Auctions vs Negotiations in Public Procurement Which Works Better?

Rafael Lalive and Armin Schmutzler and Christine Zulehner*

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Abstract

Public agencies rely on two key modes to procure goods and services: auctions and direct negotiations. The relative advantages of these two modes are still imperfectly understood. This paper therefore studies public procurement of regional passenger railway services in Germany, where regional agencies can use auctions and negotiations to procure regional passenger rail services. This offers the unique opportunity to assess the two procurement modes within the same institutional and legal framework. We first characterize the decisions of the agency in a simple reduced form framework of negotiations and auctions. This analysis suggests accounting for the endogeneity of the choice of procurement mode by estimating the mode of procurement, quantity and price simultaneously. We then test this framework using information on lines that were auctioned and lines that were directly negotiated with the former monopolist. Results indicate (i) endogeneity of procurement choice can be fully characterized by observed line characteristics; (ii) frequency of service is 16 percent higher on lines that were auctioned compared to lines that were negotiated, and (iii) the procurement price is 25 percent lower on auctioned lines than on those with direct negotiations. Taken together, these results indicate a significant efficiency enhancing effect of auctions.

Keywords: Auctions, negotiations, liberalization, passenger railways, public procurement

JEL Classification: D43,D44,R48

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1 Econometric Framework

Our econometric approach has four parts. We start by investigating quantities. We run OLS regressions and explain optimal quantities by line characteristics. We distinguish between negotiated and auctions lines, and use predicted values for counterfactual outcomes. We then analyze the prices from the negotiations. Again, we use OLS regressions and regress prices on line characteristics. The regression equation is then the basis for out-of-sample predictions. In this way, we obtain predicted prices that would have been the outcome of negotiations for the sample where we actually observe auctions. The next part of our analysis describes the determinants of winning bids from the auctions. We use a structural auction model to obtain an estimate for firms' bid distribution and to back out firms' cost. Again, we form out-of-sample predictions. In this case, we obtain predicted prices (winning bids) that would have been the outcome of auctions for the sample where we actually observe negotiations. Finally, based on the optimality condition from the Nash bargaining, we finally estimate a linear probability model to obtain estimates for the parameter τ measuring the bargaining power of the incumbent and the cost of the agency to run an auction, i.e., φ.

1.1 Prediction of Quantities and Negotiated Prices

For each set of observations (auctions and negotiations), we fit a linear regression model to log quantities, i.e.,

$$\log q_i = \alpha_0 + \alpha_X X, \tag{1}$$

where X denotes the set of line characteristics, α_0 and α_X are the parameters to be estimated. We denote the predictions with $\log \hat{q}_{negs}$ and $\log \hat{q}_{bids}$. Based on these estimates, we are able to calculate the surplus $\hat{s}_{negs}$ and $\hat{s}_{bids}$ using equation XX.

According to our model on negotiations, the incumbent sets a price equal to highest cost $c + y$. In the empirical model, we fit a linear regression model, i.e.,

$$\log p_i = \beta_0 + \beta_X X, \tag{2}$$

where X denotes the set of line characteristics, β_0 and β_X are the parameters to be estimated. We denote the predictions with $\log \hat{p}_{negs} \equiv \widehat{c+y}$.

1.2 Estimation of Bid Distribution and Bidders' Costs

For the empirical analysis of the sealed-bid auctions, we use data on winning bids and are interested to estimate the distribution of firms' bids and costs. Our econometric auction model follows the approach developed by Guerre, Perrigne and Vuong (2000). They suggest to estimate the distribution of bids in a first

step and to recover the distribution of bidders' costs in a second step by using the first order-condition for optimal bidding behavior. With the estimates of the distribution of bidders' bids and costs at hand, we can then make out-of-sample predictions.

We assume that the set of line characteristics X is known to the econometrician and the bidders. Such an assumption precludes the existence of characteristics unknown to the econometrician, but known to bidders. Bidders know their private cost c_i. We denote the distribution of bidders' costs as $F(\cdot|X)$, and assume that bidders' costs are independent conditional on X. Given these assumptions, one can write the distribution of bids as $G(\cdot|X, N)$. Following Guerre, Perrigne and Vuong (2000), the first order condition for i's bidding problem is

$$c_i \equiv b_i - \frac{1}{N-1}\frac{1-G(b_i; X, N)}{g(b_i; X, N)}, \tag{3}$$

where $G(b; X, N) = F(b_j^{-1}(b; X, N))$ is the probability that j will bid less than b and $b_j^{-1}(b; X, N) = c_j$. This provides the basis for estimating bidders' cost distributions.

Distribution of Bids. To obtain an estimate for the distribution of bidders' cost, Guerre, Perrigne and Vuong (2000) propose to estimate the distribution of bids first and back out cost then. Their approach is very general and allows the non-parametric identification and estimation of the distribution of bidders' cost. Here, we adopt a parametric approach and take into account that our sample includes winning bids only. Conditional on the observable auction characteristics X and the number of bidders N, the joint distribution of bids in a given auction is the distribution $G(\cdot|X, N)$. We specify the Weibull distribution as the distribution of bids:

$$G(b_i|X, N) = 1 - \exp\left\{-\left(\frac{b_i}{\lambda(X, N)}\right)^{\rho(X,N)}\right\}, \tag{4}$$

where $\lambda(X, N)$ is the scale and $\rho(X, N)$ is the shape of the Weibull distribution. We parameterize the scale as $\lambda(X, N) = \lambda_0 + \lambda_X X + \lambda_N N$ and the shape as $\rho(X, N) = \rho_0 + \rho_X X + \rho_N N$. We estimate the parameters of the model, (λ, ρ), by maximum likelihood. As we observe winning bids only, we use the (log) density of the first-order statistic of a Weibull distribution.[1]

Distribution of Costs. Assuming bidders behave as predicted by the theoretical auction model, the distribution $F(\cdot|X)$ is identified from the distribution of observed winning bids.[2] The advantage of this approach is that no differential equation has to be solved and no numerical integration has to be applied. The estimation of bidders' costs is directly derived from equation 3.

