Buyers' Ability in Public Procurement: A Structural Analysis of Italian Medical Devices*

Alessandro Bucciol
† Riccardo Camboni ‡ and Paola Valbonesi §
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Abstract

By empirically exploiting an original dataset on standardized medical devices purchased in the period January–December 2013 by 135 Italian local public buyers (i.e., hospitals and health units), we investigate each buyer's ability to run the procurement process.

Our results show that: i) the average prices vary substantially among public buyers; ii) this variation is largely captured by the buyer's fixed effect; iii) the buyer's ability is correlated with institutional characteristics, geography, and size; iv) mandatory reference prices determine higher average purchasing prices for high-ability public buyers, no effect for medium-ability and lower prices for low-ability public buyers. (98 words)

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[†]University of Verona, alessandro.bucciol@univr.it

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

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

1 Introduction

In 2015, the European Union market for medical devices was worth $110bn \in$, or about 7.9% of total health expenditures in the same year; it is the second largest market of medical devices in the world, after the United States. However, compared to the United States, where such expenditure is mainly managed by the private health sector, in the European Union, about 79% of healthcare costs are paid for by national governments (OECD-EU, 2016). Such relevant differences between the EU's and U.S.'s health systems also include the purchasing of medical devices: in the United States, this purchasing usually relies on direct trade between private hospitals and suppliers, characterized by strategic discretion and flexibility; instead, in EU countries, such activity is heavily regulated, being the public officials' choice about the awarding mechanisms often restricted by law and resulting the contract's management in a transactional-based approach (Lian and Laing, 2004; Spagnolo, 2012). Thus, although in the private health sector the managers' bargaining ability in buying medical devices is expressed in B2B's direct negotiations with suppliers (Grennan, 2013 and 2014), in the public health sector, the officials' ability must cope with B2G's regulated procedures, often including open auction mechanisms.

In Italy—as in many other European national health systems—the procedures to purchase medical devices are run at the local level; interestingly, anecdotal evidence shows that different public hospitals and local public health units often pay different prices for the same standard item, for example, a simple syringe. This difference in prices highlights systemic inefficiencies in purchasing, and in a period of tight public budgets, it has attracted the attention of the national press and fueled an extended public debate.² With the aim of limiting these price differences, the Italian Authority of Public Contracts (the national regulator for public procurement) was tasked in 2011 to set a "reference price" for each of the several classes of functionally equivalent medical devices. These reference prices (RFs), active from July 2012 to May 2013, worked as a cap to unitary prices in procurement auctions for medical devices: the policy maker intended RFs to lower public buyers' spending in running procurement.³

The primary goal of this paper is to empirically investigate the role of the public

¹Public health is one 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 of 29 June 2011 'A budget for Europe 2020').

²See also, among many articles, Paolo 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, 03/07/2012 and Emanuele Vendramini "I costi standard sono giusti? Dipende" (Are reference prices fair? It depends) in Il Sole 24 Ore, 30/10/2015.

³References prices were mandatorily adopted and soon cancel out - after 10 months - as a result of an appeal by some medical devices' suppliers to the Lazio regional administrative court (TAR, Tribunale Amministrativo del Lazio); this court motivates the reference prices' abrogation because of the large heterogeneity of products in many of the 149 classes.

buyer's ability versus the role of the seller's production costs and competition within auctions in determining awarding the prices of standard medical devices. We do this by combining a simple structural model on purchasing with an original dataset on Italian public procurement that provides the quantities purchased and price paid for standard medical devices sold to 135 Italian local public buyers (PB), that is, local public hospital and health units, in the period January-December 2013. We first develop a structural estimate to derive the unobserved marginal cost for each medical device. Then, we collect functionally homogeneous medical devices with given characteristics in classes, and for each class, we set a common marginal cost. Finally, we use it as a benchmark to compare the PB's price paid when buying medical device. Considering the PB's purchase of different (classes of) medical devices, we thus derive each PB's fixed effect and use it as a measure of the PB's ability to manage the procurement process. Then, exploiting information from local public hospitals' and health units' balance sheet open data, we investigate the determinants of the PBs' ability to manage the procurement of medical devices. Finally, considering the exogenous policy change regarding reference prices in the period our dataset refers to, we explore the RFs' impact on the PBs' ability.

Based on real market data, our analysis is a key step toward bridging real procurement outcomes with the adopted procedure and each public buyer's features and behavior. Our main findings can be summarized as follows: First, the average prices of standard medical devices paid by different Italian PBs vary substantially. Second, the differences across the PBs' purchasing prices are explained by PB fixed effects, which in turn depend on institutional characteristics, geography, and size. In particular, the PB's size (measured by the overall personnel costs, corresponding to the sum of health and non-health personnel costs) has a general positive and significant effect on the ability to run the procurement process. Interestingly, when we disentangle health- and non-health personnel costs, we find both significant but with different sign. Furthermore, controls show that it is the non-health personnel costs that drive the overall positive and significant effect on the PB's ability.

At the geographical level, the north and south divide in Italy is confirmed in our empirical analysis. In the southern regions, the PB's positive size effect disappears at the regional level, and the non-health personnel costs have a negative sign.

Our results also highlight significant difference in the ability to procure between the PBs of different organizational structures: local public health units record higher prices in purchasing standard medical devices than public hospitals. The latter have a more centralized procurement management than the former and are also more closely related to regional offices, where the health policy is decided.

Finally, the adoption of a reference price as a cap to medical devices' prices has a non-linear effect on the PBs' ability: it has a significant negative effect on high-ability PBs (*i.e.*, it increases the procurement's average prices), no effect on medium-ability PBs and a positive effect on low-ability PBs.

Our paper mainly contributes to two strands of economic literature on procure-

ment. The first is on the procurement of medical devices. Grennan (2013, 2014) investigates such purchasing on a detailed U.S. database of coronary stents. He empirically studies the negotiation process between private hospitals and suppliers and the resulting price discrimination (Grennan 2013); his focus on the private hospitals' bargaining ability shows that this ability has a large firm-specific component that explains 79\% of price variations in purchasing (Grennan 2014). Our analysis adds to this research's original results regarding the ability of public buyers in managing the procurement of medical devices. As for Europe, Sorenson and Kanavos (2011) present and discuss medical device procurement policies and practices in England, France, Germany, Italy, and Spain, highlighting large heterogeneity in procedures therein adopted and little in the way of analysis on 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) discuss procurement practices and policies recently set forth in the Greece procurement of health technologies, particularly regarding reference price setting and centralized tenders, and discuss the first measurable outcomes (in terms of cost savings) resulting from these policies. We contribute to this literature by providing empirical results for the Italian case, with a focus on the determinants of the PBs' ability and on outcomes from the adoption of a reference price regime.

