Purchasing medical devices: The role of buyer competence and discretion☆

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ABSTRACT

This paper investigates the price variability of standardized medical devices purchased by Italian Public Buyers (PBs). A semiparametric approach is used to recover the marginal cost of each device. Average prices vary substantially between PBs; we show that most of the difference between the purchase prices and estimated costs is associated with a PB fixed effect, which, in turn, is related to the institutional characteristics and size of the PB. Repeating the main estimation using device fixed effects yields similar results. Finally, an exogenous policy change, i.e. the termination of the mandatory *reference price* regime, is used to assess how discretion affects medical device procurement given the skills of each PB. Our results show that less PB discretion — i.e. when mandatory reference prices apply — determines efficiency gains and losses for low- and high-skilled PBs, respectively.

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1. Introduction

The European medical technology market – comprising mainly medical devices and in vitro diagnostics – was valued at roughly €115 billion in 2017. At 27% of the world market, it is the second largest in the world, after the United States. Medical technology is characterised by a continuous innovation,[1] and the short life-cycle of products (on average, 18–24 months). In 2017, in this sector, more than

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[1] Entry regulations and quality information requirements for new medical devices play a key role in this process. Grennan and Town (2020) exploit differences between US and EU regulations on testing new medical devices to address the trade-offs arising from more frequent testing, which can overcome consumer uncertainty about product efficacy but increases entry costs and delays product launches. Their empirical results for stents show that US regulation is close to the optimal policy in terms of trading off testing with access to innovation, while EU regulation is too lax.

13,000 patent applications were filed with the European Patent Office (EPO), twice the number from the pharmaceutical sector.[2] Medical technologies provide value in various ways, saving and improving lives by promptly detecting disease and providing effective treatment options for patients and healthcare systems. They can also deliver significant savings (i.e. via efficiency) to the health system over time.

This paper empirically investigates public procurement for medical devices in Italy, decomposing price variation into components explained by buyer fixed effects and buyer characteristics. The study period overlaps with a time when reference pricing was temporarily imposed at a national level, allowing examination of the heterogeneous effects of the policy on different buyers.

In the US healthcare system the purchase of medical technologies is usually by direct trade negotiated by private hospital managers and suppliers. The resulting contracts are characterised by strategic discretion and flexibility (Grennan, 2013, 2014). By contrast, in EU countries, purchasing is heavily regulated: in particular, public buyer (PB) discretion, awarding mechanisms and contract management are restricted and determined by law. Accordingly, PB competence involves coping with regulated business-to-government procedures, often with open tender mechanisms (Lian and Laing, 2004; Spagnolo, 2012).

In Italy, as in many other national health systems in Europe, the procurement of medical technologies is managed at the local level. Occasionally, the national press has reported prices differences for the same standard medical device (e.g. a simple syringe) paid by different PBs (public hospitals and healthcare units).[3] In a period of tight public budgets, this evidence has fuelled an extensive public debate and – in 2012 – led to the introduction of *reference prices*, a policy imposing a cap on the unit price of each standard medical device procured by tender. The aim of this policy was to limit PB discretion in an attempt to reduce public procurement expenditure. Reference prices for medical devices were applied from July 1, 2012 to May 2, 2013 and were then scrapped after a ruling of the Administrative Court of Rome. This provides a quasi-natural experimental setting for a clean test on how PB discretion affects the procurement of medical devices.

Based on procurement data,[4] this paper initially estimates the net contribution of PB competence to price variability and then assesses how reference prices, which reduce PB discretion, interact with that competence. Our analysis was run on an original Italian dataset including 76 classes of standard medical devices sold to 131 local PBs between January and December 2013. The empirical approach is based on two important features of the medical devices investigated: i) they are standardised and relatively cheap, so renegotiations are rare; ii) they are grouped into classes of functionally homogeneous products (i.e. in each class, quality differentiation is not an issue). Given these features, a semiparametric approach is adopted, inspired by Guerre et al. (2000), to recover the marginal cost of each device. Using the official classification provided by the Italian technical advisor for health policies (AGENAS), we group functionally homogeneous medical devices into classes and, for each class, establish its benchmark marginal cost. We then show empirically that most of the discrepancy between purchasing prices and estimated costs is related to the PB fixed effect. This way, we infer a *proxy* for PB competence in managing each purchase. The main estimate is repeated, in the spirit of Best et al. (2017), using device fixed effects rather than marginal costs, obtaining similar results. Hence, the findings are not specific to the structural approach used to infer the marginal cost of medical devices. As a further step in the analysis, the determining factors of PB competence are investigated based on balance sheet data from local public hospitals and healthcare units. Finally, the exogenous termination of the reference price policy is used to identify its impact on the competence of PBs.

Our main findings are summarised below. First, the average prices of standard medical devices paid by Italian local public hospitals and healthcare units vary substantially. Second, the differences between PB purchase prices can be explained by PB fixed effects, which, in turn, are related to the size and characteristics of the PB. Specifically, size (measured either via overall personnel costs or by the procurement of health-related materials) has a generally positive and significant effect on competence in managing procurement efficiently. Furthermore, the ratio of non-health personnel over total personnel costs drives the overall positive and significant effect of size on PB competence. By contrast, once PB size has been accounted for, overall procurement expenses for health-related goods push competence down, in line with the definition of PB competence we adopted in this paper. Regarding organizational characteristics, our results indicate significant differences in purchasing medical technology between local public healthcare units and hospitals, with higher prices paid for standard medical devices by the former.

Comparing the period of reference pricing during which PB discretion was restricted with the period after the

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[2] Estimation of market values and information on patents from MedTech Europe (2019).

[3] See, amongst others, P. Russo 'Garze e siringhe d'oro: le spese pazze delle ASL' (Bandages and syringes of gold: the berserk expenditure of Italian local health agencies) in La Stampa, July 3, 2012. Greater attention to price differences (and corruption) for the purchase of medical devices has been paid during the recent Coronavirus pandemic. Indeed, the public healthcare system in Italy has faced severe challenges regarding procurement strategies for masks, hand sanitizers, ECMOs, etc., speed having been prioritised over transparency, with competitive bidding and other safeguards dropped to keep pace with the pandemic. As reported by the international press, the same has occurred in many other countries affected by the Coronavirus (see: A. Faiola and A.V. Herrero, 'A pandemic of corruption', in Washington Post, April 26, 2020).

[4] As here, Bergman et al. (2016) use public procurement data from the health sector but, unlike this paper, investigate elderly care services in Sweden, estimating how private provision affected a non-contractible quality dimension, i.e. the mortality rate. Their results indicate that privatization and the related increase in competition significantly improved non-contractible quality.

removal of reference pricing suggests that this policy reduced price dispersion, but had a non-linear effect on PB competence to purchase efficiently. Indeed, reference pricing increased the average prices paid by highly competent PBs and reduced the prices paid by PBs with lower competence. When reference prices were in force, the main determinants of PB competence decreased in magnitude or lost their overall significance, reducing the disparity between PBs, with observations moving towards an average value. In a period in which, in many countries, regulatory policies for medical device are often set to improve procurement efficiency, such a non-linear effect calls for the careful adoption of measures that evenly affect PBs in the healthcare system and their discretion in managing purchasing procedures.

Our study contributes mainly to three strands of economic literature. The first is the empirical literature on the effect of PB discretion on purchasing activities. Di Tella and Schargrodsky (2003) investigate the prices of standard medical devices following the introduction of a strict monitoring policy for hospital purchases in Buenos Aires. They estimate a 10% reduction in the average prices paid by hospitals because of the crackdown.[5] Similarly to these authors, we investigate the effects of a policy to reduce public procurement expenditure for standard medical devices. By exploiting exogenous changes in the size (i.e. threshold value) of the public works tenders in which PBs are granted larger degrees of discretion in managing procedures, recent studies have focussed on the effect of PB discretion on procurement performance (Palguta and Pertold, 2017; Baltrunaite et al., 2018; Coviello et al., 2018a). Our work differs from these as our empirical strategy is able to isolate the net effect of reference prices on PB discretion and, in turn, on public expenditure.

