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Buyers' Ability and Discretion in Procurement: An Empirical Analysis on Standardised Medical Devices

Alessandro Bucciol, Riccardo Camboni, Paola Valbonesi

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Buyers' ability and discretion in procurement:

an empirical analysis on standardised medical devices*

Alessandro Bucciol[†], Riccardo Camboni[‡] and Paola Valbonesi[§]

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Abstract

Using a dataset of medical devices purchased by Italian Public Buyers (PBs), for each purchase, we measure the difference between each item's price and its marginal cost. We define PBs' ability in purchasing as PBs' fixed effect (FE) on that difference.

We find that average prices vary substantially amongst PBs, and this variation is largely captured by PBs' FE. We then exploit the exogenous termination of the mandatory reference price regime to assess how discretion affects procurement performance, given each PB's ability. Our results highlight that reduced PBs' discretion - in presence of mandatory prices - determines efficiency gains and losses for low- and high-ability PBs, respectively.

JEL Classification: D44; D73; H57; I18.

Keywords: Public Procurement; Medical Devices; Buyer's Ability; Reference Price; Regulatory Discretion.

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[†]University of Verona and Netspar. Email: alessandro.bucciol@univr.it

[‡]University of Padova. Email: riccardo.camboni@unipd.it

[§]University of Padova and NRU-HSE Moscow. Email: paola.valbonesi@unipd.it

1 Introduction

The EU medical devices market is the second largest in the world, after the United States.[1] However, compared with the United States, where expenditures are mainly managed by the private health sector, approximately 79% of the healthcare costs in the EU are paid for by national governments (OECD–EU, 2016).[2] Such a relevant difference between the EU and US health systems also includes the purchasing of medical devices. In the US, this purchasing usually relies on the direct trade between private hospitals and suppliers, characterised by strategic discretion and flexibility. By contrast, in EU countries, such an activity is heavily regulated, and public officials' discretional choice regarding the awarding mechanisms and management of contracts is largely restricted by law (Lian and Laing, 2004; Spagnolo, 2012). Thus, in the private health sector, managers' bargaining ability in buying medical devices is expressed in business-to-business direct negotiations with suppliers (Grennan, 2013; 2014). By contrast, in the public health sector, Public Buyers' (PBs') ability involves coping with business-to-government regulated procedures, often relying on open auction mechanisms.

In Italy, as in many other national health systems in Europe, the purchasing of medical devices is managed at a local level. Recently, the national press highlighted that for the same standard item (i.e., a simple syringe), different PBs' (i.e., local public hospitals and health units) often pay very different prices.[3] In a period of tight public budgets, this evidence has fuelled an extensive public debate and led to the introduction of *reference prices*, a policy imposing a cap on the price of each procured standard medical device. The aim of this policy was to limit buyers' discretion in an attempt to reduce public procurement expenditure,[4] but it was eventually canceled by a decision of the administrative court of Rome. This setting provides a quasi-natural experiment for a clean test on how discretion affects procurement performance. A key insight of our findings is that discretion has a different (i.e., heterogeneous) impact, according to the ability of the PBs.

[1] In 2015, the EU market for medical devices was worth €110 billion or about 7.9% of the total health expenditures in the same year (OECD-EU, 2016).

[2] Public health is a relevant goal pursued in the Europe 2020 strategy. The European Commission stated that 'Promoting good health is an integral part of the smart and inclusive growth objectives for Europe 2020. Keeping people healthy for longer has a positive impact on productivity and competitiveness' (Communication dated June 29, 2011, 'A budget for Europe 2020').

[3] See, amongst many articles, P. Russo 'Garze e siringhe d'oro: le spese pazze delle ASL' (Bandages and gold syringes: the crazy expenditures of Italian local health agencies) in La Stampa, July 3, 2012, and E. Vendramini 'I costi standard sono giusti? Dipende' (Are reference prices fair? It depends) in Il Sole 24 Ore, October 30, 2015.

[4] In 2011, the Italian Authority for Public Contracts—at the time the national regulator for public procurement that our dataset refers to—was tasked to set a reference price for each of the several classes of functionally equivalent medical devices in the aim to lower the prices paid by PBs in purchasing such items. These reference prices, active from July 2012 to May 2013, worked as a cap to unitary prices in procurement auctions for medical devices.

By exploiting an original Italian dataset, this study, as a first step, empirically investigates the ability of PBs as a determinant of price differences in the procurement of standard medical devices. The second step involves assessing how reference prices interplay with buyers' ability. We ran our empirical analysis on an original Italian dataset including 75 classes of standard medical devices sold to 135 Italian local PBs in the period spanning January 2013 to December 2013**.** Our empirical approach grounds on two important features: i) the medical devices we investigate are standardised, relatively cheap and, thus, renegotiations are rare; ii) they can be grouped into classes of functionally homogeneous products (i.e., in each class, quality differentiation would not be an issue). Accordingly, we first estimate the unobserved marginal cost for each procured medical device. Then, using an official classification provided by the Italian technical advisor for health policies, we group functionally homogeneous medical devices into classes, and for each class, we set a benchmark marginal cost. Thus, we compute the difference between the observed price for each medical device and its benchmark marginal cost. This way, we infer a *proxy* for the PB's ability in running each purchase. We further investigate the determinants of such a PB's ability by exploiting information from local public hospitals' and health units' balance sheet open data. Finally, we assess the impact of the reference price policy and its exogenous termination on the PB's ability.

Based on real market data, our analysis is a key step towards bridging real procurement outcomes with each PB's features and discretion on procurement procedures. Our main findings can be summarised as follows. First, the average prices of standard medical devices paid by different Italian PBs vary substantially. Second, the differences across PBs' purchasing prices are explained by PB fixed effects, which, in turn, relate to PBs' institutional characteristics and size. In particular, PBs' size (measured either by overall personnel costs or by overall health-related costs) has a general positive and significant effect on the ability to run the procurement process. Furthermore, we find that it is the ratio of non-health over total personnel cost that drives the overall positive and significant effect of size on PBs' ability. By contrast, once PBs' size has been controlled for, the overall procurement expenses for health-related goods push ability down, which is consistent with the adopted definition of PBs' ability. Our results also highlight significant differences in the ability to procure between the PBs of different organisational structures: local public health units record higher prices in purchasing standard medical devices than public hospitals do.

Considering the reduction in PBs' discretion in the period in which reference prices were at work and comparing with the period in which they were removed, we found that this policy determined a non-linear effect on PBs' ability to run procurement procedures. Specifically, it records a significantly negative effect on high-ability PBs (i.e., it increases average prices) and a positive effect on low-ability PBs. Overall, when reference prices were in force, the main determinants of PBs' ability decrease in magnitude or lose their overall significance so that the dispersion of PBs' ability is reduced and observations become more concentrated towards an average value. Such non-linear effect of reference prices calls for the careful adoption of this policy and, more generally, of policies that evenly affect the discretion of PBs with a different ability in managing procurement procedures.

Our study mainly contributes to three strands of the economic literature on procurement. The first is on the procurement of medical devices. Grennan (2013, 2014) investigates such purchasing on a detailed US database of coronary stents. He empirically examines the negotiation process between private hospitals and private suppliers, as well as the resulting price discrimination (Grennan, 2013). His focus on private hospitals' bargaining ability shows that this has a large private hospital-specific component that explains 79% of the price variations in purchasing (Grennan, 2014).[5] Focusing on Europe, Sorenson and Kanavos (2011) present and discuss medical device procurement policies and practices in several European countries, highlighting the large heterogeneity in the procedures used therein and little in the way of analysing their effects. Laing and Lian (2004) compare public and private health procurement in the UK, showing suboptimal outcomes in the former. Kastanioti et al. (2013) present the procurement practices and policies set forth in the Greek procurement of health technologies, particularly regarding reference price setting and centralised tenders, and discuss the first measurable outcomes (in terms of cost savings) resulting from these policies. We add to this literature by providing empirical results for the Italian procurement of standard medical devices, with a focus on the determinants of PBs' ability in managing a very regulated process and on outcomes from the use of a reference price regime.

The second strand of literature we contribute to is on the role played by PBs' competence in procuring goods or services and on the linked regulation policies. By investigating procurement performance as related to the competence of the public workforce, a recent work by Decarolis et al. (2018) empirically assesses such a causal effect on US bureaus. Using an instrumental variable strategy and combining data on office-level competencies and procurement performance (i.e., cost and time overruns), the authors find that cooperation within the office matters the most to improve bureaus' outcomes. Considering the price paid for standardised goods and services by different classes of Italian PBs, Bandiera et al. (2009) find that the expenditure would be reduced by 21% – corresponding to a saving between 1.6% and 2.1% of the Italian GDP – if all PBs were to pay the same prices as the one at the tenth percentile. These authors also found that at least 82% of such estimated waste is related to burocratic inefficiency. On a large dataset on Russian procurement in 2011–2015, Best et al. (2017) estimate that 60% of within-product purchase price variation across 16 million purchases is due to bureaucrats and organisations administering procurement. Moreover, investigating a specific procurement policy, i.e., bid preferences for domestic firms, the authors show that the design of such an optimal

[5] Grennan and Swanson (2019) empirically highlight how information available to parts (i.e. transparency) can affect unexplained heterogeneity documented in negotiated prices for coronary stents in a business-to-business setting.

procurement policy depends on the effectiveness of the procurers at implementing the policy itself. To these studies, we add a novel approach to measure PBs' ability in managing procurement purchases and its determinants.

Finally, we contribute to the empirical literature on the effect of PBs' discretion on procurement. Di Tella and Schargrodsky (2003) investigate the medical procurement prices of standard medical devices following the introduction of a strict monitoring policy on Buenos Aires hospitals' purchasing. They estimate a 10% reduction in the average prices paid by hospitals because of the crackdowns.[6] Similar to these authors, we investigate the effect of a policy to reduce the public procurement expenditure of standard medical devices. By exploiting exogenous changes in the size (i.e., threshold value) of the tender below which PBs are granted with larger degrees of discretion in managing procedures, recent studies investigate the effect of discretion on procurement performance (Palguta and Pertold, 2017; Baltrunaite et al., 2018; Coviello et al., 2018). Our work differs from these, as our empirical strategy permits disentangling the impact of a policy reducing the PB's discretion in managing the procurement of standard goods from each PB's ability in running the procurement itself. To the best of our knowledge, we are the first to isolate the clean effect of reference prices on PBs' discretion, and the effect of such policy on public expenditures.

The remainder of the paper is organised as follows. Section 2 describes the institutional setting (2.1) and our dataset (2.2), and it presents some typical reduced-form estimates (2.3). Section 3 illustrates the structural theoretical framework by, first, introducing the definition of PBs' ability (3.1) and, second, showing the marginal cost estimate for the medical devices included in our dataset (3.2). Section 4 derives PBs' ability (4.1) and estimates its determinants (4.2). Section 5 replicates the same analysis exploiting the event of reference price termination as a quasi-natural experiment. Therefore, PBs' ability (5.1) and its determinants (5.2) are compared before and after this event. Finally, Section 6 concludes by summarising our findings and providing policy implications. In the Appendix we report further details on the estimations and further robustness checks: among others, we explore the role of repeated interactions between pairs of PB and suppliers - which could result in favoritism or corruption - as an alternative explanation to the observed variability in prices.

2 Context, data and preliminary evidence

2.1 Context: institutional setting

The Italian healthcare system is a regionally based national health service that provides universal coverage mostly free of charge. The main sources of its financing are

[6] They also find a significant (and negative) effect of public managers' wages on the prices paid by hospitals, a result consistent with the theory of corruption by Becker and Stigler (1974), i.e., better-paid managers are less tempted to engage in corrupted processes.

national and regional taxes that are supplemented by co-payments for pharmaceuticals and outpatient care. The system consists of three levels of action: national, regional and local. The highest level is responsible for ensuring the general goals and fundamental principles of the national health system. Regional governments are responsible for ensuring the delivery of services through a network of population-based local public health units (Aziende Sanitarie Locali, ASL) and local public hospitals.[7]

Procurement for standardised medical devices in Italy is decentralised at the local level. In 2013, the year covered in our dataset, approximately 350 local public buyers (PBs) had procurement responsibilities.[8] According to Italian public procurement law, goods and services should be awarded through public tenders, and direct negotiation can be used in some specific situations.[9] As for medical devices, in 2013, scoring-rule auctions were often used for complex services, whereas first-price auctions, together with direct negotiation, were almost always used for simpler and more standard goods.