The second strand of literature we contribute to is deterring misbehavior in public procurement. Di Tella and Schargrodsky (2003) investigate the medical procurement prices of standard medical products following the introduction of a strict monitoring policy on Buenos Aires hospitals' purchasing in 1996–1997. They estimate a 10% reduction on average prices paid by hospitals because of the crackdowns, and they find a significant (and negative) effect of public managers' wages on the prices paid by hospitals (consistent with the theory of corruption by Becker and Stigler, 1974). Similar to Di Tella and Schargrodsky (2003), we investigate public procurement of standard medical goods and the effect of a policy on prices; in contrast to them, our focus is on the determinants of PBs' ability in managing public procurement for medical devices. Our study also directly relates to the empirical results obtained by Bandiera, Prat, and Valletti's (2009) regarding the Italian public procurement of simple and standardized goods and services: these authors empirically disentangle between active and passive waste, the first being a result of corruption and the latter a result of the PB's lack of knowledge and capabilities that simply does permit a minimization of costs through managing auctions. In the former case, the utility of the PB increases because of such waste (i.e., it determines personal gains); while in the latter case, the efficient outcome would weakly dominate the inefficient one if the PB can achieve it. They found that at least 82 percent of estimated waste was passive. Consistent with this result on Italian public procurement, in our setting, we

⁴Considering procurement performance as related to competence of public workforce, a recent paper by Decarolis et al. (2017) empirically assesses such causal effect on the USA bureaus in the period 2010-2015. Using an instrumental variable strategy, and combining data on office-level

investigate the PBs' ability to lower the markup between the price paid and estimated marginal costs of standard medical devices. We add to this literature both the effect of the PB's ability in purchasing medical devices and the effect of a reference price regime, that is, a policy designed and implemented to reduce passive waste.⁵

The remainder of the paper is organized as follows: Section 2 describes the institutional setting and our dataset. Section 3 presents our structural theoretical framework (3.1) and proceeds with the description of the marginal cost estimate (3.2), the PB's ability estimate (3.3), and its determinants (3.4); in (3.5), we focus on corruption as an alternative explanation for our results. Finally, Section 4 addresses the analysis on reference prices, and Section 5 concludes by summing up the findings and providing policy implications. In the Appendix, we provide further details on the estimations and robustness checks.

2 Environment

2.1 Institutional Setting

The Italian healthcare system is a regionally based national health service that provides universal coverage largely free of charge. The main sources of its financing are 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 are followed. Regional governments are responsible for ensuring the delivery of services through a network of population-based "local public health units" (*i.e.*, aziende sanitarie locali, ASL) and local public hospitals.⁶.

Procurement for standardized medical devices in Italy is decentralized at the local level: in 2013, there were about 350 local PBs with procurement responsibilities.⁷ According to Italian public procurement law, goods and services should be awarded through public tenders, and direct negotiation can be used under some precise circumstances.⁸ As for medical devices, we observe that scoring-rule auctions are often

competencies and on procurement performance, these authors find that cooperation within the office matters the most to improve the bureaus' outcomes.

⁵Batty and Ippolito (2017) investigate a different source of waste in the US health sector. They specifically address the effects of a recent policy aimed to reduce price discrimination by US hospitals on insured and non-insured patients. They find that limiting the price paid by non-insured patients does not reduce the quality of the service provided.

⁶To cover local demand, in some regional areas, there are also private hospitals accredited with providing health services with the same characteristics of the public ones.

⁷Source: http://www.salute.gov.it/portale/documentazione/p6 2 8 1 1.jsp?id=13

⁸According to the Italian Code of Procurement in force at the time our dataset refers to (DLGS 163/2006 - Art. 125), direct negotiations could be used only for goods and services with a reserve price below 211.000€ and only for urgent needs arising (i) because of an unexpected early termination

employed for complex services while first-price auctions are almost always adopted 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.*, to present standard tender documents and have the financial and technical qualifications required); in this respect, it is also important to note that PBs have some discretion in requiring additional qualifications and procedures. As a result, each PB in charge of procurement for medical devices can play a significant role in deciding the awarding mechanism used—although there are only a finite set of mechanisms defined by law—and, to a certain extent, to "burden" the suppliers' entry in the auction with costly requirements.

In 2012, the Italian Authority for Public Contracts (AVCP)⁹ was assigned the task of setting RPs for classes of functionally equivalent medical devices purchased by local public hospitals and health units. Each RP consists of a cap on unitary prices for a class of medical devices, and it is important to note that a class could include complex products such as stents and prostheses or simpler ones such as syringes and needles. RPs also include a safeguard clause: if the auction with the RP's application is voided, the public buyer could then proceed with a new auction where the RPs are not applied anymore. RPs were mandatorily applied on the public purchasing of medical devices from July 1, 2012 to May 2, 2013. On this latter date, the Administrative Tribunal of Rome (TAR)—replying to the appeal jointly submitted by some suppliers—canceled out the RPs, a decision motivated by the fact that the listed goods in some classes were—both functionally and technically—too heterogeneous to refer to the same price. In our analysis, we empirically exploit the discontinuity originated by the RPs' adoption and elimination to test the impact of such exogenous policy change on the PBs' ability.

2.2 Data Overview

For the present analysis, we assemble data from three sources to obtain the original dataset. First, detailed information on each open tendered public contract is taken from a hitherto unexploited dataset consisting of the transcripts of competitive auctions for standard medical devices conducted by Italian PBs from January 1st to December 31st, 2013. These transcripts are provided by the Italian Authority for Public Contracts and for each auction contain the name of the PB organizing it and the awarding mechanism adopted (*i.e.*, first-price auction, scoring-rule auction, or direct negotiation); the medical device purchased (*i.e.*, class of product and code), its

of a previous contract in existence, (ii) the period 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.

⁹The Italian Authority for Public Contracts (AVCP) was renamed Anticorruption Authority (ANAC) in 2014.

quantity, and the unitary price paid; the number of bidders for 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 to be allowed to participate 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 have information about when the awarding auction includes lots of two or more different medical devices¹⁰ and about the possibility one PB carries out a joint tender for a number of different PBs: in this latter case, we observe the identity of the leading PB—the one that is responsible for the procurement process—as well as all the above information about the auction, number of bidders, winning price and quantity purchased.

Second, we collect information about each of the local Italian PBs that purchased standard medical devices in 2013. Specifically, we have information from each PB's financial statement downloaded from its official website.¹¹ In accordance with the Italian local and regional health system, these PBs can have varied sizes and usually offer different service packages. From the PB's balance sheet, we got information on total revenues, total costs, costs for the personnel split in health-related personnel (i.e., doctors, nurses, and healthcare assistants) and non-health related personnel (i.e., clerks), and costs for the procurement of health-related goods and services. We also observe in which region PBs are located and if they are in a rural or a metropolitan area.

Finally, at the regional level, we observe per capita health expenditure and the share of overall regional spending devoted to health; PBs located in the Lazio, Abruzzo, Molise, Campania, and Calabria regions face special budget and administrative constraints because of excessive deficit spending in health (*i.e.*, according to the EU Stability Pact).

In summary, we end up with a dataset of 2,156 unitary prices paid by 135 local PBs in the period January–December 2013 for the procurement of syringes, needles, and bandages. On average, 16 observations are associated with each PB. The medical devices included in our database belong to 149 different classes of functional homogeneous products, a classification done by AGENAS, the National Agency for Regional Health Services that provides technical support for regional health departments in Italy.¹² For the sake of our empirical analysis, we only consider classes of functional

¹⁰Note that according to Italian procurement law, there are no specific rules about which auction format should be used to award lots.

¹¹According to Italian law, each local PB's financial statement, which includes the balance sheet and profit and loss account, has to be disclosed and follow a standard format jointly set by the Ministry of Health and the Ministry of Economy and Finances.