Second, we add to the literature on the role played by PB competence[6] to purchase goods or services and on the related 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 the 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 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 of between 1.6% and 2.1% of the Italian GDP – if all PBs paid the same prices as the PBs at the tenth percentile. These authors also found that at least 82% of the estimated waste is related to bureaucratic inefficiency. Using a large dataset for Russian procurement in 2011–2015, Best et al. (2017)

estimated that 60% of within-product purchase price variation over 16 million purchases was due to bureaucratic (in)competence. Moreover, investigating a specific procurement policy which sets preferences for domestic firms, these authors show that its optimal design depends on how effective the purchasers are in implementing the policy itself. To these studies, we add the novel approach of measuring PB competence and its effects in managing the procurement of standard devices in the healthcare sector.

Finally, we contribute to the literature on medical technology procurement (Lian and Laing, 2004; Sorenson and Kanavos, 2011; Grennan, 2013, 2014; Kastanioti et al., 2013; Grennan and Swanson, 2014; den Ambtman et al., 2020) by focusing on standard medical devices and the determinants of purchasers' competence in managing a highly regulated process, partly by investigating the effect of a reference price regime.

The remainder of the paper is organised as follows: Section 2 describes the institutional setting (2.1) and our dataset (2.2), presenting some preliminary evidence (2.3). Section 3 illustrates the theoretical structural framework by introducing the definition of PB competence (3.1) and showing the marginal cost estimate for our medical devices (3.2). Section 4 estimates PB competence (4.1) and its determinants (4.2). Section 5 replicates the analysis, exploiting the event of reference price termination as a quasi-natural experiment. PB competence (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. The Appendix sets out details estimation and further robustness checks.

2. Context, data and preliminary evidence

2.1. 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 funding are national and regional taxes, supplemented by co-payments for pharmaceuticals and outpatient care. The system comprises 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]

In Italy, the purchasing of medical technologies is decentralised at the local level. In 2013, the year covered in our dataset, approximately 350 local public buyers (PBs) had procurement responsibilities for these items.[8] According to Italian public procurement law, these items are purchased through public tenders (first price auctions and scoring rule

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auctions, FPAs and SRAs respectively), with direct negotiation only in certain special cases.[9]

To take part in a public procurement tender for medical devices, potential suppliers must meet a minimum set of common requirements (e.g. submit standard tender documents and meet certain financial and technical prerequisites). Each PB uses its discretion when establishing procedures or adding further requirements. Hence, each PB responsible for purchasing medical devices, within the finite set of mechanisms established by law, chooses the award method and sets sometimes costly requirements.

In 2012, the Italian Authority for Public Contracts (AVCP)[10] was asked to set *reference prices* for classes of functionally equivalent medical devices purchased by public hospitals and local healthcare units. Each reference price consists of a cap on unit prices for a class of medical devices. The aim of this policy was to help standardise the prices paid for very similar items by different PBs.[11] Reference prices were mandatory for the public procurement of medical devices from July 1, 2012 to May 2, 2013. On the latter date, responding to an Appeal jointly submitted by some suppliers, the Administrative Tribunal of Lazio (TAR), outlawed the reference price regime.[12] This decision was taken because the listed devices in *some classes* were too heterogeneous both functionally and technically to come under a single price. The differences were mainly related to complex devices such as stents and prostheses. Note that heterogeneity within classes of medical devices is not a problem for the present empirical analysis, because our investigation is carried out using the database including only simple medical devices, as confirmed in a subsequent, more detailed classification precisely dealing with this issue.[13]

2.2. Data

To investigate unit prices paid by PBs when purchasing standard medical devices, we base our empirical analysis on a database with four sources of information.

The first and main source of information is an original dataset consisting of unit prices paid by Italian PBs to purchase simple medical devices from January 1, 2013 to December 31, 2013. All these devices were subject to reference prices until May 2, 2013, and the related information on awarding tenders was collected by the AVCP.

PBs usually adopt procedures under which they aggregate the purchase of similar medical devices into lots,[14] with a separate tender for each lot. Each procedure corresponds to a framework with common rules for supplier requirements, bank guarantees, etc.

As an example, let us consider a public buyer, PB_a, awarding a lot, lot_1, through a tender in the form of a first price auction, FPA. Let us assume lot_1 includes 3 different devices, e.g. three bandages of different lengths (say, 5, 10 and 50 cm), and that only the first two are subject to the reference price regime. In this tender for lot_1, all participating suppliers offer a price for each of the three bandages. The winner of lot_1 is the supplier who offers the lowest price for the whole lot_1, corresponding to the sum of each device's unit price multiplied by the quantity requested. Accordingly, our database records the unit price offered by the winner for each of the two devices subject to the reference price regime, as well as the quantity and the classes of functionally equivalent medical devices they refer to. However, no information is available for the third device in lot_1 which is not subject to reference prices (or for lots including only these devices). Our database also has information regarding the ID of the PB organising the tender, the awarding mechanism and, for a subset of observations, the number of bidders for each lot.

Second, from the Financial Statements of each PB in our database, we collected information on the total value of services supplied, total costs, costs for personnel split into health-related personnel (doctors, nurses, healthcare assistants) and non-health related personnel (clerks), and procurement costs for health-related goods and services.[15] Summary statistics on the Financial Statements are set out in Table 1. PBs were also classified according to rural or metropolitan location.[16]

Third, we gathered information from the National Institute of Statistics (ISTAT) on the size of the regional population and total annual regional spending on healthcare. This information is relevant, given the decentralised nature of the Italian health system, because political decisions at

[9] The Italian Procurement Code (Italian Legislative Decree no. 163/2006, Art. 125), applicable at the time of our dataset, allows for direct negotiations only for goods and services with a reserve price below €211,000 and only in the following cases of urgency (i) the unexpected advance termination of an existing contract, (ii) the period is between one contract and the awarding of the following tender, (iii) the previous contract has expired and no participants bid in the following tender or (iv) unpredictable events.

[10] In 2014, the responsibilities of the AVCP were transferred to the Italian Anticorruption Authority (ANAC).

[11] The policy on reference prices included a safeguard clause. If a tender applying reference prices was null, the PB could then proceed with a new tender where reference prices were no longer applied. Anecdotal evidence suggests the clause was rarely implemented.

[12] In line with the date and with reference to the date recorded in each tender transcript, in our database we divided unit prices for medical devices into two groups, when the reference price regime was applicable or not, i.e. before/after May 2, 2013.

[13] The Italian National Agency for Regional Health Services (AGENAS) produced two lists for classes of homogeneous products. The first, published in 2009, was used to set the reference prices, ruled out on May 2, 2013. The second, published in 2013, is a more detailed list created to address the tribunal's concerns about excessive intra-class product heterogeneity (mainly stents and prostheses). Our empirical analysis uses the latter.

[14] Via the CND code (National Device Classification, a top-down digit structure from general to narrow descriptions of devices), we investigated the extent of heterogeneity within each lot in our database. For the first level of classification, which gives the general description of the device, we found that only 2.8% of the lots included heterogeneous items, and this percentage becomes 11.7 at the third level of classification. Summary statistics at the lot level are presented in Appendix A.1.2.

[15] According to Italian law, the Financial Statements of each PB, which include the balance sheet and profit/loss account, are disclosed following a standard format. Financial Statements were downloaded from official PB websites. For two PBs in our database, the 2013 Financial Statements were not available on their websites.

[16] A PB is located in a metropolitan area if its headquarters are in a municipality which is part of a metropolitan city as defined by Italian Law. Data are available from the National Institute of Statistics (ISTAT), at the following link: https://www.istat.it/it/archivio/6789, accessed on 10/06/2020.

Table 1
PB financial statements, location and type.

