Research Article

Riccardo Camboni* and Paola Valbonesi

Incumbent and Entrant Bidding in Scoring Rule Auctions: A Study on Italian Canteen Services

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Abstract: We empirically investigate incumbents' and entrants' bids on an original dataset of 192 scoring rule auctions for canteen services in Italy. Our findings show that winning rebates are lower (i.e., prices paid by the public buyer are higher) when the contract is awarded to the incumbent supplier. This result is not explained by the observable characteristics of the auction or the service awarded. We develop a simple theoretical model showing that the result is consistent with a setting in which the buyer exploits specific information on the incumbent supplier's production cost.

Keywords: scoring rule auctions, procurement, incumbent and entrant, favoritism
JEL codes: D44, D47, H57, L88

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***Corresponding author: Riccardo Camboni**, Department of Economics and Management, University of Padova, Via del Santo 33, Padova, 35123, Italy, E-mail: riccardo.camboni@unipd.it
Paola Valbonesi: Department of Economics and Management, University of Padova, Via del Santo 33, Padova, 35123, Italy; and Higher School of Economics - National Research University (HSE-NRU), Moscow, Russian Federation, E-mail: paola.valbonesi@unipd.it

1 Introduction

In the procurement of complex works, goods or services, that is, when suppliers have to meet quality specifications,[1] scoring rule auctions (SRAs) are often suggested as mechanisms for the task. SRAs are multidimensional auctions in which bids are competitively evaluated using a linear function that weights both the price and the levels of quality dimensions: in this setting, the winner is the bidder who obtains the highest score. Following the instructions provided by the EU Directive 2014/24/EU, SRAs have been increasingly adopted in European countries. On the other side of the Atlantic, SRAs have been widely used, for example, to award highway construction projects in California. As Lewis and Bajari (2011) highlight, SRAs' weighting price and time to completion (i.e. quality dimension) have succeeded in increasing total welfare compared to first price auctions (FPAs) adopted in the same setting to award similar projects.

SRAs differ significantly from conventional procurement auctions because, in designing them, the buyer has discretion in defining the quality to be procured. Such discretion operates *ex ante* in the selection of the weights for the price and quality (or qualities) included in the linear function used to evaluate the bids: the buyer can choose strategically which elements to assign the greater weight in the score. This discretion also operates *ex post* in the assessment of the quality component of each bid: the buyer can adopt a subjective valuation, and bidders cannot be certain about the score they will achieve, given the level of quality offered (Burguet 2017; Huang 2016; Prabal Goswami and Wettstein 2016). For instance, a risk-averse buyer might favor an incumbent supplier simply to continue an ongoing, efficient outsourcing process. The prospect of "exchanges" with a predetermined supplier, which increases the public buyer's utility, would also provide an incentive to manipulate the design of the awarding mechanism and/or the bids' evaluation.[2]

In this paper, we investigate incumbent and entrant winning bids in SRAs, specifically taking into consideration the public buyer's *ex ante* discretion in

1 Elements of quality can include the technical characteristics of the procured item, delivery date and conditions.

2 There could be a fine line between "exchanges" with a predetermined supplier, i.e., favoritism, and corruption. See Burguet and Che (2004) for a procurement model on buyer's *ex post* manipulation on the bids' evaluation in the presence of bribes, and Wolfstetter and Lengwiler (2006) for a survey of corruption in procurement auctions.

designing such mechanisms.[3] We use a small, original dataset of 192 SRAs for canteen services in Italy, awarded between 2009 and 2013.[4] We first provide descriptive empirical evidence of a positive correlation between the price the buyer pays and the awarding of the contract to the incumbent supplier. Then, running an econometric model, we show that this correlation does not relate to differences in the service or buyer's characteristics, in the level of competition (even allowing for endogenous entry), or in the overall importance given to quality in the scoring function. We argue that our empirical findings can be explained considering the buyer's *ex ante* discretion in the scoring rule auction design. In this aim, we develop a simple theoretical setting where an item with two qualities has to be procured. We show that, when the buyer already knows the incumbent supplier's characteristics, the optimal weights for the two qualities in the linear function used to evaluate the bids differ from those used when the buyer faces all new entrant suppliers. When the incumbent wins the auction and the buyer has considered that supplier characteristics in designing the awarding mechanism, the final price is often higher than if absent such consideration. These results are driven by the trade-off the buyer faces when designing the SRA: on one hand, to reduce the incumbent's market power, he should decrease the weight given to the quality where the incumbent has the greatest cost-efficiency; on the other hand, to increase the expected quality the seller provides, he should increase that weight. It turns out that, in our simple theoretical setting, the second effect prevails for all but the most cost-efficient incumbents.

De Silva, Dunne, and Kosmopoulous (2003) investigate the asymmetry between incumbent and entrant in first-price sealed-bid procurement auctions for road construction contracts in Oklahoma. These authors empirically document differences in the bidding patterns and winning bids between entrants and incumbents and find that the former bid more aggressively than the latter do; moreover, entrants win auctions with significantly lower bids than the incumbents do.[5] To the best of

3 In what follows, we will refer to the public buyer using "he" and to the bidder (i.e., incumbent or entrant) using "she".

4 In many countries, canteen services are typically awarded through SRAs because their characteristics—that is, the quality of cooked food provided, the ingredients used, the distance from where meals are cooked to where the service is supplied, etc.—matter a great deal. Accordingly, buyers usually devote a lot of attention to the design of the awarding mechanism to procure such services: this is a key element of our empirical and theoretical investigation.

5 Hyytinen, Lundberg, and Toivanen (2018) use Swedish data on public procurement of cleaning services to investigate incumbents (i.e., in-house suppliers) and entrants. They exploit the change of regime from beauty contests to sealed-bid FPAs and SRAs. They find that procurement prices did not change in the new regime, where favoritism towards incumbents was reduced, suggesting that entrants' bids were less aggressive than they were in the older regime; that is, entrants have adjusted for the lower/null favoritism in the new regime.

our knowledge, our paper is the first to investigate empirically and theoretically the case of incumbent and entrant bidding asymmetry in multidimensional SRAs. In so doing, we contribute to three main strands of literature.

First, we add to the theoretical literature on SRAs' design and on its distortion. Che's (1993) seminal theoretical analysis shows that, when both the quality and the bidder's type (the latter determined by her private information on the production cost) are unidimensional, quality is enforceable by court, and the scoring rule is quasilinear, the most efficient firm (incumbent or entrant) will always win, regardless of the weight assigned to quality in the scoring function. That weight determines only the level of quality each bidder provides in equilibrium.[6] When quality and the bidder's type are multidimensional, it is not always possible to rank firms according to their overall efficiency without having previously defined a scoring function. As a result, the weights assigned to each quality dimension also determine the probability of each bidder's winning the auction. Asker and Cantillon (2008) show that the multidimensionality of suppliers' private information can be reduced to a single dimension (i.e., the "pseudotype"). Our paper contributes to this literature on multidimensional SRAs by means of a simple theoretical framework that adopts Asker and Cantillon's pseudotype to investigate a setting where the buyer can *ex ante* manipulate the weights of the SRA's components.

The buyer's manipulation of the SRAs to provide the incumbent with higher probability of winning the auction is investigated in Laffont and Tirole (1991) as "favouritism." These authors distinguish between soft and hard information disclosed to the public buyer and, based on their theoretical results, discuss which steps have to be taken to reduce such collusion between the auction designer and one particular bidder. Burguet and Perry (2007) investigate a different kind of favoritism in procurement auctions: in return for a bribe from the dishonest supplier, the auctioneer has the discretion to allow this supplier to revise her bid downward to match the low bid of the honest supplier. They study the effect of the bribe share and the cost distributions on the bidding functions, the allocative distortion, and the expected price paid by the buyer. Both Celentani and Ganuza (2002) and Compte, Lambert-Mogiliansky, and Verdier (2005) study the effect of bribing on competition in procurement auctions. The former paper identifies which elements affect the equilibrium in the presence of bribes and show that corruption

6 Branco (1997) and Asker and Cantillon (2010) study the optimal mechanism to procure a good or a service when price and its quality matter, assuming different hypotheses on suppliers' costs. Branco (1997) investigates a setting where costs are correlated across firms. In Asker and Cantillon (2010), costs are independent and, differently from Branco, the bidders' private information structure is bidimensional.

may well be increasing in competition. The latter paper highlights how bribing can facilitate collusion in price between firms, generating a price increase that goes far beyond the bribe received by the buyer as a consequence. We add to this literature a simple theoretical investigation of the SRA's outcomes, focusing on the buyer's (*ex ante*) manipulation of the mechanism design that follows from additional information gained on the incumbent's type.

Second, we contribute to the empirical and experimental results on buyer discretion in the design of SRAs in public procurement.[7] SRAs leave a considerable amount of discretion to the buyer, who can choose which qualities to include and how to evaluate them. In a field experiment, Decarolis, Pacini, and Spagnolo (2016) show empirically that including past performance in the scoring function improves SRAs' performance. Koning and Van de Meerendonk (2014) show empirically that, the higher the weight of the quality component set by the buyer in the scoring rule, the higher the price paid.[8] Our empirical analysis of Italian canteen services adds novel evidence showing that the positive relationship between the price paid and the weight of quality in the SRA holds for auctions the entrant has won (and not for auctions the incumbent has won).

Third, we contribute to the literature on empirical tests to detect collusion in auctions. Conley and Decarolis (2015) present two statistical tests to detect coordinated entry and bidding choice in a dataset of average bid auctions[9] for awarding public works in Turin, Italy. These authors study collusion among suppliers in bidding in a setting where such anticompetitive practice was detected by the judge of the local court of law. Differently, we empirically investigate a form of collusion

7 In private exchanges, Lacetera et al. (2016) and Tadelis and Zettelmeyer (2015) investigate auctioneer discretion in English auctions for wholesale used cars. In a different setting, Garicano, Palacios-Huerta, and Prendergast (2005) offer empirical evidence regarding how professional soccer referees favor home teams to satisfy the crowds in the stadium. In their setting, referees have discretion over the addition of extra time at the end of a game to compensate for lost time that was due to unusual game-stoppages. They find that referees systematically favor home teams by shortening close games when the home team is ahead and lengthening close games when the home team is behind. Similarly, in our setting, public buyers, having discretion over the weights of the SRA components, could favor incumbent suppliers by manipulating the SRA's design.

8 Similarly, Albano et al. (2018) study the impact of different price-quality weights in SRAs using an experimental setting: their findings show that the SRA that gives more weight to quality than price is more efficient.

9 In the Italian framework, an average-bid auction works as follows: the first 10 percent of the highest and lowest discounts, respectively above and below the reserve price, are eliminated. Then the average among all remaining discounts is computed (A1), and a second average (A2) is calculated among the bids that are above A1. The winning discount is the highest discount that is lower than A2. For a detailed description of average-bid auctions, see Albano, Bianchi and Spagnolo (2006) and Decarolis (2018).

between buyers and incumbent suppliers in a setting with no external assessments of which auction, if any, involved collusion. Our approach is in line with those of Bajari and Ye (2003) and Aryal and Gabrielli (2013), who provide a test to disentangle collusion and competition when collusion is not directly observed. Both works use nonparametric techniques that are based on Guerre, Perrigne and Vuong's (2000) FPA estimation and settle a statistical test to inspect collusion. We add to this literature a new test, specifically designed for SRAs, that detects the buyer's potential favoritism toward the incumbent bidder.

The rest of the paper is organized as follows. Section 2 presents the institutional setting, the descriptive statistics of our dataset and some preliminary results. Section 3 implements a novel empirical strategy to investigate entrant and incumbent bidding in SRAs and illustrates results from our analysis. Section 4 develops a simple model to investigate the optimal design of a SRA based on two different sets of information the buyer has about the bidders' characteristics. Section 5 wraps up our empirical results and theoretical insights, draws conclusions and policy implications.