¹²AGENAS (Agenzia Nazionale per i Servizi Sanitari Regionali, http://www.agenas.it/contenutoinglese) produced two lists for classes of homogenous products. The first one, published in 2009, was used to set the reference prices that later on were ruled out by the Lazio Regional Administrative Tribunal (TAR). 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 the present empirical

homogeneous products for which we have at least 10 observations; thus, we end up with a database of 1,776 observations that have 76 classes of medical devices. Note that because some auctions include many different medical devices, we end up with a larger number of prices for medical devices than the number of awarding auctions. Table 1 summarizes the information in our dataset, referring to the awarding mechanisms adopted and the presence of entry restrictions.

Table 1. Awarding mechanisms in our dataset

Awarding mechanism	Obs.	Classes
Direct negotiations	741	76
Tenders, of which:	1035	76
by awarding mechanism:		
- Scoring rule auctions	227	66
- First price auctions	808	76
by entry restrictions:		
- with "entry restrictions"	635	76
- without "entry restrictions"	400	74
Total	1776	76

In our dataset, the awarded contracts have an average value of 126,425€ with an average unitary price of 1.37€. Within each class of functional homogeneous medical devices, we observe price variations across the PBs' purchases. Consider, for example, the following class: "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". The unitary prices for this medical device range between 0.05 and 0.17€; the price distribution is plotted in Figure 1. Investigating the determinants of these price differences is the main goal of this paper, and in what follows, we present our empirical model and estimates to address this question.

analysis, we adopt the latter AGENAS list for the classes of medical devices.

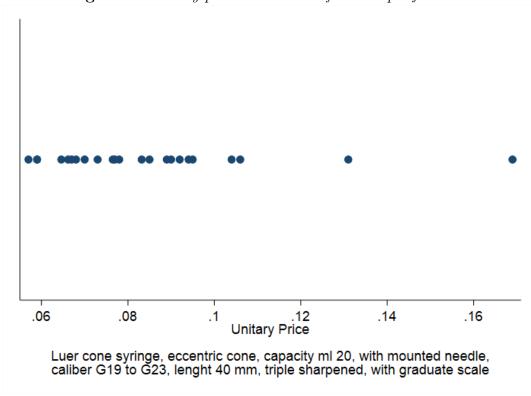


Figure 1. Unitary price distribution for one specific class

3 Empirical Model

3.1 Set-up

Consider a market in which there is a PB in charge of managing requests to purchase medical devices for a local public hospital or health unit $h \in \{1, H\}$. Typically, each request refers to a class of functionally homogeneous medical devices, $d \in \{1, D\}$, such as hypodermic needles for syringes with given characteristics.¹³

The PB's objective is to purchase the required quantity q_{dh} of class d's medical device at the lowest price, which will then be used at the public local hospital or health unit h.

On the supply side, there are S firms, and each firm $s \in \{1, S\}$ is willing to sell the requested medical device. We assume that, for a medical device of type d, each supplier's profit function, π_{ds} , with constant return to scale is given by the following

¹³According to Italian law on public procurement, requests to procure medical devices cannot refer to a particular brand existing in the market, but they should describe the required medical device in a very detailed way so as not to favor a particular brand or supplier.

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

where p is the medical device's awarding price, $c_d(\cdot)$ is the cost function to produce medical device d, and $\theta_s \in [\underline{\theta}, \overline{\theta}]$ is the supplier's type, which is known only by the supplier. We assume that θ_s is distributed according to a cumulative distribution function $F(\theta)$, which is common knowledge among suppliers, but this is not observed by the econometrician. Note that 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, that is, no cross-subsidization between different medical devices in the same lot is admitted.

Finally, some firms may not be active for a specific tender. We define $N_{dh} \leq S$ as the number N of active firms in a specific tender for class d of medical devices, run for the usage of local public hospital or health unit h.

Within a given class d, medical devices supplied by different firms are homogeneous, and for d, the PB pays the unitary price p_{dhs} to the winning firm s in the tender. p_{dhs} can be written as the sum of the marginal cost c_{ds} plus a mark-up Ψ_{dhs} , as follows:

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

For a medical device d of a given quality, PB aims to pay the lowest purchasing price p_{dhs} . To this end, assuming that all goods of class d are functionally homogeneous and equivalent, PB is willing to i) award the contract to the most efficient supplier (i.e., the one with the lowest marginal cost) and ii) obtain a price as close as possible to that marginal cost. We define \underline{c}_d as the marginal cost for d supplied by a benchmark producer. We rewrite (1), incorporating Ψ'_{dhs} , that is, Ψ_{dhs} plus the difference between the selected supplier marginal cost c_{ds} and \underline{c}_d , as follows:

$$p_{dhs} = c_d + (\Psi_{dhs} + (c_{ds} - c_d)) \tag{2}$$

$$p_{dhs} = \underline{c}_d + \Psi'_{dhs} \tag{3}$$

The higher the value for Ψ'_{dhs} , the larger the difference between the marginal cost and the price paid, and the lower the PB's ability to manage the medical device's purchase. Note that Ψ'_{dhs} can be thought of as composed of two parts: the one referring to a PB's specific component γ_h and the other to a residual part γ_{ds} . By assuming multiplicative separability between these two components, we get:

$$\Psi'_{dhs} = \gamma_h \cdot \gamma_{ds} \tag{4}$$

where we can interpret γ_h as a PB's specific fixed effect in managing the procurement process. A positive value for γ_h could mean a lack of the PB's skills in choosing the awarding mechanism or managing the procurement procedure (*i.e.*, defining the

reserve price, spreading widely the information about the auction to promote firms' participation, etc.).

To investigate the γ_h component, we use four steps, as follows:

- 1. We estimate the marginal costs for each class of medical devices;
- 2. By focusing on each PB's purchase for different classes of medical devices, we derive each PB's fixed effect, and we interpret it as the buyer's ability to run the procurement process;
- 3. We explore the determinants of the PB's ability using each buyer's balance sheet data;
- 4. We exploit the end of mandatory RPs for medical devices to investigate whether they affected the γ_h component.

In the next subsections, we present our empirical analysis accordingly.

3.2 Marginal Cost Estimate

We run our analysis on the PBs' ability to manage procurement for medical devices by exploiting the entire dataset. However, we use only observations on first-price auctions (FPA) to define the marginal cost for each class of medical devices awarded. This is because, first, the FPA's outcome is potentially less affected by the PB's discretion than other awarding mechanisms. In particular, in FPA, PBs could determine the bidders' entry by imposing or reducing requirements and qualifications to participate in the auction or by implementing a larger or smaller level of advertising about the awarded procedure¹⁴. Second, to derive bidders' marginal cost for each medical device through a structural model, we invert the equilibrium bidding strategy. Note that for the other awarding mechanisms included in our dataset—scoring-rule auctions (SRAs) or direct negotiations—deriving the marginal cost cannot be gained so easily.

Our estimation of the marginal cost for each class of medical device is in line with the one proposed in the seminal paper by Guerre, Perrigne and Voung's (2000; henceforth GPV). However, to consider the specific features of the setting we are investigating, we proceed by implementing the GPV methodology with some modifications. We precisely take into account the (i) auctions' heterogeneity; (ii) sealed-bid mechanism and noisy signal on the level of competition in auctions; and (iii) the rule in procurement according to which the lowest price wins the auction (and not the highest one like in GPV) and the fact that our database contains only transaction prices (and not all the bidders' offers). In what follows, we discuss these modifications before moving on to the empirical analysis.

¹⁴See Kelman (1990) and Bandiera, Prat and Valletti (2009) for more about the PBs' discretion on entry requirement.