Expected Winning Bids. To predict winning bids in-sample and out-of-sample, we calculate the expectation of the first-order statistic of a Weibull distribution, i.e.,

$$\hat{b}_{[1]} \equiv \mathbb{E}[b_{[1]}] = N\hat{\lambda}(X, N)\left(\frac{1}{N}\right)^{\left(\frac{1}{\hat{\rho}(X,N)}+1\right)}\Gamma\left(\frac{1}{\hat{\rho}(X, N)} + 1\right), \tag{5}$$

[1] Here, the first-order statistic is the lowest of N random variables $X = (X_1, \ldots, X_N)$. The density of this statistic is $h(x_{[1]}) = \frac{n!}{(n-1)!}(1 - G(x))^{(N-1)}g(x)$, where $x_{[1]}$ ist the lowest value of the random variables, G is the distribution function of the random variable X and g the density function. See for example, XX for more information on order statistics.

[2] For a discussion on identification in first-price auctions, see Athey and Haile (2006).

where $\mathbb{E}[b_{[1]}]$ is the expected winning bid, Γ the gamma function, and $\hat{\lambda}(X, N)$ and $\hat{\rho}(X, N)$ are the estimated scale and shape of the Weibull distribution.[3]

1.3 Determinants of Procurement Choice

Using the optimal conditions for Nash bargaining under negotiations and under auctions, we are able to set up a linear probability model to estimate the parameter τ measuring the bargaining power of the incumbent and the cost of the agency to run an auction, i.e., φ. The optimal values XX (ref to equation in theory part) under negotiations and XX (ref to equation in theory part) under auctions depend on these two parameters. The agency chooses an auction, if the received welfare under auctions is larger than the welfare under negotiations. This condition forms the basis of the linear probability model and is equal to

$$\tau \log \varphi + \tau \log \left(\frac{\log \frac{\hat{s}_{bids}}{\hat{b}_{[1]}} - 1}{\log \frac{\hat{s}_{negs}}{\widehat{c+y}} - 1} \right) + (1-\tau) \log \left(\frac{(\hat{b}_{[1]} - \hat{c}_{[1]})(\widehat{c+y})}{\hat{y} N \hat{b}_{[1]}} \right) > 0, \tag{6}$$

where $\hat{c}_{[1]}$ are the estimated (backed out) cost of the winning bidder, $\hat{y}$ the mean value of the cost interval[4] and τ and φ the parameters to be estimated.[5]

The second model assumes that the surplus enters the welfare function not in logs, but with the square root. The respective linear probability model has to be adjusted and is equal to

$$\log \left(\frac{(\widehat{c+y})}{\hat{b}_{[1]}} \right) + \tau \log \varphi + (1-\tau) \log \left(\frac{(\hat{b}_{[1]} - \hat{c}_{[1]})(\widehat{c+y})}{\hat{y} N \hat{b}_{[1]}} \right) > 0, \tag{7}$$

where again τ and φ are the parameters to be estimated.

2 Data

The empirical analysis uses information on service quantity and procurement prices. We first require a measure of the service quantity on a line. We use the *frequency of service,* the ratio between train kilometers per year (tkm) and the length of a line (lkm).[6] We chose its value in the year 2004 on a particular line as the quantity to be explained, but we also included a lagged frequency of service (for 1994) as a control variable. The division of the network into different lines follows the 2004 timetable.[7]

We do not have data that measure aspects of service quality such as punctuality, comfort, etc. However, while we believe it would be interesting in itself to see how these variables are affected by competition, we

[3] For the calculation of the expectation, see Appendix XX.

[4] We calculate this value by taking the arithmetic mean between the predicted upper limit of the cost interval, i.e., $\widehat{c+y}$, and the predicted lower limit of the interval, i.e., $\min(\hat{c}_{[1]})$.

[5] Note that the term s drops out once we divide XX (ref to equation in theory part – negotiations) by XX (ref to equation in theory part – auctions) as consumers' willingness to pay for a line does not change in the counterfactual.

[6] Thus, the frequency of service corresponds to the average number of trains per year on each kilometer of tracks.

[7] Some adjustments were necessary, however, to avoid double-counting of trains. Lines that were closed down between 1994 and 2004 were not included.

do not expect competition to affect quality strongly. For one thing, many aspects of quality are narrowly specified in most contracts. For another, to the extent that there is flexibility in the choice of quality, anecdotal evidence does not suggest there is lower quality on the competitive lines.

To identify competition effects, we classified lines as competitive if at least 20% of the services were procured competitively.[8] Clearly, the fact that a line is served competitively says nothing about ownership: If *DB Regio* has won a line in a competitive tender, then the line is defined as competitive even though the owner is the incumbent. Conversely, but much less importantly, a few small lines are served by other companies, but have been procured by direct negotiations. We discuss the role of ownership and auctions in a separate analysis below.[9]

Apart from these basic variables, we added further controls, corresponding to the line characteristics discussed in Section 1. These characteristics are mostly determined by geography. We consider the geographic distance to the nearest city with at least 100,000 inhabitants as a measure of remoteness. We also include the number of inhabitants of both the largest and the second-biggest city served by the line in 1994. We do not condition on the number of inhabitants in 2004 since frequency of service may affect population growth along a line. We discuss the role of auctions in affecting population below. Finally, we include dummies for the agency that procures the railway services.

