The Effect of Revenue Uncertainty on Procurement Outcomes

Evidence from Railway Passenger Services

Stefan Weiergraeber*
Christoph Wolf†

May 4, 2017

- Preliminary and Incomplete -
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Abstract

Many procurement auctions involve both private value and common value elements. Bidding firms are often asymmetric in both dimensions. First, former state monopolists or incumbents may be better informed about the common value, for example the revenue component of a procurement contract. Second, incumbents and entrants may have very different cost distributions (a typical private value component). Understanding the bidding behavior in a setting with private and common value components and asymmetries among bidders in both dimensions is essential to evaluate auction outcomes. We develop and estimate a structural auction model using a detailed contract-level data set of the market for short-haul railway passenger services (SRPS) in Germany. This allows us to disentangle the effects of asymmetries in the cost distribution between the incumbent and the entrants from the effects of asymmetric information about the revenue component of a SRPS contract. Data on *gross auctions*, in which firms do not face revenue risk, allow us to back out the cost distribution for each firm. Data on *net auctions*, in which firms bear the revenue risk, enable us to quantify the effect of revenue uncertainty on bidding strategies. Our results indicate that (1) bidding behavior is indeed systematically different in gross and net auctions, (2) the incumbent is only slightly more cost-efficient on most lines, (3) the incumbent has substantially more information about future ticket revenues than an entrant. We use our parameter estimates to run a series of counterfactuals. If net auctions were procured as gross auctions, we find that (1) entrants would have bid much more aggressively than in the status quo, (2) on average, the probability of selecting the efficient firm would increase from 64% to 75%.

*Department of Economics, Indiana University; E-mail: `sweiergr[at]iu[dot]edu`

†Center for Doctoral Studies in Economics, University of Mannheim; E-mail: `christoph.wolf[at]gess[dot]uni-mannheim[dot]de`. We thank Yonghong An, Mike Baye, Marc Ivaldi, Stephan Lauermann, Andras Niedermayer, Volker Nocke, Daniel Quint, Armin Schmutzler, Michelle Sovinsky, Xun Tang, Hidenori Takahashi and Ruli Xiao for helpful discussions and comments. We thank Felix Berschin from Nahverkehrsberatung Südwest for providing us with the data.

JEL Classification: H57, L92, R42, C57

Keywords: railway passenger services, procurement with asymmetric bidders, structural estimation of auctions

1 Introduction

Public procurement is an important sector of economies: In the OECD countries, public procurement accounted for 12.1% of GDP in 2013.[1] The use of auctions in public procurement aims at creating competition between bidders and at selecting the efficient firm to carry out the service. While auctions perform well in selecting the efficient bidder when participants are symmetric, this is not necessarily the case when participants are asymmetric. Importantly, bidders in procurement auctions are likely to be asymmetric: First, former monopolists or incumbents may be better informed about the common value component due to their experience or have access to superior information. Second, incumbents with a larger network may be either more or less efficient, for example, due to economies of scale or capacity constraints.

Many procurement auctions involve both a private and a common value component. While private value components typically consist of idiosyncratic cost components, typical common values are common cost components or potential revenues from the object. However, empirical studies of asymmetric auctions predominantly study private value auctions.[2] Neglecting potential asymmetries in common value components has substantial implications on the results: if incumbents win systematically more often the theory of asymmetric private value auctions attributes this to a more efficient cost distribution (see Maskin and Riley (2000a)). From an efficiency perspective the incumbent wins too few auctions because its competitors bid more aggressively. We show in a theoretical model with private and common value component that the dominance of a firm can also be explained by asymmetrically precise common value signals. In this case, the incumbent firm wins too many auctions from an efficiency perspective. Hence, it is an important empirical questions to distinguish and to quantify the respective importance of asymmetries in private and common value components.