To enter a public procurement auction for medical devices, potential suppliers must satisfy a minimum set of common requirements (i.e., present standard tender documents and have the financial and technical qualifications required). In this respect, each PB has some discretion in requiring additional qualifications and procedures. As a result, each PB in charge of procurement for medical devices can play a role in burdening suppliers' entry in the awarding procedure with costly requirements and, within the finite set of mechanisms defined by law, in choosing the awarding mechanism to use.

In 2012, the Italian Authority for Public Contracts (AVCP)[10] was assigned the task of setting *reference prices* for classes of functionally equivalent medical devices purchased by local public hospitals and health units. The aim of this policy was to help standardise the prices paid for very similar items by different PBs.[11] Each reference price consists of a cap on unitary prices for a class of medical devices: it is important to note here that a class of medical devices could refer to complex products, such as stents and prostheses, or to much simpler ones, such as syringes and

[7]In some regional areas, there are also private hospitals accredited with providing health services with the same characteristics as the public ones in order to cover local demand.

[8]Source: http://www.salute.gov.it/portale/documentazione/p6_2_8_1_1.jsp?id=13, accessed February 19, 2019.

[9]The Italian Code of Procurement (Italian Legislative Decree no. 163/2006, Art. 125), which was in force at the time and which our dataset refers to, states that direct negotiations could be used only for goods and services with a reserve price below €211,000 and only for urgent needs arising because (i) of an unexpected early termination of a previously existing contract, (ii) the period is between the end of the previous contract and the awarding of the following tender, (iii) the previous contract has expired and any participants showed up in the following tender or (iv) unpredictable events occurred.

[10]In 2014, the competencies of the AVCP were transferred to the Anticorruption Authority.

[11]The policy on reference prices also includes a safeguard clause. If an auction applying reference prices is annulled, the PB could then proceed with a new auction where reference prices are no longer applied. Our discussions with PBs highlight that such a clause was rarely implemented.

needles. The present empirical investigation is performed on a dataset including only simpler medical devices. Reference prices were mandatorily applied on the public purchasing of medical devices from July 1, 2012 to May 2, 2013. In the latter date, the Administrative Tribunal of Lazio (TAR), replying to the appeal jointly submitted by some suppliers, cancelled out the reference prices,[12] a decision motivated by the fact that the listed devices in *some classes* were both functionally and technically too heterogeneous to refer to the same price. Such heterogeneity is not an issue for the present empirical analysis, as our dataset refers to a later and more detailed classification.[13] Thus, one contribution of our analysis is empirically exploiting the discontinuity originated by the reference prices' adoption and elimination to test the impact of such an exogenous policy change on PBs' ability.

2.2 Data

We assembled four sources of data to obtain our final dataset. The main source is an original dataset consisting of all the transcripts of competitive auctions for standard medical devices conducted by Italian PBs in one year, from January 1, 2013 to December 31, 2013. These transcripts have been provided by the AVCP. For each auction, we have information regarding the ID of the PB organising the awarding procedure, the mechanism used (i.e., first-price auction, scoring-rule auction or direct negotiation), the medical device purchased (i.e., class of device and code), its quantity, the unitary price paid and the number of bidders in each auction. In these transcripts, it is also recorded if the PB has discretionally set a restriction to bidders regarding entry into the auction in the form of (i) a pre-qualification phase that has to be passed by bidders before taking part in the auction or in the form of (ii) a pre-selection phase that precisely indicates which bidders are allowed to participate. Finally, in our dataset, we know if the awarding auction includes lots of two or more different medical devices and if the PB carries a joint tender for a number of other PBs. In the latter, we observe the identity of the leading PB, which is the one responsible for the procurement process, as well as all the above information regarding the auction, number of bidders, winning price and quantity purchased.

In our dataset, the awarded contracts by each PB, $h = 1, \dots, H$, have an average value of €126,425, with an average unitary price of €1.37. The average number of bidders, $s = 1, \dots, S$, is 4. Within each class of functional homogeneous medical

[12] Consistently, the inclusion of an observation in the group of auctions where the reference price was or was not in force depends only on the date of the auction as recorded in the transcript.

[13] The Italian National Agency for Regional Health Services (AGENAS), which provides technical support for regional health departments in Italy, produced two lists for classes of homogenous products. The first one, published in 2009, was used to set the reference prices that were later on ruled out by the Lazio Regional Administrative Tribunal. The second one, published in 2013, is a more detailed list created to address the tribunal's concerns about excessive intra-class product heterogeneity. In our empirical analysis, we use the latter AGENAS list for the classes of medical devices.

devices, $d = 1, \ldots, D$, we observed price variations across the PBs' purchases. For example, the class defined as "syringes with three-piece eccentric cone, luer type; capacity 20 ml, graduate, with a triple-sharpened needle, mounted gauge G 19–G 23 and a length of 40 mm" shows unitary prices ranging between €0.05 and €0.17.[14]

Second, we collected information from each PB's financial statement[15] on the total value of the production, total costs, total costs for the personnel, costs for the personnel split in health-related personnel (i.e., doctors, nurses, healthcare assistants) and non-health related personnel (i.e., clerks), and costs for the procurement of health-related goods and services. Balance sheets show that the heterogeneity of PBs and their information on costs and outcomes could be used to measure PBs' efficiency. Summary statistics on PBs' financial statements are reported in Table 1. We also observe the region in which the PBs are based and if they are located in a rural or a metropolitan area.

Table 1: *PBs' summary statistics. Data in million euros*

	Obs.	Mean	S.d.	Min	Max
Total value production	129	535	458	41	2706
Costs: total	127	503	401	41	2533
Costs: personnel (Total)	129	126	96	11	686
Costs: personnel (health)	128	101	78	1	543
Costs: procurement (health)	129	64	61	1	404

Third, as a result of the decentralised nature of the Italian health system, different political decisions at the regional level may have an impact on PBs' ability. To this end, we collect information on the total regional spending devoted every year to health and on the regional population size. The ratio between these two variables, the per-capita health expenditure, is a dimensionally invariant measure of the amount of resources each region devotes to health every year. On average, the per-capita health expenditure is equal to €1,891.[16]

Finally, Italian PBs experience very large delays in their payments (Guglieri and Carbone, 2015). Clearly, delays affect PBs' ability to obtain a better deal because suppliers may discount an expected late payment by initially asking a higher price. We collected data on average days payable outstanding at the PB level.[17] Delays vary

[14] Table A1 in the Appendix reports, for each device class, the average, minimum and maximum price observed.

[15] According to Italian law, each local PB's financial statement, which includes the balance sheet and profit and loss account, has to be disclosed and should follow a standard format jointly set by the Ministry of Health and the Ministry of Economy and Finances. Financial statements were downloaded from official websites.

[16] To check if the regional per-capita health expenditure is driven by economies of scale, we compare the per-capita health expenditure for regions above and below the median population by using the Kolmogorov–Smirnov test. We find no significant difference.

[17] We have missing information on 12% of our observations. In this case, we use the regional

extensively, from 55 to 1,603 days, with a median value of 160 days. Delays on the same year may present a simultaneity problem when studying the impact on PBs' ability. To address this issue, we use delays in 2012 to study PBs' ability in 2013.

2.2.1 Data cleaning

The unit of observation in our dataset is the price paid by each PB in procuring each medical device. Starting from the larger AVCP original dataset which includes 2,149 observations in the period spanning January 2013 to December 2013, we consider only classes of medical devices for which we have at least 10 observations, thus reducing our dataset to a total of 1,776 observations.

In managing the procurement of medical devices, PBs can choose, within the limits described in Italian law, the awarding mechanism in the form of first price auctions (FPAs), direct negotiations and scoring rules. Our database includes all these procedures. Considering that our empirical strategy takes its steps on standard goods, we exclude scoring rule auctions from the database for our analysis: these procedures may introduce a source of within-category device heterogeneity by making suppliers compete also on quality elements. As a result, we end up with 1,474 observations, which are split almost equally according to the awarding mechanism used, i.e., 733 FPAs and 741 direct negotiations. For both of these mechanisms, PBs can affect bidders' entry by imposing requirements and qualifications to participate in the auction and/or by implementing a larger or smaller level of advertising regarding the awarded procedure.[18] In Table 2, we report the descriptive statistics of our dataset by the awarding mechanism and observed number of bidders in each auction.[19]

Table 2: *Awarding mechanism and bidders*

Type		Obs.
Direct negotiations		741
FPA		733
number of bidders:	1	236
number of bidders:	$[2, 4]$	131
number of bidders:	5+	155

All in all, our dataset includes the procurement purchases of 133 different PBs from 89 suppliers and for 76 classes of medical devices.

average as a proxy. The regional average delay is highly correlated with local delays (correlation 0.73). Data were provided by Assobiomedica, an Italian association of medical device producers.

[18] See Kelman (1990) and Bandiera et al. (2009) for a discussion about PBs' discretion on auctions' entry requirement. For the effect of advertising on procurements' auction outcomes, see Coviello and Mariniello (2014).

[19] Data on the number of bidders in each auction are missing for 211 first price auctions.

2.3 Preliminary evidence

In this sub-section, we present preliminary evidence on our unit of observation, i.e., unitary price. First, we check if prices vary separately with the medical device, with the PB and with the identity of the supplier. Second, we compare some common reduced-form estimates, and we detect the most appropriate one to describe unitary prices.

As for the first task, we ran a set of one-way ANOVA tests to see if unitary prices, on average, change with the medical device, with the PB and with the supplier (one dimension per time). The three tests, reported in Column (1) of Table 3 with p-values within squared parentheses, always reject the null hypothesis, indicating that prices indeed vary with all the three dimensions, especially with the device categories (as implied by the higher value of the test). We then checked if unitary prices change with each dimension, even after controlling for the other two. For this purpose, we applied the same test as before, in which prices are now cleaned from their average by two dimensions. In one case, we considered the difference between prices and average prices by PB plus average prices by supplier, and we tested if this difference changes with the medical device. This way, we study if, after removing PB- and supplier-specific linear fixed effects, there is still something that varies with the devices. Column (2) reports that the tests always reject the null hypothesis, indicating that prices still vary with each dimension, once we remove the fixed effects of the other two. In another case reported in Column (3), we repeated the ANOVA exercise using the ratio, instead of the difference between the price and the average price paid. The purpose here was to see if after the removal of PBs' and suppliers' specific multiplicative fixed effects, there is still something that varies with the devices. All in all, this evidence suggests that prices are determined by all the three dimensions and that isolating the contribution of each is possible. Our results are confirmed also using a non-parametric Kruskal–Wallis test in place of the ANOVA test (output available upon request).

Table 3: *One-way ANOVA tests*

	(1) Price	(2) Price - avg. price	(3) Price / avg. price
Device	8.90	6.50	6.95
	[0.000]	[0.000]	[0.000]
PB	2.28	1.60	1.75
	[0.000]	[0.000]	[0.000]
Supplier	3.79	2.03	1.53
	[0.000]	[0.000]	[0.000]

Note. "Price - avg. price" and "Price / avg. price" respectively subtract and divide to the price its average by the two remaining dimensions (e.g., the average by PB and the average by supplier when running the test on the device dimension); p-values in squared parentheses.

As for the second task, a standard approximation requires unitary prices to be explained by costs, quantity purchased and measures of market power. As we run our analysis on medical devices grouped into classes of functionally homogeneous products, a vector of device dummies is a good proxy for their costs. Quantity purchased is used to control for the presence of economies of scale. To consider market power, we take two variables: the number of different suppliers recorded in our dataset for each category of medical devices (to account for potential competition) and the number of bidders (to account for effective competition in the tender). We also incorporate a dummy for FPAs. The reason is that FPAs generally host a larger number of bidders than direct negotiation does.

Using a linear regression model of prices on device dummies, number of suppliers and number of bidders, we find that 59% of the medical device dummies are significant at the 5% significance level, with $R^2 = 0.31$. With the use of a log-log model, the fit increases to $R^2 = 0.89$, with 87% of the medical device dummies being significant (see Columns (1)–(2) of Table 4). This evidence suggests that the log transformation is better suited to describe prices. Moreover, F-tests strongly reject the hypothesis that all device dummy coefficients are equal. Moving from a fixed-effect (FE) to a random-effect (RE) model has no relevant impact on these results. Variables on the number of bidders and the awarding mechanism may be affected by endogeneity; Columns (3) and (4) then replicate the two previous analyses without including these variables in the specification. The log-log model is still largely preferred to the linear model. In what follows, we then stick to FE regressions with log prices as a dependent variable.

