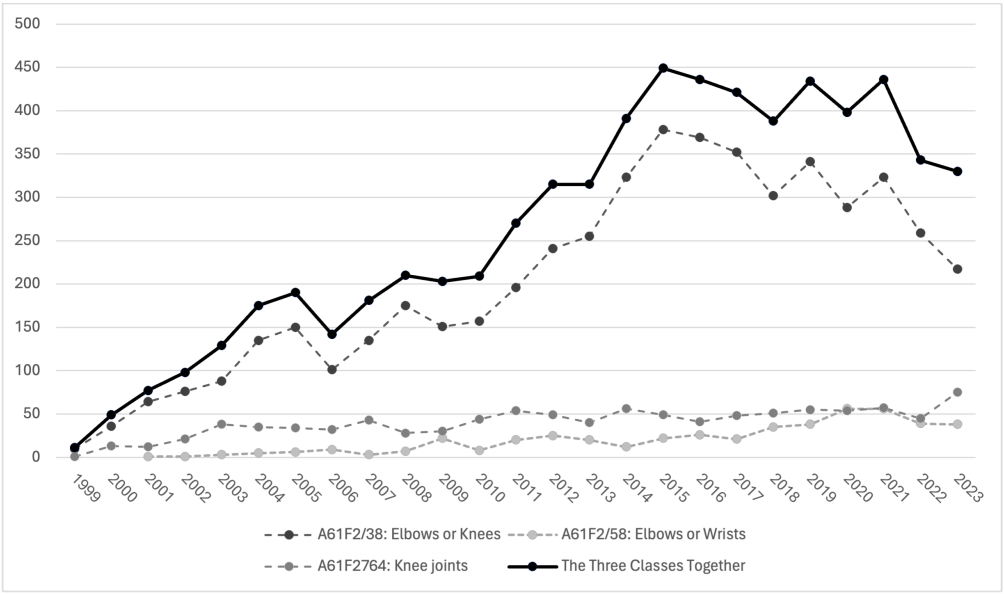
Note: The IPC database on Orbis has some missing values. In particoular, for year 2014 the data on granted patents for class (i) *A61F2/32 – Hip*, (ii) *A61F2/40 – Shoulders* and (iii) *A61F2/44 – Spine*, was incomplete. Since we are interested in the trend overtime, we imputed the missing values for 2014 by averaging the number of granted patents of the year before (2013) and year after (2015).

As we can see in Figure A.4, the vast majority of patents in these three overlapping knee-elbow-wrist classes are granted under one of them, class *A61F2/38 for Elbows or Knees*. This same class displays a positive trend in the number of granted patents until

2015, followed by a downturn afterwards, while the other two classes (*A61F2/58 for Elbows or Wrists* and *A61F2/64 for Knee Joints)* demonstrate a relatively constant and flat trend over time. For the sake of our descriptive analysis focused on understanding the long-term quality effects, we aggregated the data from the three classes and use the resulting total as a proxy for patents within the elbow and knee prosthesis market.

Figure A.4: Granted Patents for Treated Markets at Firm-Level

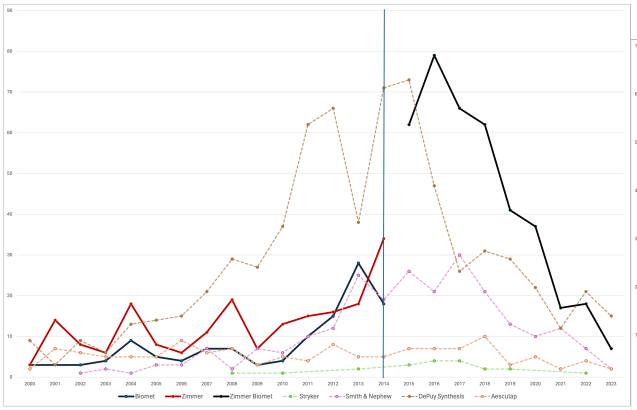
(a) Granted Patents for the Overlapping Classes Overtime: (i) *A61F2/38 - Elbows or Knees*; (ii) *A61F2/58 - Elbows or Wrists*; (ii) *A61F2/64 - Knee Joints*



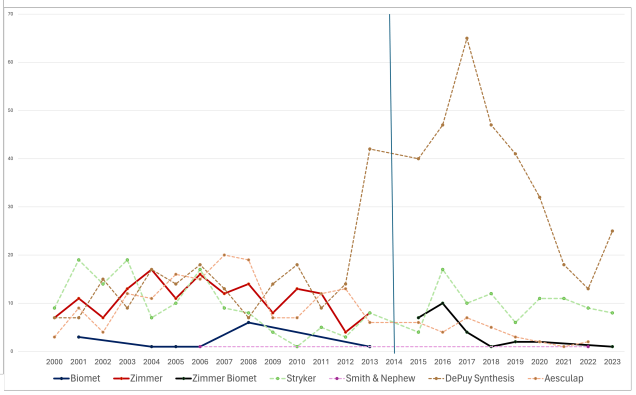
Next we look at firm-level data for each of the identified product markets. Figure A.5 shows the number of granted patents of Zimmer Biomet and its competitors before and after the Transaction in the treated markets. The firm level analysis substantiates the findings observed at the sector level. Following the 2015-2016 period, Zimmer Biomet experienced a very sharp decrease in the number of granted patents in the knee and elbow product segment as a whole. One the one hand, this aligns with the remedy decision that compelled Zimmer Biomet to divest a portion of its knee and elbow segment globally. On the other hand, this downward trajectory appears to be consistent across all markets. Even the biggest market player, Depuy Synthesis (J&J), witnessed a great decline in patent counts after 2016 across all product segments.

In summary, our descriptive analysis indicates a widespread decline in innovation, as measured by the number of patents, across all distinct markets. This trend seems to apply to all active firms, including major players, who are obtaining fewer patents over time.