Asymmetries between firms are particularly important in markets with experienced incumbents and entrants that recently became active in the market. In the 1990s, many European countries started to liberalize markets that used to be controlled by a state monopolist. The aim was a more efficient provision of publicly subsidized goods due to increased competition. In many markets experiences with privatization have been mixed, however. We exploit a detailed data set on awardings in the German market for short-haul railway passenger services (SRPS) from 1995 to 2011. Since SRPS are generally not profitable, the state procures specific tracks to train operating companies and subsidizes them for the provision of the service. While the aim of the liberalization was to attract competitors, the former state monopolist (DB Regio) still operates the majority of the tracks (71%, FAZ Nr. 281 (2015)). An explicit concern by procurement agencies and industry experts is that entrants are either not participating at all or bidding cautiously. The German market for SRPS is only one example, but given its size of 8 billion EUR in subsidies for 2016, is an important one that shares many features with similar markets in other countries. DB has more experience for the services and as a publicly held firm

[1] See OECD (2015).
[2] See Athey et al. (2011), Suzuki (2010), Estache (2008) and Tas (2017).

may have advantages for financing compared to its rivals. In addition, DB Vertrieb, which is integrated with the DB holding has access to all the ticket revenue and passenger data. Entrants and even agencies typically do not have access to this information (Monopolkommission 2013). Considering these asymmetries, the reasons for DB still being the dominant firm are not clear. On the one hand, it could be the efficient firm for most services. On the other hand, entrants might bid very cautiously due to DB's informational advantage about future revenues.

Comparing the winning bids of entrants with those of DB in gross auctions we find that entrants win with significantly lower bids than DB. However, in net auctions there is no significant difference in the winning bids. We take this as first evidence that DB is indeed better informed about the common value component as entrants shade their bids relatively more in net compared to gross contracts. Moreover, Hunold and Wolf (2013) provide reduced-form evidence for the fact that using net contracts makes it more likely that DB Regio wins the awarding.

We take our model that builds on the theoretical work of Goeree and Offerman (2003) to a detailed contract-level data set on German short-haul railway passenger service (SRPS) procurement auctions. With this data set we can disentangle the two asymmetries by making use of a variation in the contract design: local state agencies that procure these services can choose who bears the revenue risk from ticket sales. If the ticket revenues remain with the agency (*gross contract*) the auction is a standard asymmetric independent private values auction. If the train operating company is the claimant of the ticket revenues (*net contract*), the auction is one with a private value (cost) as well as a common value (ticket revenues) component. In a first step, we estimate the cost distributions of DB and the entrants from the winning bids in gross auctions. Identification follows from Athey and Haile (2007) who show that asymmetric independent private value auctions are identified from the winning bid and the winner's identity only. We use several contract characteristics to control for the specifics of the respective contracts and obtain the cost distribution conditional on contract characteristics. In a second step, we make use of the net auction data. Given the first-step results, we know the cost distribution for each of the awarded tracks. Hence, differences in bidding behavior that are not explained by the differences in cost distributions can be attributed to the common value component. We can estimate the bid distribution as functions of a *net cost signal* that consists of the private and common value signal as well as the informativeness of the common value signal.

The results of our structural analysis show no systematic cost advantage of DB over its rivals. Importantly, they are not as large as one may initially expect - under a pure private value assumption - given DB's dominance in the market for SRPS. The estimation of the informational advantage over its competitors reveals that indeed in most auctions DB holds significantly more precise information about future ticket revenues. This highlights the concerns in Monopolkommission (2015) that DB's dominance is at least partially due to its informational advantage which may call for regulatory interventions that symmetrize the information across the bidders. Alternatively, efficiency could be increased by awarding more gross contracts which eliminates the common value component from the auction. We study this intervention in a counterfactual

analysis and find that entrants shade their bids less than in net contract auctions, making bid distributions more symmetric. This increases ex ante efficiency of the auctions from 64% to 75%.

The assumption that the choice between net and gross contracts is exogenous is important for our analysis. This choice is typically strongly agency-dependent and there is only very little variation within an agency over time, while track characteristics differ within and across agencies. Therefore, we believe that the contract type (gross vs. net) is indeed not driven by fundamental characteristics of a track but rather exogenously determined by the preferences of the agency.[3]

Related literature The SRPS industry is characterized by asymmetries of bidders due to the presence of a former state monopolist and incumbent on many tracks, DB. Therefore, our methodology builds on the theory of first-price asymmetric auctions.[4] For example, theory predicts that stochastically weaker firms bid more aggressively and stochastically stronger firms win with higher profits (Maskin and Riley 2000a). Moreover, the release of public information in a symmetric model implies more aggressive bids by all firms (reduced information rents). Our application is also reminiscent of the theoretical literature on auctions of fixed price vs. cost-plus contract as in Laffont and Tirole (1986) and McAfee and McMillan (1986). While they focus on asymmetric information between the procurement agency and bidders and moral hazard after a contract has been awarded, we abstract from the latter and focus on informational asymmetries between competing bidders during the auction stage.