	Obs.	Mean	S.d.	Min	Max
Total value of supplied services	129	535	458	41	2706
By location:					
North	87	533	484	68	2706
Center-South	42	540	404	41	1529
By type:					
Hospital	56	292	245	41	1767
Local healthcare unit	73	722	496	98	2706
Total personnel cost	128	126	96	11	686
(of which: healthcare personnel)	(126)	(101)	(78)	(1)	(543)
By location:					
North	86	117	101	11	686
	(84)	(92)	(82)	(1)	(543)
Center-South	42	143	84	17	453
	(42)	(118)	(69)	(14)	(377)
By type:					
Hospital	56	113	59	17	287
	(55)	(92)	(49)	(14)	(221)
Local healthcare unit	72	136	117	11	686
	(71)	(107)	(95)	(1)	(543)
Total healthcare purchases	129	64	61	1	404
By location:					
North	87	59	66	1	404
Center-South	42	72	50	9	228
By type:					
Hospital	56	55	40	7	183
Local healthcare unit	73	70	73	1	404

Note. Data in million euros.

the regional level may impact on PB competence. Note that the ratio between these two variables, i.e. per-capita health expenditure, is a dimensionally invariant measure of the resources each region devotes to healthcare every year. On average, in 2013, the per-capita health expenditure was €1891.[17]

Finally, from Assobiomedica, the main Italian Association of medical device producers, we gathered data on average days of delay in payment at the PB level.[18] This information is of interest as delays in payment affect PB competence in obtaining a better deal. Indeed, suppliers may discount expected late payments by initially offering a higher price. In 2012-2013, we observed such delays varying from 55 to 1603 days, recording a median of 160 days. Note that overdue payments are a lagging indicator, so delays in 2012 are used to study PB competence in 2013.

2.2.1. Data cleaning

The unit of observation in our dataset is the price paid by each PB for the purchase of medical devices subject to the reference price regime. Starting from the AVCP original dataset of 2149 observations in the period from January to December 2013, we discarded 373 observations relative to classes of medical devices where fewer than 10 observations were available; we discarded further 75 observations for which the awarding mechanism was unspecified.

According to Italian statutory requirements for public procurement, each PB can choose the awarding mechanism to adopt in the form of first price auctions (FPAs), direct negotiations or scoring rules auctions (SRAs). Our original database includes unit prices resulting from all these awarding mechanisms (see Appendix A.6 for summary statistics on SRAs, compared to FPAs). Given our research question and the empirical strategy of focusing on simple items in order to avoid confusing effects relating to PB competence and their discretion when purchasing medical devices, we exclude SRAs from our analysis. Indeed, unlike FPAs, the SRA format includes competition between suppliers on quality elements.[19]

As a result, we end up with 1474 observations, split almost equally between FPAs (733 observations) and direct negotiations (741 observations).[20] This dataset records observations on 76 classes of functionally homogeneous medical devices subject to reference prices. The median unit price for each device is €0.32. Within each class, $d = 1, \ldots, D$, we observe the price paid by each PB for the

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[17] 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 average population size by Kolmogorov–Smirnov test. We find no significant difference.

[18] Information is missing for 21% of our observations. In these cases, we use the regional average as a proxy. The regional average delay in payments is highly correlated with local one (correlation 0.73). For data on overdue payments, see also Guglieri and Carbone (2015).

[19] Inspecting quality components in SRA tender documents, we found no significant supplementary services, but frequent references to subjective characteristics as suggested by operators (e.g. the ease of slipping the needle, the force required to press the plunger, etc.), unrelated to the direct choice of the PB in the purchasing process.

[20] For the 522 FPAs for which information is available, 4 is the bidders' av-er-age num-ber.

Table 2
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 the price by its average over 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.

purchase of medical devices subject to the reference price regime. For example, the class of "syringes with three-piece eccentric cone, luer tip; capacity 20 ml, graduated, with a triple-sharpened needle, mounted gauge G 19–G 23 and a length of 40 mm" has unit prices ranging between €0.05 and €0.17.[21]

2.3. Preliminary evidence

This sub-section presents preliminary findings on the unit price. First, we investigate whether prices vary according to the PB and the identity of the supplier. Second, we compare some common reduced-form estimates, to find the most appropriate to describe unit prices.

For the first task, we ran a set of one-way ANOVA tests to see if unit prices, on average, change according to medical device, PB or the supplier (one at a time). The three tests, shown in Column (1), Table 2, (with *p*-values in square brackets), always reject the null hypothesis, indicating that prices indeed vary for all three dimensions, especially for the device categories (as suggested by the higher value of the test). We then checked if unit prices change for each dimension, after controlling for the other two. Hence, the same test was carried out, with prices now cleaned of their average in two dimensions. For example, in one case we considered the difference between prices and average prices by PB plus average prices by supplier, and looked to see if this difference changes according to medical device. This way, after removing PB- and supplier-specific linear fixed effects, we can see if something nonetheless varies according to the device. Column (2) shows that the tests always reject the null hypothesis, indicating that prices still vary for each dimension, once the fixed effects of the other two are removed. In another case, shown 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 removing PB- and supplier-specific multiplicative fixed effects, there is still something that varies according to the device. This evidence suggests that prices are determined by all the three dimensions and that identifying the contribution of each is possible. Our results are also confirmed using a non-

parametric Kruskal–Wallis test in place of the ANOVA test (output available upon request).

For the second task, a standard approximation requires unit prices to be explained by costs, quantities 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. Quantities purchased are 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 in the auction (to account for actual competition). We also incorporate a dummy for FPAs, which generally have a larger number of bidders than is the case for direct negotiations.

Using a linear regression model of prices on device dummies, the number of suppliers and 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) and (2) of Table 3). This 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) replicate the two previous analyses without including these variables in the specification. The log-log model is still largely preferable to the linear model. In what follows, we 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 to control for potential economies of scale, allowing 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, removing quantity and quantity–device interactions. Furthermore, 91% of the log quantity and device–dummy interactions are not significant at the 5% significance level. Similar results are obtained using a linear regression model. Hence, the analysis suggests that in our dataset, no economies of scale are present in the levels of quantity purchased by PBs.

3. Theoretical framework

3.1. Definition of the PBs competence

Consider a market in which – on the demand side – a PB, $h \in \{1, H\}$, is in charge of managing the purchase of medical devices – such as hypodermic needles for syringes – belonging to class $d \in \{1, D\}$.[22] On the supply side, there

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[21] Appendix A.1.1 reports, for each device class, the average, minimum and maximum price observed.

[22] According to Italian law, requests to procure medical devices cannot refer to a specific brand existing in the market, so as not to favour a specific supplier. Requests are limited to a detailed technical description of the medical device required.

Table 3
Preliminary regressions.

	(1)	(2)	(3)	(4)	(5)
Method	OLS	OLS	OLS	OLS	OLS
Dependent variable	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***		−5.494***	
		(0.616)		(0.543)	
ln(Bidders)		−0.044			
		(0.030)			
Direct negotiation	0.243	0.091*			
	(0.279)	(0.054)			
Reference price	−0.223	0.028	−0.077	0.035	
	(0.254)	(0.045)	(0.135)	(0.035)	
ln(Quantity)					0.004
					(0.091)
Constant	2.091***	9.250***	1.883***	8.400***	−0.461
	(0.694)	(1.133)	(0.391)	(0.941)	(0.584)
Device fixed effects	YES	YES	YES	YES	YES
ln(Quantity) × 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	1474	1474	1474

Note. Robust standard errors in Columns (1)–(4); clustered standard errors using PB ID in Column (5). Asterisks denote significance levels (*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$).

Table 4
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	0.487	193	0.149
With ref. price	0.516	85	0.403
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.

are S suppliers, and each supplier $s \in \{1, S\}$ is willing to sell the requested quantity q_{dh}. We assume that, for a medical device of class d, each supplier's profit function, π_{ds}, with constant return to scale, is given by

$$\pi_{ds} = q_{dh}\left(p - c_d\left(\theta_s\right)\right) \tag{1}$$

where p is the awarding price of the medical device, $c_d(\cdot)$ is the cost function to produce the medical device d, and $\theta_s \in \left[\underline{\theta}, \bar{\theta}\right]$ 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, means it is possible to use unit prices in the presence of lots. In other words, no cross-subsidisation between different medical devices in the same lot is allowed. 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 managed by a local PB h, for class d of medical devices.

The observed unit 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:

$$p_{dhs} = c_{ds} + \mu_{dhs}. \tag{2}$$

When standard devices are purchased, the aim of the PB is to buy them at the lowest possible price. Under full information, the PB 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 (with the lowest marginal cost) and obtain a price as close as possible to that supplier's marginal cost. However, in a realistic framework, several elements might prevent a PB from obtaining this price: some of them are exogenous to PB choices, whereas others can be totally or partially controlled by the PB.