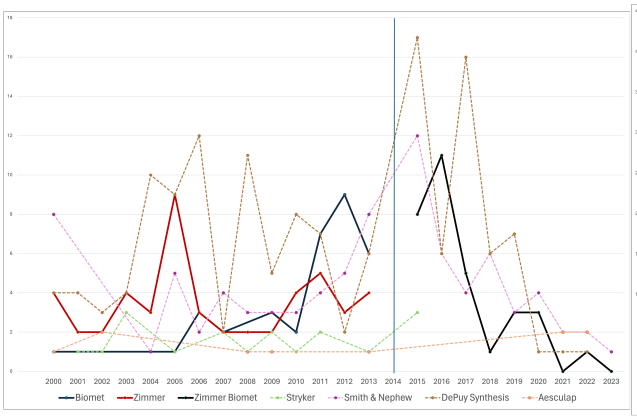
Figure A.5: Granted Patents for Treated Markets at Firm-Level



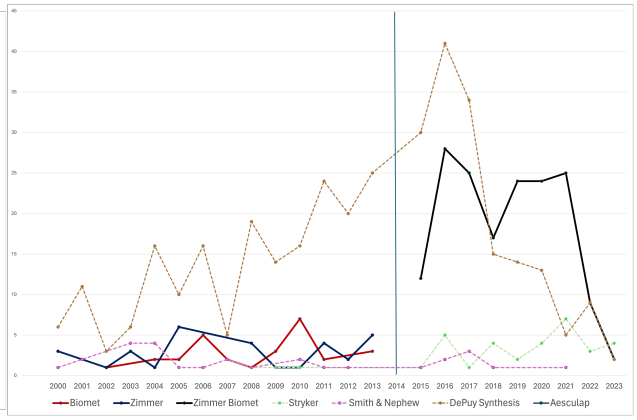
(a) For the following classes together: A61F2/38 - Elbows or Knees, A61F2/58 - Elbows or Wrists, A61F2/64 - Knee Joint



(b) For class A61F2/44 – Spine



(c) For class A61F2/32 – Hip

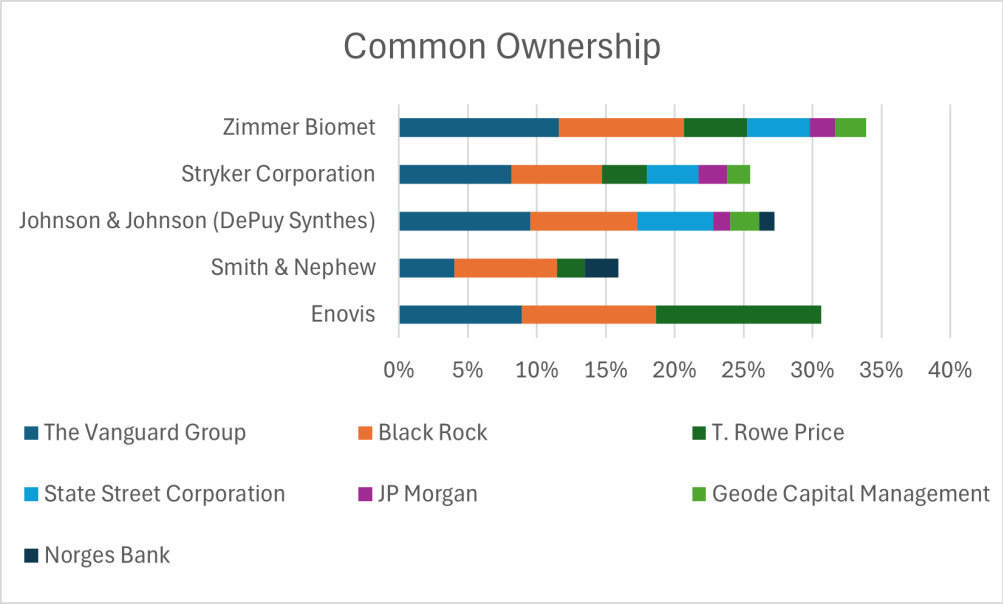


(d) For class A61F2/40 – Shoulder

Common Ownership -

In Figure A.6, we examine the largest institutional shareholders for five publicly listed major medical device producers to elucidate common ownership structures. We identify major shareholders that are shared among at least two of the five companies. Vanguard and BlackRock emerge as top shareholders for all five companies, collectively owning at least 10% of the shares in each. Additionally, T. Rowe Price is a major shareholder in four of the five companies.

Figure A.6: Common Ownership



Note: The figure reports ownership data about 5 major publicly listed medical device producers. In particular, it lists institutional shareholders appearing among the top 10 owners for at least 2 of the 5 producers, along with their share of ownership in each company. Vanguard and BlackRock are among the top shareholders for all 5 companies, collectively owning at least 10% of the shares in each company. T. Rowe Price is also a major shareholder in 4 of the 5 companies. Since DePuy Synthes is owned by Johnson & Johnson, data on the parent company's ownership has been included. The data sources for Zimmer Biomet, Stryker Corporation, Johnson & Johnson, and Enovis are Yahoo Finance, with data updated as of 31/12/2023. The data source for Smith & Nephew is Marketscreener, last consulted on 23/04/2024. https://finance.yahoo.com/; https://www.marketscreener.com/

B. Reserve Price

We report here some extracts and translation from documents of procurement auctions of medical devices that validate the anecdotal evidence provided in Section 3.1.

As we mentioned in Section 3.1, contracting authorities are not obliged to publish any information on the procedure they adopt to set the reserve price of each auction. A preliminary research on the Internet was unsuccessful in providing an answer to this question. We identified several formal documents, wherein these procedures are succinctly outlined. Each document originates from ARIA spa, the Central Purchasing Body of the Lombardy region (also referred to as ARCA in the documents, which is its former name).

Panel a) and b) of Figure B.1 shows some extracts from documents called "Delibere

Figure B.1: Extract from procurement auctions documents on the reserve price

seguito, per brevità, "**Servizio**"), per un importo massimo di Euro **2.600,00** (duemilaseicento/00), oltre IVA, stimato sulla base delle tariffe della convenzione messa a disposizione da ARIA S.p.A. ed utilizzata in precedenza per l'acquisto di servizi analoghi;

(a) Extract A

Translation: "... estimated on the basis of the contract provided by ARIA S.p.A. and previously used to purchase similar services."