There is relatively little empirical literature on asymmetric common value auctions due to known difficulties with identification in common value auctions (see Athey and Haile (2002). Li and Philips (2012) analyze the predictions of the theoretical asymmetric common value auction model in Engelbrecht-Wiggans et al. (1983) in a reduced-form analysis. They find evidence for private information of neighbor firms in drainage lease auctions. Hong and Shum (2002) investigate the effect of competition in a model with both private and common value components and symmetric bidders. They find that the winner's curse effect can outweigh the competition effect so that more bidders can results in less aggressive bidding. In addition, Hong and Shum (2002) estimate the relative importance of private and common value components in procurement contracts in New Jersey. In contrast to their study, we have relatively precise information about which parts of the contracts correspond to private and which to common value components. Furthermore, we observe exogenous differences in the design of different auctions that eliminate or add specific parts of risk for the bidding firms. This allows us to focus on the effect of asymmetric information about the common value across incumbent and entrant bidders.

De Silva et al. (2003) analyze an asymmetric procurement model and confirm the theoretical

[3]A comparison of track characteristics between the two different contract modes shows no significant difference in either of the observed contract characteristics. In Bahn-Report (2007) it is also argued that the choice is rather agency-dependent than an endogenous choice due to contract characteristics.

[4]See, for example, Parreiras (2006), Kirkegaard (2009), Maskin and Riley (2000a), Reny and Zamir (2004).

predictions of Maskin and Riley (2000a) with reduced form regressions using data on highway procurement in Oklahoma. In a follow up paper, De Silva et al. (2009) argue that asymmetric information about contract characteristics is a particularly important problem for new entrants. However, their application is quite different from ours: We analyze a setting in which the incumbent is usually more cost-efficient, but also faces less uncertainty about ticket revenues than the entrants. In order to estimate our auction model, we rely on the literature on the structural estimation of asymmetric auctions. In particular, we borrow elements from Brendstrup and Paarsch (2006), Brendstrup and Paarsch (2003), Athey et al. (2011) and Hendricks et al. (2003) and adapt them to our application.

While recent research (Lalive et al. 2015) analyzes the respective benefits of auctions and negotiations in the context of our application, to the best of our knowledge, we are the first to analyze the role of auction designs and asymmetric information in this market using structural econometric methods. Lalive et al. (2015) analyze how the agency's choice of whether to engage in direct negotiations or to run an auction affects procurement outcomes. While they focus on the trade-off between competitive auctions and non-competitive negotiations, we focus on the specific auction design, in particular the implications of procuring net or gross contracts.

2 Auction Model and the Effect of Asymmetries

In this section, we present our model for procurement auctions of gross and net contracts and study the effect of two asymmetries: (i) the effect of asymmetric private value distributions, and (ii) the effect of asymmetric precision of the common value signals. All auctions are standard first-price sealed-bid auctions. The valuation for a contract as well as the bidding behavior of firms crucially depend on whether a gross or a net contract is tendered. For a

- *gross* contract, the valuation consists solely of the firm-specific costs of the contract (c_i) since the firm's revenue is fully determined by the winning bid.
- *net* contract, the valuation consists of the firm-specific costs of the contract (c_i) and additionally the ticket revenues R, which are unknown to all firms when bidding for a contract.

We index bidding firms by i, its bid by b_i and denote the number of bidders by N. The cost component c_i is a private value drawn for each firm i from F_{c_i} and is observed by i only. The ticket revenue, R, is an unknown common value for which firms observe only a private signal, r_i drawn from F_r. We allow F_{c_i} to differ across firms to model differences across incumbent and entrants in cost efficiency. The differential information about expected revenues comes from the reliability of the own signal drawn from the common distribution F_r as discussed later on. All signals are independent across firms and cost signals are independent of revenue signals within firms. We assume that bidders are risk neutral.