Finally, in Column (5), we use a log-log model of prices on quantities, device dummies and device–quantity interactions;[20] to control for potential economies of scale, we allow device dummies to interact with the quantities purchased. The fit is high ($R^2 = 0.90$) and we would find almost no variation ($R^2 = 0.88$) with the same specification but with quantity and quantity–device interactions removed. Furthermore, 91% of the log quantity and device–dummy interactions are not significant at the 5% significance level. We obtain similar results using a linear regression model. In conclusion, our analysis suggests that in our dataset, no economies of scale are present in the levels of quantity purchased by our PBs.

[20]Given that products are different, we do not consider it appropriate to use a single measure of quantity.

Table 4: *Preliminary regressions*

	(1)	(2)	(3)	(4)	(5)
Method	OLS	OLS	OLS	OLS	OLS
	Price	ln(Price)	Price	ln(Price)	ln(Price)
Suppliers	-0.265***		-0.222***		
	(0.088)		(0.050)		
Bidders	0.024				
	(0.033)				
ln(Suppliers)		-6.021***		-5.492***	
		(0.616)		(0.543)	
ln(Bidders)		-0.044			
		(0.030)			
FPA	0.240	0.091*			
	(0.274)	(0.053)			
Reference price	-0.223	0.030	-0.082	0.031	
	(0.247)	(0.044)	(0.134)	(0.034)	
log(Quantity)					0.004
					(0.091)
Constant	2.093***	9.249***	1.883***	8.399***	-0.461
	(0.694)	(1.133)	(0.392)	(0.942)	(0.584)
Device fixed effects	YES	YES	YES	YES	YES
log(qty)$\times$ Device FE	NO	NO	NO	NO	YES
R^2	0.307	0.889	0.323	0.879	0.898
Avg. dependent variable	1.513	-1.175	1.406	-1.136	-1.136
Observations	979	979	1,474	1,474	1,474

Note. Robust standard errors, except Column (5): clustered standard errors using PB ID; *** p<0.01, ** p<0.05, * p<0.1.

3 Theoretical framework

3.1 Definition of the PB's ability

Consider a market in which – on the demand side – there is a PB, $h \in \{1, H\}$, in charge of managing the purchase of medical devices – such as hypodermic needles for syringes[21] – belonging to class $d \in \{1, D\}$. On the supply side, there are S suppliers, and each supplier $s \in \{1, S\}$ is willing to sell the requested quantity q_{dh}. We assume

[21] According to Italian law, requests to procure medical devices cannot refer to a specific brand existing in the market, but they should describe the required medical device in a very detailed and technical way so as not to favour a specific supplier.

that for a medical device of class d, each supplier's profit function, π_{ds}, with constant return to scale, is given by

$$\pi_{ds} = q_{dh}\left(p - c_d\left(\theta_s\right)\right)$$

where p is the awarding price of the medical device, $c_d\left(\cdot\right)$ is the cost function to produce the medical device d, and $\theta_s \in \left[\underline{\theta}, \overline{\theta}\right]$ is the supplier type, known only by the supplier. We assume that θ_s is distributed according to a cumulative distribution function $F(\theta)$, which is common knowledge amongst suppliers and not observed by the econometrician. Assuming a cost function with unidimensional private information θ_s and no economies of scale, makes it possible to use unitary prices in the presence of lots. In other words, no cross-subsidisation between different medical devices in the same lot is admitted. Finally, some suppliers may not be active for a specific tender. We define $N_{dh} \leq S$ as the number of active suppliers in a specific tender run by a local PB h, for class d of medical devices.

The observed unitary price paid, p_{dhs}, can be written as the sum of the supplier's marginal cost $c_{ds} = c_d\left(\theta_s\right)$ and a mark-up μ_{dhs}, as follows:

$$p_{dhs} = c_{ds} + \mu_{dhs}. \tag{1}$$

When standard devices are procured, the PB's goal is to purchase them at the lowest possible price. Under full information, the PB's utility is then maximised if $p_{dhs} = c_d^{MIN}$, where c_d^{MIN} is the marginal cost of the most efficient supplier. To maximise its utility, a PB needs to both award the contract to the most efficient supplier (i.e., the one with the lowest marginal cost) and obtain a price as close as possible to such a supplier's marginal cost. However, in a realistic framework, several elements might prevent a PB from obtaining such a price. Indeed, the PB can have limited information on the suppliers' cost structure, and the PB can attract a small number of competitors in the awarded mechanism chosen, among other elements. Some of these elements are exogenous with respect to the PB's choices, whereas others can be totally or partially controlled by the PB.

In order to investigate PBs' ability in the purchasing of different classes of medical devices, we need to set a benchmark supplier $s = 0$ with marginal costs $c_{d0} = c_d\left(\theta_0\right)$. Defining $\Psi_{dhs} = \mu_{dhs} + \left(c_{ds} - c_{d0}\right)$, Equation (1) can then be rewritten as follows:

$$p_{dhs} = c_{d0} + \Psi_{dhs}. \tag{2}$$

We define PBs' ability as a persistent effect on Ψ_{dhs} recorded across all the tenders (i.e., FPAs and direct negotiations) to procure medical devices. Such an effect refers to PBs' choice of the awarding mechanism, the definition of the reserve price, and the promotion of the best suppliers' participation to the tender, among other factors. The higher PBs' persistent effect, the higher the price paid on average by these PBs (the lower their utility), and the lower PBs' ability in managing the procurement process.

To estimate this effect, we assume that Ψ_{dhs} can be broken down into a PB-specific effect γ_h and a residual component γ_{ds}. Assuming linear separability (i.e., $\Psi_{dhs} = \gamma_h + \gamma_{ds}$), implies that γ_h can be estimated consistently from Equation (2) by using a regression of prices on medical devices' and PBs' FEs. In this case, the choice of the benchmark supplier is irrelevant, as its effect is captured by the medical devices' FEs.

However, our preliminary analysis in Sub-section 2.3 suggests that a log-log structure and hence a multiplicative separability (i.e., $\Psi_{dhs} = \gamma_h \gamma_{ds}$), better fits our data. Accordingly, Equation (2) can be rewritten as follows:

$$\ln(\Psi_{dhs}) = \ln(p_{dhs} - c_{d0}) = \ln(\gamma_h) + \ln(\gamma_{ds}) \tag{3}$$

thus requiring a structural estimation of marginal costs and a careful choice of c_{d0}. In the following Sub-section 3.2, we focus on how to derive the benchmark marginal cost for each class of medical devices, and, in Section 4, we estimate each PB's FE γ_h, and then explore the correlation between PBs' ability and PBs' balance sheet data.

3.2 Marginal cost estimate

Following the methodology proposed in the seminal work of Guerre et al. (2000; henceforth GPV), we use only FPAs' observations to estimate the marginal cost for each class of awarded medical devices.[22] In so doing, we implemented GPV with three main changes. First, we account for heterogeneous devices in our dataset (see Section 3.2.1). Second, we adapt the GPV methodology developed on direct auction - in which the highest price wins - to procurement auctions, in which the lowest price wins (see Section 3.2.2). Finally, we extend GPV to consider sealed bid auctions in which bidders do not directly observe their competitors, i.e., they may receive a noisy signal on the level of competition (see Appendix A2).

3.2.1 Device heterogeneity

Medical devices include different goods which are usually categorised by class. It is reasonable to expect that the price distribution shifts within each class of medical device. Unfortunately, the number of observations in our dataset is too small to compute the conditional distribution of bids for each class d. To address this issue, and consistent with the preliminary evidence presented in Section 2.3 suggesting that a log-transformed model is well-suited to describe our data, we assume that bidders' private valuation (i.e., their marginal cost) is multiplicative separable in the supplier's type θ_s and in a technological parameter α_d specific for each class of medical device. This separability is preserved by equilibrium bidding (Haile et al., 2003). For example, suppose the marginal cost of a medical device of class d is twice the marginal cost

[22] The underlying hypothesis is that for standard goods, each supplier's marginal cost does not change under different awarding mechanisms (i.e., FPAs, negotiations).

of a medical device of class d'. With this assumption, the same ratio between the marginal costs of d and d' applies to all suppliers. In this case, also in equilibrium and for each supplier, the price of d will be two times the price of d'.

Accordingly, we assume that in an auction for medical device d, marginal costs (i.e., the bidders' private values) are given by the following:

$$c_d(\theta_s) = \alpha_d \theta_s \tag{4}$$

with the bidder-specific private information θ_s being independent from the device-category parameter α_d. The assumption of multiplicative separability in the cost function has already been used in the literature (e.g., to model adaptation costs in Bajari et al., 2014) and is consistent with the preliminary results presented in Subsection 2.3.

Let a category $d = 0$ be such that $\alpha_d = 1$. Then, the equilibrium price maintains the same separable structure as the marginal costs:

$$p_d(\alpha_d, \theta_s, N_{dh}) = \alpha_d p_0(\theta_s, N_{dh})$$

where $p_d(\cdot)$ is the equilibrium bidding function for device d. Given this functional form, the technological parameter α_d can be obtained using a regression of the observed log bids on the medical devices' FEs (the dummy variable D_d) and on the number of bidders in each FPA (N_{dh}), as follows[23] (output available upon request):

$$\ln(p_{dhs}) = \sum_{d=1}^{D} (\ln(\alpha_d) D_d + \beta_{dh} \ln(N_{dh})) + \varepsilon_{dhs}. \tag{5}$$

As a robustness check and to exclude the fact that devices with few observations lead to biased estimates, we repeated the estimation of Equation (5) in two subsamples of our medical device classes, namely for all medical devices for which we have at least five observations (roughly half of the medical device classes) or eight observations (roughly half of the observations used to estimate the α parameter). Then, in both cases, we test whether the estimated α_d (for the considered devices) are equal to the same α_d estimated in the entire sample. In both cases and for all the devices considered, we find no statistical difference with a 95% confidence interval.

All observed unitary prices p_{dhs} paid by PBs, that is, the winning bids, are then normalised dividing by α_d. We define homogeneous price p_{0hs} as follows:

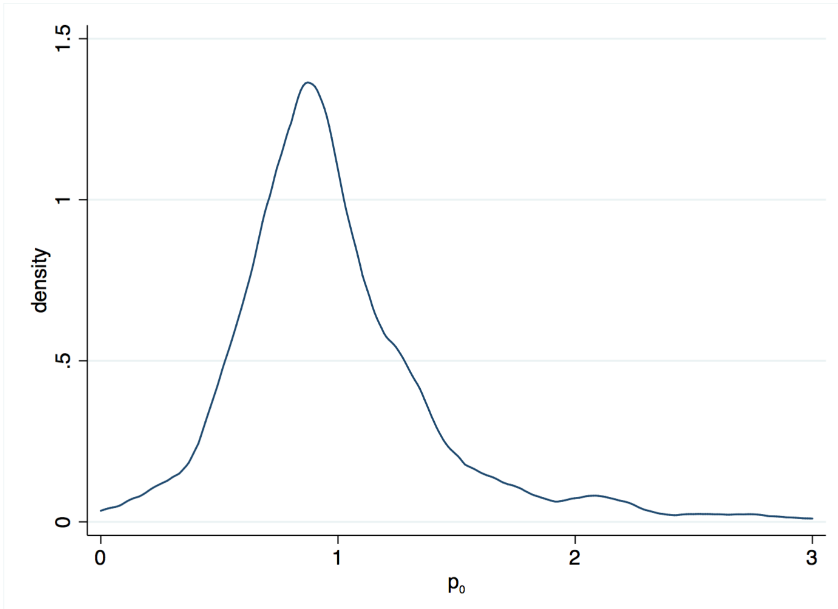
$$p_{0hs} = \frac{p_{dhs}}{\alpha_d}. \tag{6}$$

This price p_{0hs} is used from now on to make all observations of our dataset comparable and get a consistent estimate of the bid that each supplier would have submitted in an FPA for the provision of a medical device of class 0, with $\alpha_0 = 1$ and with the

[23] We report in Table A1 all device-category parameters α_d.

level of competition N_{0h}. The distribution of p_{0hs} extracted from the data is presented in Figure 1.