4. con riferimento al suddetto acquisto la Struttura Richiedente ha individuato un importo massimo di **Euro 800,00** (ottocento/00), oltre IVA, stimato sulla base di una preliminare consultazione dei prezzi di mercato;

(b) Extract B

Translation: "... identified a ceiling amount of Euro 800.00, excluding VAT, estimated on the basis of a preliminary inquiry on market prices."

La base d'asta è stata stabilita secondo il seguente criterio: per ciascun lotto si è calcolato il prezzo medio ponderato (PMP) degli attuali prezzi d'acquisto lombardi confrontandola con i prezzi di aggiudicazione della convenzione ARCA in vigore. Definito il PMP di ciascun lotto, si è proceduto a definire il prezzo a base d'asta che, in alcuni casi risulta superiore ai prezzi di aggiudicazione della gara ARCA_2015_51 in ragione della necessità di consentire l'accesso alla gara anche a modelli protesici innovativi e di recente commercializzazione. Tuttavia, al contempo, viene garantito comunque un risparmio complessivo su scala regionale: la spesa totale annuale calcolata con il PMP di ciascun lotto ammonta a 3.155.779,14 €, la spesa totale annuale calcolata con la BdA ammonta a 2.811.000,00€ con una flessione rispetto alla spesa storica del 10,93%.

(c) Extract C

Translation: "The reserve price is set according to the following criterion: for each lot, the weighted average price (PMP) of the current prices at which Lombardy purchases has been computed and compared with the prices awarded in the last ARCA procedure, still valid. Once the PMP for each lot has been established, the reserve price has been computed, resulting occasionally higher than the awarding prices of auction ARCA-2015-51 due to the necessity of allowing innovative prostheses implants and recently-commercialized implants to participate. However, at the same time, savings are guaranteed..."

a contrarre" and refer to two procurement procedures on services purchased by ARIA.[44] The first statement clearly indicates that ARIA determined the reserve price based on the

[44]These documents can be found at the following address `https://www.finlombarda.it/societatrasparente/bandidigaraecontratti/determine`.They represent internal administrative formal acts that contracting authorities often do not release. Furthermore, legislative provisions on these acts do not oblige the contracting authorities to describe the process through which the reserve price has been derived (see art. 11 of D.Leg. n. 163/2006 and art. 192 of T.U.E.L. n. 267/2000). Therefore, we consider the availability of this information to be an exception.

results of previous auctions involving the same items. The second statement asserts that ARIA established the reserve price after inquiring about the current market value of the items it wished to acquire.

One particularly interesting document is found in panel c). It is part of the documentation for auction ARCA-2019-024, a procedure by ARIA to purchase spine prostheses, easily accessible at `https://www.sintel.regione.lombardia.it/`. This document, the "Progetto di Gara," provides background information on the auction, such as regional need analysis, legislative context, and more. However, we believe this type of document is rare and likely not mandatory since we could not find it for any other auction or locate any legislation referencing it. The excerpt reveals that the reserve price was based on the last procedure issued by ARCA to purchase spine devices, ensuring it wasn't set too low so as not to exclude more innovative (and costly) devices recently launched. Simultaneously, this reserve price aimed at generating savings for regional accounts.

Table B.1: Merger impact accounting for procurement thresholds.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	LPA	LPA	LPA	LPA	LPA+CPB	LPA+CPB	LPA+CPB	LPA+CPB
VARIABLES	Discount	Discount	Ln(NP)	Ln(NP)	Discount	Discount	Ln(NP)	Ln(NP)
Treated x Post	-0.076***	-0.076***	0.135***	0.143***	-0.065***	-0.063***	0.112***	0.097***
	(0.010)	(0.010)	(0.017)	(0.024)	(0.010)	(0.010)	(0.017)	(0.024)
First Price	0.069***	0.067***	-0.099***	-0.049	0.057***	0.056***	-0.084***	-0.051
	(0.018)	(0.018)	(0.030)	(0.041)	(0.018)	(0.018)	(0.030)	(0.040)
Negotiation	-0.141***	-0.142***	0.210***	0.228***	-0.143***	-0.144***	0.213***	0.224***
	(0.012)	(0.013)	(0.022)	(0.027)	(0.012)	(0.013)	(0.021)	(0.027)
Scoring Rule	0.024*	0.020	-0.015	0.076***	0.026**	0.023*	-0.020	0.072***
	(0.013)	(0.013)	(0.022)	(0.028)	(0.013)	(0.013)	(0.022)	(0.028)
Ln(Maturity)	0.007***	0.007***	-0.006	0.001	0.008***	0.008***	-0.006	0.005
	(0.003)	(0.003)	(0.004)	(0.006)	(0.003)	(0.003)	(0.004)	(0.006)
80,0000-208,999	0.048***			0.741***	0.053***			0.733***
	(0.004)			(0.010)	(0.004)			(0.010)
209,000-417,999	0.068***			1.483***	0.073***			1.465***
	(0.007)			(0.014)	(0.007)			(0.014)
418,000-999,999	0.098***			2.191***	0.098***			2.187***
	(0.009)			(0.020)	(0.008)			(0.018)
≥1,000,000	0.106***			3.255***	0.105***			3.306***
	(0.010)			(0.026)	(0.009)			(0.023)
Medical Device Ratio	0.048*	0.054**	-0.068	-0.113**				
	(0.025)	(0.025)	(0.042)	(0.057)				
Ln(Reserve Price)		0.033***	0.940***			0.030***	0.945***	
		(0.003)	(0.005)			(0.002)	(0.004)	
Constant	0.093***	-0.255***	0.519***	10.656***	0.114***	-0.183***	0.425***	10.766***
	(0.020)	(0.036)	(0.062)	(0.059)	(0.016)	(0.033)	(0.058)	(0.217)
Observations	5,632	5,632	5,632	5,632	6,660	6,660	6,660	6,660
Adjusted R-squared	0.340	0.342	0.923	0.864	0.355	0.355	0.932	0.871
FE Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE Market	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE Region	Yes	Yes	Yes	Yes	No	No	No	No
FE Region x CPB	No	No	No	No	Yes	Yes	Yes	Yes

Note: Robust standard errors in parenthesis.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1

C. Checking the merger effect on different time windows

We propose this robustness analysis in light of our earlier findings of a difference in the magnitude of the estimated effects in the initial three years post-merger and in the subsequent phase. Table C.1 presents results from estimating the preferred specification of the baseline model for an increasing number of years post-treatment. To avoid working with an excessively small sample, we rely on the LHA+CPB sample.