Gross contract auctions Firms compete for a single indivisible item (one track) by submitting bids b_i (the requested subsidy). Firm i's ex-post value of winning and the expected value of a bid is given by the formulas for an independent private values (IPV) auction:

$$v_i = b_i - c_i \tag{1}$$

$$E[v_i(b_i)] = (b_i - c_i) \cdot \Pr(b_i < min_{i \neq j} b_j | c_i, b_i) \tag{2}$$

Ties are broken randomly. For reasons to be discussed in the next subsection, we assume that F_{c_i} is logconcave. As the incumbent is vertically integrated with the network operator, DB Netz, and is the former state monopolist as well as still publicly held by the Federal Republic of Germany, we assume that the incumbent draws its costs from a different distribution than the entrants. We further assume that entrants are symmetric for simplicity. As this gives rise to an asymmetric auction, we build on the theoretical work on asymmetric IPV auctions, in particular, we build on the predictions in Maskin and Riley (2000a).

In a gross contract, there is only ex ante uncertainty about the operating costs c_i. Before bidding, a firm receives private information about its costs which is distributed according to $F_{c^i} \in \mathcal{C}^2$ with strictly positive density on support $[c_{i,L}, c_{i,H}]$. After having received the signal, firm i knows its cost perfectly. However, it does not know its rivals' cost realizations.

Therefore, firm i chooses b to maximize expected profit:

$$\pi_i(b, c_i) = (b - c_i) \prod_{j \neq i} (1 - F_j(\phi_j(b))$$

where $\phi_j(b)$ is bidder j's inverse bid function. Rodriguez (2000) and Reny and Zamir (2004) establish that a unique equilibrium in pure strategies with strictly increasing and differentiable bid functions exists. The equilibrium is implicitly defined by a system of differential equations in inverse bid functions with boundary conditions. The solution to that system gives equilibrium existence. Denote by G_i the distribution of the opponents' maximum bid given own bid b being pivotal and a set of bidders N. Inverse bid functions have to satisfy:

$$b_i = c_i + \frac{1 - G_i(b, b, N)}{g_i(b, b, N)}. \tag{3}$$

We borrow the following Lemma and definition of conditional stochastic dominance[5] both adapted to the procurement setting from Maskin and Riley (2000a).

Lemma 1 (Maskin and Riley (2000a), Proposition 3.3 and Proposition 3.5.)**.** *If the private value distribution of i conditionally stochastically dominates the private value distribution bidder j, then i is the weak bidder and bids more aggressively than bidder j. The bid distribution of i*

[5] Conditional Stochastic Dominance is defined as follows: There exists $\lambda \in (0, 1)$ and $\gamma \in [c_{j,L}, c_{i,H}]$ such that $1 - F_i(x) = \lambda(1 - F_j(x))$ for all $x \in [\gamma, c_{j,H}]$ and $\frac{d}{dx}\frac{1-F_i(x)}{1-F_j(x)} > 0$ for all $x \in [c_{j,L}, \gamma]$.

is stochastically dominates the bid distribution of j.

Lemma 1 shows that the weaker bidder bids more aggressively. As a result, the auction may be inefficient and the strong bidder wins too few auctions from an efficiency perspective. This result has been generalized by De Silva et al. (2003) to also hold in the presence of an additional common value component and therefore, also holds for the net auction case.

Net contract auctions When net contracts are procured, the bidders' value of a contract consist of a private cost and a common value component. We develop an asymmetric first-price auction model with both, private and common value components. The value of the item differs among bidders and consists of two components: (i) a private component, which is the cost of fulfilling the contract c_i drawn from distribution F_{c_i} (same as in gross auctions), and (ii) a common component, the ticket revenues, R. In addition to the private value signal, firms receive an additional signal r_i drawn from F_r on the common value, i.e. the expected ticket revenues R. Revenue signals, r_i, are conditionally independent given R. Because of the additional revenue component, the ex-post value of winning and the expected value of a bid is:

$$\pi_i = R - c_i + b_i \tag{4}$$

$$\mathbb{E}[\pi_i(b)|b, c_i, r_i] = \left(b - c_i + \alpha_i r_i + \sum_{j \neq i} \alpha_j \mathbb{E}\left[r_j | \rho_i \geq B_j^{-1}(b)\right]\right)\left(1 - F_{\rho_j}^{1:N-1}(B_j^{-1}(b)\right) \tag{5}$$