In order to investigate PB competence 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 $\Psi_{dhs} = \mu_{dhs} + \left(c_{ds} - c_{d0}\right)$, Eq. (2) can then be rewritten as follows:

$$p_{dhs} = c_{d0} + \Psi_{dhs}. \tag{3}$$

We define PB competence as a persistent effect on Ψ_{dhs} recorded for all the tenders (i.e. FPAs and direct negotiations) to procure medical devices. This effect refers to the PB choice of awarding mechanism, the definition of the reserve price, collecting information on supplier cost structures and inviting the best suppliers to take part in the tender, among other factors. According to Eq. (3), the higher the persistent PB effect, the higher the price paid on average by these PBs (the lower their utility), and the lower the PB competence 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. $\Psi_{dhs} = \gamma_h + \gamma_{ds}$), means that γ_h can be estimated consistently from Eq. (3) by using a regression of prices on medical devices' and PB 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 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, Eq. (3) can be rewritten as follows:

$$\ln(\Psi_{dhs}) = \ln(p_{dhs} - c_{d0}) = \ln(\gamma_h) + \ln(\gamma_{ds}) \qquad (4)$$

thus requiring a structural estimation of marginal costs and a careful choice of c_{d0}. In Section 3.2, we focus on how to derive the benchmark marginal cost for each class of medical device and, in Section 4, we estimate each PB FE γ_h. We then explore the correlation between PB competence and PB balance sheet data.

3.2. Marginal cost estimates

Following the methodology of the seminal work of Guerre et al. (2000) (henceforth GPV), we use only FPA observations to estimate the marginal cost for each class of awarded medical device.[23] In so doing, we implement the GPV approach 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 for direct auctions – where the highest price wins – to procurement auctions, where 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 A.2).

3.2.1. Device heterogeneity

Medical devices include different goods – bandages, syringes, etc. – which are categorised by class. 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, in line with the preliminary evidence of Section 2.3 suggesting that a log-transformed model is well-suited to describing our data, we assume that a bidder's private evaluation (i.e. its marginal cost) is multiplicatively separable in the supplier 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 of a medical device of class d', then the same ratio between the marginal costs of d and d' applies to all suppliers. In this case, in equilibrium and for each supplier, the price of d will be twice 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 equation:

$$c_d(\theta_s) = \alpha_d \theta_s \qquad (5)$$

where the bidder-specific private information θ_s is independent of 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 in line with the preliminary results of Section 2.3.

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

$$p_d\left(\alpha_d, \theta_s, N_{dh}\right) = \alpha_d p_0\left(\theta_s, N_{dh}\right) \qquad (6)$$

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 medical device FEs (the dummy variable D_d) and on the number of bidders in each FPA (N_{dh}), as follows (output available on request):

$$\ln(p_{dhs}) = \sum_{d=1}^{D} (\ln(\alpha_d)D_d + \beta_{dh} \ln(N_{dh})) + \varepsilon_{dhs}. \qquad (7)$$

Appendix A.1.1 collects all device-category parameters α_d. As a robustness check and to exclude the fact that devices with few observations lead to biased estimates, we repeated the estimation of Eq. (7) in two subsamples of the medical device classes, i.e. for all medical devices where we have at least five observations (roughly half of the 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 unit prices p_{dhs} paid by PBs, hence the winning bids, are then normalised by dividing by α_d. We define homogeneous price p_{0hs} as follows:

$$p_{0hs} = \frac{p_{dhs}}{\alpha_d}. \qquad (8)$$

This price p_{0hs} is used from now on to make all observations of our dataset comparable and to obtain 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 $\alpha_0 = 1$ with the level of competition N_{0h}. The distribution of p_{0hs} derived from the data is presented in Fig. 1.

3.2.2. Procurement rules and the winning price

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

$$p(\theta_i) = \theta_i + \int_{\theta_i}^{\bar{\theta}} \left(\frac{1 - F(y)}{1 - F(\theta)}\right)^{n-1} dy. \qquad (9)$$

Following GPV, Eq. (9) can be inverted to express the unobserved marginal cost θ_i as a function of the observed

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[23] The underlying hypothesis is that for standard goods, each supplier's marginal cost does not change under different awarding mechanisms (i.e. in our setting, FPAs and direct negotiations).
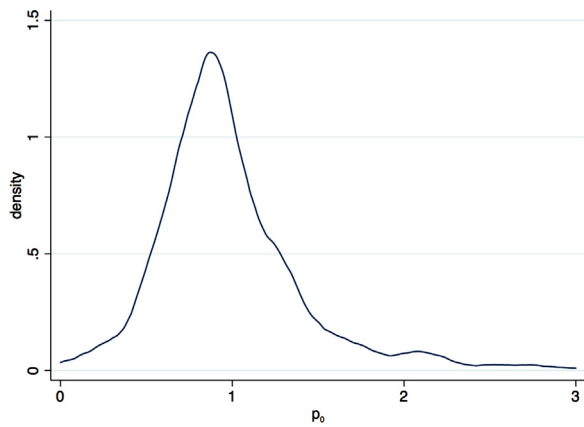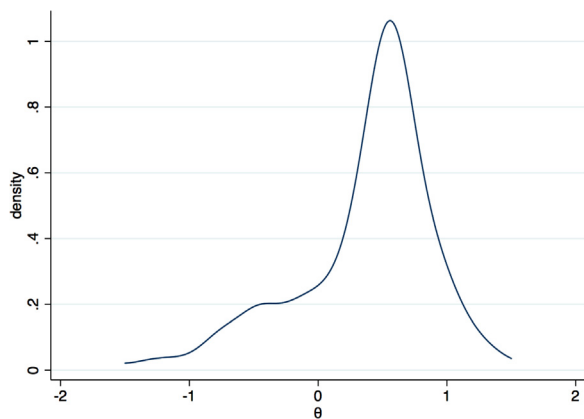
Fig. 1. Distribution of homogeneous prices.

Fig. 2. Distribution of the private value.

Fig. 3. Private value distribution: robustness checks.

prices and price distribution observed through kernel estimation. In our dataset, for each auction, we observe the winning price 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 bid 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 bid distribution.

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

$$\theta_s = p_{0hs} - \frac{N_{0h}}{N_{0h} - 1} \frac{1 - G_{(1)}(p_{0hs}|N_{0h})}{g_{(1)}(p_{0hs}|N_{0h})} \qquad (10)$$

where $N_{0h} = \{3, 8\}$ is the noisy signal about the level of competition that bidders receive for the given auction, $G_{(1)}(p_{0hs}|N_{0h})$ is the cumulative density function of all transaction prices, conditional on N_{0h}, evaluated at p_{0hs}, and $g_{(1)}(p_{0hs}|N_{0h})$ is its relative probability density function. The derivation of Eq. (10) is presented in Appendix A.3. The resulting distribution of θ_s based on our sample is plotted in Fig. 2.

Since we impose no constraint on Eq. (10), estimates of the private value θ_s can be negative. Indeed, the distribu-
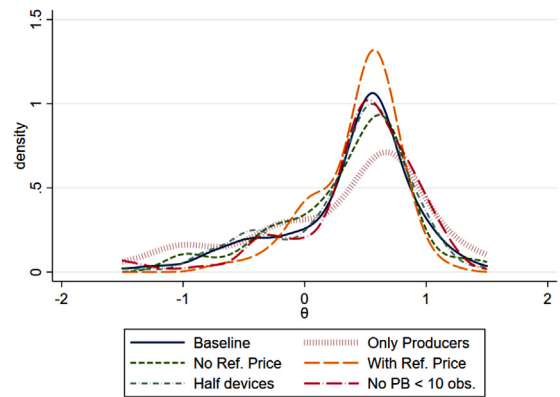
tion in Fig. 2 displays negative values in 26% of cases. The distribution of private values is based on our benchmark sample in order to use as many observations as possible. However, we find a similar distribution if we restrict our attention to several sub-samples of the data, that is, if we concentrate on bidders who manufacture the devices (ignoring bidders who are merely sellers), if we separate auctions with reference prices from auctions without reference prices, and if we look at devices or PBs with more observations. Details of these robustness checks are discussed in Section 3.2.3. The fact that the distribution of private values includes negative values is not a problem for subsequent analysis, because we need only one representative value from the distribution. Indeed, our analysis requires us to choose a benchmark supplier, the same for all medical devices. The prices paid by different PBs are then compared to the marginal costs of that supplier. We choose the median value θ_0 of the distribution and, accordingly, use Eq. (5) to obtain the benchmark marginal cost c_{d0} for each class d, as follows:[24]

$$c_{d0} = \alpha_d \theta_0. \qquad (11)$$

We use the median marginal cost mainly for two reasons: (i) deviations from a median value provide a simple interpretation of the price-cost difference $(p_{dhs} - c_{d0})$ used to derive PB competence, as it measures how much the winning supplier differs from a representative, median value; (ii) the median value is a robust choice, as the distribution of the private values is structurally estimated and not directly observed by the econometrician.