Figure 1: *Distribution of homogeneous prices*



3.2.2 Procurement rule and winning price

In a procurement framework, the lowest bid wins. The resulting Nash equilibrium bid $p(\theta_i)$ of the i-th bidder of type θ_i is given by the following:

$$p(\theta_i) = \theta_i + \int_{\theta_i}^{\overline{\theta}} \left(\frac{1 - F(y)}{1 - F(\theta)} \right)^{n-1} dy. \tag{7}$$

Similar to GPV, Equation (7) can be inverted to express the unobserved marginal cost θ_i as a function of the observed prices and price distribution observed through kernel estimation.

In our dataset, for each auction, we observe the winning prices rather than all the bids. For standard FPAs, Athey and Haile (2002) propose using the winning prices of multiple auctions to identify private values because the winning price is the maximum order statistic of the bids' distribution for a given level of participation. In a procurement framework, winning prices can be considered as the first (i.e., minimum) order statistic of the bids' distribution.

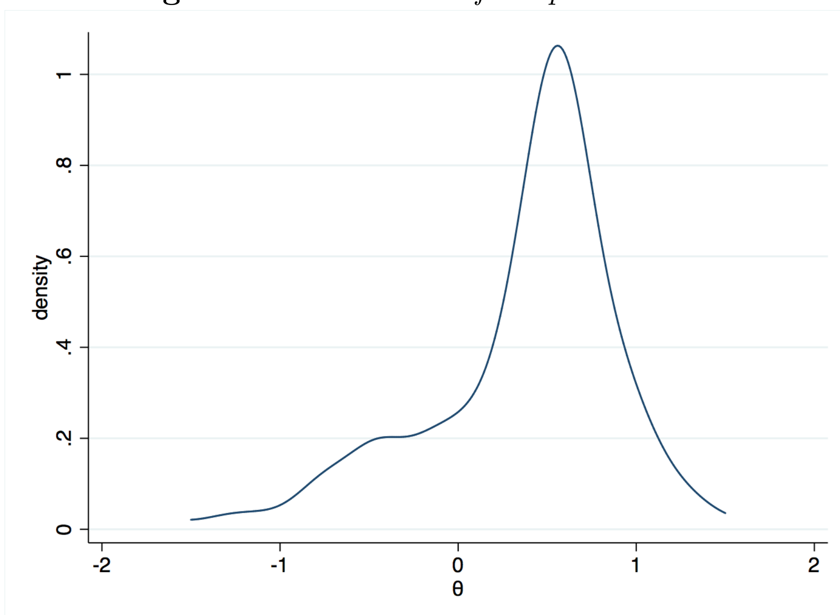
The structural equation that states unobserved marginal costs as a non-parametric function of observed winning prices, winning prices' distribution and level of competition is as follows:

$$\theta_s = p_{0hs} - \frac{N_{0h}}{N_{0h}-1}\frac{1-G_{(1)}\left(p_{0hs}|N_{0h}\right)}{g_{(1)}\left(p_{0hs}|N_{0h}\right)} \tag{8}$$

where $N_{0h} = \{3, 8\}$ is the noisy signal about the level of competition that bidders receive for the auction considered, $G_{(1)}\left(p_{0hs}|N_{0h}\right)$ is the cumulative density function of all transaction prices, conditional on N_{0h}, evaluated at p_{0hs}, and $g_{(1)}\left(p_{0hs}|N_{0h}\right)$ is its relative probability density function. The derivation of Equation (8) is presented in Appendix A.3.

The resulting distribution of θ_s is plotted in Figure 2.

Figure 2: *Distribution of the private value*



As we impose no constraint to Equation (8), some estimates of the marginal cost θ_s are apparently negative. However, this is not a problem for our subsequent analysis, as we concentrate on a central value of the distribution. Indeed, our analysis requires choosing a benchmark supplier, equal across all medical devices. Then, the prices paid by different PBs are compared to the marginal costs of that supplier. We use the median value θ_0 of θ_s to define such a supplier, and, accordingly, we use Equation (4) to obtain the benchmark marginal cost c_{d0} for each class d, as follows[24]:

$$c_{d0} = \alpha_d \theta_0.$$

We use the median marginal cost mainly for two reasons: (i) deviations from a median value provide an easy interpretation of the price-cost differences $(p_{dhs} - c_{d0})$ used to

[24] We report in Table A1 all marginal costs of the benchmark supplier.

derive PBs' ability, as it measures how much the winning supplier differs from a median one; (ii) the median value is a safer choice, as the distribution of the marginal costs is structurally estimated and not directly observed by the econometrician.

The choice of the benchmark marginal cost has consequences on Equation (3) and in particular on the PB specific effect γ_h. In our case, γ_h describes the PB effect relative to the median supplier. Changing benchmark marginal costs does not alter our subsequent analysis; as it is constant with respect to the PB, the PB-specific effect γ_h may change in size, but it preserves the same ranking.[25]

To investigate the PB's ability across the markets of different medical devices, we consider c_{d0}, along with the price paid by the PB. In our dataset, benchmark marginal costs are always above zero and, excluding 5% of our observations, below the actual prices paid by PBs.

3.2.3 Robustness checks

In this sub-section, we replicate the marginal cost estimate to control for different issues which may arise from our structural model. We are particularly concerned about the median value θ_0 used to define the benchmark marginal cost c_{d0} because the prices paid by PBs are compared to such a cost. To further strengthen our results, for each robustness check listed below, we also compare the distribution of private values θ_s with the baseline estimate depicted in Figure 2.

Only producers A concern with our analysis might be the use of a private value model to structurally estimate the auction game. This model is consistent with a setting where bidders are, at the same time, "producers and sellers", that is, are endowed with a privately observed cost function. The presence of bidders which are, at the same time, "distributors and sellers" may introduce a common-value component into the information structure, thus determining biased estimates. Non-parametric tests to control for the presence of a common value component exist in the literature, but they require to observe either all bids (Haile, Hong and Shum, 2003) or, at least, the winning bid and the second lowest bid (Athey and Haile, 2002). To address this issue, as our dataset contains information on winning bids only, we collect additional data on bidders to identify them as "producers and sellers" or "distributors and sellers". [26] Then, the marginal cost estimate is repeated using only bidders identified as "producers and sellers".

Reference price Understanding under which conditions the reference price may affect bidding decisions is relevant. Note that inconsistencies in estimation of θ may

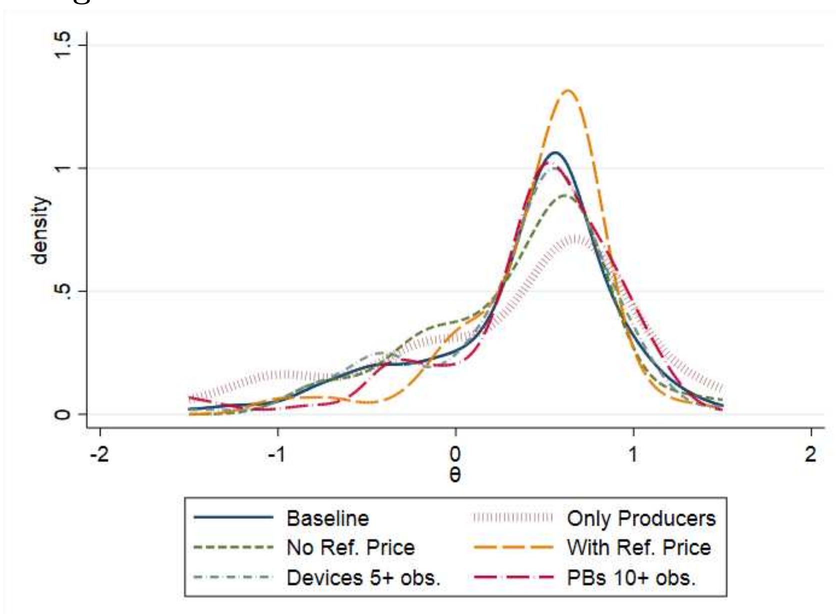
[25] We tried with the 33-th and 67-th percentiles of the distribution of private values. Our results, available upon request, are qualitatively confirmed.

[26] Data come from the Orbis dataset from Bureau Van Dijck. The relevant variable is the NACE rev2 main category: C for the producer or G for the distributor. We find that 75.5% of the winners in FPA are producers, and only 24.5% are distributors.

arise only when both the following conditions are satisfied: (i) the reference price is greater than the winning firm's marginal cost, but smaller than its equilibrium bid when the reference price policy is not adopted, and (ii) at least a second firm with marginal costs smaller than the reference price participated in the auction. As a robustness check, we separately consider observations before and after the termination of the reference price policy.

Device and public buyers' restrictions To exclude the fact that devices with few observations lead to biased estimates, we repeat the estimation excluding device classes with less than five observations. We perform a similar exercise for PBs, and consistently with what we run in the next section, we exclude PBs with less than 10 observations.

Figure 3: *Private value distribution: robustness checks*



The resulting distributions of the private values θ_s are plotted in Figure 3. The different median values θ_0, together with the result of a Kolmogorov–Smirnov test for the equality of distributions between the baseline model and each robustness check, are reported in Table 5.

Table 5: *value of θ_0: robustness checks*

	θ_0	Obs.	p-value
Baseline	0.491	278	
Only Producers	0.496	162	0.002
Without Ref. Price	0.493	183	0.166
With Ref. Price	0.559	94	0.232
Devices 5+ obs.	0.471	218	0.742
PBs 10+ obs.	0.507	192	0.061

Note. The column "p-value" reports the p-value of a Kolmogorov-Smirnov test comparing the baseline distribution with the one in the robustness check. The null hypothesis is that the distributions are identical.

The median θ_0 in Table 5 shows that the largest deviation from the baseline estimate of θ_0 arises when the marginal cost estimate is repeated using only auctions when the reference price policy was in force. However, the estimate of θ_0 is only 13.8% larger than the baseline estimate, the sample is the smallest amongst the robustness checks considered and the Kolmogorov–Smirnov finds no difference between the two distributions.

Remarkably, differences in θ_0 from the remaining robustness checks are tiny: for example, the deviation in θ_0 from the baseline when considering only producers is equal to only 1%. This is, with the use of the Kolmogorov–Smirnov test, the only distribution of θ_s found to be significantly different from the baseline estimate. However, the included suppliers are also different: producers and distributors in the baseline distribution, but producers only in the robustness check. To assess whether differences in the distributions arise because different suppliers are included or because of biased estimates, in the baseline model we estimate θ_s using both distributors and producers; then, *after the estimate,* we remove the distributors. In the robustness check, distributors are removed *before the estimate of the marginal costs*. In both cases, we end up with the same suppliers in the two distributions of θ_s. We found no differences between the two distributions (p-value of the Kolmogorov–Smirnov test: 0.310). Note that distributions would have remained different if the introduction of distributors in the baseline model would have determined biased estimates.

4 Public Buyer's ability

4.1 Estimation

We now investigate each PB's specific fixed effect to run procurement procedures for standard medical device purchase. Considering the price paid for each medical device and having estimated the benchmark marginal cost c_{d0} of each medical device, we get

$\Psi_{dhs} = p_{dhs} - c_{d0}$. We then proceed by estimating the PB-specific component γ_h by using the following OLS regression:

$$\ln(\Psi_{dhs}) = \ln(p_{dhs} - c_{d0}) = \sum_{h=1}^{H} (\widetilde{\gamma}_h A_h + \phi_h A_h R) + \epsilon_{dhs}. \tag{9}$$

The specification in Equation (9) includes the PB dummies A_h and the dummy variable R equal to 1 when the reference price regulation was in force and 0 otherwise. This variable interacts with the PB dummies to capture any change in the PB's fixed effect attributable to the reference price.[27]

We exclude from this estimation the PBs for which we have fewer than 10 observations, i.e., those PBs that have managed less than 10 different auctions in the period considered. We end up with 57 PBs and 1,192 observations on awarded medical devices. In the analysis, we use standard errors clustered at the level of medical devices to control for potential serial correlation.

Our goal is to provide an estimate for the PB parameters $\widetilde{\gamma}_h = \ln(\gamma_h)$, where γ_h is the PB's specific fixed effect in managing the procurement process, as defined in Equation (3). The higher the coefficient, the lower the ability of the PB. In the regression, almost all dummies are significant, suggesting that each PB is endorsed with its own specific ability in managing the procurement process. The R^2 of the regression is equal to 0.63, which means that about two-thirds of the distance between prices and marginal costs can be explained by the PBs' fixed effects. Estimates are available upon request.