Both, F_{c_i} and F_r, are assumed to be logconcave. From a theoretical perspective, this model is a modified version of Goeree and Offerman (2003) which studies the symmetric case and the extension by De Silva et al. (2003) which allows for asymmetric private-value distributions.

We employ a standard but important assumption: the common value component is given by the weighted average of the signals received, i.e., $R = \sum_{i=1}^{N} \alpha_i r_i$. This assumption is crucial due to the following reason: The strategic variable for a bidding firm is its bid, i.e. a scalar. However, the valuation for the success is two-dimensional, consisting of the private and common value component. There is typically no straightforward mapping from two-dimensional signals into a one-dimensional variable. However, with the linear specification and logconcavity of the signal distribution this is possible as shown in Goeree and Offerman (2003): the expected value of winning can be rewritten as a linear composition of the private signals, r_i and c_i as $\rho_i \equiv c_i - \alpha_i r_i$, and terms independent of the private information. This scalar statistic is sufficient to capture the private information in one dimension. Therefore, the standard auction theory methods as in (Milgrom and Weber 1982) can be applied.

We extend the model of Goeree and Offerman (2003) and its extension in De Silva et al. (2003) by allowing for asymmetries not only in the private value component and but also in the common value component. Denote $R = \sum_{i=1}^{N} \alpha_i r_i$ with $\sum_{i=1}^{N} \alpha_i = 1$. While every firm draws its signal r_i from the same distribution, the asymmetry between incumbent and entrants is captured by α_i. We denote the incumbent's and entrants' weights by α_I and α_E, respectively.

Intuitively, α_i measures informational value of a bidder's signal. A higher α_i indicates a more reliable revenue signal for bidder i. The variance $var[R] = \sum_{i=1}^N \alpha_i^2 \sigma_r$ and conditional on a signal r_i, we get:

$$\mathbb{E}[R|r_i = r] = \alpha_i r + \sum_{j \neq i} \alpha_j \mathbb{E}[r_j] = \alpha_i r + \sum_{j \neq i} \alpha_i R$$

due to independence of the revenue signals $\{r_j\}_{j=1}^N$, the variance is given by:

$$var[R|r_i = r] = \sum_{j \neq i} \alpha_i^2 \sigma_r$$

As $\alpha_i = \alpha_E$ for all entrants and $\alpha_i = \alpha_I$ for the incumbent, we get:

$$var[R|r_E = r] = ((N-2)\alpha_E^2 + \alpha_I^2)\sigma_r \text{ for the entrant} \tag{6}$$

$$var[R|r_I = r] = (N-1)\alpha_E^2 \sigma_r \text{ for the incumbent} \tag{7}$$

and hence $var[R|r_E = r] > var[R|r_I = r]$ if $\alpha_I > \alpha_E$. Note that the vector $\alpha = (\alpha_I, \alpha_E)$ effectively consists only of one parameter since we can normalize $\alpha_I + (N-1)\alpha_E = 1$. For now, we assume that the asymmetry is constant across all auctions.[6]

A bidder maximizes expected utility conditional on the observed signals. The structure of the common component allows us to write this as $\alpha_i r_i - c_i + b_i + \sum_{j \neq i} \alpha_j r_j$ where the last term is independent of the own signals. We can summarize the bidder's private information as $\rho_i = c_i - \alpha_i r_i$ which should be interpreted as a *net cost signal* or *negative profitability signal.* Bidding behavior is described by a system of differential equations as derived in the following Lemma. The standard derivation is carried out in the Appendix.