3.2.1 Auction heterogeneity

Medical devices are not identical goods and differ in their observable characteristics; this permits categorizing them class by class, that we denote with subscript d. It is reasonable to expect that the price distribution shifts inside 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. To tackle this issue, we assume that the 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. Then, this separability is preserved by equilibrium bidding (Haile, Hong and Shum, 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. By 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, consider the following specification of marginal costs:

$$c_d(\theta_s) = \alpha_d \theta_s \tag{5}$$

Equation (5) allows different classes of medical devices to have different prices, but it requires the supplier's type to remain the same. Under this assumption, the technological parameter α_d can be obtained using a regression of observed log-bids on the medical devices' fixed effects and on the number of bidders in each FPA. Accordingly, we estimate the following:

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

where D_d are the medical devices classes' dummies.¹⁵ The estimated coefficients α_d for all classes of our devices, and some descriptive statistics from out dataset for the prices paid by PBs are presented in Table A.2. All observed unitary prices p_{dhs} paid by PBs, that, is the winning bids, are then normalized dividing them by α_d . We define thus the homogeneous price p_{0hs} the following:

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

which is used from now on to make all observations of our dataset comparable. This way, we get a consistent estimate of the bid each supplier would have submitted in a FPA for the provision of a medical device of class 0, such that $\alpha_0 = 1$ and with the level of competition N_{0h} . In so doing, we choose as a baseline the class of medical devices for which we have more observations.

The distribution of p_{0hs} is presented in Figure 2.¹⁶

¹⁵The output of this regression is available upon request.

¹⁶The right tail extend upt to 0.19 but only 1% of $p_{0h} \in [0.1, 0.19]$

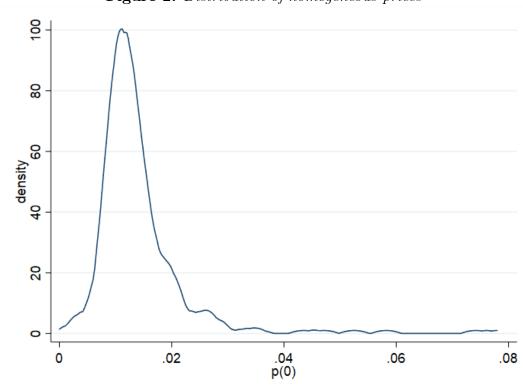


Figure 2. Distribution of homogeneous prices

3.2.2 Noisy signal on level of competition in auctions

Tenders in our dataset are sealed bid auctions in which bidders are supposed to not 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 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 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 rejects this hypothesis.¹⁷

Thus, we assume that in our setting, the 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—see Appendix 1—that the bids' distribution results are different in auctions, respectively, with $N_{0h} = 1$, with $N_{0h} \in [2, 5]$ and

¹⁷Kendall's score: -20757. Test of H_0 : the normalized prices and number of bidders are independent, Prob>|z|=0.0000.

with $N_{0h} \in [6, S]$ participants: within each of these three subsamples, the bids' distribution does not change with the number of bidders, but across those subsamples, it does. Because we cannot derive the equilibrium bidding condition for $N_{0h} = 1$, we discard these observations. We define the subsample for $N_{0h} \in [2, 5]$ 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 $N_{0h} \in [6, S]$, defined as a high-competition subsample, using the median value $N_{0h} = 8$ as the noisy signal.

3.2.3 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:

$$p(\theta_i) = \theta_i + \int_{\theta_i}^{\overline{\theta}} \left(\frac{1 - F(y)}{1 - F(\theta)} \right)^{n-1} dy$$
 (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 observed—through kernel estimate—price distribution.

However, in our database, for each auction we do not observe all bids; we do observe only the transaction prices, that is, the winning ones. For standard FPA, Athey and Haile (2002) propose using the transaction prices of multiple auctions to identify private values, being the transaction price 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 function of observed winning prices, winning prices' distribution, and level of competition is the following:

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

where $N_{0h} = \{3, 8\}$ is the noisy signal about the level of competition bidders have received for the auction considered, $G_{(1)}(p_{0h}|N_{0h})$ is the cumulative density function of all transaction prices, conditional on N_{0h} , evaluated at p_{0hs} , and $g_{(1)}(p_{0h}|N_{0h})$ is its relative probability density function. The derivation of Equation (8) is presented in Appendix 2.

The resulting distribution of θ_s is plotted in Figure 3.

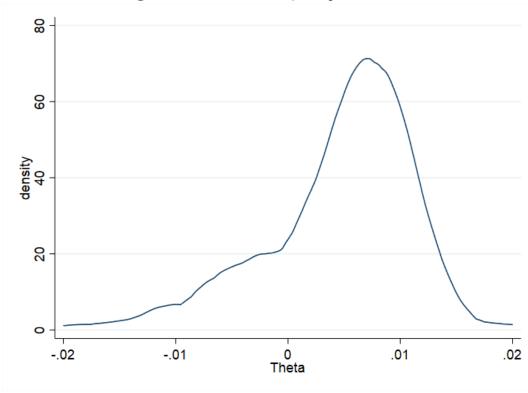


Figure 3. Distribution of the private value

Finally, we move from each producer's marginal cost to each class of medical device's d marginal cost. For each functionally homogeneous class d of medical devices, we calculate a benchmark marginal cost \underline{c}_d as the following:

$$\underline{c}_d = \alpha_d \theta^m \tag{9}$$

where θ^m is the median value of θ_s .¹⁸ In our dataset, benchmark marginal costs are always above zero and, excluding 5% of our observations, below the actual prices paid by public buyers. We report them in the last column of *Table A.2*.

We consider \underline{c}_d as the lowest price that can be paid by the PB, that is, a situation where the PB is able to extract all the supplier's surplus through the auction. In principle, all surplus can be extracted when the PB can set the reserve price in the auction. This is the case for Italian public procurement, where, by law, each PB has to choose a reserve price equal—or close—to the medical device's marginal cost in the aim to extract all or part of the supplier's rent. Similarly, in a direct negotiation,

¹⁸We use the median value because it is a "safer" choice because the distribution of θ_p is structurally estimated and not directly observed by the econometrician. Note also that the producer with marginal cost \underline{c}_d is the same across all classes d.

¹⁹In a standard FPA with no reserve price, this is not possible, and the rent left to the winning supplier is given by its shading; see for example Krishna (2010), p.16, for a discussion of equilibrium bidding in a standard FPA auction.

getting $p_{dhs} = \underline{c}_d$ can be interpreted as the outcome when an efficient supplier is selected and the PB is endorsed with all the possible bargaining power. In both cases—open tender and direct negotiation— \underline{c}_d should be considered the "first best" benchmark where PBs are able to extract all rent from private firms. Thus, it seems appropriate considering \underline{c}_d along with the price paid to investigate the PBs' ability across the markets of different medical devices.

3.3 Estimating the PB's ability

Although the marginal costs for medical devices were estimated on data about FPAs only, we now exploit our entire dataset—consisting of tenders in the form of FPA, SRA, or direct negotiations—to investigate each PB's specific ability to run procurement procedures. Considering the price paid for each medical device and having estimated each medical device's marginal cost \underline{c}_d , we can get Ψ'_{dhs} from the above Equation (3). Specifically, we proceed by estimating the PB's ability-specific component using the following OLS regression:

$$-\ln(p_{dh} - \underline{c}_d) = \beta_0 + \beta_1 \ln(q_{dh}) + \sum_{h=1}^{H} (\gamma_h A_h + \phi_h A_h R) + \sum_{d=1}^{D} \delta_d D_d + \Psi_{dhs}$$
 (10)

The specification (10) includes the quantity of the medical device auctioned q_{dh} , PB dummies A_h , and market fixed effect through the medical device dummies D_d . Finally, (10) accounts for the presence or absence of reference prices, which is an important change in the regulation on public procurement for medical devices during the period observed. This change, that is, the removal of the reference price for classes of homogeneous medical devices, is likely to directly affect the PB's ability in running the procurement, and it is discussed in the next section; here, we consider the dummy variable R as being equal to 1 when the reference price regulation was in force and 0 otherwise, and we let it to interact with all the specific PB dummies.