Table C.1: Different Time Splits - Net Price (NP) and Discount Estimates (LPAs+CPBs)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Ln(NP) 2012-2019	Ln(NP) 2012-2018	Ln(NP) 2012-2017	Ln(NP) 2012-2016	Ln(NP) 2013-2019	Ln(NP) 2013-2018	Ln(NP) 2013-2017	Ln(NP) 2013-2016
Treated x Post	0.112***	0.114***	0.127***	0.099***	0.096***	0.096***	0.101***	0.079***
	(0.017)	(0.017)	(0.019)	(0.018)	(0.018)	(0.019)	(0.020)	(0.020)
Constant	0.425***	0.417***	0.407***	0.319***	0.560***	0.483***	0.645***	0.254***
	(0.058)	(0.060)	(0.068)	(0.058)	(0.069)	(0.067)	(0.070)	(0.084)
Observations	6,660	6,222	5,398	4,384	5,986	5,548	4,724	3,710
Adjusted R-squared	0.932	0.930	0.929	0.932	0.931	0.928	0.927	0.928
FE Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE Market	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE Region x CPB	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Discount 2012-2019	Discount 2012-2018	Discount 2012-2017	Discount 2012-2016	Discount 2013-2019	Discount 2013-2018	Discount 2013-2017	Discount 2013-2016
Treated x Post	-0.065***	-0.066***	-0.075***	-0.063***	-0.055***	-0.055***	-0.060***	-0.050***
	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.013)
Constant	0.114***	0.118***	0.095***	0.109***	0.084***	0.118***	-0.021	0.242***
	(0.016)	(0.016)	(0.033)	(0.014)	(0.022)	(0.023)	(0.024)	(0.026)
Observations	6,660	6,222	5,398	4,384	5,986	5,548	4,724	3,710
Adjusted R-squared	0.355	0.349	0.337	0.351	0.379	0.372	0.360	0.377
FE Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE Market	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE Region x CPB	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

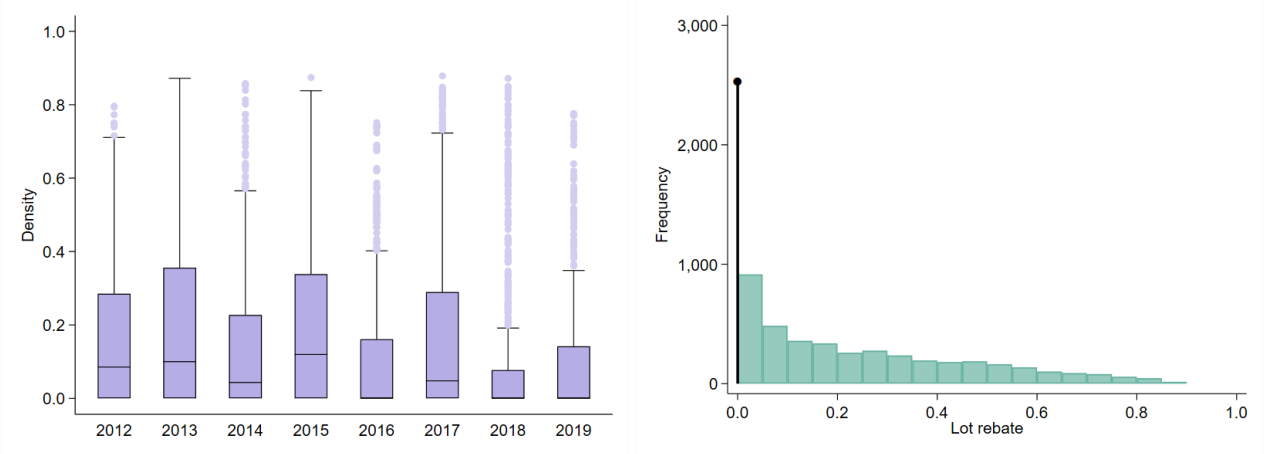
In the first three columns, we maintain the same starting year as in the baseline analysis but shorten the post-treatment period. We immediately notice that the coefficient remains stable across these columns, peaking when the final two years of the sample (2018 and 2019) are excluded from the estimation in column (3). When shorter time windows are considered by excluding the earliest pre-merger years (starting in column (4)), lower treatment effects are observed compared to the first three columns. This suggests that the merger had an immediate impact on prices following 2015, which did not diminish over time. Overall, these results underscore the robustness of the baseline qualitative findings,

regardless of how the time window around the merger is trimmed.

D. The empirical model in presence of not normal data and zero values

The results obtained using as dependent variable the winning discount can be evaluated using alternative empirical specifications which try to accommodate more flexibly its specific distribution. As mentioned in the text, this distribution presents two peculiar features. Firstly, the conditional distribution of the errors is not normal since discounts are expressed in percentage terms. To address this "fractional outcome", we run a first robustness check using a Beta regression. [45] The ability of the beta distribution to assume different shapes based on its location and dispersion parameters is also relevant in this case since the discount distribution is notably right-skewed, with most observations concentrated close to 0. Panel a) of Figure D.1 illustrates this by displaying box-plots of the sample outcome variables over time.

Figure D.1: Empirical distribution of the discount



(a) Boxplot of discounts over the years

(b) Histogram of discounts

The second key challenge posed by the data is the concentration of winning discount values at zero, as depicted in panel b) of Figure D.1. Considering a histogram of discounts values to approximate the empirical density function, a large probability mass is observed

[45] The literature offers various approaches to deal with this type of "fractional outcome," ranging from simply ignoring this feature to sophisticated methods like that in Papke and Wooldridge (1996). Tobit models have been used, as well as models which link the predictors to the conditional expectations of the outcome through function mapping in the unit interval, such as the logistic function (for an overview, see Ramalho et al. (2011).) The beta regression approach we test in this section belongs to this latter category.

at the value 0 (indicated by the vertical thick black line). This conflicts with the beta distribution, which is not defined at boundary values 0 and 1. To address this issue, we consider an additional empirical specification which adapts the beta distribution to accommodate the value 0. This model, referred to as *zero inflated beta regression* (ZIBR), is proposed by Ospina and Ferrari (2012).