2 Institutional Setting and Descriptive Analysis

We build a small, original database of 192 public procurement contracts for canteen services in Italy awarded using sealed-bid SRAs between 2009 and 2013. This market has an HHI of 0.4, so it is moderately concentrated.[10] The awarded contracts in our dataset last from three to five years and have a reserve price (i.e., the maximum price the public buyer is willing to pay) higher than €150,000.[11] Our cross-sectional dataset includes information on the public buyers that manage such auctions, that is, their names and whether they are *elected bodies*, *semi-autonomous bodies*, or *administrative bodies*.[12]

The group of public buyers who belong to an *elected body*—mostly municipalities—awards 78% of the auctions in our dataset. These buyers are locally elected every four or five years, so the canteens they outsource (i.e., canteens for

10 Our dataset records 78 winners among which 4 big players won 44 percent of the total 192 auctions, and 45 smaller players won one auction each.

11 Using data provided by EU-TED on Italian public procurement auctions for canteen services, we observe that their total sector value in 2015 (the most recent year available) was approximately €100 million. The average participation in the corresponding auctions was 3.2 bidders.

12 This classification follows that of Bandiera, Prat, and Valletti (2009). Using Italian public procurement data, they exploit the presence of a central procuring agency and study the determinants of price variability for the same object paid by different public buyers.

schools in the municipal area) are politically sensitive services. Another 15% of the auctions in our dataset are awarded by public buyers who belong to an *administrative body*, such as firefighters and local branches of the Italian Tax Agency. These bodies are run by civil servants, and their canteens are for internal staff only. Finally, 7% of our auctions are awarded by public buyers who belong to a *semiautonomous body*, usually public hospitals whose canteens are for internal staff and patients. Their governance is in between that of elected and administrative bodies, as their internal management consists of public career managers, while their executive management is appointed by the locally elected president of the region.

Whatever group these public buyers belong to, they all have discretion in designing the outsourcing for their canteens' services and are free to choose the weights for price and quality in the scoring function. Our database records the weights chosen in each SRA for quality and price: on average, quality is weighted 60 points of 100. Our database also includes information on whether there was urgency in providing the service. Moreover, for each auction in our database, we have information about the identity of the winner and whether it was the canteen's service provider in the period immediately before the recorded auction took place (i.e., the *incumbent supplier*) or an entrant supplier.[13] We also observe the winning rebate (i.e., the ratio of the winning price to the reserve price), the ratio of the maximum and minimum bids to the reserve price, and the number of participants.

We collect data on the geographic characteristics of the area where the service was to be provided and the local Purchasing Parity Power (PPP) index;[14] we use the latter as a proxy for geographic differences in the costs of raw materials and services. To control for effects of the electoral cycle, we gather information on the time between the year in which the service was awarded and the next electoral year. We define this variable as year-to-elections, and include it in the empirical analysis.[15] Finally, in the case of an elected public buyer, we observe the size of its constituency. Table 1 shows the descriptive statistics of our dataset.

Table 2 presents the average winning rebate and the average number of bidders (controlling also for the reserve price) by splitting the dataset into two groups: auctions the incumbent wins and auctions an entrant wins.

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13 For a subset of auctions, we also have information about whether the incumbent participated but did not win the contract. See Section 3.2 for additional details.

14 These data come from Cannari and Iuzzolino (2009), Table A2.1, Column 7. The PPP index includes food, clothing, furniture, services, and energy costs and excludes house prices.

15 We consider the national electoral year for all administrative bodies, the regional electoral year for hospitals (since, in Italy, health is managed at the regional level), and the local electoral year for municipalities.

Table 1: Descriptive statistics.

Reserve price	2,533,063
	(5,357,094)
Winning rebate	4.302
	(6.302)
Maximum rebate	5.548
	(7.420)
Minimum rebate	1.597
	(3.490)
Number of bidders	2.682
	(2.371)
Weight of quality in SRA (max 100)	59.93
	(11.00)
PPP index nuts	106.0
	(10.38)
Years-to-election	2.318
	(1.395)
Incumbent wins	56.2%
Subcontracting	13.5%
Buyer's type	
Elected body	77.6%
Administr. body	15.1%
Semiauton. body	7.29%
NUTS	
North West	30.2%
North-East	29.7%
Center	16.1%
South	14.6%
Islands	9.4%
Observations	192

Table 1 reports the average values (standard deviations in parenthesis) of the main variables recorded in our dataset. The *reserve price* is the maximum price, in euro, the buyer is willing to pay. The *winning rebate*, and similarly the *maximum rebate* and the *minimum rebate*, are expressed in percentage (from 0 to 100) over the reserve price. *Number of bidders* accounts for the number of participants in the auction. The *weight of quality* records the total weight of all the quality components in the SRA, over 100 total points. The *PPP index nuts* records the local Purchasing Parity Power (PPP), where 100 corresponds to the Italian average. The *years-to-election* records the time lasting between the year in which the service was awarded and the next electoral year. *Incumbent wins*, *subcontracting*, all the *buyers' types* and the *NUTS* are 0-1 dummies (the average value is reported as a percentage). Geographic dummies are at the NUTS-1 level.

The descriptive statistics in Table 2 show that the incumbent is the winner in 56% of the auctions in our database. In such auctions, the number of competitors and the winning rebate are lower, and the public buyer pays a higher price than it does in auctions that an entrant wins. In particular, the mean number of bidders in auctions where the incumbent wins is 2.1, while it is 3.5 when an entrant wins; the mean winning rebates are 2.44% and 6.70%,

Table 2: Auction outcome and size: entrant (*E*) or incumbent (*I*) wins.

	E wins	I wins	Total	*t*-test. H0: *diff* = 0	
				H1: *diff* > 0	H1: *diff* < 0
Winning rebate	6.700	2.436	4.302	0.000	1.000
	(7.355)	(4.573)	(6.302)		
Number of bidders	3.464	2.074	2.682	0.000	1.000
	(2.636)	(1.946)	(2.371)		
Reserve price	2,265,744	2,740,977	2,533,063	0.728	0.272
	(3,640,989)	(6,391,012)	(5,357,094)		
Observations	84	108	192		

Table 2 records the average *winning rebate*, the average *number of bidders* and the average *reserve price* (standard deviations in parenthesis) by splitting the whole dataset into two sample groups: auctions an entrant wins (E wins) and auctions the incumbent wins (I wins). *t*-tests are used to evaluate the difference between the means of the two sample groups. The null hypothesis (H0) is that the two means are equal.

respectively. These differences in means are statistically significant at the 99% confidence level.[16]

A two-sample Kolmogorov-Smirnov test of the equality of distributions confirms that both the winning rebate and number of bidders are distributed differently in the two subsamples, but the test finds no difference in the distribution of the reserve price, the weight of quality in the scoring function, the public buyer's type, the year the contract was awarded, the electoral cycle, or—using NUTS' groups of region codes from Eurostat—the public buyers' geographical location. Thus, comparing the auctions that the incumbent wins with those that an entrant wins reveals that all of the SRA's characteristics and those of the service awarded are identically distributed in the two groups.

In summary, descriptive statistics (Tables 1 and 2) show that i) in more than half of the auctions in our dataset, the incumbent supplier is the winner; ii) when the incumbent wins the auction, the number of bidders is lower and the price paid by the public buyer is higher; and iii) the characteristics of the SRAs and the service awarded do not differ based on whether the incumbent wins or the entrant wins.

3 Empirical Analysis

We run an econometric analysis to investigate the evidence on entrants' and incumbents' bids, discussed in Section 2, by implementing the following empirical

16 The average number of bidders in the overall dataset is equal to 2.68: under symmetry, each bidder wins with a probability of 0.37.

strategy. We begin by separating our dataset into two subsamples: one includes all the auctions an entrant wins (i.e., the entrants' winner subsample; EWS henceforth) and, the other, all the auctions the incumbent wins (i.e., the incumbents' winner subsample; IWS henceforth). The EWS and the IWS contain 84 and 108 auctions, respectively. We then run an econometric model on the EWS and construct two tests as a result. Finally, we apply these tests to the whole sample to determine which auctions fail to be predicted by our econometric model.

Specifically, on the EWS, we run the following parametric estimate of the winning rebate r^W for each auction i:

$$r_i^W = \alpha_1 + \beta_{11}N_i + \beta_{12}q_i + \beta_{13}X_i + \varepsilon_i \tag{1}$$

and we then estimate the difference between the maximum and the minimum rebate offered by bidders, r^{diff}, according to:

$$r_i^{diff} = \alpha_2 + \beta_{21}N_i + \beta_{22}q_i + \beta_{23}X_i + \varepsilon_i' \tag{2}$$

where N is the number of bidders, $q \in [0, 100]$ is the weight of quality in the *SRA*, and X is a vector of the auction characteristics that includes the NUTS groups of region codes, the type of buyer (i.e., elected body, semiautonomous body or administrative body), the population of the municipality if the public buyer is an elected body, the log-reserve price,[17] the number of years until the next election and whether or not subcontracting was adopted. Finally, ε_i and ε_i' are the error components.

In the empirical literature on procurement auctions, the winning rebate is often used as a measure of competitiveness.[18] In an SRA, where bidders compete on both price and quality, the higher the weight given to quality, the less important is the price component in the bid. To account for the relevance of price when quality has a positive weight, we include in our estimation the difference between the maximum and the minimum rebate submitted by all bidders in the same auction, r^{diff}. To illustrate the interpretation for r^{diff}, consider the following example: in an SRA in which $q_i = 0$ (thus corresponding to an FPA), competition is only on the price side and, depending on bidders' heterogeneity, r_i^{diff} has a positive value. In contrast, in an SRA where $q_i = 100$, the price component of all bids is

17 The empirical procurement literature adopts the log-reserve price as both a measure for the awarded contract's size and as a normalization factor for the auction's outcome. For example, using data on Italian procurement for public works, Bucciol, Chillemi, and Palazzi (2013) investigate cost overruns, defined as the difference between the final execution price and the auction winning price. As a dependent variable they adopt the cost overrun normalized by the reserve price, regressed on the log-reserve price.

18 See, for example, Coviello and Gagliarducci (2017).

equal to the reserve price, and the difference between the highest and lowest price discount is zero, so we expect to find a significant effect of q on r^{diff}.

Our results of the model (1) on r^W and of the model (2) on r^{diff} are presented in Tables 3 and 4, respectively. The estimation for model (2) considers only auctions with at least two participants. Columns *1a* and *1b*, both in Tables 3 and 4, report results from a standard OLS model. Taking into account the endogeneity of the awarding mechanism relative to the buyer's type and the contract's size, Columns *2a* and *2b* present results related to a two-stage least squares (2sls) approach, where q is instrumented using the buyer's type, the reserve price, and a dummy variable that is equal to one if urgency is a requirement in awarding the service.

In considering the buyer's choice on quality in SRA, the following elements have to be taken into account. For a given service, different buyers may assign different importance to quality in their utility function and, in so doing, define different weights in the scoring function they design. Moreover, the importance of quality may depend on the size of the contract, measured through the reserve price value. Finally, quality takes more time to be defined in the tender specifications and more time to be evaluated in the bids received; accordingly, we expect that, when urgency is a requirement, fewer quality elements are included in the SRA's design and, as a result, quality is given a lower weight in the scoring function.

Our results on the EWS show that the weight the buyer assigns to quality in SRAs has a strong impact on the winning rebate: the higher this weight, the lower the competition on the price component. This result is also confirmed by the significant negative effect of quality on r^{diff}, that is, on the difference between the maximum and the minimum rebate over the reserve price in each auction.

As we would expect, the number of bidders is significant and has a positive effect on r^W and on r^{diff}: more competition reduces the price the buyer pays and increases the heterogeneity across bids.

The electoral cycle also influences both r^W and r^{diff}, as the fewer the number of years before the next election, the lower the price paid and the larger the difference between the maximum and the minimum rebate. This result is consistent with the idea of third-party opportunism (i.e., larger/better use of competitive auctions in periods close to elections).[19] Consider, for example, an SRA to award the canteen service for local schools: in this setting, a mayor close to election time will be as efficient as possible in managing the procurement process. In so doing, the mayor wants to show she is a capable administrator in getting "value for money": this

19 In considering the political cycle, Moszoro and Spiller (2014) highlighted that the procurement process could be managed to reduce political hazards from opportunistic third parties (i.e., political opponents).

Table 3: Winning rebate.