We exclude from this estimation those PBs for which we have fewer than 10 observations, that is, those local public hospital or health units that—in the period considered—have purchased less than 10 different medical devices: in doing so, we end up with 72 PBs and 1,499 observations on awarded medical devices.

Notice that, in Equation (10), the negative sign before the logarithm of the dependent variable makes the estimated coefficients able to measure the marginal effects on the PBs' ability, rather than the PBs' inefficiency to contract the best price in each tender for the medical devices. In the regression, almost all of the dummies are significant, indicating that each PB is endorsed with a specific ability when managing such procurement.

As a descriptive statistic, we compute a regional average of γ_h , excluding the smallest—in size, measured using total value of production—25% of PBs. The results are shown in Figure 4 and, Figure A.2 reports the regional average of γ_h for the entire dataset.



Figure 4. Ability across Italian regions

Figure 4 shows that the PBs located in the Northern regions on average have more of an ability to run the procurement for medical devices than the Southern regions. This North-South pattern, which is not surprising with Italian data, persists when using the entire dataset as in Figure A.2, but here, it is somewhat less evident. In the next sections, we investigate what the determinants of the PBs' ability are and how the adopted RP policy interacted with this ability.

3.4 Determinants of the Public Buyer's Ability

To study the correlation of the PBs' ability with the PBs' known characteristics and with the auction's mechanisms, we run OLS and IV regressions of the proxy for each PB's ability on a set of explanatory variables, as follows:

$$\ln\left(\widehat{\gamma}_h\right) = \beta_0 + \beta_1 M_h + \beta_2 H_h + \beta_3 P_h + \beta_4 C_h + \epsilon_h \tag{11}$$

where the M_h variables refer to the adopted auction mechanism (i.e., the fractions of scoring rule auctions and of direct negotiation), H_h variables refer to potential scale

economies in purchasing (i.e., the logarithm of the purchases of health material), P_h variables refer to the cost of personnel working in the public local hospital or health unit (i.e., the logarithm of the health personnel cost and the logarithm of the non-health personnel cost), C_h refers to control variables on the PBs' local health unit (i.e., ASL) or nature of the hospital, its location in the North or in the Center-South, in a metropolitan or rural area, as well on the per capita health expenditure in the region the PB belongs to. Because the dependent variable is an estimate itself, we correct the standard errors for potential heteroskedasticity and hence use robust standard errors.

Table 2 reports the output of our weighted regressions, where the weight is the number of auctions per PB included in our dataset; accordingly, we attribute more importance to the observations that refer to the PBs that more frequently organized tenders to award medical devices.²⁰ Column (1) shows the OLS regression of our baseline specification.

We then proceed by running IV regressions. The reason is that we are concerned that there may be simultaneity on the mechanism's variables: 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 produce inconsistent estimates. Column (2) shows the output of an IV regression where we instrument the two mechanism variables (SRA and direct award) with five variables: a) the fraction of multiproduct auctions (i.e., as a measure of capability in running complex procurement procedures), b) the fraction of auctions where the PB managed a joint procurement process with other PBs (i.e., as a measure of experience), c) the fraction of auctions involving needles and syringes as opposed to other standard medical devices (i.e., to inform on the type of product auctioned), d) the fraction of auctions with the marginal cost below the median (i.e., as a proxy for product's complexity), and e) a dummy for regions with additional constraints on their expenditures because of excessive debt (i.e., these regions face additional external control in the mechanisms they use).²¹ Our regression shows a negative effect of SRA (mechanism variables, M_h), a negative effect of health purchases (scale economies variables, S_h), a positive effect of the non-health personnel cost and a negative effect of the health personnel cost (personnel variables, P_h), a negative effect of local units and a positive effect of the center-south dummy as well as per capita health expenditures (control variables, C_h).

The effect of SRA is negative, as typically found in the empirical literature, that is, the price paid under SRA is typically higher (Bajari and Lewis, 2011; Koning and Van de Meerendonk, 2014). However, we are not fully convinced of the output

²⁰In the dataset used for this analysis (1499 observations), the number of auctions attributed to a single PB goes from 10 to 93.

²¹We consider here all regions (1) that have signed a binding plan to reduce health-related public deficit and (2) where the central government has appointed a commissioner to manage health services and implement the above plan.

in Column (2) because some coefficients are unexpected. In particular, we find a positive coefficient of the Center-South dummy variable while according to the well-known North-South divide, we should expect the opposite (e.g., Bigoni et al., 2016). We suspect that the results in Column (2) are driven by structural breaks in the geographic dimension. Moreover, our instruments, which are supposed to correlate with the mechanism variables but not with the error term, show mixed statistical validity with several statistical tests whose p-values are reported in the bottom of Table 2. In fact, from Column (2), we learn that the instruments correlate with the mechanism variables (the relevance test rejects at 5% the null hypothesis of irrelevant instruments) but are not compatible with the absence of correlation with the error term (the Sargan test rejects at 5% the null hypothesis that the over-identifying restrictions are exogenous). This is possibly due to over-feeding the model with five instruments when there are only two endogenous variables.

For this reason, we move to the models in Columns (3) and (4) that allow for structural breaks because of our ability to add to our specification the interactions between the explanatory variables and the dummy variables for the Center-South location of the PB. This way, we have four endogenous variables (SRA and direct award, alone and interacted with the Center-South dummy). In these two cases, the set of instruments works properly because the tests reported at the end of Table 2 indicate that they correlate with the mechanism variables but not with the error term (the Sargan test now accepts at 5% the null hypothesis). Moreover, the Hausman-Wu test rejects at 5% the null hypothesis, indicating that there is a problem of endogeneity; therefore, it is advisable to use an IV model rather than an OLS model to obtain consistent estimates.

In the two new models, the dummy for the Southern regions is no longer significant, indicating that the effect we previously attributed to the Center-South is actually due to structural differences with the North. We consider these regressions as our benchmark models. Most of the interactions are significant, and a Chow test indicates that structural breaks are indeed present (for instance, in Column (3), F-statistic: 23.83; p-value < 0.05). The only difference between Columns (3) and (4) is in personnel costs: in Column (3), we separate it between health and non-health related personnel, while in Column (4), we consider the overall personnel cost as a proxy for the PB's size and the percentage share of administrative personnel among the total.

We find that the PB size effect—measured using the overall personnel cost—is positive and significant. Note that when we disentangle the costs referring to health personnel and non-health personnel, the former has a negative and strongly significant sign while the latter has a positive and strong significant sign. Considering then the ratio of non-health personnel over total personnel cost, we find a positive and strong significant sign that seems to indicate that the PB's size effect is driven by the non-health personnel variable. That is, for two PBs with the same size (*i.e.*, measured by the overall personnel cost, that is non-health personnel plus health personnel costs),

the one recording the larger cost for non-health personnel would show a higher ability to procure medical devices. Interestingly, this effect is reversed for PBs located in the center-south; this seems to confirm the well-known difference in the "efficiency" of institutions in the two geographical areas.