According to Ospina and Ferrari (2012) the random variable Y follows a beta distribution with parameters μ and ϕ ($0 < \mu < 1, \phi > 0$) if its density function is:

$$f(y;\mu,\phi) = \frac{\Gamma(\phi)}{\Gamma(\mu\phi)\Gamma((1-\mu)\phi)} y^{\mu\phi-1}(1-y)^{(1-\mu)\phi-1}, \qquad y \in (0,1) \tag{2}$$

where $\Gamma(\cdot)$ is the gamma function. If $Y \sim \mathcal{B}(\mu,\phi)$ then $E(Y) = \mu$ and $Var(Y) = \mu(1-\mu)/(\phi+1)$, hence μ is the distribution mean and ϕ plays the role of a precision parameter. To account for the value of zero, we introduce a mixed continuous-discrete distribution defined *zero-inflated beta distribution* (ZIBD) with the following density:

$$ZIBD(y;\alpha,\mu,\phi) = \begin{cases} \alpha & y = 0 \\ (1-\alpha) f(y;\mu,\phi) & y \in (0,1), \end{cases} \tag{3}$$

where $f(y;\mu,\phi)$ is the beta density as parametrized above and α is the probability mass at 0. Essentially, the ZIBD is a mixture distribution of a beta and a degenerate distribution at 0. The mean and the variance are respectively:

$$E(y) = (1-\alpha)\mu, \tag{4}$$

$$Var(y) = (1-\alpha)\frac{\mu(1-\mu)}{\phi+1} + \alpha(1-\alpha)(-\mu)^2. \tag{5}$$

The expected value is thus the weighted average of 0 and μ. We are now ready to define our regression model, the *zero-inflated beta regression* (ZIBR). Given our matrix of data in which we have n independent realizations of $(y_i, \mathbf{x}_i)$, where y_i is the outcome variable for observation and $\mathbf{x_i} = (x_{1i},...,x_{ki})^\intercal$ its vector of covariates, we assume that:

$$y_i|\mathbf{x}_i \sim ZIBD(\mu_i,\phi_i,\alpha_i), \tag{6}$$

with $g_1(\mu_i) = \mathbf{x_i}^\intercal\beta$ and $\beta = (\beta_i,...,\beta_k)^\intercal$ the vector of unknown regression parameters. This

implies that:

$$E(y_i|\mathbf{x}_i) = \mu_i = g_1^{-1}(\mathbf{x_i}^\top \beta). \tag{7}$$

We further assume that also the precision parameter (ϕ_i) and the probability at 0 (α_i) are functions of our linear predictors:

$$g_2(\phi_i) = \mathbf{x_i}^\top \gamma, \tag{8}$$

$$g_3(\alpha_i) = \mathbf{x_i}^\top \rho, \tag{9}$$

where again γ and ρ are vectors of unknown regression parameters to be estimated. In this setup, g_1, g_2, g_3 are called *link functions* and we assume that $g_1 : (0,1) \to \mathbb{R}$, $g_2 : (0, +\infty) \to \mathbb{R}$ and $g_3 : (0,1) \to \mathbb{R}$ and that they are strictly monotonic and twice differentiable (thus, invertible). There are several alternatives available for these functions. We use the standard logit link for g_1 and g_3 (e.g. $g_1(\mu) = \log[\mu/(1-\mu)]$) and the log link for g_2 ($g_2(\phi) = \log(\phi)$). This model is estimated by maximum likelihood, which under the usual regularity conditions allows us to obtain consistent estimates of (β, γ, ρ).[46]

Our DID identification strategy is embedded into the $g_1(\mu)$ link function, where the set of linear predictors is then defined according to equation (1):

$$g_1(\mu_i) = X_{i,t}\beta = \beta_0 + \beta_1 Treat_{i,t} + \beta_2 Treat_{i,t} \text{ x } Post_t + \beta_3 Z_{i,t} + \nu_t + \eta_r + \xi_p + \epsilon_{i,t}. \tag{10}$$

In Table D.1 (LHA sample) and D.2 (complete sample) we present the presents the results of estimating Equation 1 under different models: the baseline linear regression (column (1)), ZIBR (column (3)), fractional logit (column (4), see Papke and Wooldridge (1996)), and beta regression (column (5)) with the outcome variable transformed according to Smithson and Verkuilen (2006) (specifically, the corrected response variable is $y'' = [(N-1)y' + 0.5]/N$). The coefficients across all four models exhibit similar signs and significance levels, supporting the robustness of our estimates. However, slight discrepancies emerge in the coefficients' magnitudes. In particular, while the effect of the merger computed through fractional logit is in line with our baseline estimations, this becomes

[46] Finite-sample properties are studied by Ospina and Ferrari (2012) through a Monte-Carlo simulation and confirm the ability of the estimation algorithm to provide unbiased estimates when the model is valid for the underlying data.

lower in both the standard and the zero-inflated beta regression.

Table D.1: Merger effect under different models (LHA sample)

VARIABLES	(1) LPA Baseline	(2) LPA ZIBR	(3) LPA Fract. Logit	(4) LPA Beta regression
Treated x Post	-0.076***	-0.059***	-0.076***	-0.034***
	(0.010)	(0.012)	(0.011)	(0.006)
First Price	0.069***	0.035***	0.035***	0.033***
	(0.018)	(0.012)	(0.012)	(0.010)
Negotiation	-0.141***	-0.126***	-0.179***	-0.092***
	(0.012)	(0.010)	(0.011)	(0.007)
Scoring Rule	0.024*	0.011	0.011	0.036***
	(0.013)	(0.009)	(0.010)	(0.007)
Ln(Maturity)	0.007***	0.003	0.009***	0.015***
	(0.003)	(0.003)	(0.003)	(0.002)
80,0000-208,999	0.048***	0.082***	0.096***	0.028***
	(0.004)	(0.007)	(0.008)	(0.003)
209,000-417,999	0.068***	0.096***	0.111***	0.033***
	(0.007)	(0.008)	(0.009)	(0.004)
418,000-999,999	0.098***	0.109***	0.130***	0.046***
	(0.009)	(0.008)	(0.009)	(0.005)
$\geq 1,000,000$	0.106***	0.110***	0.133***	0.050***
	(0.010)	(0.009)	(0.010)	(0.006)
Medical Device Ratio	0.048*	0.033	0.030	0.062***
	(0.025)	(0.024)	(0.028)	(0.015)
Constant	0.087***			
	(0.022)			
Observations	5,632	5,632	5,632	5,632
Adjusted R-squared	0.340			
FE Years	Yes	Yes	Yes	Yes
FE Market	Yes	Yes	Yes	Yes
FE Region	Yes	Yes	Yes	Yes
FE Region x CPB	No	No	No	No