	(1a) OLS	(1b) OLS	(2a) IV	(2b) IV	(3a) IV Lewbel	(3b) IV Lewbel	(4a) 3sls	(4b) 3sls
Q	−0.171***	−0.200***	−0.340***	−0.402***	−0.171***	−0.201***	−0.339***	−0.391***
	(0.053)	(0.0515)	(0.092)	(0.107)	(0.048)	(0.048)	(0.083)	(0.075)
Log reserve price	−0.305	−0.257			−0.299	−0.228		
	(0.519)	(0.551)			(0.478)	(0.519)		
Population	0.009***	0.009***	0.009***	0.010***	0.008***	0.009***	0.008***	0.009***
	(0.002)	(0.0012)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Elected body	0.211	0.305			0.270	0.494		
	(2.049)	(2.070)			(1.868)	(1.926)		
Administr. body	2.157	2.938			2.275	3.448		
	(2.197)	(2.458)			(2.018)	(2.316)		
South	7.004**		7.291***		6.909***		8.220***	
	(2.769)		(2.245)		(2.506)		(2.460)	
Islands	−0.395		0.773		−0.481		0.439	
	(1.916)		(1.741)		(1.729)		(1.640)	
North East	−1.364		−1.365		−1.419		0.454	
	(1.930)		(1.752)		(1.738)		(1.706)	
North West	−4.078**		−4.128***		−4.110**		−2.891*	
	(1.861)		(1.498)		(1.693)		(1.714)	
Number of bidders	0.912***	0.947***	0.893***	0.938***	0.862***	0.739***	0.956***	0.851***
	(0.281)	(0.286)	(0.256)	(0.271)	(0.261)	(0.266)	(0.280)	(0.243)
Subcontracting	3.949**	4.239***	3.702***	3.933***	3.891***	4.019***	4.651***	4.710***
	(1.502)	(1.477)	(1.397)	(1.454)	(1.389)	(1.448)	(1.526)	(1.506)
Years to election	−1.388**	−1.436**	−1.567***	−1.634**	−1.385***	−1.421**	−1.403***	−1.405***
	(0.575)	(0.603)	(0.586)	(0.657)	(0.532)	(0.575)	(0.479)	(0.530)

Table 3: (continued)

	(1a) OLS	(1b) OLS	(2a) IV	(2b) IV	(3a) IV Lewbel	(3b) IV Lewbel	(4a) 3sls	(4b) 3sls
PPP index nuts		−0.288***		−0.319***		−0.279***		−0.273***
		(0.071)		(0.068)		(0.067)		(0.068)
Constant	19.90***	50.24***	26.51***	63.13***	19.98***	49.33***	24.95***	57.42***
	(7.414)	(9.804)	(6.601)	(11.94)	(6.814)	(9.198)	(5.211)	(9.422)
Observations	84	84	84	84	84	84	84	84
R^2	0.537	0.481	0.489	0.410	0.537	0.476	0.539	0.475

Robust standard errors in parentheses
*p < 0:10; **p < 0:05; ***p < 0:01
All regressions of Table 3 are estimated on the EWS. The dependent variable is r^W . Standard errors are in parenthesis. Columns (1a) and (1b) report estimates from an OLS model. Columns (2a) and (2b) report estimates from a two-stages least squares model where q, the weight of quality in the scoring function, has been instrumented using the buyer's type (dummies for *elected body* and *administrative body*), the *log reserve price*, and whether or not there was a requirement for urgency in the awarding of the service. Columns (3a) and (3b) report estimates of a Lewbel model, where the endogeneous variable is the *number of bidders*. Columns (4a) and (4b) report estimates from a three-stages least square model. In the first stage, q is instrumented as in the model of Columns (2a) and (2b). Then, the predicted values of q are used in the second and third stages to estimate the model proposed by Lewbel (2012), considering the *number of bidders* as endogeneous.

Table 4: Difference between the maximum and the minimum rebate.

	(1a) OLS	(1b) OLS	(2a) IV	(2b) IV	(3a) IV Lewbel	(3b) IV Lewbel	(4a) 3sls	(4b) 3sls
Q	−0.089**	−0.121***	−0.191***	−0.218***	−0.088**	−0.120***	−0.208**	−0.241***
	(0.042)	(0.042)	(0.058)	(0.061)	(0.039)	(0.039)	(0.085)	(0.080)
Log reserve price	−0.871*	−0.716			−0.842*	−0.670		
	(0.489)	(0.507)			(0.447)	(0.489)		
Population	$2*10^{-4}$	$5*10^{-4}$	$-1*10^{-4}$	$3*10^{-4}$	$3*10^{-4}$	$2*10^{-4}$	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Elected body	1.579	2.135			1.776*	2.262		
	(1.171)	(1.426)			(1.068)	(1.385)		
Administr. body	5.273***	5.407**			5.680***	5.929***		
	(1.634)	(2.058)			(1.460)	(1.938)		
South	6.561***		6.685***		6.193***		7.043***	
	(1.929)		(1.786)		(1.767)		(1.942)	
Islands	0.314		0.932		−0.0979		0.303	
	(1.772)		(1.738)		(1.623)		(1.585)	
North East	−0.453		−0.428		−0.730		0.404	
	(1.682)		(1.509)		(1.547)		(1.554)	
North West	−0.532		−1.081		−0.716		−0.589	
	(2.054)		(2.012)		(1.837)		(2.064)	
Number of bidders	1.059***	1.094***	1.127***	1.161***	0.874**	0.837**	1.001***	0.811**
	(0.395)	(0.376)	(0.359)	(0.349)	(0.372)	(0.386)	(0.385)	(0.400)
Subcontracting	3.086	3.152	1.622	1.805	3.040	3.114	2.299	2.517
	(2.334)	(2.312)	(2.033)	(2.079)	(2.205)	(2.279)	(1.920)	(1.953)
Years to election	−0.945**	−0.981**	−0.776*	−0.826*	−0.952**	−0.988**	−0.657	−0.672
	(0.446)	(0.471)	(0.438)	(0.471)	(0.397)	(0.425)	(0.451)	(0.496)

Table 4: (continued)

	(1a) OLS	(1b) OLS	(2a) IV	(2b) IV	(3a) IV Lewbel	(3b) IV Lewbel	(4a) 3sls	(4b) 3sls
PPP index nuts		−0.185***		−0.209***		−0.173***		−0.172***
		(0.056)		(0.053)		(0.052)		(0.059)
Constant	17.87**	37.16***	13.71***	37.85***	18.13***	36.02***	14.59**	36.18***
	(7.176)	(7.815)	(4.496)	(8.144)	(6.528)	(7.518)	(5.755)	(9.011)
Observations	71	71	71	71	71	71	71	71
R^2	0.533	0.480	0.475	0.428	0.528	0.470	0.460	0.380

Robust standard errors in parentheses
$^{*}p < 0{:}10$; $^{**}p < 0{:}05$; $^{***}p < 0{:}01$
All regressions of Table 4 are estimated on the EWS, using only auctions with 2 or more bidders. The dependent variable is r^{diff} . Standard errors are in parenthesis. Columns (1a) and (1b) report estimates from an OLS model. Columns (2a) and (2b) report estimates from a two-stages least squares model where q, the weight of quality in the scoring function, has been instrumented using the buyer's type (dummies for *elected body* and *administrative body*), the *log reserve price*, and whether or not there was a requirement for urgency in the awarding of the service. Columns (3a) and (3b) report estimates of a Lewbel model, where the endogeneous variable is the *number of bidders*. Columns (4a) and (4b) report estimates from a three-stages least square model. In the first stage, q is instrumented as in the model of Columns (2a) and (2b). Then, the predicted values of q are used in the second and third stages to estimate the model proposed by Lewbel (2012), considering the *number of bidders* as endogeneous.

would lead to gain consensus with the aim of being re-elected or of increasing support for a candidate from the same political party.

Finally, to explain fixed-effect geographic differences, in Columns *1b* and *2b* both in Tables 3 and 4, we replace NUTS dummies with the local PPP Index. The resulting significant effect shows that at least part of the geographic variation observed is due to the differing costs of raw materials. Southern Italy has a significantly lower cost of living, about 75% of that of northwestern Italy, a difference reflected in the positive coefficients of the NUTS dummy variable *South* and in the negative and significant sign of the PPP index's coefficients.

The results presented in Tables 3 and 4 remain significant when different errors (standard, robust, corrected for small sample and bootstrapped) are used. We run other three tests on the IV model as follows: i) F-test of the joint significance of the additional instruments used for q on q, which reveals that the instruments are sufficiently correlated with the endogenous regressor; ii) Sargan test, which verifies that the instruments are uncorrelated with the error term; and iii) Durbin-Watson test which verifies that q is endogenous and, as such, should be treated with instrumental variables. Specifically, this last test shows that q is endogenous for the regression (1) on r^W but not for the regression (2) on r^{diff}. We also use the IV on the second regression because q is endogenous with respect to the reserve price and the type of buyer in (1); moreover, an exogenous regressor estimated using the IV model remains consistent although it is less efficient. Our results do not change significantly when OLS is used. Finally, when we estimate the regression (1) on the IWS, we find that q is no longer significant and we obtain a much lower R^2 (specifically, 0.09 vs. 0.49). Similarly, estimating regression (2) on the IWS reveals that q is no longer significant. These results highlight that auctions' outcomes in the IWS are not well explained by the auction mechanism or the service's characteristics.

Robustness Check: Endogenous Participation

As a robustness check, we first estimate a regression in which q (the weight of quality in the SRA) is assumed to be exogenous, and N (the number of bidders) and r^W (the winning rebate) are simultaneously determined. We find that N correlates with all the other regressors. Since it is difficult to select an instrument that correlates only with N and not with r^W, and instrumental variables/other solutions are not available, we adopt the model proposed by Lewbel (2012). This approach exploits heteroskedasticity in data to construct an instrument for models with such issues. Then, we use the same approach to estimate r^{diff}. The results, presented in Columns *3a* and *3b* of both Table 3 (for r^W) and Table 4 (for r^{diff}), do not differ significantly from the standard OLS estimates. As done previously, we also use the local PPP index to check for local (geographic) heterogeneity in the data.

As a further robustness check, we estimate a three-stage least squares (3sls) model that considers the SRA mechanism to be endogenous, given the size of the awarded contract and the type of buyer. In contrast to *N*, the weight of quality, *q*, in the SRA can be instrumented using this information: this is why we should treat the endogeneity arising from *q* differently from how we treat the simultaneity problem arising from *N*.

As the first stage of the model, we estimate *q* using the reserve price, dummies for the type of buyer, and dummies for whether the service is urgent. Then, the predicted values of *q* are used in the second and third stages. Specifically, following Lewbel (2012), in the second stage we construct an instrument to estimate the number of bidders, *N*. In the third stage we estimate r^W and r^{diff}, having corrected for the endogeneity of *q* and for the simultaneity problem of *N*. The stages are designed as follows:

1	$q_i \sim res.price,\ elected,\ hosp$	*Buyer's decision on q*
2. (Lewbel)	$N_i \sim \widehat{q}_i, X_i', p_{wi}$	*Firms' decision to entry the auction*
3.	$r_i^W \sim \widehat{N}_i, \widehat{q}_i, X_i$	*Auction outcome*
	$r_i^{diff} \sim \widehat{N}_i, \widehat{q}_i, X_i$	*Auction outcome*

(3)

The results, presented in Columns *4a* and *4b*, of both Tables 3 and 4, are consistent with our baseline model.

Finally, we explore whether the reserve price affects firms' entry into auctions.[20] We regress *N* over the reserve price (Table 5) and find no significant relationship between the two variables.

3.1 Results on the Whole Sample

Using the whole sample, we now estimate predictions from our IV model with geographic dummies that were gained on the EWS, and we compare the predicted and observed values. We also estimate confidence intervals (CIs) for the difference

20 The reserve price might affect bidders' participation at least in two ways. On one hand, the reserve price is a proxy for the contract's size, so the canteen services with high reserve prices can allow a small number of firms (i.e., the largest firms in the sector) to provide the service and to enter the awarding auction. On the other hand, services with high reserve prices provide suppliers with larger room for bidding up the price, so more bidders could be interested in entering the auction. These two effects work in opposite directions in affecting the number of bidders in the auction, and it is not obvious which one will dominate.