Obtaining information on the procurement prices is difficult. We were able to get information on procurement prices of the winning bid in auctions from a firm that is specialized in consulting on regional passenger train service (*Nahverkehrsberatung Südwest, Heidelberg, Felix Berschin).* This data contains information on prices for 63 of the 138 competitively procured lines in the sample. We have studied whether these lines represent a selected sample but, conditional on the observed line characteristics, we did not find any differences between the lines with price data and lines without price data.[10]

The prices resulting from direct negotiations are publicly available but only quoted at the state level. We construct individual line specific estimates of the negotiation price as follows. As usual in network industries, the downstream firms have to pay access fees to the network owner, which almost always is *DB Netz*. These access fees, which constitute a substantial part of the costs of downstream firms, vary considerably across lines. We reconstruct negotiation prices to reflect the access fee along with a region specific cost component so as to match the quoted state level price (see the Appendix for details).[11]

[8] We also included lines of the following – comparatively rare – types: (i) Services were procured on the basis of offers from at least two firms that were approached directly by the agency; (ii) Apart from the incumbent, at least one firm offered a contract to the agency without having been asked to do so. (iii) A competitor took over the infrastructure and the task of running services from *DB Regio* for a symbolic price (see Lalive and Schmutzler (2008) for examples).

[9] In analogy to our definition of competitive lines, we define a line as operated by DB Regio if at most 20% of the services were run by competitors.

[10] We have also explored another source of data on prices. The official source of the European Union, the databank *Tender Electronic Daily*, contains useful information on which lines were grouped together in a particular auction and what the overall volume of the contract is. Procurement price data are only available in some cases.

[11] We are grateful to DB Netz for providing us with information on the access charges.

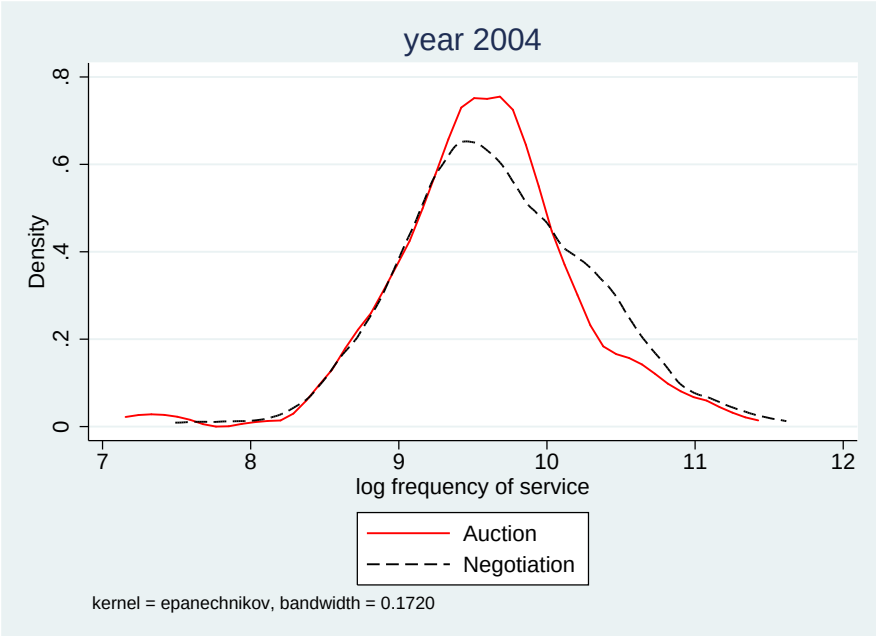
3 Empirical Results

We now present our main observations about frequency of service and procurement prices on lines that were negotiated and on lines that were auctioned. In the following, we compare auctions and direct negotiations in an econometric analysis based on the model of Section 1.

3.1 Descriptive Statistics

Figure 1 displays kernel density estimates of the distribution of frequency of service in 2004 for two sets of lines: lines that were auctioned between 1994 and 2004 as opposed to lines that were negotiated directly with the incumbent supplier. The main difference is that the auctioned group contains relatively fewer lines with very high frequency of service and more lines with medium frequency of service. In itself, this observation does not lend itself to a clear interpretation. It could reflect a pure selection effect or a causal effect that competition stifles growth.

Figure 1: Frequency of Service by Procurement Mode, in 2004



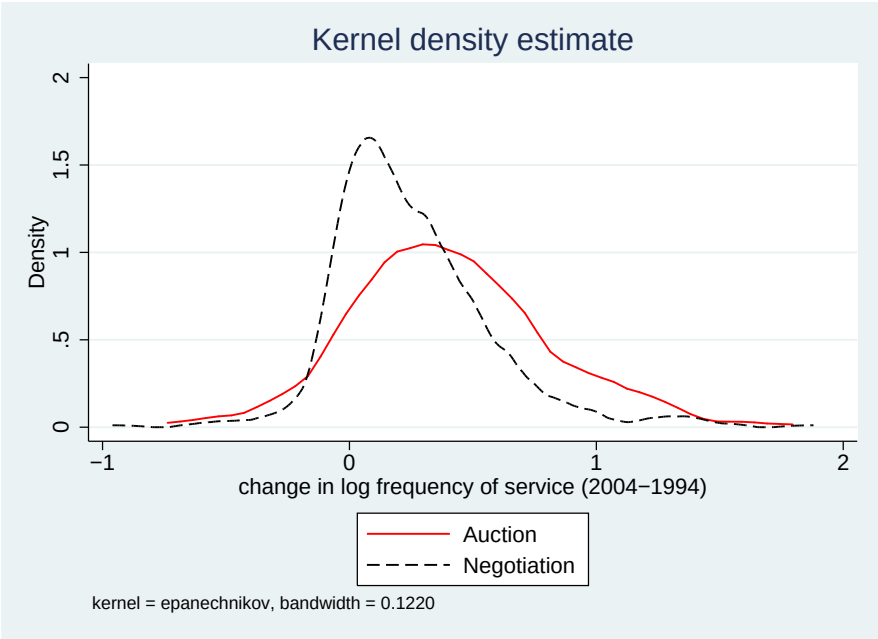
Notes: Figure displays log train kilometers per line kilometers in the timetable year 2003/2004. Auction means the services on the line were auctioned between 1994 and 2004. Negotiation means the services on the line were negotiated between the incumbent supplier and the regional transport agency.