Note: Robust standard errors in parenthesis.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Next, we reevaluate the baseline estimates presented in section 5.1 and 5.2, while omitting data points where the outcome variable is zero. This approach helps determine if the significant proportion of zero-response data influences our findings. Table D.3 displays the results, revealing that nearly 2,500 observations were omitted. Despite of this substantial reduction of the sample, the estimates closely resemble our baseline. This is especially true for the coefficients of the effect of the merger (whose baseline are reported in the last row of Table D.3): while these are in line with those presented in the main text in the full sample (columns (3) and (4)), in the LHA sample they becomes even larger, both when we use as independent variable the discount and the net price (column (1) and (2)). These findings offer reassurance: although zero-outcome observations account for roughly one-third of our sample, their distribution across time and groups does not affect the price impact coefficient. This strengthens the evidence supporting their independence from other covariates, ultimately increasing our design's robustness.

Table D.2: Merger effect under different models (LHA+CPB sample)

VARIABLES	(1) LPA+CPB Baseline	(2) LPA+CPB ZIBR	(3) LPA+CPB Fract. Logit	(4) LPA+CPB Beta regression
Treated x Post	-0.065***	-0.033***	-0.058***	-0.032***
	(0.010)	(0.011)	(0.011)	(0.007)
First Price	0.057***	0.020	0.026**	0.032***
	(0.018)	(0.013)	(0.013)	(0.011)
Negotiation	-0.143***	-0.136***	-0.200***	-0.101***
	(0.012)	(0.010)	(0.012)	(0.008)
Scoring Rule	0.026**	0.001	0.009	0.045***
	(0.013)	(0.009)	(0.010)	(0.008)
Ln(Maturity)	0.008***	0.001	0.010***	0.017***
	(0.003)	(0.003)	(0.003)	(0.002)
80,0000-208,999	0.053***	0.092***	0.109***	0.032***
	(0.004)	(0.007)	(0.008)	(0.003)
209,000-417,999	0.073***	0.106***	0.124***	0.039***
	(0.007)	(0.008)	(0.009)	(0.004)
418,000-999,999	0.098***	0.119***	0.139***	0.048***
	(0.008)	(0.008)	(0.009)	(0.005)
≥ 1,000,000	0.105***	0.123***	0.144***	0.053***
	(0.009)	(0.008)	(0.009)	(0.006)
Constant	0.089***			
	(0.019)			
Observations	6,660	6,660	6,660	6,660
Adjusted R-squared	0.355			
FE Years	Yes	Yes	Yes	Yes
FE Market	Yes	Yes	Yes	Yes
FE Region	No	No	No	No
FE Region x CPB	Yes	Yes	Yes	Yes

Note: Robust standard errors in parenthesis.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table D.3: Merger effect removing observation with zero discount

VARIABLES	(1) LPA Discount	(2) LPA Ln(NP)	(3) LPA+CPB Discount	(4) LPA+CPB Ln(NP)
Treated x Post	-0.105***	0.202***	-0.067***	0.122***
	(0.017)	(0.029)	(0.015)	(0.025)
First Price	0.056**	-0.079**	0.026	-0.035
	(0.022)	(0.038)	(0.021)	(0.037)
Negotiation	-0.168***	0.271***	-0.169***	0.274***
	(0.017)	(0.031)	(0.017)	(0.030)
Scoring Rule	-0.039**	0.080***	-0.049***	0.095***
	(0.017)	(0.030)	(0.016)	(0.030)
Ln(Maturity)	-0.013***	0.024***	-0.013***	0.027***
	(0.005)	(0.008)	(0.004)	(0.008)
80,0000-208,999	0.080***		0.089***	
	(0.009)		(0.008)	
209,000-417,999	0.117***		0.122***	
	(0.012)		(0.010)	
418,000-999,999	0.144***		0.147***	
	(0.013)		(0.011)	
≥ 1,000,000	0.146***		0.149***	
	(0.013)		(0.011)	
Medical Device Ratio	-0.030	0.034		
	(0.038)	(0.066)		
Ln(Reserve Price)		0.923***		0.932***
		(0.007)		(0.006)
Constant	0.274***	0.482***	0.045*	0.625***
	(0.106)	(0.178)	(0.027)	(0.080)
Observations	3,195	3,195	4,118	4,118
Adjusted R-squared	0.236	0.897	0.237	0.915
FE Years	Yes	Yes	Yes	Yes
FE Market	Yes	Yes	Yes	Yes
FE Region	Yes	Yes	No	No
FE Region x CPB	No	No	Yes	Yes

Note: Robust standard errors in parenthesis.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1

E. Further Results

In this section we report further results. In particular, Table E.1 and Table E.2 report the product-specific estimates for the full sample, respectively for the net price and the discount.