Table 5: Number of bidders, robustness check.

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Reserve price	$-4.02{*}e-9$		$-4.94{*}e-9$	
	$(3.21{*}e-8)$		$(3.05{*}e-8)$	
Log reserve price		0.146		0.144
		(0.142)		(0.144)
Subcontracting			−0.618	−0.737
			(0.473)	(0.482)
Population			0.0004	0.0009
			(0.0008)	(0.0007)
Buyer's type FE	NO	NO	YES	YES
Year FE	NO	NO	YES	YES
NUTS FE	NO	NO	YES	YES
Constant	2.692***	0.648	6.224***	4.218*
	(0.190)	(1.985)	(0.936)	(2.191)
Observations	192	192	192	192
R^2	0.000	0.006	0.217	0.221

Robust standard errors in parentheses
*p < 0:10; **p < 0:05; ***p < 0:01
All regressions in Table 5 report estimates from an OLS model on the whole dataset. The dependent variable is the *number of bidders* in each auction. Standard errors are in parenthesis. FE stands for Fixed Effects.

between the maximum and the minimum rebate r^{diff} (both above and below the predicted value) and for the winning rebate r^W (only below the predicted value).

As usual, the CIs are calculated as:

$$CI = Xb \pm \alpha SE \tag{4}$$

where Xb is the predicted value, SE is the standard error, and α is the t-value parameter that defines the width of the confidence interval. Equation (4) shows that the larger the α, the wider the CI. We use both the standard error of the prediction (STDP) and the standard error of the forecast (STDF)—that is, the standard error of the predictions plus the error variance of the regression.[21] By construction, the STDF is larger than the STDP. As a result, it produces larger CIs, and fewer observations will fail to be predicted by the model.

21 STDP is used for within-sample predictions, while STDF is used for out-of-sample predictions to control for differences in the domains on which the models are estimated (i.e., extrapolation issues). Since we derive our predictions both within- and out-of-sample, we report both related statistics.

Figure 1 plots α (the t-value parameter that defines a CI) against the proportion of correctly predicted values in the IWS and in the EWS for r^W and for r^{diff}, using both the STDP and the STDF. We find a significant difference in the precision of the models that estimate r^W and r^{diff}, depending on whether the EWS or the IWS is used. Regardless of the CI and the standard error adopted, the predictions in the EWS are systematically closer to the real values than the predictions in the IWS are. However, this result no longer holds if the model is estimated on a randomly chosen subsample, that is, if observations are randomly allocated to the EWS or to the IWS (see the next Section).

Finally, on the basis of these results, we move from the estimate on the EWS to that on the whole database. We use the predicted values of our models as a test: specifically, the test is passed if the observed value is within a given CI of the predicted value. Note that, given the predicted values for r^W and r^{diff}, we end up with two tests, respectively Test 1 and Test 2. If both these tests fail, the observed

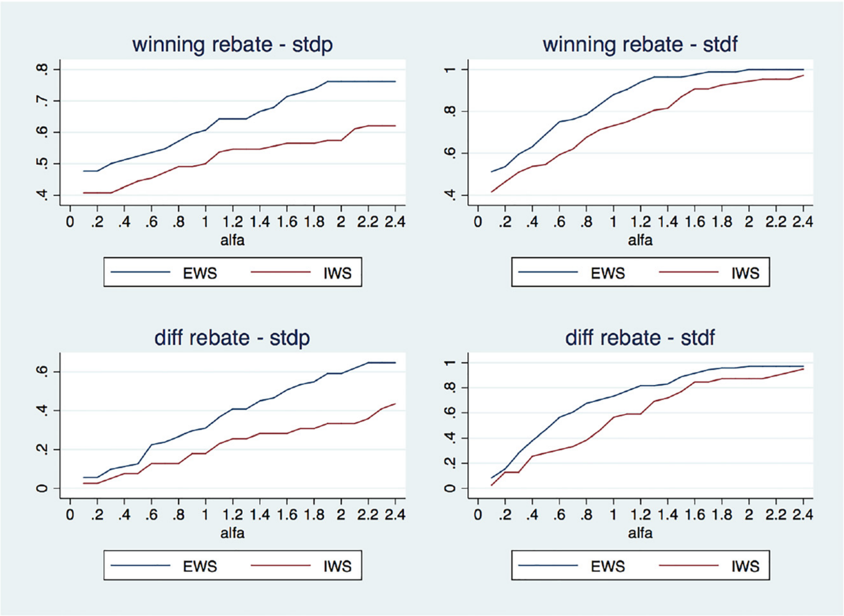


Figure 1: Proportion of correctly predicted values in the EWS and in the IWS. Figure 1 plots α (the t-value parameter that defines a CI) against the proportion of correctly predicted values for the *winning rebate*, r^W, and for the *difference between the maximum and the minimum rebate*, r^{diff}, within the subsamples IWS and EWS.

auction outcome cannot be explained by the service's and buyer's characteristics or by the auction mechanism.

Table 6 reports the proportion of incorrectly predicted values (from 0 to 1) by CI and by some of the auction's characteristics. We begin by looking at the results on the STDP and discuss the STDF results afterward.

With a 90% CI, we find that 32.8% of the auctions in our dataset fail to pass both Test 1 for r^W and Test 2 for r^{diff}. Obviously, the larger the CI, the smaller the number of auctions that do not enter within that interval. Accordingly, with CIs of 95 and 98%, we observe that 29.2 and 26% of auctions, respectively, fail to pass the tests. The proportion of incorrectly predicted auction outcomes is much higher in the IWS group of auctions. Indeed, with a 95% CI, only 15.5% of the auctions fail both the tests when the entrant wins; this proportion increases to 39.8% when the incumbent wins.

Table 6: Proportion of incorrectly predicted values (from 0 to 1), by CI.

	Confidence Interval				
	STDP			STDF	
	90%	**95%**	**98%**	**80%**	**95%**
Total	0.328	0.292	0.260	0.120	0.031
Incumbent wins					
No	0.214	0.155	0.155	0.024	0
Yes	0.417	0.398	0.343	0.194	0.056
Electoral year					
No	0.284	0.241	0.204	0.080	0.019
Yes	0.567	0.567	0.567	0.333	0.100
Buyer's type					
Elected	0.342	0.302	0.275	0.134	0.040
Administr.	0.172	0.172	0.138	0.070	0
Hospital	0.500	0.429	0.357	0.071	0
Reserve price, quartile					
1	0.312	0.271	0.271	0.188	0.021
2	0.333	0.292	0.271	0.063	0.021
3	0.333	0.313	0.271	0.083	0.021
4	0.333	0.292	0.229	0.146	0.062

Table 6 reports the proportion of incorrectly predicted values, by confidence interval, on the whole dataset and on different sample groups. Sample groups are constructed as follows: (i) auctions an entrant wins and auctions the incumbent wins, (ii) auctions awarded during an electoral year and the remaining auctions, (iii) auctions awarded by different buyer's type, (iv) auctions with different size defined by quartiles of the reserve price. The outcome of an auction is incorrectly predicted if both our predictions, on r^W and r^{diff}, are outside the stated confidence interval.

We find a similar effect for the electoral cycle. Considering all the three CIs above, a total of 56.7% of the auctions awarded during an electoral year fail to be predicted by either Test 1 or Test 2. This proportion decreases to 28.4% (for a 90% CI) and to 20.4% (for a 98% CI) for auctions that are not awarded during an electoral year.

As for the buyer's type, we found that canteen services that are awarded by a semi-autonomous body (i.e., hospitals) are more likely to fail our tests (42.9% of the auctions, using a 95% CI), followed by those awarded by an elected body (30.2%). The proportion of incorrectly predicted auction outcomes drops to 17.2% for SRAs managed by nonelected administrative bodies. Finally, we find no difference in that proportion when we separate auctions by reserve price.

These results are confirmed and are even stronger when we use the STDF. Some observations still fall outside the CIs of the predictions, even though using STDF increases the width of that interval. Among those observations, the proportion of incorrectly predicted values is higher when the incumbent wins. When we use an 80% CI, we record that 19.4% of the auctions awarded to the incumbent supplier are not predicted by our model, a percentage that falls to 2.4% when the contract is awarded to a new entrant. When we use a 95% CI instead, all the SRAs that are not correctly predicted by our model are awarded to the incumbent. The only difference we detect by using the STDF is for the buyer's type: contracts awarded by an elected body are more likely to fail our tests than are those awarded by semi-authonomous body and central bureaucratic administrations.

The econometric analysis in this Section highlights that the probability a buyer will pay a price higher than the one predicted by a standard model—which takes into consideration the contract's and the buyer's characteristics, the awarding mechanism used, and the degree of competition—is larger when the incumbent wins the auction than when an entrant does.

3.2 Endogeneous Entry and Additional Robustness Checks

In this Section we present some robustness checks testing for alternative explanations of our empirical results, i.e. alternative with respect to the one sketched in the theoretical setting (Section 4 below). The case an incumbent supplier wins the SRA with an higher winning price and lower competition can be referred to an "endogenous entry" story as follows. Assume a setting in which firms face costs to enter the auction,[22] and that potential entrants may observe the incumbent's level of efficiency. As a consequence, auctions that include an inefficient incumbent are more likely to see stronger competition, which decreases the winning price and makes the incumbent less likely to win the auction. In contrast, auctions with an efficient incumbent may deter entry, increasing the likelihood that the incumbent will win the auction and that the buyer will pay an higher final price. While this "endogenous entry story" could be considered a natural explanation for our empirical results, the following robustness checks lead us to reject it.

Our dataset contains sealed-bid auctions where participants, *ex-ante*, do not observe the number of competitors. Accordingly, in the case only one bidder enters the auction, she cannot anticipate to be the only participant and bid the reserve price as a result. This is confirmed in our dataset: the 75% of auctions with one bidder record a winning price different from the reserve price. On the other hand, assuming bidders do not have any signal on the strength of competition in the auctions should lead the distribution of winning rebates not to change with the number of participants: a Kendall's rank correlation coefficient test rejects this latter hypothesis. All in all, we conclude that bidders receive a noisy signal on the level of competition they face in auctions. When we compare the distributions of winning rebates among samples of auctions, we find that these distributions differ among samples of, respectively, one bidder, two to three bidders, and four or more bidders; and, they do not change within each sample group.

Table 7 reports the summary statistics on the auctions' outcomes and reserve prices by splitting the whole dataset in: (i) auctions the incumbent wins and auctions an entrant wins; (ii) auctions with, respectively, one bidder, two to three bidders, and four or more bidders. *Table 7* also highlights that differences in the winning rebate based on whether the contract is awarded to the incumbent or to a new entrant remain significant when comparing auctions with the same level of competition.

Next, we estimate the same model as in Section 3, making the estimation conditional on a low (two to three bidders) or a high (four or more bidders) level of competition.[23] A simultaneity problem between the number of bidders and the winning rebate no longer exists, but we still have to address the endogeneity problem of the scoring function. Table 8 reports both the OLS and IV estimates for

22 We are not necessarily referring to monetary costs but, for example, to extra time or extra effort to prepare the multidimensional bid.

23 Only 13 auctions with one bidder in our sample were awarded to a new entrant, an inadequate subsample on which to repeat the econometric analysis.

Table 7: Auction outcome and size: entrant (*E*) or incumbent (I) wins and n. bidders.

	E wins	I wins	*t*-test. H0: *diff* = 0	
			H1: *diff* > 0	H1: *diff* < 0
Winning rebate				
1 bidder	3.570	1.466	0.029	0.971
(Obs.)	(13)	(69)		
2–3 bidders	5.851	2.904	0.041	0.959
(Obs.)	(43)	(20)		
4+ bidders	9.458	5.464	0.046	0.954
(Obs.)	(28)	(19)		
Reserve price, m€				
1 bidder	3.052	3.002	0.491	0.509
(Obs.)	(13)	(69)		
2–3 bidders	1.707	1.804	0.552	0.447
(Obs.)	(43)	(20)		
4+ bidders	2.758	2.780	0.507	0.493
(Obs.)	(28)	(19)		

Table 7 records the average *winning rebate* and the average *reserve price* by splitting the whole dataset into different sample groups (the number of observations for each sample group is in parenthesis): (i) auctions an entrant wins (E wins) and auctions the incumbent wins (I wins), (ii) auctions with, respectively, one bidder, two to three bidders, and four or more bidders. Keeping costant the number of bidders, *t*-test are used to evaluate the difference between the mean of sample groups where the incumbent wins and where an entrant wins. The null hypothesis (H0) is that the two means are equal.

r^W and for r^{diff}, with separate regressions using EWS auctions with two to three bidders and with four or more bidders. The results, shown in Table 8, are similar to those in Tables 3 and 4.