Considering the per capita regional expenditures, our results show a positive and significant effect on the PBs' ability, but this effect disappears for southern regions. Interestingly, health policy is decided mostly at the regional level, which is also where institutional quality should have the greatest impact on PBs' ability in managing their procurement process. Finally, the amount of money used for health-related procurement has a negative impact on hospital ability: this is consistent with our definition of PB ability, which increases when the price paid by the PB shrinks.

As for the awarding mechanism, both scoring-rule auctions and direct awards now have a negative and significant impact on the PBs' ability. The reason behind this similar effect for the two formats is based on different grounds: usually, scoring-rule auctions are adopted to buy items where "quality" matters while direct negotiations are used when the awarded item is endorsed with specific characteristics that the competition will not be permitted to address. In the first case, either SRA was misused or the medical device was different and of greater quality (and thus with a higher price). As for the second case, with competition absent, it is logical to observe higher prices and thus a negative impact on the PBs' ability. Note also that direct negotiations have a positive effect on PBs located in Southern regions: this apparently counter-intuitive result is explained by the fact that regions with additional constraints on their expenditures because of excessive debt make a reduced use of direct awarding, and all these regions are located in the South of Italy.

Finally, the dummy ASL identifies local public health units that provide health services on a county-level territory and sometimes manage medium-small hospitals. Local health units have a negative overall effect, and we observe a similar effect for all the PBs located in large metropolitan areas.

 ${\bf Table~2.~} {\it Mark-up~across_Italian~regions}$

Table 2. Man ap				(4)
	(1)	(2)	(3)	(4)
Method	OLS	IV	IV	IV
SRA	-0.176	-0.529	-7.723	-7.913
	(0.060)	(0.163)	(3.010)	(3.145)
Direct award	0.022	0.243	-7.305	-7.998
	(0.041)	(0.234)	(3.247)	(3.560)
ln(health purchases)	-0.168	-0.132	-2.041	-2.136
	(0.014)	(0.035)	(0.801)	(0.875)
ln(health personnel)	-0.089	-0.085	-0.435	
	(0.015)	(0.020)	(0.172)	
$\ln(\text{non-health personnel})$	0.398	0.396	2.849	
, - ,	(0.018)	(0.021)	(0.917)	
ln(cost of personnel)	,	,	,	2.332
` - /				(0.842)
Non-health/total personnel cost				$7.432^{'}$
, -				(2.674)
ASL	-0.233	-0.203	-2.073	-1.923
	(0.031)	(0.037)	(0.757)	(0.736)
Metropolitan area	-0.042	0.012	-2.568	-2.778
•	(0.036)	(0.072)	(1.160)	(1.265)
Health expenditure pc	1.139	1.488	5.956	$5.725^{'}$
	(0.164)	(0.242)	(1.965)	(1.970)
Center-South (CS)	0.512	0.590	-1.531	5.236
- (22)	(0.031)	(0.066)	(6.072)	(3.575)
(continues in the next page)	(0.001)	(0.000)	(0.012)	(0.010)
Note Debugt stands	1	•	1	

Note. Robust standard errors in parentheses

Table 2. (Continued)

	(1)	(2)	(3)	(4)
Method	OLS	IV	IV	IV
$SRA \times CS$			-3.822	-2.794
			(4.988)	(4.330)
Direct award x CS			8.511	8.949
			(3.814)	(3.951)
ln(health purchases) x CS			0.808	1.034
			(0.503)	(0.601)
$\ln(\text{health personnel}) \times \text{CS}$			2.608	
			(1.350)	
$\ln(\text{non-health personnel}) \times CS$			-3.796	
			(1.511)	
$\ln(\text{cost of personnel}) \times \text{CS}$				-1.309
				(0.665)
Non-health/total personnel cost x CS				-14.600
				(7.482)
$ASL \times CS$			9.774	9.054
			(5.654)	(5.168)
Metropolitan area x CS			11.090	10.630
			(6.242)	(5.777)
Health expenditure pc x CS			-5.689	-5.631
			(2.431)	(2.527)
Constant	-1.052	-2.496	-5.856	-7.702
	(0.394)	(0.415)	(2.342)	(2.904)
Observations	1,399	1,399	1,399	1,399
Relevance test (p-value)		0.000	0.033	0.037
Sargan test (p-value)		0.000	0.879	0.678
Hausman-Wu test (p-value)		0.000	0.000	0.000

Note. Robust standard errors in parentheses

3.5 Alternative Explanation: Corruption

We now explore whether an alternative explanation may justify our results: 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 PBs' lack of knowledge or experience in running it (*i.e.*, passive waste), as well as by the PBs' actions supporting corruption and favoritism (*i.e.*, active waste). Unfortunately, in the setting we investigate, we have no way to cleanly disentangle these two dimensions. However,

we follow Bandiera et al. (2009) and consider a variant of the regression in Equation (10), 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:

$$-\ln(p_{dh} - \underline{c}_{d}) = \beta_{0} + \beta_{1} \ln(q_{dh}) + \sum_{h=1}^{H} \left(\gamma_{h} A_{h} + \phi_{h} A_{h} R + \sum_{j=1}^{J} \lambda_{hj} A_{h} S_{j} \right) + \sum_{d=1}^{D} \delta_{d} D_{d} + \Psi_{dh}.$$
(12)

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 negative coefficients λ_{hj} would be a signal of corruption or favoritism, while a significantly positive coefficients λ_{hj} would be a signal of a valuable relationship.

We find that the introduction of a large number of coefficients (the 486 interaction variables) induces only a modest improvement in the fit of the model, whose R^2 statistic goes from 0.86 to 0.95. This indicates that repeated relations can describe no more than 10% (0.95-0.85) of a PB's ability. Moreover, our estimates show that just 84 out of the 486 coefficients are significantly positive, and only 27 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 PBs' ability.

4 Impact of the Reference Price

We conclude our empirical analysis with an investigation of the effects of the RPs for the classes of medical devices included in our dataset on the PBs' ability to carry out the procurement process. Our dataset covers the period from January 1st to December 31st, 2013; from its start to May 2nd, PBs had to apply the RP defined by the Italian Authority for Public Contracts (AVCP) for each class of homogeneous medical devices they awarded. RPs worked as a price cap, and if the awarding procedure with the RP's application went void, the PB could then start a new awarding procedure where the RPs would not be applied. The rationale for this safeguard rule on organizing the awarding procedure with no mandatory application of the RP is

to guarantee the PB could buy medical devices needed to provide the local health services in a reasonable amount of time (*i.e.*, in a second auction).

We consider here the same specification as in Equation (10), but we add a dummy specific for reference prices to control for a general – and not only hospital-specific – effect. Again, the introduction of a negative sign in the dependent variable makes the coefficients measure the effect on the PBs' ability rather than on their inefficiency. We now consider the OLS regression as follows:

$$-\ln(p_{dh} - \underline{c}_d) = \beta_0 + \beta_1 \ln(q_{dh}) + \sum_{h=1}^{H} (\gamma_h A_h + \phi_h A_h R) + \sum_{d=1}^{D} \delta_d D_d + \rho R + \Psi_{dhs}$$
 (13)

where we use the same notation as in the previous section. Results are in Column (1), Table (3). We obtain that – after having controlled for specific hospital effects – RP shows a positive impact on PBs' abilities. To further investigate on this issue, we run again the regression in Equation (13) separately by category of PB characterized by "low," "medium-low," "medium-high," and "high ability." Each category corresponds to one quartile of PB's abilities, as estimated in the previous section. The idea is to explore if the RPs play a different role that is conditional on the PBs' characteristics. Columns (2), (3), (4) and (5) in Table 3 shows the key results from this regression. We observe that the RPs have a strong and negative impact on PBs with high ability, a null impact on PBs with medium ability and a positive impact on PBs with low ability.