Table E.1: Product Specific Estimates - Net Price (LPA+CPB Sample)

VARIABLES	(1) Ln(NP) hip	(2) Ln(NP) knee	(3) Ln(NP) shoulder	(4) Ln(NP) spine	(5) Ln(NP) trauma	(6) Ln(NP) unic. knee
Treated x Post	0.127***	0.175***	0.072	0.233***	0.123***	0.103
	(0.027)	(0.050)	(0.059)	(0.034)	(0.020)	(0.102)
Constant	0.224**	0.038	0.081	0.363***	0.325***	0.472***
	(0.109)	(0.141)	(0.095)	(0.111)	(0.073)	(0.123)
Observations	2,614	2,094	1,992	2,456	3,998	1,900
Adjusted R-squared	0.951	0.952	0.953	0.939	0.935	0.955
FE Years	Yes	Yes	Yes	Yes	Yes	Yes
FE Market	Yes	Yes	Yes	Yes	Yes	Yes
FE Region x CPB	Yes	Yes	Yes	Yes	Yes	Yes
Treated obs.	777	257	155	619	2161	63

Note: Robust standard errors in parenthesis.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table E.2: Product Specific Estimates - Discount (LPA+CPB Sample)

VARIABLES	(1) Discount hip	(2) Discount knee	(3) Discount shoulder	(4) Discount spine	(5) Discount trauma	(6) Discount unic. knee
Treated x Post	-0.077***	-0.117***	-0.045	-0.129***	-0.073***	-0.069
	(0.017)	(0.030)	(0.037)	(0.020)	(0.012)	(0.060)
Constant	0.111	0.140***	0.187***	0.133***	0.149***	0.016
	(0.074)	(0.021)	(0.037)	(0.040)	(0.021)	(0.043)
Observations	2,614	2,094	1,992	2,456	3,998	1,900
Adjusted R-squared	0.326	0.345	0.355	0.320	0.369	0.350
FE Years	Yes	Yes	Yes	Yes	Yes	Yes
FE Market	Yes	Yes	Yes	Yes	Yes	Yes
FE Region x CPB	Yes	Yes	Yes	Yes	Yes	Yes
Treated obs.	777	257	155	619	2161	63

Note: Robust standard errors in parenthesis.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1

F. Coordinated Effects Post Merger

Bid Test

We do not mean for this test to prove the existence of collusion (or to rule it out), but simply to offer descriptive evidence that might shed light on whether the merger increased the likelihood of coordination in the choice of how to bid (Bid Test) or whether to participate (Entry Test). The simple bid test that we use compares the observed drop in the winning discount due to the merger (as estimated in the main text) with a benchmark change in the winning discount. Ideally, this benchmark would be the discount predicted by reducing participation in the auction by one bidder. The idea behind this test is that if the observed drop in the winning discount is significantly larger than the benchmark, the drop might be due not only to the mechanical reduction in competition associated with one fewer bidder, but could also signal a shift toward more collusive behavior.

In practice, we calculate this benchmark as the predicted value of the discount using the coefficients of a linear model estimated on pre-merger data, applying the post-merger data for all covariates except for the number of bidders, for which we use the lower (upper) bound of the confidence interval. Table F.1 reports the estimates of the six models used in our baseline regressions, including the number of bidders as a covariate and restricting the sample to pre-merger data for the treated products in auctions with between 1 and 5 bidders.[47] This restriction is intended to focus on the subset of auctions where a change of one bidder might credibly impact outcomes. The estimates in Table F.1 indicate a relatively large impact of the number of bidders on the discount: in our preferred model (6), the lower (upper) bound of the 95% confidence interval implies that a reduction by one bidder corresponds to a drop in the winning discount between 1.11 and 7.99 percentage points.[48] In Table F.2, we use the lower (upper) bound on the number of bidders coefficient, along with the point estimates of the other coefficients and the post-merger data, to predict the discount and then report its average across auctions. As seen from the table, the range between the upper and lower bounds is wide enough to allow us to rule

[47] This conditions rules out virtually all the lots awarded by CPBs. This is why we run this exercise on the LPA sample, using the model from Table 3.

[48] Notice that our baseline estimate of the merger effect of 7.6% falls within this interval.

out that the merger effect is so extreme that it necessitates invoking a switch to a (more) collusive behavior by market participants.

Table F.1: Bid Test Sample - Regression Results

VARIABLES	(1) Discount	(2) Discount	(3) Discount	(4) Discount	(5) Discount	(6) Discount
Number of bidders	0.037	0.045**	0.041**	0.042**	0.045**	0.045***
	(0.023)	(0.022)	(0.020)	(0.020)	(0.019)	(0.017)
First Price		0.191***	0.268***	0.195**	0.179**	0.290**
		(0.053)	(0.087)	(0.091)	(0.086)	(0.114)
Negotiation		-0.089	-0.002	-0.007	-0.031	0.096
		(0.059)	(0.080)	(0.083)	(0.077)	(0.107)
Scoring Rule		-0.022	0.020	-0.043	-0.074	-0.008
		(0.054)	(0.071)	(0.075)	(0.071)	(0.083)
Ln(Maturity)			-0.018	-0.017	-0.009	-0.058*
			(0.022)	(0.022)	(0.022)	(0.033)
80,0000-208,999			0.103***	0.080**	0.094**	0.129***
			(0.039)	(0.039)	(0.042)	(0.042)
209,000-417,999			0.175***	0.162***	0.158***	0.165***
			(0.059)	(0.058)	(0.057)	(0.057)
418,000-999,999			0.286***	0.280***	0.286***	0.297***
			(0.058)	(0.055)	(0.057)	(0.058)
≥ 1,000,000			0.239***	0.245***	0.284***	0.291***
			(0.055)	(0.053)	(0.058)	(0.066)
Budg. Plan			-0.166***	-0.140***	-0.159***	
			(0.051)	(0.051)	(0.050)	
Medical Device Ratio				0.491***	0.400**	0.725***
				(0.170)	(0.169)	(0.191)
Constant	0.216**	0.214**	0.091	-0.038	-0.037	-0.086
	(0.085)	(0.095)	(0.124)	(0.135)	(0.134)	(0.320)
Observations	207	207	207	207	207	207
Adjusted R-squared	0.028	0.162	0.276	0.297	0.322	0.376
FE Years	Yes	Yes	Yes	Yes	Yes	Yes
FE Market	No	No	No	No	Yes	Yes
FE Region	No	No	No	No	No	Yes

Note: Robust standard errors in parenthesis.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table F.2: Bid Test Results

Model	Lower Bound	Upper Bound
Model 1	-0.0254	0.2334
Model 2	0.0044	0.2474
Model 3	0.0056	0.2254
Model 4	0.0101	0.2267
Model 5	0.0226	0.2317
Model 6	0.0311	0.2243

Note: The table reports the predicted average discount, post-merger using the lower (upper) bound on the number of bidders' confidence interval (95 percent) estimates from the pre-treatment sample.