Finally, we use the IV models to compare the predictions of r^W and r^{diff} with the observed values in the EWS and in the IWS, separately for different levels of competition (Table 9). As in the previous Section if both observations fall outside the CIs of the predicted values, the test is not passed. We then compare the proportion of incorrectly predicted values (from 0 to 1) by CI, conditioned on whether the contract is awarded to the incumbent or the entrant.

Comparing auctions where the incumbent or the entrant wins, we find that the unobserved difference in the price paid by the buyer persists, even if we separately use estimates that are conditioned on a low or high level of competition. All in all, these results are consistent with the estimates of the Lewbel model on the EWS and show that an “endogenous entry story” cannot explain our findings on the whole sample.

We then run two further robustness checks as follows. First, when the entrant wins, in 39.3% of the observations we have information about all the bidders. In

Table 8: Winning rebate and difference between max and min rebate, by number of bidders.

	Winning Rebate				Difference max-min rebate			
	2-3 bidders		4+ bidders		2-3 bidders		4+ bidders	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Q	−0.201**	−0.325***	−0.145	−0.258*	−0.010	−0.246***	−0.025	−0.163*
	(0.086)	(0.057)	(0.129)	(0.138)	(0.077)	(0.038)	(0.085)	(0.087)
Log reserve price	−0.630		−0.135		−1.017		−1.279	
	(0.618)		(2.106)		(0.655)		(1.557)	
Population	0.007***	0.008***	0.018	0.017	−0.001	$-3*10^{-4}$	0.279	0.080
	(0.002)	(0.001)	(0.230)	(0.099)	(0.001)	(0.001)	(0.194)	(0.075)
Elected body	3.699		5.234		3.131***		−5.626	
	(2.538)		(14.65)		(1.108)		(11.06)	
Administr. body	3.439		6.575		4.926***		4.411	
	(2.289)		(11.38)		(1.681)		(8.138)	
South	2.000	4.019	10.06	10.96**	2.554	4.033***	3.466	6.145
	(3.477)	(2.501)	(7.042)	(5.083)	(2.269)	(1.398)	(5.442)	(4.208)
Islands	−4.760*	−2.528	−3.514	−1.843	−2.614	−0.830	−2.795	−4.510
	(2.379)	(2.104)	(7.235)	(5.484)	(2.054)	(1.783)	(5.838)	(4.734)
North East	−6.543***	−4.562***	−1.047	−0.282	−2.721	−1.105	−1.495	−3.516
	(2.093)	(1.724)	(5.591)	(3.348)	(1.747)	(1.522)	(4.224)	(3.778)
North West	−8.241***	−6.568***	−6.949	−5.766	−1.757	−0.890	−5.790	−6.791*
	(2.344)	(1.653)	(5.248)	(3.822)	(1.983)	(1.849)	(4.060)	(4.062)
Subcontracting	1.349	0.881	5.650	4.571	−2.539	−3.939***	−0.315	2.364
	(1.875)	(1.486)	(10.08)	(4.315)	(2.088)	(1.503)	(7.730)	(3.535)
Years to election	−2.065***	−2.298***	−1.523	−1.618	−1.101*	−1.310**	0.008	0.486
	(0.730)	(0.662)	(2.343)	(1.910)	(0.545)	(0.535)	(1.458)	(1.001)

Table 8: (continued)

	Winning Rebate				Difference max-min rebate			
	2-3 bidders		4+ bidders		2-3 bidders		4+ bidders	
	OLS	**IV**	**OLS**	**IV**	**OLS**	**IV**	**OLS**	**IV**
Constant	31.19***	32.04***	18.78	28.40**	24.66***	21.91***	28.01	18.06***
	(8.957)	(4.948)	(32.87)	(11.93)	(8.952)	(3.369)	(26.06)	(4.406)
Observations	43	43	28	28	43	43	28	28
R^2	0.650	0.602	0.518	0.486	0.433	0.319	0.565	0.452

Robust standard errors in parentheses
$^{*}p < 0{:}10$; $^{**}p < 0{:}05$; $^{***}p < 0{:}01$
All regressions of Table 8 are estimated on different sample groups of the EWS as follows: auctions with two to three bidders, and auctions with four or more bidders. The dependent variable is either r^W, or r^{diff} ; in this latter case, only auctions with at least two participants are considered. Standard errors are in parenthesis. For each sample group and for each dependent variable, two different models are estimated: (i) OLS and, (ii), a two-stages least squares model where q, the weight of quality in the scoring function, has been instrumented using the buyer's type (dummies for *elected body* and *administrative body*), the *log reserve price*, and whether or not there was a requirement for urgency in the awarding of the service.

Table 9: Proportion of incorrectly predicted values (from 0 to 1), by CI and number of bidders.

	Confidence Interval, 2-3 bidders					Confidence Interval, 4+ bidders				
			STDP		STDF			STDP		STDF
	90%	95%	98%	80%	95%	90%	95%	98%	80%	95%
Total	0.222	0.159	0.143	0.048	0	0.128	0.106	0.085	0.043	0.021
Incumb. winner										
No	0.163	0.116	0.116	0.023	0	0.071	0.036	0	0	0
Yes	0.350	0.250	0.200	0.100	0	0.211	0.211	0.205	0.105	0.053

Table 9 reports the proportion of incorrectly predicted values, by confidence interval, on different sample groups. Sample groups are constructed as follows: (i) auctions an entrant wins and auctions the incumbent wins, (ii) auctions with two to three bidders, and auctions with four or more bidders. The outcome of an auction is incorrectly predicted if both our predictions, on r^W or r^{diff} , are outside the stated confidence interval.

such a subsample, we find that the incumbent participates in only 18.2% of the auctions. We compare the winning and the reserve price in auctions where the incumbent either wins or does not enter in the auction. As Table 10 shows, the unobserved differences in the winning rebate (and also in the number of bidders) between the two subsamples persist, while no differences in the auctions' size are recorded.

Second, we repeat the analysis performed in Section 3 by randomly allocating observations to the EWS and to the IWS. In this case, we find no discrepancy in our model's ability to predict winning rebates and differences between the maximum and the minimum rebate in the random EWS or in the random IWS. Figure 2 reports the proportion of correctly predicted values in the random EWS and the random IWS as a function of the width α of the CI and of the type of standard error chosen (i.e., STDP or STDF).

Table 10: Auction outcome and size: incumbent (I) wins or does not partecipated.

Incumbent:	**I wins**	**I does not partecipated**	***t*-test. H0:** *diff* $= 0$	
			H1: *diff* > 0	**H1:** *diff* < 0
Winning rebate	2.436	4.577	0.020	0.980
Number of bidders	2.074	3	0.028	0.972
Reserve price, m€	2.741	2.585	0.548	0.451
(Obs.)	(108)	(27)		

Table 10 records the average *winning rebate*, the average *number of bidders* and the average *reserve price* on two sample groups: auctions the incumbent wins and auctions where the incumbent does not participated. *t*-tests are used to evaluate the difference between the means of the two sample groups. The null hypothesis (H0) is that the two means are equal.

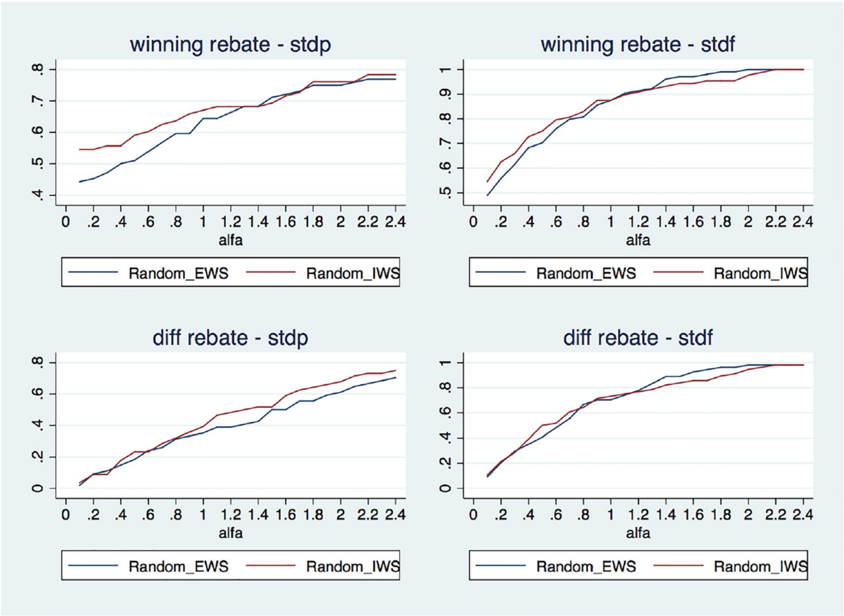


Figure 2: Proportion of correctly predicted values, random subsamples. Figure 2 plots α (the t-value parameter that defines a CI) against the proportion of correctly predicted values for the *winning rebate*, r^W, and for the *difference between the maximum and the minimum rebate*, r^{diff}, within the subsamples IWS and EWS. Observations are randomly allocated to the EWS or to the IWS.

Figure 2 shows that the difference in the predictive ability of our model disappears when the two random subsamples are used. This difference is obtained only when the EWS is used.

4 A Theoretical Setting on Favoritism in Multidimensional SRA

We are concerned about why a large number of SRAs fail the tests described in Section 3.1. In these SRAs, the buyer pays a higher price than the price predicted by a standard model that considers the characteristics of the contract, the awarding mechanism used, and the degree of competition. We also observe that the probability of failing these tests is higher when the incumbent wins.

In this Section we show that our empirical results are coherent with a simple theoretical setting in which the buyer has information about the incumbent's characteristics and exploits them. Specifically, we consider a public buyer that has to procure a good or a service characterized by two qualities and the price. We assume the buyer adopts an SRA and faces two bidders. We compare two cases based on the type of informational asymmetry between the buyer and the bidders. In the first case, the buyer faces two new entrant suppliers whose production costs are not observable. In the second case, the buyer faces an incumbent supplier and a new entrant supplier. In the latter case, the buyer knows the incumbent's production costs but not the entrant's ones. The increased informational set leads the buyer to manipulate the weights for the two qualities in the scoring function. Such manipulation may favor the incumbent, depending on her production costs. If the incumbent wins, the resulting price the buyer pays is generally higher than the price the buyer would have paid if he had not known that supplier's type.

Let's assume the buyer has the following utility function:

$$U(Q, p) = q_1 + q_2 - p \tag{5}$$

where p is the price the buyer has to pay to the supplier for a service of quality $Q = \{q_1, q_2\}$. To award the service, the buyer adopts the following scoring rule mechanism:

$$t_j = a_1 q_{1j} + a_2 q_{2j} - p_j \tag{6}$$

which weights each bid $B_j = \{q_{1j}, q_{2j}, p_j\}$ and includes a linear combination with positive coefficients (a_1, a_2), with $a_i > 0 \; \forall i \in \{1, 2\}$. The bidder j with the highest score t_j wins the auction. The supplier's profit from selling the service is given by the difference between the price p_j and its cost $C_j(Q_j, \theta_j)$, where $\theta_j = (\theta_{1j}, \theta_{2j})$ is the bidimensional supplier j type. The supplier's efficiency in providing the two non-monetary quality components of the bid is inversely proportional to the cost: the higher the supplier's type, the lower her cost. θ_{1j} and θ_{2j} are *i.i.d.* according to a uniform distribution on the interval $(0, 1]$. As a result, the joint distribution of θ_j equals the product of the two marginal distributions. The bidders' types are private information; that is, each bidder knows its type but only the type's distribution of its opponent in the auction.