Table 3. Impact of the RP by level of ability

	(1)	(2)	(3)	(4)	(5)
Sample	All	Low	Medium-low	Medium-high	High
Reference price	0.628	1.935	0.327	0.272	-2.320
	(0.301)	(0.443)	(0.554)	(0.230)	(0.533)
ln(quantity)	0.112	0.207	0.039	0.042	0.193
	(0.021)	(0.059)	(0.030)	(0.026)	(0.054)
Constant	-2.475	-3.385	0.598	2.542	5.569
	(0.864)	(0.829)	(0.666)	(0.447)	(0.799)
PB fixed effects	YES	YES	YES	YES	YES
Product fixed effects	YES	YES	YES	YES	YES
PB*RP fixed effects	YES	YES	YES	YES	YES
R^2	0.852	0.858	0.913	0.911	0.848
Observations	1438	248	343	448	399

Note. Robust standard errors in parentheses

These results highlight a non-linear effect of RP on PBs' abilities to manage the procurement process. The introduction of a RP has two effects: first, it modifies the reserve price a buyer would have set; second, on the supply side, for the bidders entering the auction, the RPs could represent a focal point that helps in implementing some form of tacit collusion. In the case of PBs endorsed with high-ability, *i.e.* those that purchase at a price close to marginal cost, RP increases the reserve price and creates a focal point at a level above the price it would have been paid without this policy in force; thus, it reduces the ability of the buyer to extract all the rent from the supplier. RP has no relevant effect for medium-ability buyers, because the reserve price induced is very similar to the one it would have been set by buyers without RP, and similarly for the induced competition. Finally, RP has a positive effect for buyers endorsed with low ability because it decreases their reserve price and the focal point induced is below the one without RP.

As a robustness check, we try to reduce the number of parameters in (13): first, we remove the hospital-specific interactions from (13); second, to remove products fixed effect, we use a different dependent variable, expressed as a log mark-up $\frac{p_{dh}-c_d}{c_d}$ over marginal cost. Finally, we divide PBs into three classes - low, medium and high ability - instead of four. Results are robust, except for the positive effect for the low ability PBs when three classes are used.

It could be argued that the reason of this reduced impact of RPs depends on the tresholds chosen by the national regulator. In particular, a lower treshold would have been beneficial also for medium and high ability PBs. We do not think this is the case because an excessively high RP would probably have induced a different type of collusive behavior among suppliers in the procurement of low and medium ability PBs. In fact, — given these buyers' lack of experience or knowledge of awarding procedures — only high-cost bidders potentially enter the auction. For high-cost bidders, RP might effectively bite, and it is a dominant strategy not to enter the auction with RPs, knowing that if the auction results are voided, the auction that follows would be organized without any mandatory RP application. This second auction could be thus organized with a higher reserve price and then lead to a winning price higher than the RP one. If all the high-cost bidders do no enter the auction where RP applies, the PBs with a medium and lower ability should proceed to organize a second auction without RP; most likely, they will purchase medical devices at prices higher than the RP.²² All in all, the RP policy can achieve at most mixed results.

²²Each PB should apply the RP on the first awarding procedure to purchase the needed medical devices. If these auction results are voided, a new auction will be organized where the RPs are not applied. This is a safeguard rule to ensure that the PB could buy medical devices in a reasonable time frame.

5 Conclusions

Medical devices represent a relevant market, and their public procurement is a large weight on the national budgets in European countries. In this paper, we empirically investigated the purchase of standard medical devices by Italian PBs in the period from January to December 2013. We focused on the role of the PBs' ability versus costs and competition in tenders. Our empirical measure of the PBs' ability was defined as the difference between the price paid and the medical device's marginal cost that we structurally estimated for each class of product.

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 58.31%.²³ Such differences across the procurement prices can be explained by the PBs' fixed effect—we interpreted this as the PBs' ability—which we then investigated as related to institutional characteristics, geography, and size.

We found that the PB's size (measured by the overall personnel costs, corresponding to the sum of health personnel and non-health personnel costs) has a general positive and significant effect on the ability to run the procurement process. Our empirical analysis showed that it is the non-health personnel costs that drives the overall positive and significant effect on the PB's ability. However, this result was not confirmed when we controlled for the PB's geographical location: large PBs located in the South of Italy record a lower ability in managing the procurement process, thus indicating a different quality in the institutions compared to the regions in the North of Italy. Considering the PB's geographical location also reverses the results found for our control variables (i.e., the PB's organizational form, the PB's inclusion in a metropolitan area, and the regional expenditure per-capita), thus highlighting that the North-South divide in Italy is pervasively affecting the health sector. Finally, we empirically found that the adoption of a mandatory reference price as a cap to medical devices' winning prices has a significant negative effect for high-ability PBs purchasing (i.e., higher prices compared to no application of RPs), no effect for medium-ability PBs' purchasing and a positive effect on low-ability PB's purchasing. We interpret RPs effect on the high-ability PBs - on the one hand - as reducing the PBs' discretion in successfully setting a reserve price lower than the RP and - on the other hand - as acting as a focal point for bidders in the auction. All in all, according to our empirical results, mandatory RPs seem to have been only a mildly successful policy in fostering the efficiency of public procurement for standard medical devices in Italy.

All these findings indicate that a policy aiming to increase efficiency in the procurement for standard medical devices in Italy should be designed differently and implemented in accordance with the PB's size and location. Explicit and implicit incentives for public workforce's performance in high-ability PBs located in the North

²³To 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.

of Italy could be effective in further reducing the expenditures for standard medical devices procurement. This would be not the case for public workforce in medium-and low- ability PBs, in particular for those located in the South and central areas: there, incentives to increase the personnel's qualifications, on the one hand, and the reduction in the number of public officers on the other, could be the effective way to foster the PBs' ability in performing public procurement. In particular, in the Southern areas, creating centralized purchasing authorities endorsed with a low number of qualified (and better paid) non-health personnel could be a high-impact solution.

All in all, our empirical results and policy implications provide the next step with respect to the findings of Bandiera et al. (2009) about passive waste: their empirical study on standard products in Italian public procurement highlights that passive waste accounts for 83% and is related to "the mode of governance". Our analysis adds a focus on the public procurement of standard medical devices, addressing the sources of the buyer's ability in such purchasing. Given the high value of European public procurement in the health sector—which also includes the procurement of non-standard products—our study provides the lower-bound for improvement in expenditure efficiency for a public sector considered to be the core of the Europe 2020 strategy.

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6 Appendix

6.1 Noisy Signal on Competition

We report 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 $G_{n,n+1}$. The first two columns report the lowest \underline{n} and highest \overline{n} number of bidders considered in the test, and the third column reports the Kendall's rank

correlation coefficients' p-value.