While reasonable, using the median private value is an arbitrary decision. The choice of the benchmark value has consequences for Eq. (4) and in particular for the PB-specific effect γ_h. In our case, γ_h describes the PB effect compared to the median supplier. However, changing the benchmark value does not alter the subsequent analysis: since it is constant with respect to the PB, the PB-specific effect γ_h may change in size, but it maintains the same ranking. In Appendix A.7.3 we replicate the benchmark results of Sec-

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[24] Appendix A.1.1 shows the marginal costs of the benchmark supplier.

tion 4 when taking the 33rd and 67th percentiles from the distribution of private values. The key results are unaltered.

To investigate PB competence in relation to the procurement of 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, except in 6.7% of our observations, below the actual prices paid by PBs.

3.2.3. Robustness checks

This sub-section replicates 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 this 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 shown in Fig. 2.

Only producers – One 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, simultaneously, "producers and sellers", that is, are endowed with a privately observed cost function. Differently, the presence of bidders who are, simultaneously, "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 stochastic common value component exist in the literature, but they require the observation either of all bids (Haile et al., 2003) or, at least, the winning and second lowest bids (Athey and Haile, 2002). Decarolis (2018) suggests using the reserve price in place of the second lowest bid to control for the presence of a deterministic common cost component (unobservable by the econometrician, but observed by all bidders). Unfortunately, such information is not recorded in our dataset, which has information on winning bids only. To address the issue, we collect additional data on bidders to identify them as "producers and sellers" or "distributors and sellers".[25] The marginal cost estimate is then repeated using only bidders identified as "producers and sellers".

Reference price – Understanding the conditions under which the reference price may affect bidding decisions is relevant. Note that inconsistencies in estimation of θ arise only when the following conditions are both met: (i) the reference price is higher than the winning firm's marginal cost, but lower than its equilibrium bid when the reference price policy is not adopted, and (ii) at least a second firm with marginal costs below the reference price took part in the auction. As a robustness check, we consider observations before and after the termination of the reference price policy separately.

Device and public buyers' restrictions – To prevent devices with few observations leading to biased estimates, we repeat the estimation excluding device classes with fewer than five observations. We carry out a similar exercise for PBs, and in line with the next section, exclude PBs with fewer than 10 observations.

The resulting distributions of the private values θ_s are plotted in Fig. 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 presented in Table 4. The median θ_0 in Table 4 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 applicable. However, the estimate of θ_0 is only 5.1% larger than the baseline estimate. The sample is the smallest of the robustness checks considered, and Kolmogorov–Smirnov finds no difference between the two distributions.

Remarkably, the differences in θ_0 from the remaining robustness checks are tiny. For example, the deviation in θ_0 from the baseline, considering solely producers, is equal to only 1%. This, with the use of the Kolmogorov–Smirnov test, is the only distribution of θ_s found to be significantly different from the baseline estimate. However, the suppliers included also differ, with 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. *After the estimate,* distributors are removed. In the robustness check, distributors are removed *before the estimate of 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 been different if the introduction of distributors in the baseline model had caused biased estimates.

4. Public buyer competence

4.1. Estimation

We now investigate each PB-specific fixed effect in purchasing standard medical devices. Considering the price paid, after estimating the benchmark marginal cost c_{d0} of each medical device, we obtain $\Psi_{dhs} = p_{dhs} - c_{d0}$. We then estimate the PB-specific component γ_h by using the following OLS regression:

$$\ln(\Psi_{dhs}) = \ln(p_{dhs} - c_{d0}) = \sum_{h=1}^{H} \left(\tilde{\gamma}_h A_h + \phi_h A_h R \right) + \varepsilon_{dhs}. \tag{12}$$

The specification in Eq. (12) includes the PB dummies A_h and the dummy variable R equal to 1 when the reference price regulation was in force and otherwise 0. This variable interacts with the PB dummies to capture any change in the PB fixed effect attributable to the reference price.[26]

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[25] 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. In our dataset, we find that 75.9% of FPA winners are producers, and only 24.1% distributors.

[26] In Appendix A.4, Eq. (12) is modified to include interactions between PB dummies and supplier dummies. A PB and a supplier may interact

Excluded from this estimate are PBs with fewer than 10 observations, i.e. PBs that managed under 10 auctions in the period considered. We obtained 57 PBs and 1192 observations for our awarded medical devices. In the analysis, we use standard errors clustered at the level of medical devices to control for potential serial correlation.

Our aim is to provide an estimate for PB parameters $\tilde{\gamma}_h = \ln(\gamma_h)$, where γ_h is the PB-specific fixed effect in purchasing medical devices, as set out in Eq. (4). The higher the coefficient, the lower the competence of the PB. In the regression, almost all dummies are significant, suggesting that each PB is endowed with its own specific procurement competence. The R^2 of the regression is 0.63, which means that about two-thirds of the difference between prices and marginal costs can be explained by PB fixed effects. Estimates are available on request.

4.2. Determinants

PB competence may affect various decisions in purchasing procedures such as the choice of awarding mechanism and of the reserve price, or how to attract more or better suppliers, among others. Below we study PB competence in managing the purchasing of medical devices to see if it is associated with any observable characteristics. Hence, we run the following regressions of a proxy for each PB fixed effect on a set of explanatory variables:

$$-\tilde{\gamma}_h = \beta_0 + \beta_1 M_h + \beta_2 H_h + \beta_3 P_h + \beta_4 C_h + \varepsilon_h. \tag{13}$$

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 managed in our sample period. This way, we attribute more importance to the PBs that more frequently organised tenders to award medical devices.[27] We consider two different measures for the dependent variable. First, we take PB competence derived earlier from Eq. (12) with the structural estimation of the marginal costs. Second, we take a measure of PB competence originating from the following equation:

$$\ln(p_{dhs}) = \sum_{h=1}^{H} \left(\tilde{\gamma}_h A_h + \phi_h A_h \cdot R \right) + \sum_{d=1}^{D} \left(\delta_d D_d \right) + \varepsilon_{dhs}. \tag{14}$$

Eq. (14) differs from Eq. (12) in two ways. First, the dependent variable comprises prices only and therefore excludes marginal costs which, in our approach, are recovered from prices. Second, the specification now includes medical device dummies. The purpose is to obtain estimates of the PB fixed effects unaffected by our structural approach to infer the marginal cost of medical devices.

Indeed, the heterogeneity of the costs of the devices is now captured through the assumption-free medical device dummies, similarly to Best et al. (2017). The resulting estimates of $\tilde{\gamma}_h$ are generally smaller but highly correlated (0.64) with those obtained from our benchmark analysis. The R^2 of the regression in Eq. (14) is equal to 0.94, but falls to 0.49 when the regression is repeated with only PB fixed effects. Even after excluding the structural analysis, almost half of the price disparities is explained by PB fixed effects (estimates are available on request). Note that in Eq. (13), the sign of the dependent variable is inverted to ease interpretation. In so doing, higher coefficients indicate higher competence in managing procurement. As the dependent variable is itself an estimate, we make use of bootstrapped standard errors based on 1000 iterations.

The specification includes four groups of variables: M_h refers to the auction mechanism applied (the fraction of direct negotiations), H_h refers to potential scale economies in purchasing (the logarithm of total personnel cost or the logarithm of healthcare material purchases), P_h refers to the distribution of costs (the fraction of non-health personnel over total personnel costs and the fraction of healthcare material purchases over total health costs) and the average number of days the PB takes to pay its suppliers (the logarithm of days of payable outstanding in 2012),[28] and C_h refers to control variables on the nature of the PB (the dummy ASL, identifying local healthcare units, other than hospitals), its location in a metropolitan/rural area, in the North/Center-South of the country, and per-capita health expenditure in the region of the PB. The latter variable interacts with the Center-South dummy because of countrywide disparity, with Northern outspending Southern regions.