Finally, for any positive level of quality, the bidder's cost function is quadratic and separable in the two qualities:

$$C_j(Q_j, \theta_j) = \sum_{i=1}^{2} \frac{1}{\theta_{ij}} q_{ij}^2 . \tag{7}$$

Consider now two cases of informational asymmetry between the buyer and the two bidders. In the first case, the two bidders are entrant suppliers, and the buyer

	Choice	Choice
	a_1, a_2	$p_j,\ q_{1j}, q_{2j}$
TIME	$- \ - - -1 - -- \ - \ - - -2 - - \longrightarrow$	
PLAYER	Buyer	Bidders

Figure 3: Timing of the game.

does not know their types. In the second case, the first bidder, I, is the incumbent supplier, and the second bidder, E, is an entrant supplier. The buyer knows the type $\bar{\theta}_I = (\theta_{1I}, \theta_{2I})$ of the incumbent I, but he does not observe the type $\theta_E = (\theta_{1E}, \theta_{2E})$ of the entrant E. For both the first and the second case, the timing of the game and agents' choices at each stage are described in Figure 3.

The formal solution of this simple setting is presented in the Appendix and in what follows we sketch the derivation of its solution and discuss the main results.

Moving by backward induction, we start with stage 2, where equilibrium bids can be derived following Asker and Cantillon (2008).[24] Accordingly, an SRA is equivalent to an FPA in which each bidder's private value is given by her *pseudotype*, that is, by "*the maximum level of social surplus that* a *supplier can generate, given her cost function and the scoring rule chosen*".[25] Thus, define $k(\theta_j)$ the pseudotype for bidder j as follows:

$$k(\theta_j) = \max_{q_{1j}, q_{2j}} a_1 q_{1j} + a_2 q_{2j} - C_j(Q_j, \theta_j). \tag{8}$$

Define $Q_j^{\star}(\theta_j) = (q_{1j}^{\star}(\theta_{1j}), q_{2j}^{\star}(\theta_{2j}))$ as the vector that maximizes the pseudotype and includes the levels of the two qualities $q_{1j}^{\star}$ and $q_{2j}^{\star}$. For each bidder j it is a weakly dominant strategy to offer $Q_j^{\star}$ as the quality component of her bid (Asker and Cantillon 2008). In our setting, which assumes a quadratic cost function, the pseudotype becomes a linear combination of $(\theta_{1j}, \theta_{2j})$: thus, both its distribution

24 To define the equilibrium condition in a scoring auction, Asker and Cantillon (2008) consider a scoring rule, in the form $s(Q)$-p, that is quasi-linear in price and strictly increasing in quality. Our fully linear scoring rule is consistent with their approach. In both Asker and Cantillon and our setting, costs are independent across qualities and convex on individual quality, bidders do not know their opponents' type, and the buyer commits to the auction's result. Note that the function $Q^{FB}(\theta_j) = \max\{U(Q, p) - C(Q, \theta_j)\}$, where FB stands for "First Best," has a unique and well-defined maximum. See also Hanazono, Nakabaiashi, and Tsuruoka (2015) for a more general discussion of equilibrium bidding behavior in SRAs.

25 Asker and Cantillon (2008), p. 73.

(by convolution) and the equilibrium scores can be derived. Then, we can also obtain the bids' price components as the residual in the scoring rule function. In stage 1, the buyer chooses a_1 and a_2 with the aim of maximizing his expected utility $\mathbb{E}[U(\theta_1, \theta_2)]$. Considering the case in which no incumbent (NI) enters the auction, the buyer's expected utility is:

$$\mathbb{E}\left[U(\theta_1, \theta_2)^{NI}\right] = \mathbb{E}\left[t^{WIN}(k(\theta_1, \theta_2))\right] + \frac{1}{2}\sum_{i=1}^{2}\left((1-a_i)a_i\mathbb{E}\left[\theta_i^{WIN}\right]\right) \tag{9}$$

where $\mathbb{E}[t^{WIN}(k(\theta_1, \theta_2))]$ is the expected score provided by the winning bidder, and it is equal to the expected revenue of the equivalent FPA in the pseudotypes. By the Revenue Equivalence Theorem, such expected revenue is equal to the minimum order statistic of the pseudotype, as there are two bidders in the auction. Finally, $\mathbb{E}[\theta_i^{WIN}]$ is the winner type θ_i^{WIN}, $i \in \{1, 2\}$, in expectations.

Considering the case in which the incumbent (I) enters the auction, the buyer's expected utility is:

$$\mathbb{E}\left[U(\theta_1,\theta_2)^{I}\right] = \Pr(I\,win)\cdot U(\theta_{1I}, \theta_{2I}) + [1-\Pr(I\,win)]\cdot\mathbb{E}\left[U(\theta_{1E},\theta_{2E})\middle| k(\theta_E) > k\left(\bar{\theta}_I\right)\right] \tag{10}$$

where $\Pr(I\,win)$ is the probability that I wins the auction, $U(\theta_{1I}, \theta_{2I})$ is the utility the incumbent supplier provides if she wins, and $\mathbb{E}[U(\theta_{1E}, \theta_{2E})|k(\theta_E) > k(\bar{\theta}_I)]$ is the expected utility provided by the entrant, conditional on her pseudotype $k(\theta_E)$ being greater than that of the incumbent $k(\bar{\theta}_I)$.

4.1 Results

In this subsection we present our results from the theoretical setting above referring, first, to the optimal scoring rule in the absence or presence of an incumbent. Then, we compare the price the buyer pays in both the cases.

Result 1: *Optimal scoring rule in the absence of an incumbent* – Define (a_1^{NI}, a_2^{NI}) as the optimal weights for the scoring rule t in the case the incumbent does not enter the auction. In our setting, the buyer chooses $a_1^{NI} = a_2^{NI} = \frac{37}{51}$. The optimal scoring rule produces a level of quality below what could have been obtained under full information. The optimal mechanism under informational asymmetry reduces the supplier's quality and internalizes the buyer's cost of information.[26]

Result 2: *Optimal scoring rule in the presence of an incumbent* – Define (a_1^I, a_2^I) as the optimal weights for the scoring rule t in the case where an incumbent of type

26 This result is in line with Che (1993).

$\bar{\theta}_I = (\theta_{1I}, \theta_{2I})$ enters the auction. Accordingly, the buyer exploits his additional information on the incumbent and manipulates the scoring auction, as compared to (a_1^{NI}, a_2^{NI}). Suppose, without loss of generality, that $\theta_{1I} > \theta_{2I}$. Then, the new scoring rule favors the incumbent if $a_1 > a_2$, i.e., if the buyer assigns a higher weight to quality q_1, where I has the greatest cost-efficiency, and a lower weight to quality q_2. Note that the higher a_1, the more likely the supplier I will win the auction, and the larger I's market power and price will be.

Figure 4a plots the difference $\Delta_a = (a_1^I - a_2^I)$ as a function of the bidimensional incumbent's type. We represent in red all the cases where $\Delta_a > 0$ and $\theta_{1I} > \theta_{2I}$ *or* $\Delta_a < 0$ and $\theta_{1I} < \theta_{2I}$. In all these cases, the incumbent is favored by (a_1^I, a_2^I). We represent in gray the cases where $a_1^I = a_2^I$, and in green all the optimal scoring mechanisms where the incumbent is penalized by (a_1^I, a_2^I). Recall that, if no incumbent enters the auction, $\Delta_a = 0$. Figure 4a shows the manipulation in the scoring rule when the buyer observes $\bar{\theta}_I$, and highlights that the buyer favors the incumbent when this supplier is not efficient, that is when the combined value of $\theta_{1I} \cdot \theta_{2I} \in [0, 1]$ is sufficiently low.[27]

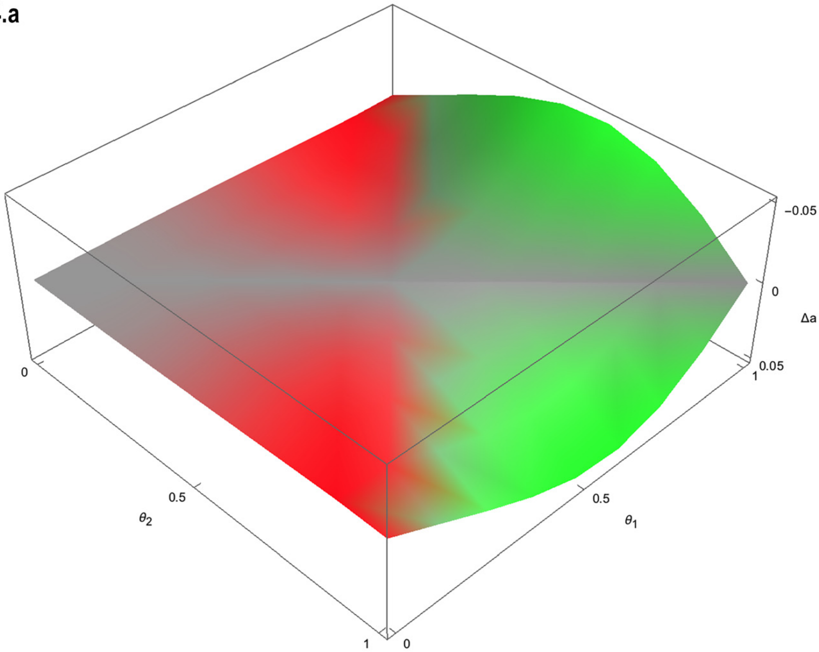
Result 3: *Price in the presence and absence of an incumbent* – We compare the price $p(a_1^I, a_2^I, \bar{\theta}_I)$ an incumbent of type $\bar{\theta}_I$ sets under (a_1^I, a_2^I), with the price $p(a_1^{NI}, a_2^{NI}, \bar{\theta}_I)$ the same supplier $\bar{\theta}_I$ would have set under the awarding mechanism (a_1^{NI}, a_2^{NI}). Figure 4b plots the difference $\Delta_p = p(a_1^I, a_2^I, \bar{\theta}_I) - p(a_1^{NI}, a_2^{NI}, \bar{\theta}_I)$ as a function of the bidimensional incumbent's type. We represent in red all the cases in which this difference is positive, that is, when the price the buyer pays under (a_1^I, a_2^I) is higher than the one he would have paid if he had not known that supplier's type. These cases account for about 75% of all possible incumbents' types, all but the most cost-efficient ones in θ_1 and θ_2. Finally, the cases where Δ_p is negative are shown in green.

These findings – shown in Figures 4a and 4b – illustrate that the buyer's manipulation of the SRA generally leads to the incumbent winning the auction with an higher price. Differently, in presence of an efficient incumbent, i.e., when both θ_{1I} and θ_{2I} record high values, such outcome does not occur.

In general, when the buyer knows the incumbent's type, he faces a trade-off in setting the optimal scoring rule: on the one hand, he can reduce the incumbent's

27 It is not possible to find an explicit solution for the values of a_1^I, a_2^I that maximize (9), depending on the incumbent's type. Figures 4a and 4b below are obtained via global numerical maximization techniques, considering 81 types of incumbents (in steps of $\frac{1}{8}$ for each θ_{iI}, $i \in \{1, 2\}$). Table A2 in the Appendix reports a group of numerical results used to construct Figures 4a and 4b.