Table A.1. Noisy signal \overline{n} Kendall's p-value 1 2 0.00 2 3 0.432 4 0.272 5 0.102 6 0.016 7 0.116 8 0.826 9 0.856 11 0.90

0.90

0.57

0.69

0.20

0.27

0.43

0.27

0.58

6

6

6

6

6

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6

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6.2 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 (PA): the functional form of the bid is different. In a PA, the lowest bid wins, thus 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 PA, the (Nash) equilibrium bid $p(\theta_i)$ of the i - th bidder of type θ_i is given by:

$$p(\theta_i) = \theta_i + \int_{\theta_i}^{\overline{\theta}} \left(\frac{1 - F(y)}{1 - F(\theta)} \right)^{n-1} dy$$
(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 CDF of all observed bids p, with PDF g(p). As noted by GPV, $G(p) = \Pr(p \le p_i) = \Pr(\theta_i \le p^{-1}(p)) = F(p^{-1}(p)) = F(\theta)$. G(p) is

absolutely continuous and has a PDF equal to $g(p) = \frac{f(\theta)}{p'(\theta)}$. Thus, Equation (15) can be rewritten as:

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

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(b) given the level of competition n, in the PA case they should be considered equivalent to the first order statistic with PDF $g_{(1)}(b)$ and CDF $G_{(1)}(b)$ equal to:

$$g_{(1)}(p) = n \cdot g(p) \cdot [1 - G(p)]^{n-1}$$

 $G_{(1)}(p) = 1 - [1 - G(p)]^n$

Thus,

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

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

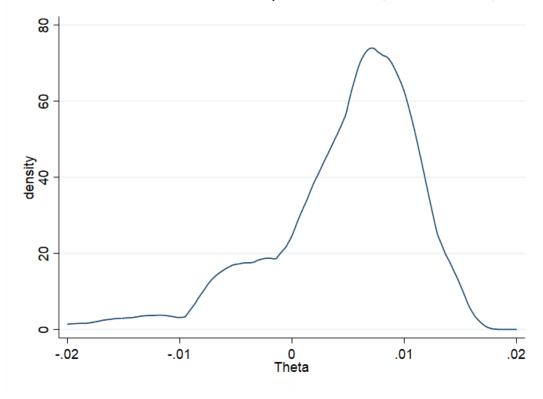
$$\theta_i = p_i - \frac{n-1}{n} \frac{1 - G_{(1)}(p)}{g_{(1)}(p)} \tag{18}$$

6.3 Different Definition of Competition

Marginal cost estimate needs knowledge of the number of participants to the bid. In Subsection 3.2 we split the sample in two categories, signaling low participation (between 2 and 5 participants) and high participation (6 or more participants). As a robustness check, we remove the distinction in two categories 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 θ_p in the 2+ competition subsample



The distribution is in line with the benchmark one in Figure 3, gives rise to similar marginal cost estimates, and provides similar estimates of a PB's ability.

6.4 Further Tables and Figures

Table A.2. Medical Devices

MDT Class	Price min	Price mean	Price max	α_d	\underline{c}_d
1	0.27	0.79	2.52	46.48	0.26
2	0.39	1.05	3.90	61.46	0.35
3	0.49	2.96	5.52	127.07	0.72
4	0.39	0.73	2.03	57.07	0.32
5	2.08	6.66	16.7	392.14	2.21
6	1.6	2.18	4	159.03	0.90
7	0.04	0.19	1.03	4.25	0.02
8	0.06	0.19	0.65	5.79	0.03
9	0.08	0.12	0.18	7.76	0.04
10	0.15	3.59	86.29	16.32	0.09
11	0.06	0.37	2.18	16.24	0.09
12	0.14	0.25	1.53	14.55	0.08
13	1.04	4.35	26.1	259.40	1.46
14	0.01	0.06	3.19	1	0.01
15	0.02	0.12	0.73	5.79	0.03
16	0.45	1.30	4.18	37.12	0.21
17	0.45	1.19	11.6	59.31	0.33
18	0.49	4.36	9.5	228.34	1.29
19	0.04	0.06	0.26	3.12	0.02
20	2.95	3.39	3.91	236.15	1.33
21	0.01	0.10	0.38	2.12	0.01
22	0.03	4.36	6.82	235.16	1.33
23	0.03	0.18	0.55	3.50	0.20
24	0.02	0.04	0.05	2.25	0.01
25	0.41	0.80	1.84	56.76	0.32
26	0.54	1.42	3.55	95.38	0.54
(continues in the next page)					

Table A.2. (Continued)

MDT Class	Price min	Price mean	Price max	α_d	\underline{c}_d
27	0.13	1.78	3.92	131.79	0.74
28	0.50	6.86	62.1	336.10	1.89
29	3.79	5.23	6.67	351.67	1.98
30	0.13	0.16	0.19	10.65	0.06
31	1.15	0.75	4.48	15.7	0.09
32	2.05	6.11	16.27	304.41	1.72
33	0.10	0.67	3.88	31.59	0.18
34	1.4	7.57	14.64	373.15	2.10
35	0.16	0.43	1.22	25.24	0.14
36	0.20	0.44	1.79	20.64	0.12
37	0.40	0.88	3.13	36.26	0.20
38	0.20	0.58	1.01	34.97	0.20
39	0.52	1.06	1.75	59.15	0.33
40	0.32	0.81	1.5	59.72	0.33
41	1.12	1.62	4.52	92.85	0.52
42	1.03	2.19	5.7	133.72	0.75
43	2.17	2.82	6.3	184.79	1.04
44	0.11	0.17	0.61	11.04	0.06
45	0.02	0.03	0.05	2.03	0.01
46	0.03	0.05	0.09	3.27	0.02
47	0.06	0.08	0.17	6.10	0.03
48	0.02	0.04	0.08	2.32	0.01
49	0.01	0.02	0.05	0.73	0.01
50	0.02	0.04	0.11	2.25	0.01
51	.10	0.16	0.66	11.62	0.06
52	0.02	0.13	1.01	8.51	0.05
(Continues in the next page)					

Table A.2. (Continued)

Price min	Price mean	Price max	α_d	
0.0%				\underline{c}_d
0.05	0.14	1.01	11.44	0.06
0.13	0.34	1.4	24.05	0.13
0.27	0.65	1.48	37.11	0.21
0.02	0.46	3.4	24.30	0.14
0.03	0.06	0.27	3.05	0.02
0.01	0.04	0.06	2.83	0.01
0.13	0.18	0.27	13.81	0.08
0.11	0.27	0.89	12.02	0.07
0.18	0.71	2.71	33.69	0.19
0.18	0.38	1.50	19.78	0.11
1.67	3.41	5.42	245.50	1.38
0.32	2.73	17	201.16	1.13
1.5	3.21	7.18	212.11	1.20
0.02	0.22	0.35	13.23	0.07
0.45	0.73	2.12	54.37	0.31
4	6.39	7.3	420.99	2.37
0.07	0.12	0.21	7.06	0.04
0.38	0.47	0.75	30.79	0.17
0.07	0.21	1.44	6.73	0.04
0.04	0.13	0.74	5.62	0.03
0.47	1.12	6	67.98	0.38
0.20	0.66	3.36	36.14	0.20
0.03	0.05	0.15	4.44	0.03
0.02	0.06	0.13	4.77	0.02
	0.13 0.27 0.02 0.03 0.01 0.13 0.11 0.18 0.18 1.67 0.32 1.5 0.02 0.45 4 0.07 0.38 0.07 0.04 0.47 0.20 0.03	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$

Note: $\theta^m = 0.0056$.