Table 5 shows the output of our regressions by using the proxy of PB competence obtained from Eq. (12) in Columns (1) and (2), using the proxy obtained from Eq. (14) in Columns (3) and (4). For each measure, we consider two variants of the specification, depending on which variable is used for H_h (either total personnel costs or healthcare material purchases). We do not include the two variables in the same specification because they both proxy for the size of the PB, and are highly correlated (the correlation is 0.79). A regression equation using both variables would not precisely identify the contribution of each. Since, a priori we have no preference for either variable, we look at them in two separate models.

Table 5 shows the output of IV rather than standard OLS regressions (shown in Appendix A.7.1). This is due to concern that there may be simultaneity for the mechanism variable M_h. The PB decision about which auction mechanism to implement may influence and, at the same time, be influenced by PB competence itself. This could create endogeneity, yielding inconsistent estimates. In all columns, we therefore instrument the mechanism variable (the fraction of direct negotiations) with two variables, the fraction of multi-device auctions and the PB-specific average quan-

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repeatedly via the procurement of different medical devices, for example, to maintain a relational contract or because of corrupt behaviour. This interaction can lead to an increase in the final price of the medical device procured and potentially have a systematic impact on estimated PB competence. However, we find this impact to be negligible.

[27] 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 20.91.

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

Table 5
Determinants of PB competence (IV regressions).

	(1)	(2)	(3)	(4)
Method	IV	IV	IV	IV
PB's competence	Using costs		Not using costs	
Fraction of direct negotiations	−1.464**	−1.916**	−0.358**	−0.485**
	(0.657)	(0.818)	(0.180)	(0.213)
ln(total personnel costs)	0.442***		0.209***	
	(0.047)		(0.018)	
ln(healthcare purchases)		0.346***		0.177***
		(0.052)		(0.020)
Non-health/total personnel cost	4.716***	4.059***	1.477***	1.217***
	(0.644)	(0.734)	(0.162)	(0.191)
Healthcare purchases/total health exp.	0.307	−1.477**	−0.320**	−1.179***
	(0.538)	(0.584)	(0.131)	(0.152)
ln(days payable outstanding)	−0.921***	−0.949***	−0.127***	−0.140***
	(0.129)	(0.140)	(0.030)	(0.032)
ASL	−0.756***	−0.769***	−0.249***	−0.248***
	(0.133)	(0.147)	(0.034)	(0.036)
Metropolitan area	−0.401	−0.541*	−0.178**	−0.213**
	(0.256)	(0.314)	(0.073)	(0.084)
Center-South (CS)	−0.507	−0.855	−0.941*	−1.072**
	(1.737)	(1.825)	(0.497)	(0.519)
Health expenditure p.c.	−0.527	−0.520	0.870***	0.823***
	(1.100)	(1.213)	(0.277)	(0.295)
Health expenditure p.c. x CS	0.901	0.986	0.744***	0.782***
	(0.945)	(0.996)	(0.269)	(0.279)
Constant	−2.515	0.833	−4.425***	−3.074***
	(2.460)	(2.438)	(0.612)	(0.582)
Kleibergen–Paap test (*p*-value)	0.000	0.000	0.000	0.000
Sargan test (*p*-value)	0.128	0.251	0.249	0.534
Hausman-Wu test (*p*-value)	0.002	0.001	0.156	0.057
Avg. dependent variable	2.060	2.060	0.341	0.341
Observations	57	57	57	57

Note. Bootstrapped standard errors (1000 repetitions) in parentheses. Asterisks denote significance levels (*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$).

tity of devices auctioned. Both instruments inform on the size of the 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 PB competence (i.e. they should be exogenous). This set of instruments is 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 accepts the null hypothesis of the Sargan test for over-identifying restrictions (p-values at the bottom of the table; see also the output of first-stage and reduced-form regressions in Appendix A.7.2). Moreover, the Hausman–Wu test suggests that endogeneity is indeed present, at least in Columns (1) and (2), and IV models (p-values at the bottom of Table 5) are therefore advisable. Below, we comment only on coefficients that are significant at least at a 5% level. Importantly, IV estimates in Table 5 and OLS estimates in Appendix A.7.1 produce similar results, with the main exception of the fraction of direct negotiations, that is the endogenous explanatory variable.

The key findings from all the models in Table 5 are qualitatively the same. Our analysis shows that direct negotiations have a negative impact on PB competence. According to Column (2), a 10% increase in the fraction of direct negotiations decreases PB fixed effects by 0.19 or 9.22% (−0.19 divided by the average of the dependent variable, 2.060); according to Column (4), the same change has an effect of −0.05 or −14.66% (−0.05/0.341). The reason

could be that, in line with Italian public procurement law, direct negotiations are used when the purchased item has specific characteristics a competition would neglect. This explains the higher prices paid by the PB, and thus a negative impact on PB competence. We also find that the PB size effect, measured using either total personnel cost or healthcare purchases, is positive and significant.

Considering the variables on costs, we find a positive and highly significant effect for the ratio of non-health personnel to total personnel costs. When two PBs of the same size are compared, the PB with higher costs for non-healthcare personnel is more competent in procuring medical devices. We also find a generally negative effect of healthcare purchases over total healthcare expenditure, in line with the definition of PB competence.

Once we focus on the type of PB, we find that local healthcare units (measured by the coefficient on the ASL dummy) are less competent than hospitals. These two types of PB differ in their form of territorial organization: local healthcare units provide services – typically, in a county – with several offices, outpatient clinics and services spread over the territory. Hospitals generally comprise numerous departments all in one location and, accordingly, are more sensitive to size-related economies of scale. Hence, we repeat the analysis adding to the specification the interaction of the ASL dummy with PB size (measured either by personnel costs or healthcare purchases). The results (available on request) show that the negative effect of local healthcare units disappears for small PBs, but

remains negative (increasingly by size) for all the others. PB type does not only influence the effect of size on competence. The negative effect of location in a metropolitan area disappears when the interaction between metropolitan area and ASL is added to the specification, and only that interaction is negative and highly significant (results available on request).

Moving on to the control variables, there is a negative overall effect for the number of outstanding days for payment. The expectation of delayed payments from a PB is built into supplier offers, i.e. they submit higher prices because they expect to be paid late.

Column (4) shows a significant and negative effect for PBs located in the Center-South. This geographical effect is in line with the well-known *North-South divide* in Italy (Federico et al., 2017). With a focus on local public institutions and procurement in Italy, Coviello et al. (2018b) show that court and public works inefficiencies are more severe in Southern regions.[29] Similarly, our analysis provides further evidence of institutional inefficiency – for PBs in the healthcare sector – located in the Center-South of Italy as compared to PBs in the North.

Significant effects can also be seen, in Columns (3) and (4), for the size of per capita health expenditures (positive) and the interaction between the latter and the geographical variable (positive). No other variable in the specification turns out to be significant.[30] Appendix A.7.3 shows, among others, the output of Columns (1)-(2) in Table 5 using, for the estimate of PB fixed effects, the 33rd and 67th percentiles (rather than the median) of the private values. Our main findings are unaltered, with the exception of the fraction of direct negotiations, which is never significant in the new estimates using the 67th percentile.

5. Reference prices and public buyer competence

5.1. Estimation

This section empirically investigates the effect of the reference price policy (for classes of medical device) on PB competence. Our dataset covers the period from January 1, 2013 to December 31, 2013. Until May 2, 2013, PBs were forced by law to apply the reference price established by the AVCP for each class of homogeneous medical device.