Source: Own calculations.

Figure 2 is more informative about the source of the differences. Rather than depicting the density of the frequency of service on auctioned vs. negotiated lines, it compares their changes. This picture is revealing. It

shows that the auctioned lines have typically grown much stronger than the negotiated lines. This strongly suggests that Figure 1 should not be given a causal interpretation: The difference between the auctioned and the negotiated lines was much larger in 1994 than in in 2004. It appears that competition has helped to close the gap between the auctioned and the negotiated lines. Of course, Figure 2 is not fully conclusive about a causal relation either. It shows that the auctioned lines have grown stronger than the others, but again this may reflect a selection effect. The auctioned lines may have been systematically different from their negotiated counterparts, and their growth may reflect these systematic differences rather than any actual merits of competition. In the following, we try to substantiate the claim that there is indeed a causal relation between competition and service quality.

Figure 2: Frequency of Service by Procurement Mode, in 2004



Notes: Growth in frequency of service is the change in log frequency of service from 1994 to 2004. Auction means the services on the line were auctioned between 1994 and 2004. Negotiation means the services on the line were negotiated between the incumbent supplier and the regional transport agency.

Source: Own calculations.

3.2 Determinants of Quantities and Prices

Here we discuss the estimation results for quantities and prices. Table 1 presents the results from our model on quantities, both for lines that were negotiated and that were procured. It depicts estimates of the effect of auctions compared to negotiations on frequency of service using an OLS-regression. Both models control for observed line characteristics including lagged frequency of service. Results identify a positive

effect of competition on the frequency of service and show that (mean) auctioned lines are 6.8 percent[12] more frequently served than (mean) lines procured in direct negotiations with the incumbent. This may reflect the fact that agencies who are facing competitive bidders understand that they can ask for more than from a monopolistic supplier, because any unit of service costs less. In addition, we find that lines that were served frequently in 1994 also are more frequently served in 2004. Note that we include lagged frequency of service to correct for time-invariant unobserved effects in our analysis, so that the coefficient attached to lagged frequency of service has no causal interpretation. Results also indicate that longer lines are less frequently served than shorter lines. Lines in remote areas are also served less frequently than lines in urban areas. The remaining control variables are not significant mainly due to the fact that we condition on lagged frequency of service.[13]

Table 1: Determinants of quantities

	Negotiations			Auctions		
	(1)		(2)	(3)		(4)
incumbent	0.007		(0.065)	-0.054		(0.080)
log frequency	0.789	***	(0.025)	0.646	***	(0.074)
electric traction	0.008		(0.041)	-0.001		(0.084)
distance to city (km)	-0.001		(0.001)	0.000		(0.001)
log track length	-0.062	***	(0.022)	-0.137	***	(0.044)
log pop largest city	0.005		(0.015)	0.073	**	(0.037)
log pop 2nd largest city	0.018		(0.015)	0.055		(0.041)
regional factor	-0.190	**	(0.073)	-0.374	***	(0.108)
Constant	9.805	***	(0.092)	10.188	***	(0.127)
adj-R-Sq	0.795			0.638		
Observations	420			139		

Notes: Results from OLS estimations. Dependent variable is the log of quantity. Columns (1) and (3) shows the estimated coefficients and columns (2) and (4) the standard errors. Standard errors are adjusted for 17 clusters (on agencies). $***$ ($**$, $*$) stands for significance at the 1% (5%, 10%) level.

Source: Own calculations.

Comparing the lines that were negotiated and those that were procured, we find also significant differences in the effects of auctions on quantity. The effects of lagged frequency of service, the length of lines and the

[12] Evaluating $\log \hat{q}_{bids}$ and $\log \hat{q}_{negs}$ at their means and using [exp(9.645-9.579)-1] * 100, we obtain 6.8 percent. See also Table 4.

[13] A regression that does not include lagged frequency of service finds all observed characteristics matter for frequency of service in 2004. That regression finds point estimate suggesting an 11% auction effect, albeit much less precisely estimated (since the standard error of regression is larger).

regional factor are significantly different across specifications. The results indicate a stronger effect of lagged frequency of service on negotiated lines. This suggests that auction-related quantity improvements are smaller on lines that were served very frequently already before the reform. In contrast, the effects of the length of lines and the regional factor are stronger for auctioned lines. This suggests that lines serving remote areas benefit more strongly from being auctioned than lines serving more urban areas. The same is true when we compare longer and shorter lines.

The preceding analysis has identified a positive effect of competition on the frequency of service. We have argued that this is likely to reflect the fact that agencies who are facing competitive bidders understand that they can ask for more than from a monopolistic supplier, because any unit of service costs less. So far, however, we have not produced any evidence to corroborate this story.[14] In principle, there could be completely different explanations for the stronger growth on auctioned lines. For instance, agencies that are experimenting with auctions might be afraid about failure of the project. As the public is more likely to be aware of low quality rather than excessively high procurement costs, agencies might want to make sure that competitively procured lines "look better" than others by pumping more money into them. In other words, the high quantity of services on competitively procured lines might simply reflect higher payments.