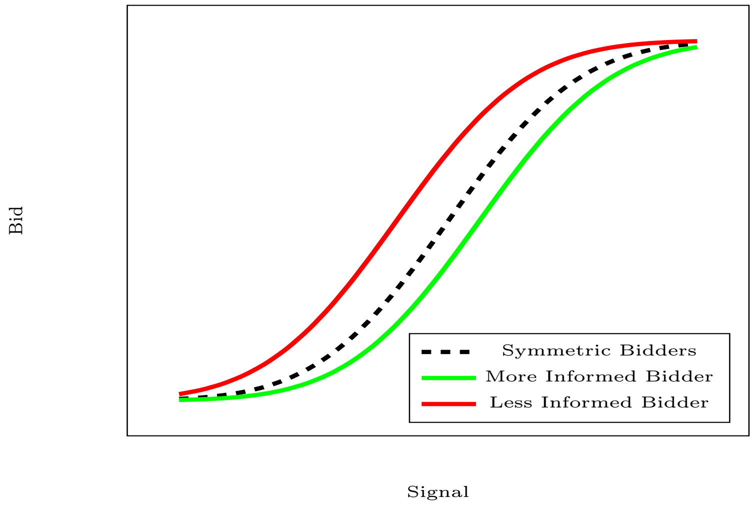
Lemma 2. *The following system of differential equations constitutes a Bayesian Nash equilibrium of the first-price auction with asymmetric cost distribution and asymmetric signal precision:*

$$b = \left(c_i - \alpha_i r_i - \sum_{j \neq i} \alpha_j \mathbb{E}\left[r_j | \rho_i = B_j^{-1}(b) \right] \right) + \frac{(1 - F_\rho^{1:N\backslash i}(B_j^{-1}(b)))}{f_\rho^{1:N\backslash i}(B_j^{-1})(b) B_j'^{-1}(b)} \tag{8}$$

where $f_\rho^{1:N\backslash i}$ and $F_\rho^{1:N\backslash i}$ denote the density and distribution function of the first-order statistic of other players' signals. $B_j^{-1}(\cdot)$ denotes the inverse bid function of bidder j.

The intuition is analogous to bidding in the gross auction. Players bid their expected valuation of winning the auction plus a bid-shading term. However, in the net auction case the expected valuation also depends on the other players' revenue signals. Because this is a common value setting, the bidder faces a winner's curse motif. This can be seen in the conditioning set of the expectation of the other players' revenue signals $\mathbb{E}\left[r_j | \rho_i = B_j^{-1}(b) \right]$. If bidder i wins with bid b, then it must be the case that other players' signals were not too good. Hence, when computing

[6] At the expense of having to estimate additional parameters, we can model σ_r and α as a function of track characteristics X.



that expectation, the player has to take that into account.

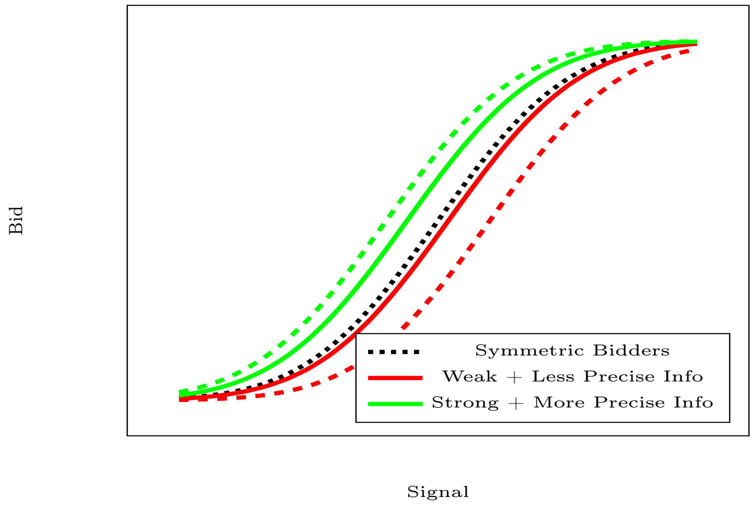
While theory gives strong predictions about how winning bids by the incumbent and the entrants compare in private value auctions, this is much less clear in net contracts because of the additional common revenue component. Especially if the revenue signal firms receive have asymmetric precision. We give an intuition on the effect of the common value asymmetry in the following Lemma that assumes a symmetric and known cost component.