Entry Test

A distinctive feature of the procurement auctions that Italian public buyers use to procure the medical devices in our study is the large share of auctions with a single participating firm bidding. Nearly half of the auctions in both the treatment and the control groups are single-participant auctions. In most of these cases, the product specification in the call for tenders is very detailed regarding the characteristics of the product needed, so it is not surprising that very few, and possibly just one, firm can bid. Although there are legitimate reasons why a public buyer might need a very specific type of medical device, the objective of the public buyers is to design calls for tenders in such a way that, whenever possible, multiple bidders should be eligible to bid and compete. Therefore, the presence of single-participant auctions might also signal the presence of a collusive agreement to split the market.

It is thus reasonable to implement a simple test for coordinated entry behavior by looking at whether the merger triggered an increase in single-participant auctions. To implement this test, we want to compare the observed instances of single-participant auctions post-merger to those that we would have expected in a benchmark where there is no possible increase in coordinated entry due to the merger. In practice, we obtain the latter by estimating, on pre-merger data, the association between an indicator of a single-participant auction and the auctioneer and tender characteristics used in our earlier analysis. Based on these estimates, we use them to predict, in the post-merger data, the outcome of the indicator of a single-participant auction. The histograms in Figure F.1

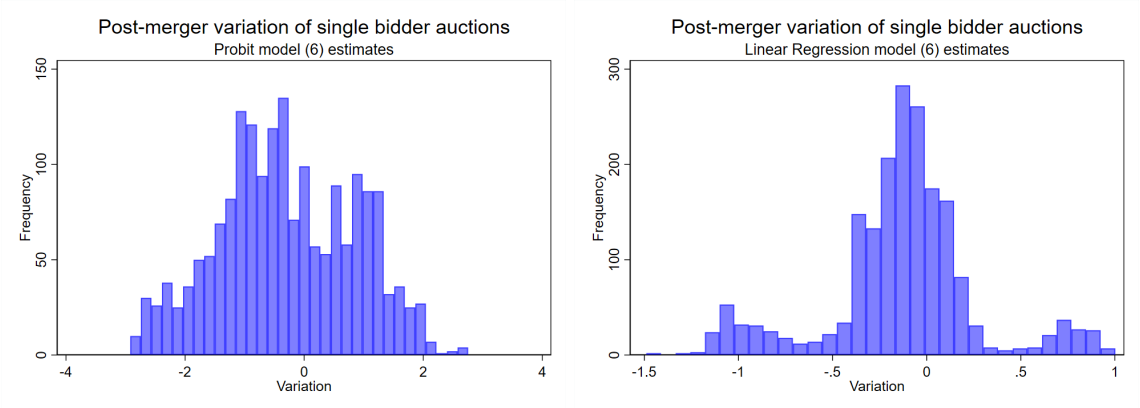
report the difference between the observed and predicted value of the index: on the left using a Probit model and on the right using a linear model. In both cases, the mass of the histogram is concentrated around zero, suggesting that the observed instances of the index taking a value of 1 align well with those predicted by the model with pre-merger data. Finally, additional evidence supportive of the interpretation that the merger has not been a clear driver of a shift toward more collusive entry is reported in Table F.3. Here we report the same DiD estimates as the main analysis in the text, but using as the outcome the index for a single-participant auction. The negative and statistically significant coefficient on the interaction between treated and post suggests that, if anything, the merger is associated with a lower likelihood of single-participant auctions occurring.

Table F.3: Merger Effects on the Probability of Single-participant Auction

VARIABLES	(1) Single part.	(2) Single part.	(3) Single part.	(4) Single part.	(5) Single part.	(6) Single part.
Treated x Post	-1.079***	-0.330***	-0.372***	-0.372***	-0.342***	-0.495***
	(0.094)	(0.111)	(0.113)	(0.113)	(0.113)	(0.123)
Treated	0.614***	0.201**	0.053	0.053		
	(0.073)	(0.088)	(0.093)	(0.093)		
First Price		0.183	0.189	0.188	0.170	0.387**
		(0.137)	(0.144)	(0.147)	(0.149)	(0.172)
Negotiation		1.482***	1.408***	1.408***	1.336***	1.600***
		(0.116)	(0.120)	(0.121)	(0.128)	(0.139)
Scoring Rule		-0.682***	-0.715***	-0.715***	-0.740***	-0.451***
		(0.119)	(0.123)	(0.126)	(0.129)	(0.141)
Ln(Maturity)			0.147***	0.147***	0.155***	0.186***
			(0.030)	(0.030)	(0.030)	(0.036)
80,0000-208,999			-0.060	-0.060	-0.056	-0.072
			(0.073)	(0.073)	(0.074)	(0.074)
209,000-417,999			-0.073	-0.073	-0.072	-0.091
			(0.080)	(0.080)	(0.080)	(0.082)
418,000-999,999			-0.083	-0.083	-0.094	-0.109
			(0.088)	(0.088)	(0.089)	(0.093)
≥ 1,000,000			-0.393***	-0.393***	-0.411***	-0.439***
			(0.092)	(0.093)	(0.094)	(0.101)
Budg. Plan			0.167**	0.167**	0.204***	
			(0.066)	(0.067)	(0.068)	
Medical Device Ratio				0.009	0.087	0.216
				(0.262)	(0.265)	(0.322)
Constant	-0.864***	-0.283*	-0.245	-0.248	0.133	-0.391
	(0.094)	(0.152)	(0.169)	(0.188)	(0.199)	(0.241)
Observations	4,054	4,054	4,054	4,054	4,054	4,054
FE Years	Yes	Yes	Yes	Yes	Yes	Yes
FE Market	No	No	No	No	Yes	Yes
FE Region	No	No	No	No	No	Yes

Note: The table reports the estimates of Probit models where the outcome is a dummy for whether the auction has a single participant.

Figure F.1: Entry Test Results for Probit and Linear Models



Note: The two histograms report the difference between the actual and predicted value of the dummy for single-participant auction. The left panel uses the estimates of the same model as model (6) of Table F.3, but on the pre-merger data (the right panel uses those from a linear model with the same specification).