Tables 2 and 3 therefore discusses the effect of auctions on procurement prices.[15] Table 2 presents the results from our price model on negotiations. The dependent variable is the log price of lines that have been negotiated. We explain about 20% of the variation in log prices with our explanatory variables. The indicator variable for the incumbent has a positive effect. This suggests that an incumbent when negotiating paid higher prices. This effect is however only marginally significant. We also find that (log) frequency and distance to next largest city are significantly negative. Prices on lines with a higher frequency and with a lower distance to a city are lower. On contrast, the effects of electric traction and remote lines (regional factor) are significantly positive.

Table 3 presents the results for the auction model. Column (1) of this table shows the estimates for the scale parameter λ, and column (2) the estimates for the shape parameter ρ. Variables that significantly influence the shape parameter of the Weibull distribution are the distance to the next largest city, the log of the track length, the log of the population of the largest city along the line, and the regional factor. An increase in the distance to the next largest city let bidders increase their bids. The same is true for track length and the population of the largest city along the line. The regional factor has a negative sign implying that a less urban area induces lower bids. The shape parameter is significantly influenced by distance to city and the log population of the second largest city along the line.[16]

[14] This problem is shared by the analysis in Lalive and Schmutzler (2008) for *Baden-Württemberg*.

[15] This analysis is based on 476 lines with procurement price information. We construct negotiation prices for all 413 lines that were directly negotiated with the incumbent (see Appendix). We also have information on auction prices for 63 lines that were auctioned.

[16] We are aware that the number of observations for a structural model is rather low. We experimented with several specifications for the winning bid. We restricted the scale parameter to be a constant only or used a log normal distribution instead of the Weibull distribution. The chosen specification gives the best fit and most sensible estimated coefficients.

Table 2: Determinants of the negotiated prices

	(1)		(2)
incumbent	0.046	*	(0.026)
log frequency	-0.030	***	(0.010)
electric traction	0.068	***	(0.016)
distance to city (km)	-0.001	***	(0.000)
log track length	-0.009		(0.009)
log pop largest city	-0.007		(0.006)
log pop 2nd largest city	-0.005		(0.006)
regional factor	0.248	***	(0.029)
Constant	1.828	***	(0.036)
adj-R-Sq	0.197		
Number of observations	420		

Notes: Results from OLS estimations. Dependent variable is the log of price from negotiations. Column (1) shows the estimated coefficients and column (2) standard errors. Standard errors are adjusted for 17 clusters (on agencies). $***$ ($**$, $*$) stands for significance at the 1% (5%, 10%) level.

Source: Own calculations.

3.3 Comparison of outcomes of negotiations and auctions

To compare the outcomes of negotiations and auctions, we provide the predicted means for negotiations and auctions for both sets of lines. In Table 4, we depict the means for the log variables and in their levels. We are in particular interested with the effect of competition on prices as the Weibull model does not allow an easy comparison with OLS model for negotiated prices. This was not an issue when we compare predicted quantities. In line with our earlier analysis, we observe that on average predicted quantities on negotiated lines are larger than predicted quantities on auctioned lines. This indicates that better lines are more often negotiated. Controlling for line characteristics, we however find that on average predicted prices in negotiations are higher than predicted prices in auctions. This suggests that auctions not only increase quantity but they also lower the procurement price, where the latter effect is rather strong.

Based on the (in-sample) predicted quantities and prices, we are then able to calculate the surplus using equations XX and YY. In Figures 3 and 4, we show a kernel density estimate of the log surplus for negotiated and auctioned lines. For both specifications, we observe that the average surplus is higher on negotiated lines than on auctioned lines. Comparing the two figures reveals that the separation between lines is more pronounced in the specification where we model the surplus with the square root instead of the logarithm. The log surplus is the sum of log quantities and log prices, and we observe that the quantity effect dominates.

Table 3: Determinants of the distribution of winning bids

	Scale λ			Shape ρ		
	(1)		(2)	(3)		(4)
incumbent	0.037		(0.058)	0.483		(5.324)
log frequency	0.047		(0.044)	3.770		(4.837)
electric traction	-0.058		(0.042)	4.294		(4.206)
distance to city (km)	0.003	**	(0.002)	-0.177	**	(0.077)
log track length	0.086	*	(0.046)	-4.770		(4.100)
log pop largest city	0.042	**	(0.020)	-0.734		(2.137)
log pop 2nd largest city	-0.036		(0.022)	-5.138	*	(2.709)
regional factor	-0.146	*	(0.085)	22.783		(22.414)
Constant	2.302	***	(0.105)	-6.740		(24.823)
Log pseudo-likelihood	35.383					
Number of observations	59					

Notes: Results from MLE estimations. Dependent variable is the log of winning bid. Column (1) shows the coefficients estimated for the scale parameter λ of the Weibull distribution of bids. Column (3) is for the shape parameter ρ. Standard errors are adjusted for 17 clusters (on agencies) and shown besides in parenthesis. $***$ ($**$, $*$) stands for significance at the 1% (5%, 10%) level.

Source: Own calculations.