First, we replicated the regression in Eq. (12), but only on the subset of 40 PBs that managed awarding procedures both before and after the termination of the reference price policy. This leads to a dataset of 902 observations, with

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[29] The authors show that – in areas with inefficient local courts – public works are delivered with longer delays and the larger the contract, the longer the delay. Specifically, since local courts enforce procurement contracts managed by local PBs, their inefficiency weakens the PB, making it less able in managing the overall purchasing process.
[30] One limitation of our study may be the treatment of endogenous entry in awarding procedures. Such entry can be affected both by the buyer choice about which awarding procedure to implement (i.e. FPA or direct negotiation) and by the supplier decision to enter the procedure. Explicitly incorporating these types of endogeneity would have required a multiple-stage model, which we leave for future research. However, it is reassuring that both the semi-parametric and parametric estimates provide similar conclusions.
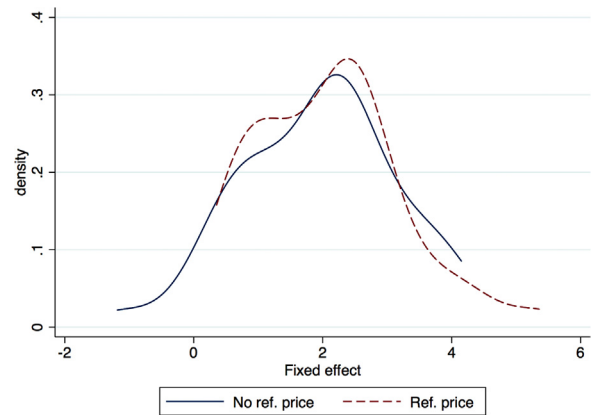

Fig. 4. Distribution of PB fixed effects.

prices paid by PBs both before and after the abolition of the reference price. Fig. 4 compares the distribution of PB FEs, as measured by $\tilde{\gamma}_h$, with PB FEs under the reference price regime, given by $\tilde{\gamma}_h + \phi_h$. With the reference price policy, the distribution of FEs is more concentrated around central values of the distribution. This is not surprising, since the reference price policy reduced PB discretion and hence removed a degree of competence.

To further clarify what is going on, we divided the sample of PBs into four groups, depending on whether their competence falls below any of the quartiles of the distribution. Ranking PBs $h = 1, ..., H$ from the lowest to the highest competence, we can create four groups of similar size (from observation H_{i-1} to observation H_i for $i = 1, ..., 4$; $H_0 = 1$ and $H_4 = H$). For each group i we then ran the following regression:

$$\ln(\Psi_{dhs}) = \sum_{h=H_{i-1}}^{H_i} \tilde{\gamma}_h A_h + \rho R + \varepsilon_{dhs}. \tag{15}$$

Eq. (15) differs from Eq. (12) for the inclusion of a common rather than PB-specific effect on the reference prices. The results are shown in Table 6 separately for the models with and without a structural estimation of the costs (panel a and panel b respectively), following the approach of Section 4.[31] Although reference prices overall have a negative impact on the final price net of the marginal cost (with a magnitude of around −45%), their effect varies widely depending on the initial level of competence of the PB. In fact, reference prices have a strong and negative impact on low-competence PBs (first quartile) and a strong positive impact on high-competence PBs (fourth quartile), and have no impact on average-competence PBs (second and third quartiles). With the reference price, the distance between prices and marginal costs shrinks for low-competence and increases for high-competence PBs. Changes are non-negligible (−137.9% in the low-competence sample and 89.1% in the high-competence sample). The findings are

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Table 6
Impact of the reference price.

	(1)	(2)	(3)	(4)	(5)
Method	OLS	OLS	OLS	OLS	OLS
Quartile	All	Q1	Q2	Q3	Q4
a) Using costs					
Reference price	−0.450**	−1.379***	−0.567*	0.352	0.891**
	(0.184)	(0.347)	(0.307)	(0.252)	(0.428)
PB fixed effects	YES	YES	YES	YES	YES
R^2	0.568	0.339	0.553	0.572	0.703
Avg. dependent variable	−1.894	−1.103	−1.756	−2.009	−2.516
Observations	836	156	171	334	175
b) Not using costs					
Reference price	0.012	−0.403*	−0.152	0.023	0.370**
	(0.051)	(0.206)	(0.130)	(0.072)	(0.179)
PB fixed effects	YES	YES	YES	YES	YES
Device fixed effects	YES	YES	YES	YES	YES
R^2	0.933	0.903	0.948	0.963	0.957
Avg. dependent variable	−1.139	−0.750	−0.825	−1.544	−1.233
Observations	902	157	232	275	238

Note. Standard errors clustered by medical device in parentheses. Asterisks denote significance levels (*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$).

similar in panel b), except that there is no longer a significantly negative effect of the reference price in the full sample. The R^2 statistics in panel b) are much higher than in panel a) due to the inclusion in the specification of device FEs accounting alone for about 40% of the fit. We interpret this non-linear effect of the reference price policy on awarding prices as directly related to PB discretion in determining the reserve price, distinguishing high-competence from low-competence PBs. Indeed, in the absence of mandatory reference prices, high-competence PBs can freely determine the reserve price (the maximum price the PB is willing to pay) so as to maximise savings via the most efficient supplier, while low-competence PBs are very far from obtaining a price close to the most efficient supplier's marginal cost.

When mandatory reference prices are at work, high-competence PBs have less discretion in each awarding procedure, and this decreases their competence in obtaining the best final price. By contrast, low-competence PBs may benefit from reference prices, as they can 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 three robustness check on the regressions in Table 6. First, we are aware that our results originate from a before-after setting with no control groups, which does not allow the effect of the reference price to be distinguished from the effect of time. In order to disentangle the two effects we would need a setting with both treatment and control groups, where we could compare our medical devices with other goods for which the reference price remained in force throughout 2013. Hence, in Appendix A.5 we comment on an exercise obtained from a dataset including homogeneous drugs no longer covered by patent. Unfortunately, the new data can be used to replicate only the analysis without structural estimation of the costs. The results of the diff-in-diff analysis are consistent with those in Table 6 panel b). Second, from panel a) we take the median in the distribution of private values. In Appendix A.7.4 we repeat the analysis using the 33rd and 67th percentiles rather than the median of the private values. Although the estimates for each column may differ from Table 6, the general pattern is clear and shows that the effect of reference prices is negative (positive) for low-(high-) competence PBs. Third, some results might be driven by devices for which we have only a few observations. Removing sparsely observed devices is challenging, as we want to preserve the threshold of at least 10 observations for each PB. We repeated the analysis excluding devices with only 5 or fewer observations. The results are set out in Appendix A.7.5. We found that the reference price significantly reduces the difference between prices and marginal costs for PBs with lower competence. Additionally, the effect of reference price on PBs endowed with high competence (in the fourth quartile) is significantly different from the effect on PBs endowed with low competence (in the first quartile).[32]

5.2. Determinants of public buyer competence with reference prices

We conclude our analysis by repeating the IV regression in Eq. (13) where the unit of analysis is an individual PB but now using, as a dependent variable, a proxy for PB competence in the reference price regime:

$$-\left(\tilde{\gamma}_h + \phi_h\right) = \beta_0 + \beta_1 M_h + \beta_2 H_h + \beta_3 P_h + \beta_4 C_h + \varepsilon_h. (16)$$

Our aim here is to determine if PB competence correlates with different variables when the reference price is in play. Table 7 shows the relevant outputs, comparing estimates of competence under the reference price $\left(-\left(\tilde{\gamma}_h + \phi_h\right)\right)$ with those without $(-\tilde{\gamma}_h)$. The latter scenario stems from Eq. (13), 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

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

Table 7
Determinants of PB competence with reference price.

Method	(1) IV	(2) IV	(3) IV	(4) IV
	No Ref. price		Ref. price	
Fraction of direct negotiations	−2.749***	−2.665***	−0.718**	−0.699**
	(0.596)	(0.583)	(0.329)	(0.323)
ln(total personnel cost)	0.721***		0.481***	
	(0.070)		(0.060)	
ln(healthcare purchases)		0.709***		0.461***
		(0.070)		(0.059)
Non-health/total personnel cost	15.698***	16.332***	5.852***	6.216***
	(2.066)	(2.069)	(1.476)	(1.503)
Healthcare purchases/total health exp.	−2.986***	−6.176***	−0.374	−2.459***
	(0.834)	(1.052)	(0.698)	(0.881)
ln(days payable outstanding)	0.966***	0.968***	0.728***	0.734***
	(0.200)	(0.198)	(0.130)	(0.129)
ASL	−0.895***	−0.892***	0.216*	0.217*
	(0.168)	(0.165)	(0.112)	(0.112)
Metropolitan area	−0.628***	−0.583***	0.657***	0.673***
	(0.223)	(0.216)	(0.171)	(0.168)
Center-South (CS)	−12.644***	−12.752***	−8.802***	−8.973***
	(2.594)	(2.563)	(1.830)	(1.825)
Health expenditure p.c.	9.920***	9.705***	0.763	0.615
	(1.677)	(1.638)	(1.143)	(1.117)
Health expenditure p.c. x CS	7.381***	7.441***	4.108***	4.193***
	(1.418)	(1.401)	(0.986)	(0.982)
Constant	−34.523***	−32.367***	−12.470***	−10.819***
	(4.618)	(4.360)	(3.219)	(3.034)
Kleibergen–Paap test (p-value)	0.000	0.000	0.000	0.000
Sargan test (p-value)	0.776	0.742	0.370	0.427
Hausman–Wu test (p-value)	0.000	0.000	0.000	0.000
Avg. dependent variable	2.053	2.053	2.072	2.072
Observations	40	40	40	40

Note. Bootstrapped standard errors (1000 repetitions) in parentheses. Asterisks denote significance levels ($*p < 0.1$, $**p < 0.05$, $***p < 0.01$).

a reference price. Appendix A.7.6 shows the corresponding estimates based on OLS regressions.