4.2 Determinants

A PB's ability may reflect its choice of the awarding mechanism, its definition of the reserve price and its capacity to attract more or better suppliers, among other factors. In what follows, we study if the PB's ability in managing the procurement process is associated with some observable characteristics (i.e., of the PB and of the awarding mechanism). For this purpose, we run regressions of a proxy for each PB's fixed effect on a set of explanatory variables, as follows:

$$-\widetilde{\gamma}_h = \beta_0 + \beta_1 M_h + \beta_2 H_h + \beta_3 P_h + \beta_4 C_h + \epsilon_h. \tag{10}$$

In these regressions, the unit of analysis is a single PB. We consider weighted regressions, in which the weight is proportional to the number of auctions the PB

[27] In Appendix A4, we modify Equation (9) to include in the specification the interactions between PB dummies and producer dummies. One PB and one supplier may interact repeatedly through the procurement of different medical devices, for example, to maintain a relational contract or because of corrupted behaviour. This interaction can lead to an increase in the final price of the medical device procured and potentially have a systematic impact on the estimated PB's ability. However, we find this impact to be negligible.

managed in our sample period. This way, we attribute more importance to the PBs that more frequently organised tenders to award medical devices.[28] We consider two different measures for the dependent variable. First, we take the PB's ability derived earlier from Equation (9) with the structural estimation of the marginal costs. Second, we take a measure of the PB's ability originating from the following equation:

$$\ln(p_{dhs}) = \sum_{h=1}^{H} (\widetilde{\gamma}_h A_h + \phi_h A_h \cdot R) + \sum_{d=1}^{D} (\delta_d D_d) + \epsilon_{dhs}. \tag{11}$$

Equation (11) differs from Equation (9) in two ways. First, the dependent variable is made of prices only and therefore excludes marginal costs which, with our approach, are in turn recovered from prices. Second, the specification now includes medical device dummies. The purpose is to obtain estimates of the PBs' fixed effects that are not affected by our structural approach to infer the marginal cost of medical devices. In fact, the heterogeneity in the costs of the devices is now captured through the assumption-free medical device dummies, in a fashion similar to that in the work of Best et al. (2017). The resulting estimates of $\widetilde{\gamma}_h$ are generally smaller in size but highly correlated (0.61) with those obtained in our benchmark analysis. The R^2 of the regression in Equation (11) is equal to 0.94, but it reduces to 0.49 when we repeat the regression with only the PBs' fixed effects. We thus notice that, even excluding the structural analysis, almost one half of the price dispersion is still explained by the PBs' fixed effects. Estimates are available upon request.

Note that in Equation (10), we inverted the sign of the dependent variable to facilitate its interpretation. In so doing, higher coefficients indicate higher ability to run the procurement procedure. As the dependent variable is an estimate itself, we make use of bootstrapped standard errors based on 1,000 iterations.

The specification includes four groups of variables: M_h refers to the applied auction mechanism (the fraction of direct negotiations), H_h refers to potential scale economies in purchasing (the logarithm of the health personnel cost or the logarithm of health material purchases), P_h refers to the distribution of costs (the fraction of non-health personnel over the total personnel costs and the fraction of health material purchases over the total health costs) and the average number of days the PB takes to pay its suppliers (the logarithm of the days payable outstanding as of 2012),[29] and C_h refers to control variables on the nature of the PB (the dummy ASL, identifying medium–small health units, different from hospitals), its location in a metropolitan/rural area, in the North/Center–South of the country, and the per-capita health expenditures in the region the PB belongs to. This last variable is interacted with

[28] In the dataset used for this analysis (57 observations), the number of auctions attributed to a single PB ranges from 10 to 95, with an average of 30.53.

[29] We consider the year 2012, i.e. one year before our sample period, to avoid potential reverse causality with the dependent variable. The source of this information is www.assobiomedica.it.

the Center–South dummy because we observed countrywide disparity, with Northern regions spending more than Southern ones.

Table 6 reports the output of our regressions by using the proxy of PBs' ability obtained from Equation (9) in Columns (1) and (2), and using the proxy obtained from Equation (11) in Columns (3) and (4). For each measure, we consider two variants of the specification, depending on which variable is considered for H_h (either health personnel cost or health material purchases). We do not consider the two variables in the same specification because they both proxy for the size of the PB, and, indeed, they are highly correlated (the correlation is 0.79). A regression equation using both variables could find it difficult to precisely identify the contribution of each. Because a priori, we have no preference for either variable, we look at them in two separate models.

Table 6 shows the output of IV regressions rather than the standard OLS ones (shown in Appendix Table A.3). The reason is that we are concerned that there may be simultaneity on the mechanism variable M_h: the PB's decision on which auction mechanism to implement may influence and at the same time be influenced by the PB's ability itself. This could create endogeneity and could produce inconsistent estimates. In all the columns, we therefore instrument the mechanism variable (fraction of direct negotiations) with two variables, the fraction of multi-device auctions and the average quantity of devices auctioned. Both instruments inform on the size of each auction. This is important, as smaller auctions face fewer legislative constraints in using direct negotiation. The two instruments should be directly correlated with the procurement mechanism (i.e., they should be relevant) but not with the PB's ability (i.e., they should be exogenous). This set of instruments is indeed found to be relevant and exogenous according to the standard tests, as it rejects the null hypothesis of the Kleibergen–Paap test of relevance, and it accepts the null hypothesis of the Sargan test of over-identifying restrictions (p-values at the bottom of the table; also see the output of first-stage and reduced-form regressions in Appendix Table A.4). Moreover, the Hausman–Wu test suggests that endogeneity is indeed present, at least in Columns (1) and (2), and using IV models (p-values at the bottom of Table 6) is therefore advisable. In what follows, we comment only on coefficients that are significant at least at a 5% level. Importantly, IV estimates in Table 6 and OLS estimates in Appendix Table A.3 show similar quantitative results, with the only exception of the endogenous explanatory variable on the fraction of direct negotiations.

The key findings from all the models in Table 6 are qualitatively the same. Our analysis shows that direct negotiations have a negative impact on the PB's ability (significant at 5% only in the specification of Columns (2) and (4)). The effect is quantitatively larger with the dependent variable in the first two columns. According to Column (2), a 10% increase in the fraction of direct negotiations decreases the PB's fixed effects by 0.17 or 8.21% (-0.17 divided by the average of the dependent variable, 2.071); according to Column (4), the same change has an effect of –0.05 or –4.04% (–0.047/1.163). The reason for this evidence could be that in line with Italian law on public procurement, direct negotiations are used when the awarded item is endorsed with specific characteristics that the competition will not allow to address. This explains the higher prices paid by the PB and thus a negative impact on the PB's ability.

We also find that the PB size effect, measured using either health personnel cost or health purchases, is positive and significant. Considering the variables on the distribution of costs, we find a positive and strong significant effect on the ratio of non-health personnel over the total personnel cost. There is a generally negative effect of health purchases over total health expenditures, which seems to indicate that PBs' ability may increase further when more resources are devoted to health personnel rather than to health purchases, or even better to non-health personnel. That is, when two PBs with the same size of expenditures are compared, that one recording larger costs for non-health personnel does show more ability in procuring medical devices. This is the only effect that is quantitatively larger with the dependent variable of Columns (3) and (4). For instance, in Column (4), a 10% increase in the ratio reduces ability by 0.116 or 9.94% (i.e., -0.116 divided by 1.163) as opposed to 7.21% (-0.148/2.047) from Column (2).

Turning to the control variables, we see a negative overall effect for small local health units (as measured with the coefficient on the ASL dummy) and the number of outstanding days for payment. This latter evidence suggests that efficiency in making quick payments is related to the ability to reach prices closer to the marginal costs. With the dependent variable in Columns (3) and (4), we also find significant effects of the geographical variables about a PB located in the Center–South (negative), the size of per capita health expenditures (positive) and the interaction between the two dimensions (positive). No other variable in the specification turns out to be significant.

Table 6: *Determinants of PB's ability – IV regressions*

	(1)	(2)	(3)	(4)
Method	IV	IV	IV	IV
PB's ability	Using costs		Not using costs	
Fraction of direct negotiations	-1.277*	-1.718**	-0.347*	-0.470**
	(0.683)	(0.841)	(0.190)	(0.225)
ln(health personnel costs)	0.463***		0.203***	
	(0.046)		(0.018)	
ln(health purchases)		0.372***		0.172***
		(0.052)		(0.020)
Non-health/total personnel cost	4.822***	4.154***	1.481***	1.226***
	(0.603)	(0.694)	(0.160)	(0.188)
Health purchases/total health exp.	0.380	-1.487***	-0.326***	-1.156***
	(0.520)	(0.545)	(0.126)	(0.147)
ln(days payable outstanding)	-0.964***	-1.004***	-0.155***	-0.170***
	(0.137)	(0.149)	(0.034)	(0.036)
ASL	-0.644***	-0.663***	-0.230***	-0.231***
	(0.139)	(0.154)	(0.036)	(0.038)
Metropolitan area	-0.155	-0.296	-0.135*	-0.171*
	(0.263)	(0.323)	(0.075)	(0.088)
Center-South (CS)	-2.134	-2.320	-1.209**	-1.297**
	(1.743)	(1.834)	(0.497)	(0.521)
Health expenditure p.c.	-0.762	-0.761	0.585**	0.543*
	(1.084)	(1.184)	(0.271)	(0.289)
Health expenditure p.c. x CS	1.777*	1.778*	0.895***	0.912***
	(0.961)	(1.019)	(0.272)	(0.285)
Constant	-0.561	2.794	-2.853***	-1.542***
	(2.443)	(2.421)	(0.616)	(0.597)
Kleibergen-Paap test (p-value)	0.000	0.000	0.000	0.000
Sargan test (p-value)	0.114	0.266	0.197	0.477
Hausman-Wu test (p-value)	0.007	0.003	0.152	0.073
Avg. dependent variable	2.071	2.071	1.163	1.163
Observations	57	57	57	57

Note. Bootstrapped standard errors (1,000 repetitions) in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

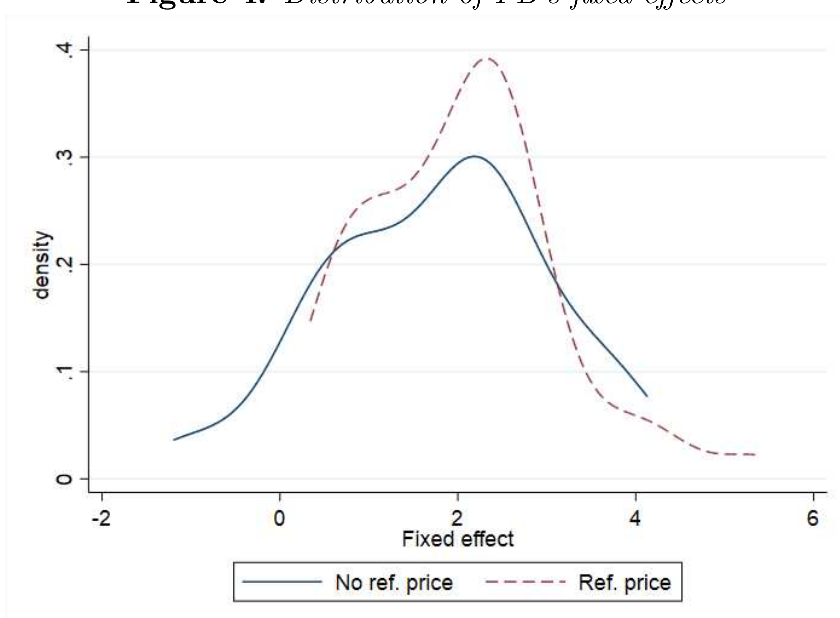
5 Reference prices and public buyer's ability

5.1 Estimation

In this section, we empirically investigate the effect of the reference price policy (for the classes of medical devices) on PBs' ability to carry out the procurement process. We remind that our dataset covers the period from January 1, 2013 to December 31, 2013. From January 1, 2013 to May 2, 2013, PBs were forced by law to apply the reference price defined by the AVCP for each class of homogeneous medical devices they awarded.