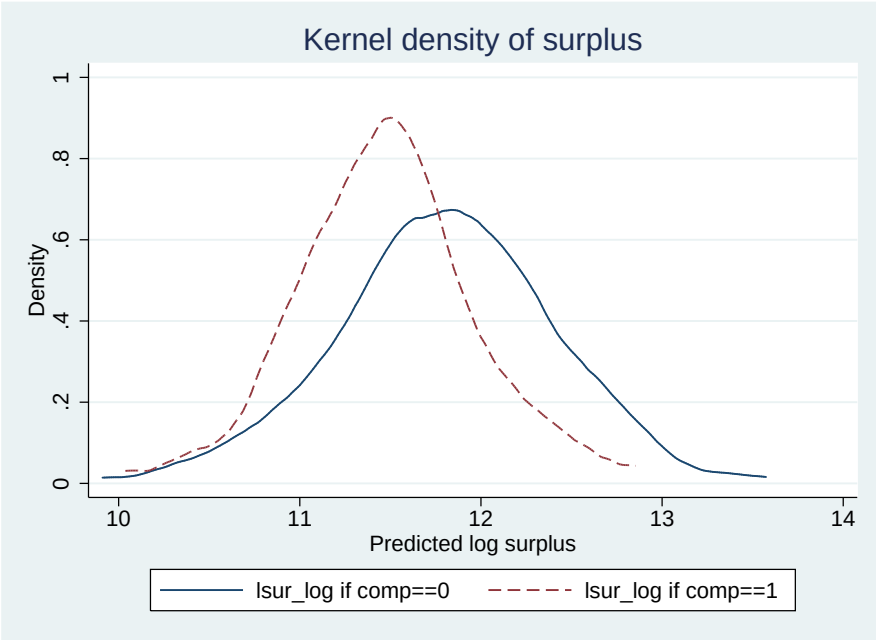
Table 4: Comparison of predicted quantities and prices

	Mean quantities		Mean prices	
	Auctions	Negotiations	Auctions	Negotiations
	(1)	(2)	(3)	(4)
in logs				
Negotiated lines	9.767	9.645	1.911	2.153
Auctioned lines	9.579	9.439	1.897	2.123
in levels				
Negotiated lines	20815.45	18648.35	6.857	8.632
Auctioned lines	16407.90	14280.29	6.785	8.383

Notes: Results based on OLS and MLE estimations in Tables 1 - 3. Mean predicted values in logarithm and levels are shown.

Source: Own calculations.

Figure 3: Kernel density estimate of surplus



Notes:

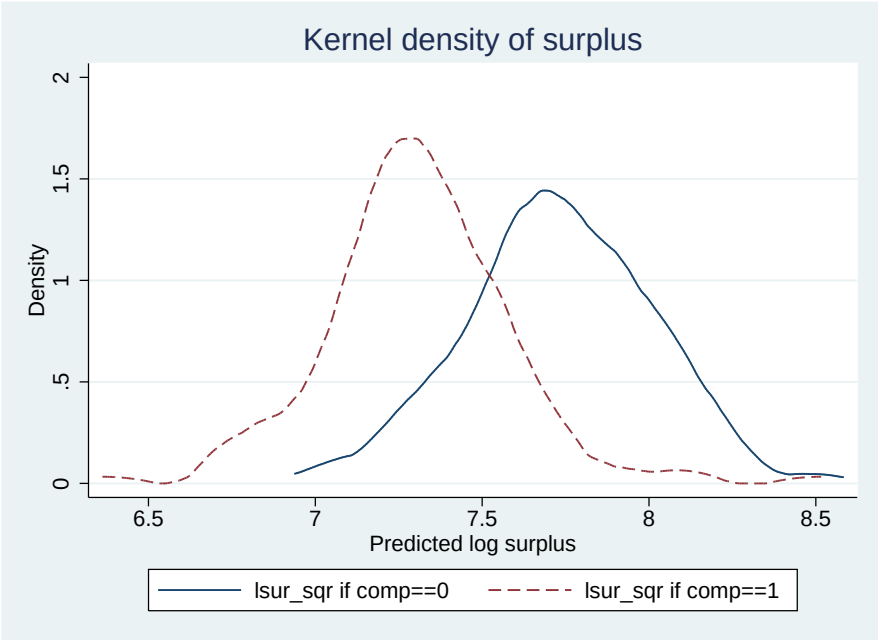
Source: Own calculations.

We also compare the predicted ex-ante welfare under negotiations and auctions using equations XX and YY. In Table 5, we show mean values for negotiations and auctions for both sets of lines and distinguish between the model where the surplus enters the welfare in logs and the model where the surplus enters with the square root. The effect of competition is the same for both models. When switching from negotiations to auctions, agencies could increase their welfare by about 28583 Euro (25071 Euro) on lines that have been negotiated. The absolute size of welfare is however different. Due to the differences in the surplus (see Figures 3 and 4), the log specification gives higher (absolute) values for the welfare than the specification with the square root.

3.4 Results for τ and ϕ

In Table 6, we show the results from two linear probability models implementing equations (6) and (7). The dependent variable is one if the regional passenger line was procured by auction and it is zero if the line was procured by negotiation with the incumbent. We run each model without and with agency specific fixed effects accounting for differences in their ability to set up an auction. We find that the parameter τ measuring the bargaining power of the incumbent is always larger than one indicating that the whole bargaining power is with the incumbent. We also find that the cost of the agency to run an auction, i.e., φ, is about 25-50% of the total welfare.

Figure 4: Kernel density estimate of surplus



Notes: Kernel density estimates of predicted surplus.

Source: Own calculations.

Table 5: Comparison of mean predicted welfare

	Surplus in logs		Surplus with square root	
	Auctions	Negotiations	Auctions	Negotiations
	(1)	(2)	(3)	(4)
in logs				
Negotiated lines	13.976	13.953	12.073	11.913
Auctioned lines	13.623	13.590	11.326	10.910
in levels				
Negotiated lines	1459870	1431288	204737	176154
Auctioned lines	961683	935137	94471	67925

Notes: Results based on OLS and MLE estimations in Tables 1 - 3. Mean predicted values in logarithm and levels are shown.