The comparison of Column (1) with Column (3), and Column (2) with Column (4) provides systematic evidence that under the reference price policy, key effects (of the fraction of direct negotiations, healthcare personnel cost, healthcare purchases and non-healthcare personnel over the total personnel cost) are generally smaller. 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, so each PB-specific competence (or incompetence) no longer significantly affects the outcome. The only exception is the dummy variable related to the metropolitan area, which switches from a negative and significant to a positive value, suggesting that PBs located in those areas benefited most from reference prices.

Focusing on the geographic dimensions in Table 7, an interesting pattern emerges. Without the reference price, PB competence was much lower in the Center-South of Italy; with reference price, PB competence was still lower in the Center-South, but not as low as without. One possible explanation for the negative effect is the inefficiency of institutions in the Center-South of Italy, as mentioned in the comments on Table 5 results. Based on our findings, inefficiency is mitigated under mandatory reference prices, possibly because PB discretion is more limited.

By using the dependent variable obtained without structural estimation of the costs, we obtain similar find-

ings. However, this estimation does not pass the Sargan test for the exogeneity of the over-identifying restrictions. The output is available on request.

6. Conclusions

In European countries, the procurement of medical devices by hospitals and local health units (PBs) takes up a large share of national budgets. In the US, healthcare expenditure is rising. Anecdotal and empirical evidence of huge variations in the prices of medical devices – among and within countries – makes procurement efficiency a relevant issue.[33]

This study empirically investigates the price differences in the purchasing of standard medical devices by Italian PBs, with a focus on PB competence in managing procurement during the period from January 1 to December 31, 2013. It also studies the effects of the mandatory *reference price* on the prices paid by PBs, a nationwide policy adopted until May 2, 2013 to increase public spending efficiency.

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[33] For variations in these prices, see MedTech Europe, 2019; Henschke and Redberg, 2018; den Ambtman et al., 2020. Analysing hospital surveys carried out by the Millennium Research Group, Wenzl and Mossialos (2018) provide evidence of large price differences between the US and Germany for cardiovascular technologies. For example, in 2014, prices for bare-metal stents and pacemakers were five times higher in the US compared to Germany and significant price differences were recorded even within EU countries.

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 PB competence as PB fixed effects on this difference for each item purchased. Our results show that Italian PBs pay substantially different prices for standard medical devices. In particular, the quartile-based coefficient of variation of the prices paid is 25.8.[34] This difference between purchasing prices can be explained by PB fixed effects, which we investigated as related to institutional characteristics, geography and size. We found that PB size (measured by overall personnel costs, corresponding to the sum of healthcare personnel and non-healthcare personnel costs or by the size of healthcare-related procurement) has a generally positive and significant effect on PB competence in relation to the procurement of medical devices. Our empirical analysis showed that non-healthcare personnel costs drive the overall positive and significant effect on PBs' competence. This result supports the centralisation of purchasing for medical devices, i.e. a few large PBs in the country with non-healthcare personnel addressing (possibly skilled) efforts in the procurement activities. A centralised system for procurement – whatever the design of the national health sector considered – would also better enable policymakers to implement measures to control prices while accounting for the value of the medical devices procured.[35]

We then investigated the effect of mandatory *reference prices* as a cap on the winning price. This policy seems to have a weak effect in fostering the efficiency of purchasing medical devices. Considering an average price of €1.37, our back-of-the-envelope calculation shows that the average price decreased by €0.05, or 4%.[36] This translates into a reduction of €800 in a median auction with a total cost of €20,000. Particularly noteworthy, this overall result masks a non-linear effect of the reference price on PBs with different abilities: we found that reference prices have a significant negative effect on high-competence PB purchasing and a significant positive effect on low-competence PB purchasing. According to our back-of-the-envelope calculation, the effect of the reference price ranges from a €0.25 (18.12%) average price decrease for low-competence PBs to a €0.12 (8.48%) average price increase for high-competence PBs.[37] This finding regarding the effect of reference prices is not free of limitations. Indeed, it relies on a before-and-after analysis which compares medical device purchases in two periods, with and without reference prices. Hence bias may arise if events not controlled for in the regression analysis take place in one only of the two periods. To remove any bias, in Appendix A.5 we compare our findings for medical devices with those from a control group of drugs (no longer covered by patent) for which reference prices were not abolished in the period considered. Our benchmark finding was supported by these further results.[38]

In a period in which, both in Europe and the US, policymakers are increasingly relying on regulatory policies for medical devices to improve procurement efficiency, our results show that PB discretion should be considered along with each PB competence in managing the process. Specifically referring to the impacts of mandatory reference prices on PB competence, our results suggest a move towards a discriminatory approach – implementing mandatory requirements only for PBs performing below a given benchmark. Note that our results were obtained in a procurement setting with standardised and simple items. Considerations of PB competence and discretion would be even more relevant regarding policies designed for the procurement of more complex items (Kelman, 1990).

Given the high value of European public procurement in the healthcare sector (both for standard and non-standard items) and the core relevance of the sector in the Europe 2020 strategy and forthcoming policies, new empirical investigations are expected to shed light on further improvements in spending efficiencies in the sector. They are also expected to address the effect of the recent policy by the Trump administration regarding the transparency of "price and quality information" in the healthcare industry.[39] The search for spending efficiency in this industry seems – both in the US and in Europe – to encourage the spread of information on prices, but more empirical work is necessary to explore the costs and benefits of the mechanisms adopted and to assess their policy implications.

Appendix A. Supplementary Data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jhealeco.2020.102370.

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[34] To make all observations comparable, the quartile-based coefficient of variation is calculated using homogeneous prices, as defined by Eq. (8), applied to the entire dataset.

[35] Note that the centralisation of purchasing for medical devices might be life-saving in some countries during crises such as the recent Covid-19 pandemic. Espitia et al. (2020) estimate that surges in demand for critical Covid-19 products (e.g. masks, gloves, aprons, suits, ventilators, etc.) and export restrictions on leading producers will drive up prices by 23% on average (aprons and masks recording 52% and 40% increase, respectively), with critical effects (very limited or no access to medical devices) in developing countries. There, the centralisation of procurement for medical devices could also address – in addition to price control – the issue of coordinating international trade policy for these products.

[36] This calculation is based on predictions of the price/cost difference from Column (1), Table 6. We obtain: $(\exp(-1.894 - 0.450) - \exp(-1.894))/1.37 = -0.040$.

[37] These calculations are based on predictions of the price/cost difference from Column (2) and (5), Table 6. Low- and high-competence PBs are

defined in – respectively – as the 1st and the 4th quartile of the overall PB competence.

[38] We are grateful to the Editor, Prof. Owen O'Donnell, for suggesting this test. Note that drug data do not give rise to the structural estimation of marginal costs. Future research may replicate our benchmark analysis with a richer dataset.

[39] On June 24, 2019, President Trump signed an Executive Order giving the Department of Health and Human Services 60 days to require hospitals to publicly post price information for "shoppable items and services" in an "easy-to-understand and consumer-friendly" format. It is not clear how such transparency will affect buyer competence in negotiations and settling final prices. (Executive Order, June 24, 2019, download from: https://www.whitehouse.gov/presidential-actions/executive-order-improving-price-quality-transparency-american-healthcare-put-patients-first/).

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