First, we replicated the same regression as in Equation (9), but only on the subset of 45 PBs that managed awarding procedures both before and after the termination of the reference price policy. In so doing, we work on a dataset of 979 observations, i.e., the prices paid by PBs both before and after the termination of the reference price. Figure 4 compares the distribution of the PBs' FEs, as measured by $\widetilde{\gamma}_h$, with the PBs' FEs in the presence of the reference prices, given by $\widetilde{\gamma}_h + \phi_h$. Under the reference price policy, we observed that the distribution of the FEs is more concentrated towards central values of the distribution. This is not surprising, as it suggests that the reference price policy reduced the PBs' discretion in the management of the procurement procedures, thus limiting each PB in exerting his/her own ability.

Figure 4: *Distribution of PB's fixed effects*



To further clarify what is going on, we divided the sample of PBs into four groups, depending on whether their ability falls below any of the quartiles of the distribution, and then ran the following regression:

$$\ln\left(\Psi_{dhs}\right) = \sum_{h=1}^{H} \widetilde{\gamma}_h A_h + \rho R + \epsilon_{dhs}. \tag{12}$$

Equation (12) differs from Equation (9) for the inclusion of a common rather than PB-specific effect on the reference prices. The results are reported in Table 7 separately for the models with a structural estimation of the costs (panel a) and without it (panel b), following the same approach as in Section 4.[30] We obtain that, although reference prices overall show a negative impact on the final price net of the marginal cost (with a magnitude of around -0.394/1.104 = - 35.69%), their effect changes widely, depending on the initial level of ability of the PB. In fact, reference prices have a strong and negative impact on low-ability PBs (first quartile) and a strong positive impact on high-ability PBs (fourth quartile), whereas they have no impact on average-ability PBs (second and third quartiles). That is, with the reference price, the (log) distance between prices and marginal costs shrinks for low-ability PBs and increases for high-ability PBs. Changes are non-negligible compared to the average value of the dependent variable (-1.835/-1.080 = 169.91% in the low-ability sample and 1.018/-2.507 = -40.60% in the high-ability sample). The findings are similar in panel b), with the difference that we no longer observe a significantly negative effect of the reference price in the full sample. We also notice that the R^2 statistics in panel b) are much higher than those in panel a). This is due to the inclusion in the specification of the device FEs that account alone for about 50% of the fit.

[30] The sample size differs in the two panels because in some observations, the price is lower than the marginal cost of the benchmark supplier, and the logarithm of a negative number is undefined.

Table 7: *Impact of the reference price*

	(1)	(2)	(3)	(4)	(5)
Method	OLS	OLS	OLS	OLS	OLS
Quartile	All	1	2	3	4
a) Using costs					
Reference price	-0.394**	-1.835***	-0.546*	0.031	1.018**
	(0.176)	(0.257)	(0.197)	(0.405)	(0.452)
PB fixed effects	YES	YES	YES	YES	YES
R^2	0.563	0.412	0.455	0.582	0.705
. Avg. dependent variable	-1.845	-1.080	-1.505	-2.025	-2.507
Observations	872	162	159	386	165
b) Not using costs					
	0.002	-0.410**	-0.186	0.019	0.475**
Reference price	(0.051)	(0.187)	(0.117)	(0.086)	(0.197)
PB fixed effects	YES	YES	YES	YES	YES
Device fixed effects	YES	YES	YES	YES	YES
R^2	0.931	0.905	0.951	0.964	0.954
Avg. dependent variable	-1.104	-0.696	-0.893	-1.471	-1.167
Observations	939	183	239	305	212

Note. Standard errors clustered by medical device in parentheses; *** p<0.01, ** p<0.05, * p<0.1

We interpret this non-linear effect of the reference price policy on awarding prices as directly related to PBs' discretion to determine the reserve price, distinguishing the case of high-ability PBs from the case of low-ability PBs. Indeed, in the absence of mandatory reference prices, high-ability PBs can freely determine the reserve price so as to extract all the rent from the most efficient supplier; differently, low-ability PBs could be very far from obtaining an awarding price close to the most efficient supplier's marginal cost.

When mandatory reference prices are at work, high-ability PBs face reduced discretion in each awarding procedure, and this decreases their ability in getting the most efficient final price. By contrast, low-ability PBs could benefit from reference prices, as these could be lower than the reserve price they would have adopted in the absence of a reference price, thus allowing PBs to pay lower final prices.

We perform a robustness check on the regressions in Table 7 to address the potential concern that some of the results might be driven by devices for which we have only few observations. Removing sparsely observed devices is challenging, as we want to preserve also the minimum-10 observations limit for each PB. We resort to repeat the analysis excluding devices with only 5 observations or even less. Results are reported in Appendix Table A.6. We found that the reference price significantly reduces the difference between prices and marginal costs for PBs with lower ability. Additionally, the effect of reference price on PBs endowed with high ability (i.e. in the fourth quartile) is significantly different from the one on PBs endowed with low ability (i.e., in the first quartile).[31]

5.2 Determinants of public buyers' ability under reference prices

We conclude our analysis by repeating the IV regression in Equation (10) where the unit of analysis is the single PB but now using, as a dependent variable, a proxy for PBs' ability under the reference prices:

$$-\left(\widetilde{\gamma}_h + \phi_h\right) = \beta_0 + \beta_1 M_h + \beta_2 H_h + \beta_3 P_h + \beta_4 C_h + \epsilon_h. \tag{13}$$

Our aim here is to determine if PBs' ability correlates with different variables when the reference price is at play. Table 8 shows the relevant outputs, comparing estimates on ability under the reference price ($-\left(\widetilde{\gamma}_h + \phi_h\right)$) with those without reference price ($-\widetilde{\gamma}_h$). This latter scenario stems from Equation (10), but the output differs from Table 6 because here, we only consider PBs facing at least one auction with a reference price and one auction without a reference price in our sample. Appendix Table A.5 shows the corresponding estimates based on OLS regressions.

From the comparison of Column (1) with Column (3), and Column (2) with Column (4), we find systematic evidence that under the reference price policy, our key effects reduce their size (the fraction of direct negotiations, health personnel cost, health purchases and non-health personnel over the total personnel cost); the only exception is the ratio between health purchases and total health expenditures, which increases. These coefficients generally become closer to zero. Our explanation is that the reference price policy limits the discretion of PBs in designing the awarding process, with the result that each PB's specific ability (or inability) no longer significantly affects the procurement's outcome.

By using the dependent variable obtained without structural estimation of the costs, we get similar findings. However, such an estimation does not pass the Sargan test of exogeneity of the over-identifying restrictions. The output is available upon request.

[31] The confidence intervals of reference price estimated in the first and the fourth quartile (at 95% with costs, at 90% without costs) do not overlap each other.

Table 8: *Determinants of PB's ability with reference price*

	(1)	(2)	(3)	(4)
Method	IV	IV	IV	IV
	No Ref. price		Ref. price	
Fraction of direct negotiations	-2.721***	-2.654***	-0.935***	-0.926***
	(0.539)	(0.529)	(0.298)	(0.293)
ln(health personnel cost)	0.728***		0.402***	
	(0.070)		(0.055)	
ln(health purchases)		0.710***		0.383***
		(0.067)		(0.054)
Non-health/total personnel cost	14.590***	15.199***	6.194***	6.470***
	(1.794)	(1.802)	(1.389)	(1.416)
Health purchases/total health exp.	-2.114***	-5.300***	-0.377	-2.103***
	(0.747)	(0.940)	(0.637)	(0.800)
ln(days payable outstanding)	0.497***	0.495***	0.730***	0.732***
	(0.186)	(0.185)	(0.118)	(0.118)
ASL	-0.909***	-0.907***	0.076	0.077
	(0.150)	(0.148)	(0.107)	(0.107)
Metropolitan area	-0.635***	-0.598***	0.520***	0.531***
	(0.193)	(0.189)	(0.154)	(0.152)
Center-South (CS)	-14.592***	-14.632***	-7.391***	-7.561***
	(2.418)	(2.402)	(1.785)	(1.780)
Health expenditure p.c.	6.893***	6.628***	1.564	1.417
	(1.528)	(1.502)	(0.992)	(0.967)
Health expenditure p.c. x CS	8.462***	8.557***	3.392***	3.477***
	(1.314)	(1.304)	(0.958)	(0.956)
Constant	-26.823***	-24.425***	-12.420***	-10.930***
	(4.219)	(4.003)	(2.761)	(2.583)
Kleibergen-Paap test (p-value)	0.000	0.000	0.000	0.000
Sargan test (p-value)	0.521	0.474	0.465	0.532
Hausman-Wu test (p-value)	0.000	0.000	0.000	0.000
Avg. dependent variable	2.022	2.022	2.026	2.026
Observations	42	42	42	42

Note. Bootstrapped standard errors (1,000 repetitions) in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

6 Conclusions

Public procurement of medical devices takes up a large share of the national public budgets in European countries, and its efficiency represents a relevant issue. In this study, we have empirically investigated the price differences in the purchasing of standard medical devices by Italian PBs, with a focus on PBs' ability in managing such a procurement during the period from January 1, 2013 to December 31, 2013, which our database refers to. In such a period, we have examined the effects of the presence/absence of the mandatory reference price on the final prices of the medical devices paid by PBs, a policy used to increase efficiency in such public spending. In our analysis, for each purchase, we measured the difference between the price of a medical device (resulting from the procurement procedure) and its benchmark marginal production cost (resulting from our structural estimation). We defined PBs' ability as PBs' fixed effects on such a difference, for each item procured.

Our results highlight that Italian PBs pay substantially different prices for standard medical devices. In particular, the quartile-based coefficient of variation of the prices paid equals 25.8.[32] This difference across procurement prices can be explained by the PBs' fixed effects, which we then investigated as related to institutional characteristics, geography and size. We found that the PB size (measured by the overall personnel costs, corresponding to the sum of health personnel and non-health personnel costs or by the size of their health-related procurement) has a general positive and significant effect on PBs' ability to run the procurement process. Our empirical analysis showed that it is the non-health personnel cost that drives the overall positive and significant effect on PBs' ability. This result somehow supports the centralisation of public procurement for medical devices, i.e., a few large PBs collecting non-health personnel and addressing (possibly skilled) efforts in the purchasing activities.

We then investigate the effect of mandatory reference prices as a cap on the winning prices. We found that this policy seems to have a weak effect in fostering the efficiency of public procurement. Specifically, our back-of-the-envelope calculation shows that the average price decreased by 3.7%.[33] Moreover, this overall result hides a non-linear effect of reference price on PBs with different abilities. Specifically, we found that reference prices have a significant negative effect on high-ability PBs' purchasing and a significant positive effect on low-ability PB's purchasing. According to our back-of-the-envelope calculation, the final effect of reference price is the result of a 20.6% average price decrease for low-ability PBs and of a 10.4% average price increase for high-ability PBs.[34]

[32] To make all observations comparable, the quartile-based coefficient of variation is computed using homogenous prices, as defined by Equation (6), applied to the entire dataset.

[33] Based on predictions of the price-costs difference from Column (1), Table 7. The average price is €1.38. Thus, we obtain: $(\exp(-.1.845 - 0.394) - \exp(-.1.845))/1.38 = -0.037$.

[34] Calculations based on predictions of the price-costs difference from Column (2) and (5), Table 7. Low-ability and high-ability PBs are defined as PBs in – respectively – the 1st and the 4st quartile of the overall abilities.

These findings suggest that policy makers aimed at increasing efficiency in public procurement (i.e., value for money) need to consider carefully reducing PBs' discretion along with each PB's ability in running the procurement process. Specifically referring to the impacts of mandatory reference prices on PBs' ability, our results suggest a move towards a discriminatory approach—implementing mandatory requirements only for PBs which perform below a defined benchmark.

Our findings and policy implications provide a first focus on the public procurement of medical devices, addressing the sources and effects of buyers' ability in such purchasing. Note that our results have been obtained in a procurement setting of standardised and simple items; considerations on PBs' ability and discretion would be even more relevant when moving to the procurement of increasingly complex items (Kelmann, 1990).

Taking into consideration the high value of European public procurement (both for standard and non-standard items) in the health sector and the core relevance of such a sector for the Europe 2020 strategy, new empirical investigations are expected to shed light on further improvement for expenditure efficiency in this setting. In a close direction, new investigations are also expected to address the effect of the recent policy by the Trump administration on transparency in "price and quality information" in the health care industry.[35] The search for expenditure efficiency in this industry seems - both in the US and in the EU contexts - to support the spread of information on prices, but more empirical work is still necessary to explore cost and benefit of the adopted mechanisms and provide accurate policy implications.