Lemma 3. *Assume there are two firms that have the same cost c. Then, if* $\alpha_1 > \alpha_2$ *and the distributions of the compound common value signals* $\alpha_i r_i$ *satisfy conditional stochastic dominance, bidder 2 shades her bid more than bidder 1.*

Lemma 3 shows that a less precisely informed bidder is affected more by the winner's curse and will shade its equilibrium bid more than a more precisely informed bidder.

In our setting, allowing for both asymmetries, there are two effects in place that determine bidding behavior: (i) one bidderis (potentially) more efficient than the other bidders on average. Hence, the less efficient bidders bid more aggressively than the more efficient bidder. (ii) One bidder is (potentially) more precisely informed about the common value component. This implies that the less informed bidders shade their bid more than the more informed bidder due to a stronger winner's curse effect. Taken together, the effects work can amplify each other or work against each other depending on the identity of the advantages.

In particular, each of the asymmetries can be a source of inefficiency in the auction. If the bidders are symmetric in the common value component, but one bidder is on average more efficient than the competitors, these bid more aggressive. Hence, the auction outcome may be inefficient, when the efficient realized cost advantage is not too big. If the bidders' private value distributions are symmetric, but their common value signals asymmetrically precise, the auction



may be inefficient as well due to an asymmetric winner's curse effect. If the less precisely informed bidder draws a lower cost but both the same common value signal, she wins the auction only if the cost advantage is sufficiently big, because she shades her bid more than the competitor. If both asymmetries are present, there are two possibilities: (i) The more efficient bidder is also more precisely informed. In this case, the more aggressive bidding by the disadvantaged bidder due to the weaker private value distribution is mitigated by the stronger winner's curse effect. (ii) The more efficient bidder is less precisely informed. In this case, the less aggressive bidding by the stronger bidder is amplified due to the winner's curse effect. This is illustrated in Section 2.

3 Application: Short Haul Railway Passenger Services in Germany

3.1 Industry description

As many other industries, the German railway sector was liberalized in the 1990s. This liberalization followed the EU Directive 91/440 *Development of the community's railways* implemented through the *Eisenbahnneuverordnungsgesetz* in 1993. One of the main objectives was to induce competition in the railway sector. Towards this, the *regionalisation* was carried out. Short hail railway passenger services are part of the universal service obligation and not profitable for operators. Therefore, procurement agencies on behalf of the federal states were assigned the task to choose an operator that provides this service. As these services require high subsidies (around 7 billion EUR in 2016, Monopolkommission (2015)), the procurement agencies aim at competition *for* the tracks to keep the required subsidies at a low level.

In another part of the reform, the former state monopolist Deutsche Bundesbahn in West Germany and Deutsche Reichsbahn in East Germany merged into Deutsche Bahn AG which is

still publicly owned by the Federal Republic of Germany. As a consequence, entrants into the market for German SRPS compete with a publicly held operator, Deutsche Bahn AG (DB), that formerly was the state monpolist.

When procuring these services, the procurement agencies have a high degree of freedom in designing the contract as well as the rules of the awarding. The agencies specifies the basic components of the contract: for example, how frequent a company has to run services on a certain line, the duration of the contract and the type of vehicles to be used. One important additional feature is that it also chooses who obtains the ticket revenues, the agency itself or the train-operating company. When the agency receives ticket revenues the contract is called a gross contract, while the contract is called a net contract, when the operating company receives the ticket revenues.

While the market share of competitors has been rising over the years since the liberalization, in 2013 DB still had a market share of 73.6% measured in train-kilometers (see Monopolkommission (2015)). This raised a debate about the underlying reasons: are features in the procurement process reinforcing the dominance of DB or is it due to DB being the efficient firm in the market? We assess this question in the empirical implementation of our auction model.