4.a


−0.05
0
Δa
0.05
0
0.5
θ_2
1
0
0.5
θ_1
1

4.b

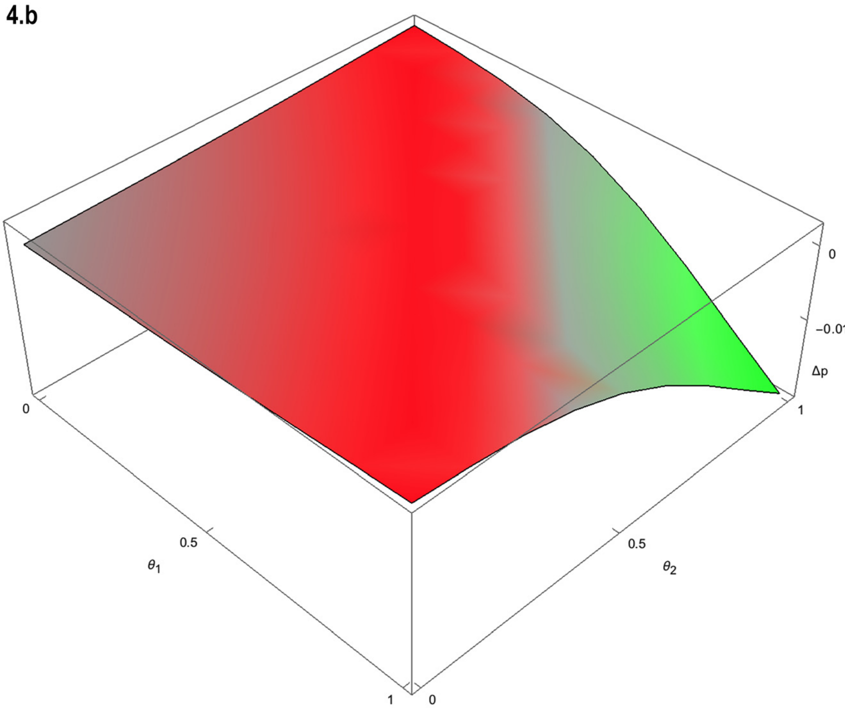

0
−0.01
Δp
0
0.5
θ_1
1
0
0.5
θ_2
1

Figure 4: (a) Changes in the scoring rule in the presence of an incumbent. (b) Changes in the price in the presence of an incumbent. Figure 4a plots, on the single vertical axis, Δ_a as a function of the bidimensional incumbent's type, θ_{1I} and θ_{2I}, on the two horizontal axes. We represent in red all the cases where $\Delta_a > 0$ and $\theta_{1I} > \theta_{2I}$ or $\Delta_a < 0$ and $\theta_{1I} < \theta_{2I}$. We represent in gray all the cases where $\Delta_a = 0$, and in green all the cases where $\Delta_a > 0$ and $\theta_{1I} < \theta_{2I}$ or $\Delta_a < 0$ and $\theta_{1I} > \theta_{2I}$. Figure 4b plots, on the single vertical axis, Δ_p as a function of the bidimensional incumbent's type, θ_{1I} and θ_{2I}, on the two horizontal axes. We represent in red all the cases where $\Delta_p > 0$, in gray all the cases where $\Delta_p = 0$, and in green all the cases where $\Delta_p < 0$.

market power by decreasing the weight of the quality where the incumbent is more cost-efficient; on the other hand, he can obtain a high level of quality by increasing that weight. When the incumbent is efficient and the quality provided is already high, reducing the incumbent's market power becomes the buyer's prevailing concern. Differently, when the incumbent is inefficient, increasing the quality provided becomes the buyer's most important goal; to pursue this goal, the buyer increases in the scoring rule the weight of the quality where the incumbent has the lowest production costs. In our simple theoretical framework, we got that the second effect prevails for all but the most cost-efficient incumbents. And the increase in the quality provision results in a higher procurement price.[28]

5 Conclusions

In this paper we study incumbents and entrants winning bids in multidimensional SRAs. We investigate a small, original database of 192 public procurement SRAs for canteen service contracts in Italy, awarded between 2009 and 2013. For these mechanisms, public buyers have discretion in choosing the weights of price and qualities in the scoring function.

The descriptive statistics and preliminary investigations of our database highlight that in 56% of our sample the winner is the incumbent supplier. In these auctions, the competition is lower and the price paid by the public buyer is higher, while the service's and buyer's characteristics and the overall importance given to quality in the SRA do not differ from the cases where the winner is the entrant.

In the aim to investigate this evidence, we run an econometric model on the auctions that are not awarded to the incumbent supplier to estimate their outcome

28 One may ask how our theoretical results could change with the different types of buyers (i.e., elected, semiautonomous, or administrative bodies) in our dataset. We suggest that our results would be stronger the higher the relevance of quality in the buyer's objective function. This seems to be the case in our database for buyers under electoral scrutiny, as the empirical analysis highlights.

as a function of the contract's and the buyer's characteristics, the awarding mechanism used, and the degree of competition. We use the predicted values of our model to construct two tests and apply them to the whole dataset. These tests are failed if the observed values do not fall within a given confidence interval of the predicted values. We find that auctions the incumbents win are significantly more likely to fail our tests, showing a higher-than-predicted awarding price. These results are confirmed by a number of robustness checks. In particular, detailed investigations lead us to reject an "endogenous entry story" in auctions, which suggests that winning prices are higher in procedures where a strong incumbent deters entry and reduces competition.

To explain our empirical findings, we then develop a simple theoretical setting in which a public buyer – who knows the characteristics of the incumbent supplier – designs the awarding mechanism in a way that differs from what he would have done if this additional information was not available. The increased informational set leads the buyer to alter the design of the scoring rule. In particular, the new awarding mechanism favors the incumbent if the buyer in the scoring rule assigns a higher weight to the quality where the incumbent has the greatest cost-efficiency. It turns out that this is the case if the combined efficiency of the incumbent in providing both qualities is sufficiently low. Our theoretical setting shows that, if the incumbent wins the auction (and she is not the most efficient incumbent), the buyer pays a higher price than he would have paid if he had not known that supplier's type.

Taken together, our empirical and theoretical results suggest that public buyers can easily distort multidimensional SRAs: the buyer's bias toward an incumbent supplier could annihilate competition and its potential positive effects. This finding is enlightening since SRAs are increasingly adopted in many countries' public procurement.[29] Moreover, even if the buyer's favoritism toward the incumbent supplier is not an issue, the design of the scoring function deserves particular attention because it may reduce competition, albeit in a different way. As Che (1993) points out, a large weight assigned to quality in SRA could provide excessive market power to the most efficient firm because of information rent. To reduce such a potential distortion, a regulator in charge of monitoring the procurement process could routinely adopt the methodology we develop in Section 3 to check for SRAs' correct design and implementation.

29 The EU directive 2014/24/EU supports the adoption of the so called "most economically advantageous tender" (MEAT) based on both quality and price, in the place of the "lowest price tender". In Italy, a similar support is included in the New Code on public procurement (Italian Legislative Decree 50/2016).

Appendix A

The model of Section 4 is solved via backward induction starting from stage 2.

A.1 Stage 2

In stage 2, we define the equilibrium bid $B_j = \{q_{1j}, q_{2j}, p_j\}$ for two generic bidders $j \in \{1, 2\}$.[30] As a convention, we refer to the buyer using "he" and to each bidder using "she".

Following Asker and Cantillon (2008), consider bidder j who has won the contract with a score to fulfill t_j^W. She chooses q_{1j}, q_{2j}, p_j, given the score submitted t_j^W, to maximize her profit:

$$\max_{Q_j, p_j} \pi_j = p_j - \sum_{i=1}^{2} \frac{1}{\theta_{ij}} q_{ij}^2 \tag{11}$$

$$s.t.\ t_j^W = \sum_{i=1}^{2} a_i q_{ij} - p_j .$$

Replace p_j in the objective function to obtain:

$$\max_{Q_j} \sum_{i=1}^{2} \left(a_i q_{ij} - \frac{1}{\theta_{ij}} q_{ij}^2 \right) - t_j^W . \tag{12}$$

An important feature here is that, in equilibrium, the optimal provision of quality q_{ij} for bidder j is independent from t_j^W. For each bidder j, define the pseudotype $k(\theta_j)$ as:

$$k(\theta_j) = \max_{Q_j} \sum_{i=1}^{2} \left(a_i q_{ij} - \frac{1}{\theta_{ij}} q_{ij}^2 \right). \tag{13}$$

Solving the pseudotype maximization problem in (13), we obtain that, once the scoring rule is fixed, in equilibrium the quality decision q_{ij} of bidder j depends only on the bidder's ability θ_{ij} in that specific quality dimension. The optimal decision of bidder j for quality i is:

$$q_{ij}^{\star} = \frac{1}{2} a_i \theta_{ij} . \tag{14}$$

30 Bidders' informational set is not modified by the participation of the incumbent supplier in the auction.

The set of pseudotypes is an interval in $\mathbb{R}$, and the density inherits the smooth property of θ_j (that is distributed according to a continuous joint density function). Replacing (14) in (13), the maximized pseudotype becomes:

$$k(\theta_j) = \sum_{i=1}^{2} \frac{1}{4} a_i^2 \theta_{ij} . \tag{15}$$

The use of a quadratic cost function results in a pseudotype that can be expressed as a linear function of the random variables θ_1 and θ_2. Denote $\frac{1}{4}a_i^2 = c_i$, $i \in \{1, 2\}$, to ease notation. By convolution, the cumulative distribution function (CDF) of $k \in [0, (c_1 + c_2)]$ is given by the piecewise function depicted in Table A1. Six different cases are possible, depending on the value of c_1 and c_2 (i.e., a monotonic transformation of, respectively, a_1 and a_2) which can be recovered by solving the buyer's maximization problem in stage 1.

We then apply Asker and Cantillon's (2008) Theorem 1 and Corollary 1: the equilibrium bid (Q, p) in the scoring auction is equal to the equilibrium bid in an equivalent first price auction (FPA) where i) the bidders' private valuations are given by their pseudotypes and, ii) the bidders' scores are replaced by bidders' bids.[31] The equilibrium bid in the FPA with two bidders is given by:

$$t(k) = k - \frac{1}{F(k)} \int_0^k F(z) dz . \tag{16}$$

For all the resulting six cases, the equilibrium bids $t(k)$ are depicted in Table A1. We then proceed in defining the price component p_j of the bid $B_j = (q_{1j}, q_{2j}, p_j)$ submitted by player j. p_j is obtained as the residual component of the scoring function, where the quality provision has been replaced with its equilibrium value derived in (14):

$$p_j = 2k - t(k) . \tag{17}$$

A.1.1 The distribution of θ_{ij} for a given pseudotype

In equilibrium, a 1:1 relation exists between pseudotypes, scores and prices. That is, each pseudotype $k(\theta_j)$ bids a unique score t_j and a unique price p_j. The equilibrium quality $q_{ij}^{\star}$, defined in (14), depends only on the bidder's specific ability θ_{ij} to provide that quality. Hence, the same pseudotype – defined in (15) – may produce

31 Formally, the required conditions to apply Theorem 1 and Corollary 1 from Asker and Cantillon are: (i), a scoring function S such that $S : \mathbb{R}_+^3 \to \mathbb{R} : (p, q_1, q_2) \to S(p, q_1, q_2)$ and S can be expressed as $\phi(q_1, q_2) - p$, i.e., S is quasilinear in the price and, (ii), costs are independent across attributes and convex in individual attributes, that is $C_{q_i q_i} > 0, \forall i \in \{1, 2\}$ and $C_{q_i q_k} = 0, \forall i \neq k \cup i, k \in \{1, 2\}$.

different level of qualities $q^{\star}_{1j}$ and $q^{\star}_{2j}$ because different types $\theta_j = (\theta_{1j}, \theta_{2j})$ end up having the same pseudotype, depending on the scoring rule chosen by the buyer. For this reason, it is important to define the distribution of all the bidders' types θ_j that have a given pseudotype.

A couple $(\theta_{1j}, \theta_{2j})$ may have a pseudotype equal to k only if:

$$\begin{aligned} \theta_{1j} &\in (0, 1] \\ \theta_{2j} &\in (0, 1] \\ k &= c_1\theta_{1j} + c_2\theta_{2j}. \end{aligned} \tag{18}$$

Note that, for a given pseudotype k, it exists a 1:1 relation between θ_{1j} and θ_{2j}: once a value θ_{1j} is fixed, then only one value of θ_{2j} (at most) will be such that the pair $(\theta_{1j}, \theta_{2j})$ satisfies the three conditions above, and this interval is continuous. It follows that the distribution of θ_{ij}, $i \in \{1, 2\}$, conditional on (18), remains uniform and, to define its PDF and CDF, it is sufficient to find the minimum and maximum value of θ_{ij} such that all conditions in (18) are satisfied. Define those values as $\overline{\theta}_i(k)$ and $\bar{\theta}_i(k)$, $i \in \{1, 2\}$, respectively: we collect them in Table A1 below.