Source: Own calculations.

4 Summary and Discussion

Table 6: Estimated bargaining power of incumbent and agency cost

	Model with surplus			
	in logs		with square root	
	(1)	(2)	(3)	(4)
τ	1.116	1.104	1.178	1.186
	(0.028)	(0.037)	(0.040)	(0.047)
ϕ	0.765	0.852	0.545	0.557
	(tbc)	(tbc)	(tbc)	(tbc)
Agency specific fixed effects	No	Yes	No	Yes
Number of observations	558	558	558	558

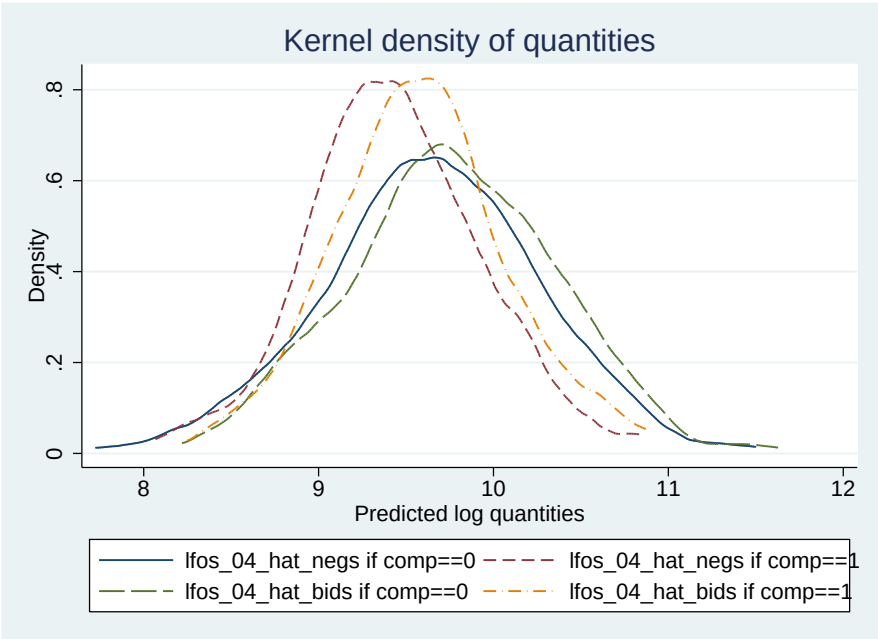
Notes: Results from linear probability models. Dependent variable is one if the regional passenger line was procured by auction and it is zero if the line was procured by negotiation with the incumbent. Columns (1) and (3) show results without agency fixed effects; columns (2) and (4) with agency fixed effects. Standard errors are adjusted for 17 clusters (on agencies) and shown are in parentheses below the parameter estimates. $***$ ($**$, $*$) stands for significance at the 1% (5%, 10%) level.

Source: Own calculations.

5 Appendix: Additional graphs

The results depicted in Table 4 have identified the mean predicted effects of competition on the frequency of service and prices. In the following, we are not only interested in the mean effects, but the effects over the distribution of quantities and prices. We thus show kernel density estimates for the predicted quantities and prices. In Figure 5, we plot the kernel density estimates of predicted quantities. We show four set of quantities: i) in-sample predictions of negotiated quantities on lines that were negotiated (solid blue line); ii) out-of-sample predictions of negotiated quantities on lines that were auctioned (dashed red line); iii) out-of-sample predictions of auctioned quantities on lines that were negotiated (long dashed green line); iv) in-sample predictions of auctioned quantities on lines that were auctioned (dash-dotted orange line).

Figure 5: Kernel density estimate of quantities



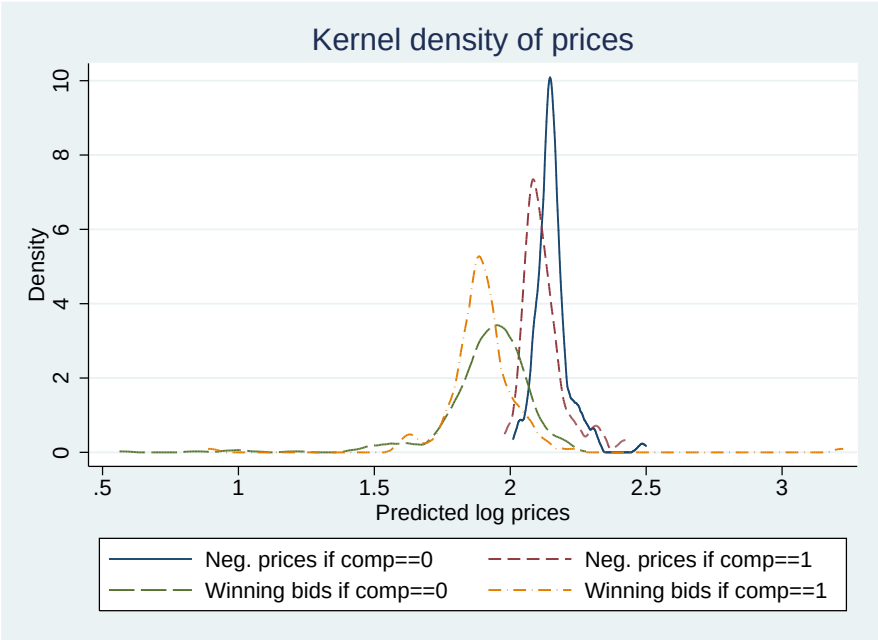
Notes: Kernel density estimates of predicted prices for four set of quantities: i) in-sample predictions of negotiated quantities on lines that were negotiated (solid blue line); ii) out-of-sample predictions of negotiated quantities on lines that were auctioned (dashed red line); iii) out-of-sample predictions of auctioned quantities on lines that were negotiated (long dashed green line); iv) in-sample predictions of auctioned quantities on lines that were auctioned (dash-dotted orange line).