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A Appendix

A.1 Summary statistics by device class

Table A.1: *Summary statistics by device class*

Device class	Descriptive statistics: Price				Structural estimation		
	Mean	SD	Min	Max	α_d	θ_0	MC
1	0.744	0.531	0.270	2.520	0.696	0.491	0.342
2	1.152	0.852	0.493	3.900	0.917	0.491	0.451
3	3.247	1.783	0.490	5.520	1.888	0.491	0.927
4	0.848	0.453	0.420	2.025	0.848	0.491	0.416
5	8.119	3.768	2.700	16.72	5.966	0.491	2.931
6	2.207	0.744	1.600	4	2.071	0.491	1.017
7	0.129	0.225	0.038	0.840	0.063	0.491	0.031
8	0.213	0.254	0.057	0.646	0.085	0.491	0.042
9	0.122	0.028	0.0768	0.180	0.111	0.491	0.054
10	3.727	17.200	0.148	86.290	0.202	0.491	0.099
11	0.362	0.469	0.064	2.186	0.237	0.491	0.116
12	0.264	0.227	0.140	1.530	0.221	0.491	0.109
13	4.767	6.702	1.050	26.100	5.332	0.491	2.619
14	0.061	0.353	0.009	3.190	0.015	0.491	0.007
15	0.118	0.134	0.0190	0.610	0.077	0.491	0.038
16	1.370	1.392	0.460	4.180	0.566	0.491	0.278
17	1.155	1.779	0.460	11.600	0.870	0.491	0.427
18	4.347	2.395	0.490	9.500	3.525	0.491	1.731
19	0.065	0.059	0.037	0.260	0.045	0.491	0.022
20	3.388	0.250	2.950	3.910	3.553	0.491	1.745
21	0.101	0.091	0.005	0.378	0.035	0.491	0.017
22	4.484	1.418	0.0347	6.700	3.339	0.491	1.640
23	0.177	0.207	0.0310	0.551	0.050	0.491	0.025
24	0.035	0.008	0.023	0.053	0.034	0.491	0.017
25	0.853	0.369	0.410	1.838	0.852	0.491	0.418
26	1.409	0.762	0.540	3.551	1.473	0.491	0.724
27	1.878	1.028	0.134	3.920	1.954	0.491	0.960
28	7.716	10.26	0.495	62.100	7.479	0.491	3.674
29	5.221	0.823	3.790	6.673	5.197	0.491	2.553
30	0.160	0.022	0.130	0.196	0.165	0.491	0.081
31	0.964	1.442	0.155	4.484	0.234	0.491	0.115
32	7.055	4.268	2.047	16.270	5.511	0.491	2.707
33	1.240	1.555	0.220	3.883	0.279	0.491	0.137
34	8.143	4.333	1.400	14.640	9.014	0.491	4.428
35	0.454	0.210	0.158	1.220	0.363	0.491	0.178
36	0.459	0.459	0.200	1.790	0.329	0.491	0.162
37	0.927	0.856	0.400	3.130	0.584	0.491	0.287
38	0.601	0.194	0.250	1.010	0.528	0.491	0.259
39	1.087	0.312	0.515	1.750	0.845	0.491	0.415
40	0.881	0.299	0.605	1.500	0.860	0.491	0.422

Table A.1: *Continued*

Device class	Descriptive statistics: Price				Structural estimation		
	Mean	SD	Min	Max	α_d	θ_0	MC
41	1.664	0.766	1.115	4.522	1.317	0.491	0.647
42	2.217	0.982	1.028	5.700	1.926	0.491	0.946
43	2.853	0.810	2.173	5.300	2.625	0.491	1.289
44	0.178	0.097	0.110	0.616	0.151	0.491	0.074
45	0.033	0.008	0.018	0.053	0.029	0.491	0.014
46	0.051	0.014	0.031	0.088	0.046	0.491	0.023
47	0.086	0.027	0.057	0.169	0.080	0.491	0.039
48	0.041	0.012	0.022	0.076	0.032	0.491	0.016
49	0.014	0.011	0.007	0.053	0.010	0.491	0.005
50	0.041	0.018	0.019	0.109	0.031	0.491	0.015
51	0.173	0.126	0.103	0.660	0.151	0.491	0.074
52	0.133	0.264	0.025	1.008	0.129	0.491	0.063
53	0.154	0.230	0.050	1.008	0.173	0.491	0.085
54	0.318	0.297	0.127	1.400	0.340	0.491	0.167
55	0.703	0.367	0.280	1.479	0.280	0.491	0.138
56	0.493	0.723	0.017	3.400	0.322	0.491	0.158
57	0.067	0.064	0.026	0.274	0.040	0.491	0.020
58	0.045	0.015	0.011	0.061	0.044	0.491	0.022
59	0.178	0.048	0.130	0.265	0.206	0.491	0.101
60	0.288	0.273	0.112	0.890	0.143	0.491	0.070
61	0.737	0.736	0.177	2.710	0.520	0.491	0.256
62	0.403	0.329	0.179	1.549	0.314	0.491	0.154
63	3.378	1.407	1.665	5.416	3.793	0.491	1.863
64	3.150	3.199	0.320	17.000	3.107	0.491	1.526
65	3.208	1.652	1.500	7.180	3.170	0.491	1.557
66	0.221	0.098	0.019	0.350	0.201	0.491	0.099
67	0.763	0.283	0.450	1	0.840	0.491	0.413
68	6.424	1.077	4	7.300	7.039	0.491	3.458
69	0.125	0.050	0.065	0.210	0.092	0.491	0.045
70	0.479	0.121	0.384	0.750	0.467	0.491	0.229
71	0.239	0.365	0.071	1.440	0.100	0.491	0.049
72	0.144	0.178	0.045	0.740	0.070	0.491	0.034
73	1.173	1.345	0.470	6	1.076	0.491	0.528
74	0.712	0.895	0.201	3.357	0.452	0.491	0.222
75	0.054	0.032	0.037	0.150	0.052	0.491	0.026
76	0.062	0.046	0.026	0.130	0.050	0.491	0.024

A.2 Noisy signal on competition in auctions

Tenders in our dataset are sealed bid auctions in which bidders are supposed not to know ex-ante how many competitors they will face. Consider the two extreme cases. First, if the level of competition is perfectly known in advance by all the bidders, then when $N_{0h} = 1$ the unique participant must bid a price $B^{(1:1)}$ equal to the reserve price r. Accordingly, if $\Pr\left(B^{(1:1)} = r \mid N_{0h} = 1\right) < 1$, then the hypothesis that N is fully observed ex-ante can be rejected. In our dataset we observe the reserve price in 21% of FPAs: among them, we only observe this for three observations when $N = 1$, and in two of them there is $B^{(1:1)} < r$. Second, if N_{0h} is totally unknown by the participants, then the distribution of the bids should not vary with N_{0h} : running in our dataset a Kendall's rank correlation coefficients test leads us to reject this hypothesis.[36]

We thus assume that, in our setting, bidders receive a noisy signal of the level of competition they will face in the auction. Using Kendall's test on auctions with similar competition, we obtain that the bids' distribution results are different in auctions, respectively, with $N_{0h} = 1$, with $N_{0h} \in [2, 4]$ and with $N_{0h} \in [5, S]$ participants: within each of these three subsamples, the bids' distribution does not change with the number of bidders, but across those subsamples, it does.

In the following we sketch how we derive the noisy signal on competition. Define with $G_{\underline{n},\overline{n}}$ the observed distribution of bids with a number of participants $n \in [\underline{n}, \overline{n}]$. Starting with $\underline{n} = 1$, for each $\overline{n} \in [2, N]$ we compare whether $G_1 ... G_k ... G_n$ originates from the same distribution using the Kendall's rank correlation coefficients test. If we accept the hypothesis that all samples originate from the same distribution, then we continue adding G_{n+1} to the comparison. If we reject the hypothesis, we stop and restart comparing $G_{n,n+1}$. In Table A.1, the first two columns report the lowest and highest number of bidders, respectively $\underline{n}$ and $\overline{n}$, considered in the test, and the third column reports the Kendall's rank correlation coefficients' p-value.

[36] Kendall's score: -20757. Test of H_0: the normalised prices and number of bidders are independent, p-value<0.01.

Table A.2: *Noisy signal*

$\underline{n}$	$\overline{n}$	Kendall's p-value
1	2	0.00
2	3	0.27
2	4	0.12
2	5	0.03
5	6	0.82
5	7	0.30
5	8	0.93
5	9	0.79
5	11	0.77
5	12	0.79
5	13	0.46
5	15	0.56
5	16	0.66
5	21	0.63
5	22	0.91
5	29	1.00
5	30	0.75

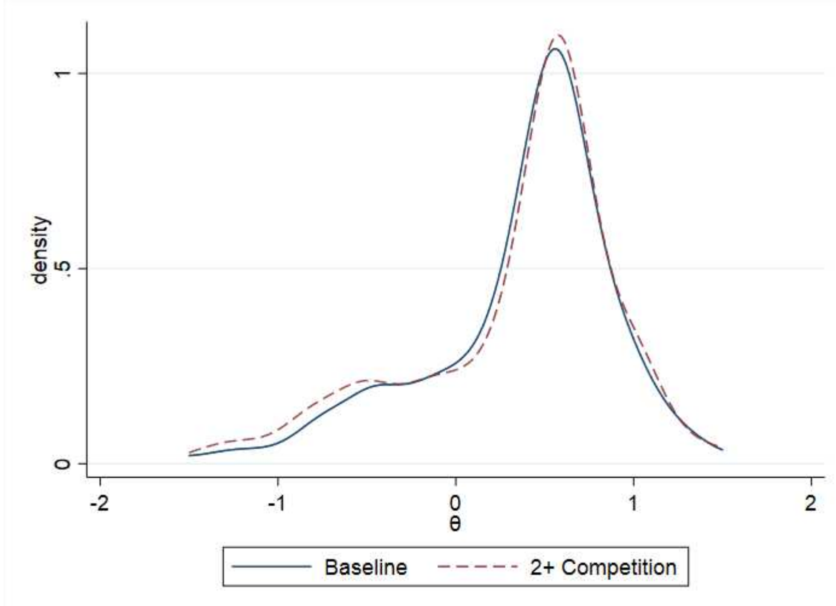
Because we cannot derive the equilibrium bidding condition for $N_{0h} = 1$, we discard these observations. We define the subsample for $N_{0h} \in [2, 4]$ as the one with *low competition,* and we use the median value $N_{0h} = 3$ as the noisy signal on the competition firms would face. Similarly, we do the same for the subsample for $N_{0h} \in [5, S]$, defined as a *high competition* subsample, using the median value $N_{0h} = 8$ as the noisy signal.

A.2.1 Robustness check: different definition of competition

Marginal cost estimate needs knowledge of the number of participants to the bid. In Sub-section 3.2.1 we split the sample in two groups, signaling low participation (between 2 and 4 participants) and high participation (5 or more participants). As a robustness check, we remove the distinction in two groups and consider a unique signal in case of two or more participants in an auction; in that case, the median value used to compute equilibrium is $N_{0h} = 5$ while the subsample is defined as *2+ competition*.

An application of Equation (8) to this alternative framework gives rise to the density function of the bidder's private value shown in Figure A.1:

Figure A.1: *The distribution of the private value in the 2+ competition subsample*



The distribution is in line with the benchmark one, as it gives rise to similar marginal cost estimates, and provides similar estimates of a PB's ability. A Kolmogorv-Smirnov test finds no difference between the two distributions.

A.3 Marginal cost estimate

The GPV approach to estimate marginal costs using observed bids has to be modified, since our data consist of winning offers of procurement auctions: the functional form of the bid is different. In a procurement auction, the lowest bid wins, and therefore the probability of victory given a bid p_i is equal to $\Pr(p_i \leq p) = (1 - F(\theta))^{n-1}$. Following Holt (1980), in a procurement auction, the (Nash) equilibrium bid $p(\theta_i)$ of the $i - th$ bidder of type θ_i is given by:

$$p(\theta_i) = \theta_i + \int_{\theta_i}^{\overline{\theta}} \left(\frac{1 - F(y)}{1 - F(\theta)} \right)^{n-1} dy. \tag{14}$$

This strategy is obtained solving the first order differential equation in $p(\cdot)$:

$$1 = \frac{f(\theta)}{1 - F(\theta)} \frac{1}{p'(\theta)} (n-1)(p(\theta) - \theta) \tag{15}$$

with boundary condition $p(\overline{\theta}) = \overline{\theta}$. The equilibrium strategy in Equation (14) is strictly increasing in θ and, as in a standard FPA, expresses the equilibrium bid as a function of the bidder's type θ.