Specifically, for all $k \in [0, c_1 + c_2]$, Table A1 reports: (i) the conditions such that a specific case applies (Condition 1 and Condition 2); (ii) the CDF $F(k)$ of k; (iii) the bidding function $t(k)$; (iv) the maximum and the minimum values of θ_i, $i \in \{1, 2\}$ such that all conditions in (17) are satisfied. Finally, to ease notation, we have that $c_i = \frac{1}{4}a_i^2$, $i \in \{1, 2\}$.

A.2 Stage 1

A.2.1 Optimal SRA in the absence of the incumbent

When the incumbent supplier does not participate in the auction, the buyer has to choose the optimal mechanism a_1 and a_2 without any additional information on the bidders' types.

We replace the equilibrium quality provision (14) in the buyer's utility (5), and we express the latter as a function of the score (6) and of the bidder's type as follows:

$$U(\theta_j) = t(k(\theta_{ij})) + \frac{1}{2}\left(\sum_{i=1}^{2}(1 - a_i)a_i\theta_{ij}\right). \tag{19}$$

The expected utility of the buyer, $\mathbb{E}[U(\theta_1, \theta_2)^{NI}]$ is a function of (i) the expected score $\mathbb{E}[t^{WIN}(k(\theta_1, \theta_2))]$ of the winning bidder and, (ii), the expected type $\mathbb{E}[\theta_i^{WIN}]$,

Table A1: Conditions, CDF, scores, $\underline{\theta}_i(k)$ and $\bar{\theta}_i(k)$ in the 6 cases.

Case	1a	1b	2a	2b	3a	3b
Condition 1	$0 \le k \le c_2$	$0 \le k \le c_1$	$c_2 \le k \le c_1$	$c_1 \le k \le c_2$	$c_1 \le k$	$c_2 \le k$
Condition 2	$c_2 \le c_1$	$c_1 \le c_2$	$c_2 \le c_1$	$c_1 \le c_2$	$c_2 \le c_1$	$c_1 \le c_2$
$F(k)$	$\frac{k^2}{2c_1c_2}$		$\frac{2k-c_2}{c_1}$	$\frac{2k-c_1}{c_2}$	$1-\frac{(c_1+c_2-k)^2}{2c_1c_2}$	
$t(k)$	$\frac{2k}{3}$		$\frac{3k^2-c_2^2}{6k-3c_2}$	$\frac{3k^2-c_1^2}{6k-3c_1}$	$\frac{c_1^3+c_2^3+2k^3-3k^2c_1-3k^2c_2}{3c_1^2+3c_2^2+3k^2-6kc_1-6kc_2}$	
$\underline{\theta}_1(k)$	0		$\frac{k-c_2}{c_1}$	0	$\frac{k-c_2}{c_1}$	
$\bar{\theta}_1(k)$	$\frac{k}{c_1}$		$\frac{k}{c_1}$	1	1	
$\underline{\theta}_2(k)$	0		0	$\frac{k-c_1}{c_2}$	$\frac{k-c_1}{c_2}$	
$\bar{\theta}_2(k)$	$\frac{k}{c_2}$		1	$\frac{k}{c_2}$	1	

$i \in \{1, 2\}$, of the winning bidder. Both depend on the scoring rule chosen by the buyer, as follows:

$$\mathbb{E}\left[U(\theta_1, \theta_2)^{NI}\right] = \mathbb{E}\left[t^{WIN}(k(\theta_1, \theta_2))\right] + \frac{1}{2}\sum_{i=1}^{2}\left((1-a_i)a_i\mathbb{E}\left[\theta_i^{WIN}\right]\right). \tag{20}$$

By the Revenue Equivalence Theorem and by Theorem 1 and Corollary 1 in Asker and Cantillon (2008), and considering there are two bidders in the auction, the expected score of the winning bidder is equal to the expected value of the minimum order statistic of the pseudotype: $\mathbb{E}[t^{WIN}(k(\theta_1, \theta_2))] = \mathbb{E}[k_{MIN}]$.

Assume that $a_1 = a_2 = a$. Then, by algebraic manipulation and using the pseudotype function (15), (19) becomes:

$$U(k) = t(k) + 2\frac{1-a}{a}k. \tag{21}$$

Taking expectation, we get:

$$\mathbb{E}\left[U(\theta_1, \theta_2)^{NI}\right] = \mathbb{E}[k_{MIN}] + 2\frac{1-a}{a}\mathbb{E}[k_{MAX}] \tag{22}$$

where the expected pseudotype of the winning bidder is given by expected value of the maximum order statistic of the pseudotype, $\mathbb{E}[k_{MAX}]$. In the case $a_1 = a_2 = a$, then $\mathbb{E}[k_{MIN}] = \frac{23}{30} \cdot \frac{a^2}{4}$ and $\mathbb{E}[k_{MAX}] = \frac{37}{30} \cdot \frac{a^2}{4}$. The maximization of (22) yields $a_1 = a_2 = \frac{37}{51}$. To prove that this is a global maximum, in the cases where $a_1 \neq a_2$, $\mathbb{E}[t^{WIN}(k(\theta_1, \theta_2))]$ and $\mathbb{E}[\theta_i^{WIN}]$ can be numerically calculated, using the distributions in Table A1.

Comparison with quality provision under first best (full information) case

With full information, the buyer can offer a contract which maximizes his utility, subject to a zero profit condition. As a result, $p_j = C_j(Q_j, \theta_j)$, and the buyer now maximizes the following utility function:

$$\max_{Q_j} \sum_{i=1}^{2}\left(q_{ij} - \frac{1}{\theta_{ij}}q_{ij}^2\right). \tag{23}$$

Solving the maximization problem, we obtain:

$$q_{ij}^{FB} = \frac{1}{2}\theta_{ij}. \tag{24}$$

Quality provision from (24) is higher than the one under the optimal scoring rule obtained from equation (14), and corresponding to:

$$q_{ij}^{\star} = \frac{1}{2} \cdot \frac{37}{51}\theta_{ij}. \tag{25}$$

A.2.2 Optimal SRA in the presence of the incumbent

When the incumbent supplier participates in the auction, the buyer has to choose the optimal mechanism a_1 and a_2. The buyer will do such choice knowing the type of one of the two bidders in the auction.

The expected utility of the buyer is equal to:

$$\mathbb{E}\left[U(\theta_1,\theta_2)^I\right]=\Pr(I win)\cdot U(\theta_{1I},\theta_{2I})+[1-\Pr(I win)]\cdot\mathbb{E}\left[U(\theta_{1E},\theta_{2E})\middle|k(\theta_E)>k\left(\bar{\theta}_I\right)\right] \quad (26)$$

where $\Pr(I win)$ is the probability that I wins the auction; $U(\theta_{1I},\theta_{2I})$ is the utility provided by the incumbent supplier if she wins; $\mathbb{E}[U(\theta_{1E},\theta_{2E})|k(\theta_E)>k(\bar{\theta}_I)]$ is the expected utility provided by the entrant, conditional on the entrant's pseudotype $k(\theta_E)$ being greater than the incumbent's one $k(\bar{\theta}_I)$.

The probability that bidder $\bar{\theta}_I$ wins the auction is equivalent to the probability that the unobserved pseudotype $k(\theta_E)$ is lower than the observed pseudotype $k(\bar{\theta}_I)$, given the scoring rule chosen. It follows that:

$$\Pr(I win) = F\left(k\left(\bar{\theta}_I\right)\right) \quad (27)$$

where the CDF of the pseudotypes is depicted in Table A1. The utility provided by the incumbent supplier, if she wins the auction, is obtained replacing θ_{1I} and θ_{2I} – observed by the buyer – into the equilibrium quality (14) and price (17). To obtain $U(\theta_{1I},\theta_{2I})$, they are both replaced into the buyer's utility (5).

The expected utility provided by the entrant, conditional on the entrant pseudotype being greater than the incumbent's pseudotype, is:

$$\mathbb{E}\left[U(\theta_{1E},\theta_{2E})\,\middle|k(\theta_E)>k\left(\bar{\theta}_I\right)\right] = \frac{1}{1-F\left(k\left(\bar{\theta}_I\right)\right)}\int_{k\left(\bar{\theta}_I\right)}^{c_1+c_2} U(k(\theta_{1E},\theta_{2E}))\cdot f(k)dk \quad (28)$$

where $f(k)$ is the PDF of the pseudotypes. Using (14), (17) and (5), Equation (28) becomes:

$$\mathbb{E}[U(\cdot)] = \frac{1}{1-F\left(k\left(\bar{\theta}_I\right)\right)}\int_{k\left(\bar{\theta}_I\right)}^{c_1+c_2}\left(\sum_{i=1}^{2}\left(\int_{\underline{\theta}_i(k)}^{\bar{\theta}_i(k)}\frac{a_i\theta_{iE}}{2}\frac{1}{\bar{\theta}_i(k)-\underline{\theta}_i(k)}d\theta_{iE}\right)\right.$$
$$\left.-(2k-t(k))\right)f(k)dk. \quad (29)$$

In equation (29) we consider all pseudotypes k such that $k>k(\bar{\theta}_I)$, weighted for the PDF of k. Additionally, when calculating the quality provision from (14), we consider all the couples $(\theta_{1E},\theta_{2E})$ that, for each pseudotype and given the scoring function (a_1,a_2), satisfy the conditions in (18). Each quality provision is then

Table A2: Numerical results for Figure 4a and 4b.

θ_{1I}	θ_{2I}	a_1^I	a_2^I	$p(a_1^I, a_2^I, \bar{\theta}_I)$	$p(a_1^{NI}, a_2^{NI}, \bar{\theta}_I)$
0	0	0.7328	0.7328	0	0
0	0.25	0.7328	0.7330	0.0224	0.0219
0	0.50	0.7326	0.7337	0.0449	0.0439
0	0.75	0.7324	0.7350	0.0675	0.0658
0	1	0.7335	0.7359	0.0903	0.0877
0.25	0	0.7330	0.7328	0.0224	0.0219
0.25	0.25	0.7332	0.7332	0.0448	0.0439
0.25	0.50	0.7333	0.7345	0.0674	0.0658
0.25	0.75	0.7341	0.7360	0.0902	0.0877
0.25	1	0.7487	0.7221	0.1070	0.1058
0.50	0	0.7337	0.7326	0.0449	0.0439
0.50	0.25	0.7345	0.7333	0.0674	0.0658
0.50	0.50	0.7352	0.7352	0.0901	0.0877
0.50	0.75	0.7366	0.7239	0.1070	0.1058
0.50	1	0.7468	0.6973	0.1164	0.1191
0.75	0	0.7350	0.7324	0.0675	0.0658
0.75	0.25	0.7360	0.7341	0.0902	0.0877
0.75	0.50	0.7239	0.7366	0.1070	0.1058
0.75	0.75	0.7136	0.7136	0.1152	0.1191
0.75	1	0.7177	0.6744	0.1176	0.1280
1	0	0.7359	0.7335	0.0903	0.0877
1	0.25	0.7221	0.7487	0.1070	0.1058
1	0.50	0.6973	0.7468	0.1164	0.1191
1	0.75	0.6744	0.7177	0.1176	0.1280
1	1	0.6667	0.6667	0.1111	0.1316

weighted for the PDF of a given couple $(\theta_{1E}, \theta_{2E})$ with a pseudotype k, i.e., $f(\theta_{ij} | k = k(\theta_j)) = \frac{1}{\bar{\theta}_i(k) - \underline{\theta}_i(k)}$ (see Section 6.1.1).

We replace (29) and (27) in (26). For a given incumbent's type, the only unknown variables in (26) are a_1, a_2. As a result, the maximization of (26) is obtained via a global numerical maximization algorithm. Finally, for each incumbent's type, the maximization has to consider all the 6 possible cases in Table A1.

A.3 Numerical results

Table A2 shows a group of numerical results used to construct Figures 4a and 4b. We report 25 types of incumbents (in steps of $\frac{1}{4}$ for each θ_{iI}, $i \in \{1, 2\}$), the values of a_1^I, a_2^I that maximize (10), the resulting $p(a_1^I, a_2^I, \bar{\theta}_I)$ and $p(a_1^{NI}, a_2^{NI}, \bar{\theta}_I)$. Results for 81 types of incumbents, in steps of $\frac{1}{8}$ for each θ_{iI}, $i \in \{1, 2\}$ are available upon request.

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