Source: Own calculations.

In Figure 6, we repeat above exercise for prices and plot the kernel density estimates of predicted prices. We again show four set of prices. Controlling for line characteristics, we observe that in-sample predictions of negotiated prices on lines that were negotiated (solid blue line) and out-of-sample predictions of negotiated prices on lines that were auctioned (dashed red line) are almost always larger than out-of-sample predictions of auctioned prices on lines that were negotiated (long dashed green line) and in-sample predictions of auctioned

prices on lines that were auctioned (dash-dotted orange line).

Figure 6: Kernel density estimate of prices

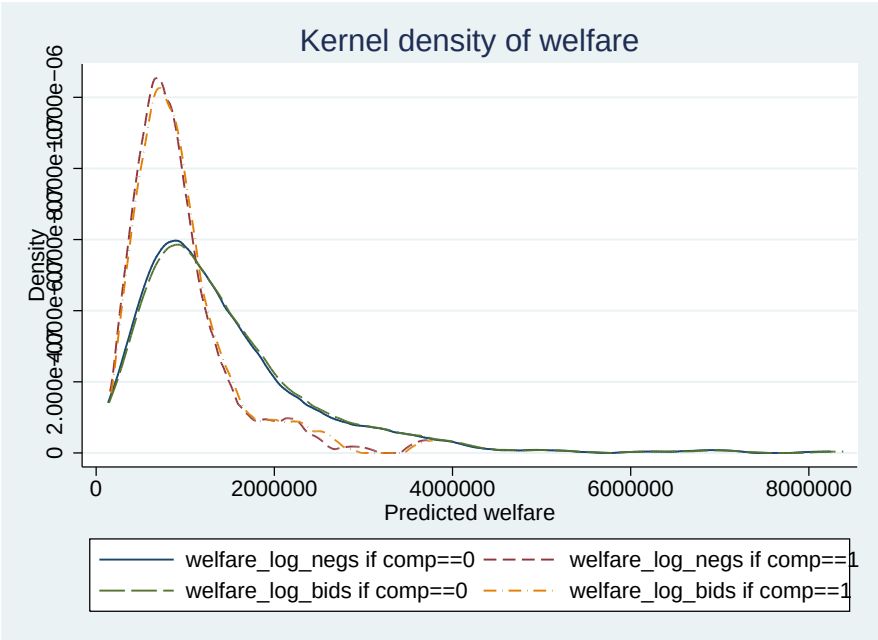


Notes: Kernel density estimates of predicted prices for four set of prices: i) in-sample predictions of negotiated prices on lines that were negotiated (solid blue line); ii) out-of-sample predictions of negotiated prices on lines that were auctioned (dashed red line); iii) out-of-sample predictions of auctioned prices on lines that were negotiated (long dashed green line); iv) in-sample predictions of auctioned prices on lines that were auctioned (dash-dotted orange line).

Source: Own calculations.

In Figures 7 and 8, we plot the kernel density estimates of the predicted ex-ante welfare using equation ZZ. We show four sets: i) in-sample predictions of welfare under negotiations on lines that were negotiated (solid blue line); ii) out-of-sample predictions of welfare under negotiations on lines that were auctioned (dashed red line); iii) out-of-sample predictions of welfare under auctions on lines that were negotiated (long dashed green line); iv) in-sample predictions of welfare under auctions on lines that were auctioned (dash-dotted orange line).

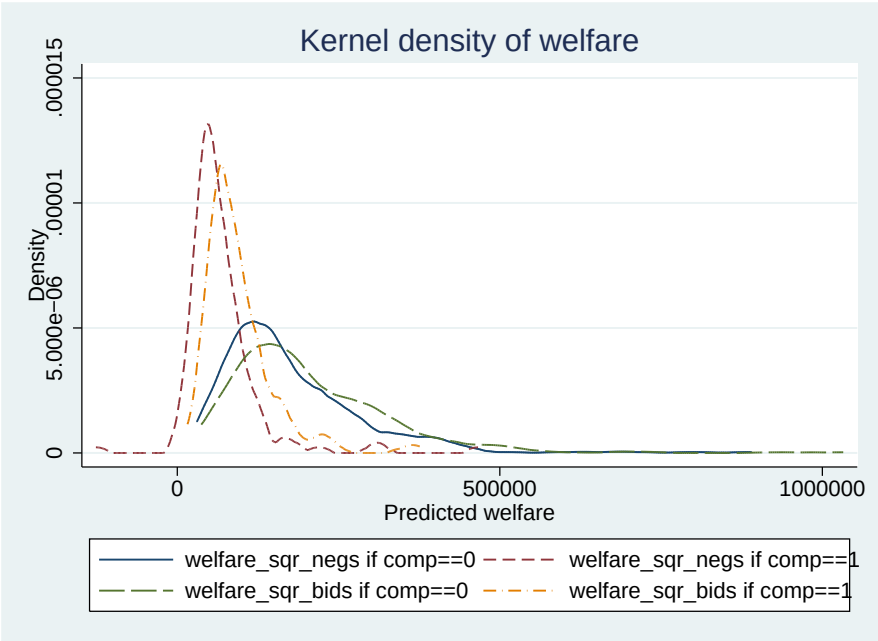
Figure 7: Kernel density estimate of welfare



Notes: Kernel density estimates for predicted welfare.

Source: Own calculations.

Figure 8: Kernel density estimate of welfare



Notes: Kernel density estimates for predicted welfare.

Source: Own calculations.

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