Define with $G(p)$ the cumulative distribution function of all observed bids p, and with $g(p)$ the density function. As noted by GPV, $G(p) = \Pr(p_i \leq p) = \Pr(\theta_i \leq p^{-1}(p)) = F(p^{-1}(p)) = F(\theta)$. $G(p)$ is absolutely continuous and has a density function equal to $g(p) = \frac{f(\theta)}{p'(\theta)}$. Thus, Equation (15) can be rewritten as:

$$\theta_i = p_i - \frac{1 - G(p_i)}{(n-1) \cdot g(p_i)}. \tag{16}$$

A further difference from GPV is that we observe winning bids only. As in Athey and Haile (2002) winning bids are considered equal to the maximum order statistic of $G(p)$ given the level of competition n, in the procurement auction case they should be considered equivalent to the first order statistic with density function $g_{(1)}(p)$ and cumulative distribution function $G_{(1)}(p)$ equal to:

$$\begin{aligned} g_{(1)}(p) &= n \cdot g(p)(1 - G(p))^{n-1} \\ G_{(1)}(p) &= 1 - (1 - G(p))^n. \end{aligned}$$

Thus,

$$\frac{1 - G_{(1)}(p)}{g_{(1)}(p)} = \frac{[1 - G(p)]^n}{ng(p)[1 - G(p)]^{n-1}} = \frac{n-1}{n} \frac{1 - G(p)}{(n-1)g(p)}. \tag{17}$$

Replacing Equation (17) into Equation (16) yields the structural Equation (8):

$$\theta_i = p_i - \frac{n}{n-1} \frac{1 - G_{(1)}(p_i)}{g_{(1)}(p_i)}.$$

A.4 Alternative explanation: corruption

We now explore whether an explanation alternative to PB's ability may describe the variability we observe on the ability to manage the procurement process. We focus on corruption because misbehavior can potentially lead to similar effects on the final prices for procured medical devices. According to Bandiera et al. (2009), each awarding procedure in public procurement could be affected by the PB's lack of knowledge or experience in running it (i.e., passive waste), as well as by the PB's actions supporting corruption and favoritism (i.e., active waste). Unfortunately, in the setting we investigate, we have no way to disentangle these two dimensions. However, we follow Bandiera et al. (2009) and consider a variant of the regression in Equation (9), where we include in the specification the interaction between PB dummies ($A_h, h = 1, ..., H$) and producer dummies ($S_j, j = 1, ..., J$), as follows:

$$\ln(\Psi_{dhs}) = \sum_{h=1}^{H} \left(\widetilde{\gamma}_h A_h + \phi_h A_h R + \sum_{j=1}^{J} \lambda_{hj} A_h S_j \right) + \sum_{d=1}^{D} \delta_d D_d + \epsilon_{dhs}.$$

We also include medical device dummies ($D_d, d = 1, ..., D$) to control for the characteristics of the auctioned products. The purpose of this OLS regression is to understand if the repeated relation between a specific PB and a specific producer (i.e., the PB's repeated purchasing from the same seller) has a systematic impact on the PB's ability. Note that, as highlighted by the literature on relational contracting (Levin, 2003; Asanuma, 2002), a repeated relationship could be a signal of corruption or favoritism (i.e., when a producer bribes the PB to avoid competition or obtain gains through the auction; Rose-Ackerman, 1999), leading to a benefit for all the involved parties (i.e., mitigate potential hold-up problems and incentives for ex-post renegotiation arising from contractual incompleteness; Gil and Marion, 2011). Accordingly, as an outcome from our regression, significantly positive coefficients λ_{hj} would be a signal of corruption or favoritism, while significantly negative coefficients λ_{hj} would be a signal of a valuable relationship.

The introduction of the interactions between PBs and producers (403 parameters) induces only a modest improvement in the fit of the model, whose R^2 statistic ranges from 0.87 to 0.96. This indicates that repeated relations can describe no more than 9% (0.96-0.87) of a PB's ability. Moreover, our estimates show that just 50 out of the 403 coefficients are significantly positive, and only 20 are significantly negative. Taken together, this evidence leads us to note that corruption seems infrequent in our data and plays a marginal role in explaining the PB's ability.

A.5 OLS regressions

Table A.3: *Determinants of PB's ability – OLS regressions*

	(1)	(2)	(3)	(4)
Method	OLS	OLS	OLS	OLS
PB's ability	Using costs		Not using costs	
Fraction of direct negotiations	0.219***	0.272***	-0.071**	-0.048
	(0.082)	(0.082)	(0.034)	(0.034)
ln(health personnel cost)	0.470***		0.204***	
	(0.038)		(0.016)	
ln(health purchases)		0.427***		0.184***
		(0.036)		(0.015)
Non-health/total personnel cost	4.817***	4.328***	1.480***	1.263***
	(0.408)	(0.431)	(0.130)	(0.133)
Health purchases/total health exp.	1.084***	-0.811**	-0.197**	-1.013***
	(0.365)	(0.361)	(0.098)	(0.132)
ln(days payable outstanding)	-0.857***	-0.876***	-0.135***	-0.143***
	(0.102)	(0.103)	(0.029)	(0.030)
ASL	-0.385***	-0.343***	-0.182***	-0.163***
	(0.089)	(0.088)	(0.030)	(0.029)
Metropolitan area	0.415***	0.458***	-0.030	-0.011
	(0.100)	(0.099)	(0.032)	(0.031)
Center-South (CS)	-3.352**	-3.889**	-1.467***	-1.629***
	(1.612)	(1.611)	(0.497)	(0.500)
Health expenditure p.c.	-2.644***	-3.042***	0.238	0.060
	(0.831)	(0.824)	(0.230)	(0.230)
Health expenditure p.c. x CS	2.721***	2.893***	1.069***	1.148***
	(0.866)	(0.867)	(0.270)	(0.273)
Constant	0.771	3.500*	-2.608***	-1.393**
	(2.187)	(2.061)	(0.649)	(0.602)
R-squared	0.251	0.245	0.250	0.239
Avg. dependent variable	2.071	2.071	1.163	1.163
Observations	57	57	57	57

Note. Bootstrapped standard errors (1,000 repetitions) in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A.4: *Determinants of PB's ability – First stage and reduced form*

	(1)	(2)	(3)	(4)	(5)	(6)
Method	OLS	OLS	OLS	OLS	OLS	OLS
Dep. variable	Fraction of direct neg.		PB's ability			
Model using/not using costs	Both	Both	Using costs		Not using costs	
Fraction of multi-device auctions	-0.147***	-0.120**	-0.039	0.037	-0.009	0.022
	(0.048)	(0.048)	(0.164)	(0.164)	(0.055)	(0.055)
Avg. quantity of devices auctioned	-0.001***	-0.001***	0.002***	0.002***	0.000***	0.000***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
ln(health personnel cost)	0.034**		0.421***		0.191***	
	(0.015)		(0.050)		(0.019)	
ln(health purchases)		0.003		0.365***		0.171***
		(0.014)		(0.047)		(0.018)
Non-health/total personnel cost	0.616***	0.397**	3.826***	3.300***	1.213***	1.005***
	(0.191)	(0.186)	(0.600)	(0.596)	(0.189)	(0.183)
Health purchases/total health exp.	-0.444***	-0.455***	0.815**	-0.797**	-0.207**	-0.961***
	(0.105)	(0.123)	(0.377)	(0.387)	(0.103)	(0.143)
ln(days payable outstanding)	-0.071***	-0.066**	-0.861***	-0.881***	-0.127***	-0.137***
	(0.027)	(0.027)	(0.107)	(0.108)	(0.030)	(0.030)
ASL	-0.209***	-0.189***	-0.347***	-0.314***	-0.149***	-0.137***
	(0.025)	(0.024)	(0.091)	(0.091)	(0.032)	(0.032)
Metropolitan area	-0.348***	-0.351***	0.300***	0.314***	-0.011	-0.004
	(0.025)	(0.025)	(0.090)	(0.090)	(0.026)	(0.026)
Center-South (CS)	1.153**	0.963**	-3.989**	-4.277**	-1.709***	-1.810***
	(0.462)	(0.462)	(1.678)	(1.684)	(0.526)	(0.530)
Health expenditure p.c.	1.477***	1.313***	-2.556***	-2.959***	0.097	-0.063
	(0.217)	(0.215)	(0.899)	(0.884)	(0.240)	(0.236)
Health expenditure p.c. x CS	-0.701***	-0.616**	2.883***	3.002***	1.193***	1.234***
	(0.246)	(0.247)	(0.892)	(0.896)	(0.285)	(0.287)
Constant	-2.145***	-1.248**	1.992	4.866**	-2.158***	-0.971
	(0.596)	(0.548)	(2.586)	(2.376)	(0.763)	(0.686)
R-squared	0.474	0.472	0.253	0.245	0.250	0.241
Avg. dependent variable	0.520	0.520	2.071	2.071	1.163	1.163
Observations	57	57	57	57	57	57

Note. First-stage (Columns 1-2) and reduced form (Columns 3-6) equations for the model in Table 6. Bootstrapped standard errors (1,000 repetitions) in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: *Determinants of PB's ability with reference price*

	(1)	(2)	(3)	(4)
Method	OLS	OLS	OLS	OLS
	No Ref. price		Ref. price	
Fraction of direct negotiations	-0.324***	-0.318***	1.063***	1.069***
	(0.082)	(0.081)	(0.092)	(0.092)
ln(health personnel cost)	0.558***		0.260***	
	(0.039)		(0.047)	
ln(health purchases)		0.554***		0.250***
		(0.038)		(0.046)
Non-health/total personnel cost	8.061***	8.734***	0.748	0.951
	(0.704)	(0.713)	(0.958)	(0.993)
Health purchases/total health exp.	-0.056	-2.590***	1.339***	0.210
	(0.382)	(0.414)	(0.341)	(0.459)
ln(days payable outstanding)	0.090	0.096	0.390***	0.392***
	(0.110)	(0.111)	(0.088)	(0.088)
ASL	-0.308***	-0.323***	0.582***	0.581***
	(0.088)	(0.088)	(0.085)	(0.086)
Metropolitan area	0.144	0.159	1.170***	1.177***
	(0.098)	(0.097)	(0.081)	(0.081)
Center-South (CS)	-12.750***	-12.880***	-5.967***	-6.068***
	(1.398)	(1.402)	(1.173)	(1.169)
Health expenditure p.c.	1.372*	1.308*	-3.040***	-3.124***
	(0.777)	(0.784)	(0.684)	(0.675)
Health expenditure p.c. x CS	7.636***	7.710***	2.703***	2.754***
	(0.743)	(0.746)	(0.634)	(0.633)
Constant	-12.790***	-11.440***	-0.718	0.188
	(2.229)	(2.174)	(2.239)	(2.121)
R-squared	0.290	0.292	0.431	0.430
Avg. dependent variable	2.022	2.022	2.026	2.026
Observations	42	42	42	42

Note. Bootstrapped standard errors (1,000 repetitions) in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A.6: *Impact of the ref. price, devices with 6+ obs.*

	(1)	(2)	(3)	(4)	(5)
Method	OLS	OLS	OLS	OLS	OLS
Quartile	All	1	2	3	4
a) Using costs					
Reference price	-0.517***	-1.768***	-0.541*	-0.106	0.412
	(0.172)	(0.459)	(0.306)	(0.199)	(0.521)
PB fixed effects	YES	YES	YES	YES	YES
R^2	0.573	0.397	0.467	0.582	0.717
. Avg. dependent variable	-1.873	-1.087	-1.554	-2.030	-2.559
Observations	811	148	149	357	157
b) Not using costs					
Reference price	-0.037	-0.437**	-0.188	0.021	0.272*
	(0.059)	(0.217)	(0.177)	(0.092)	(0.155)
PB fixed effects	YES	YES	YES	YES	YES
Device fixed effects	YES	YES	YES	YES	YES
R^2	0.934	0.900	0.953	0.964	0.959
Avg. dependent variable	-1.123	-0.711	-0.896	-1.492	-1.168
Observations	877	165	216	293	203