3.2 Data description

Our data set consists of (almost) all procurement contracts from the German market for SRPS from 1995 to 2011. The data contain detailed information on the awarding procedure, contract characteristics, the number of participating firms, the winning bid and the identity of the winning firm. Table 1 displays an overview of our sample size for different subset of awardings. While

Table 1: Number of observed train line awardings by winning firm and auction mode

Auctions	gross contracts	net contracts
Incumbent wins	22	39
Entrant wins	55	51
$\sum$	77	90

this data set contains relatively few observations, it is to our knowledge the most comprehensive data set on the German market for SRPS out there and we plan to supplement it with the most recent awardings from 2012-2016. Moreover, we collected data on demographic characteristics of the track region and data on track access charges and frequency of service from the German Federal Statistical Office and additional publicly available sources. Currently, the estimation of gross (net) auctions is based on 77 (90) awardings respectively.

3.3 Relating the theory to the application

The procurement agencies choose, when procuring a contract, whether the agency or the operator receives the ticket revenues. We assume that this choice is exogenous. In general, one might be worried that these differences across gross auctions and net auctions are driven by selection issues and endogenous procurement decisions by the agencies. This is a potential problem if agencies decide the contract mode (net vs. gross) based on unobservable contract characteristics that inherently favor either the incumbent or the entrants. We argue that the role of endogenous contract mode is negligible in our application for two reasons. First, we do not find systematic differences in the most important track characteristics across our two groups of auctions from which we conclude that the two sets of tracks are very similar. Second and more importantly, industry experts also proclaim that the main procurement features are mostly determined by agency preferences that generally are orthogonal to the structural cost and revenue characteristics of a track, cf. the extensive discussion in Bahn-Report (2007).

Theoretically, the difference between net and gross contracts is the presence of a common value component, the ticket revenues. As most features of the contract that affect demand are pre-specified by the agency, for example, the frequency of the service, the type of vehicle to be used, we consider the demand to be a common value for all firms. Moreover, we consider the costs to be a private value as the firms have different access to vehicles, funding opportunities, and can apply different wages.[7]

While we expect entrants to be symmetric with respect to their cost distribution, we expect the cost of DB to be potentially different from the entrants' cost. First, DB owns a large pool of vehicles that it can easily reuse for various services, entrants typically have to buy or lease vehicles. The cost for vehicles is a significant component of the costs of serving a contract. Also, DB is likely to have cheaper access to funds as a publicly held firm. Altogether, we expect DB to have a cost advantage.

In net auctions, there is additional uncertainty about future demand and therefore about ticket revenues. Again, we expect systematic differences between DB and its competitors. DB Regio (the branch of DB that operates in the SRPS sector) is vertically integrated with DB Vertrieb GmbH. Most tickets - even when DB is not operating the track - are sold through DB Vertrieb GmbH. Therefore, DB possesses an informational advantage about demand as competitors cannot access the information that DB Vertrieb GmbH has (see Monopolkommission (2015)).

Given these observations, we model gross auctions as an asymmetric independent private value auction and net auctions as an auction with private and common values in which we allow for asymmetries in the private value component and asymmetric precisions of the common value signal.[8]

[7] There certainly are common components in the cost like electricity and infrastructure charges. However, these can be anticipated by the firms in advance and involve relatively little uncertainty.

[8] The main criticism of the model by Goeree and Offerman (2003) is that the uncertainty about the common value increases in the number of bidders N. We believe that is less of a concern for our model. First, we expect

3.4 Reduced-form evidence and descriptive statistics

An analysis of the raw data provides support for our initial conjecture that DB has an informational advantage over its competitors. However, we do not find strong evidence that DB is more cost-efficient than its competitors (in a conditional stochastic dominance sense). The theoretical model predicts that if a bidder has a cost advantage over a competitor, than his bid distribution is also shifted to the left. As a consequence, the winning bid of the more cost-efficient bidder should be systematically lower than the winning bids of its competitors. If the common value is added to the model and the precision of the common value signal is asymmetric, the model predicts bids of the informationally disadvantaged bidder to be systematically higher, if the cost are symmetric.

Figure 1 show that when entrants win with lower bids than DB in gross auctions, which provides evidence that DB might not be more efficient than its competitors. Comparing the winning bids in net auctions, the winning bids are closer for DB and the entrants. This is partial evidence that the bid function of the entrants is stronger affected by the common value component than the bid function of DB. Also, Hunold and Wolf (2013) show that DB wins significantly more when the contract that is auctioned is a net and not a gross contract.

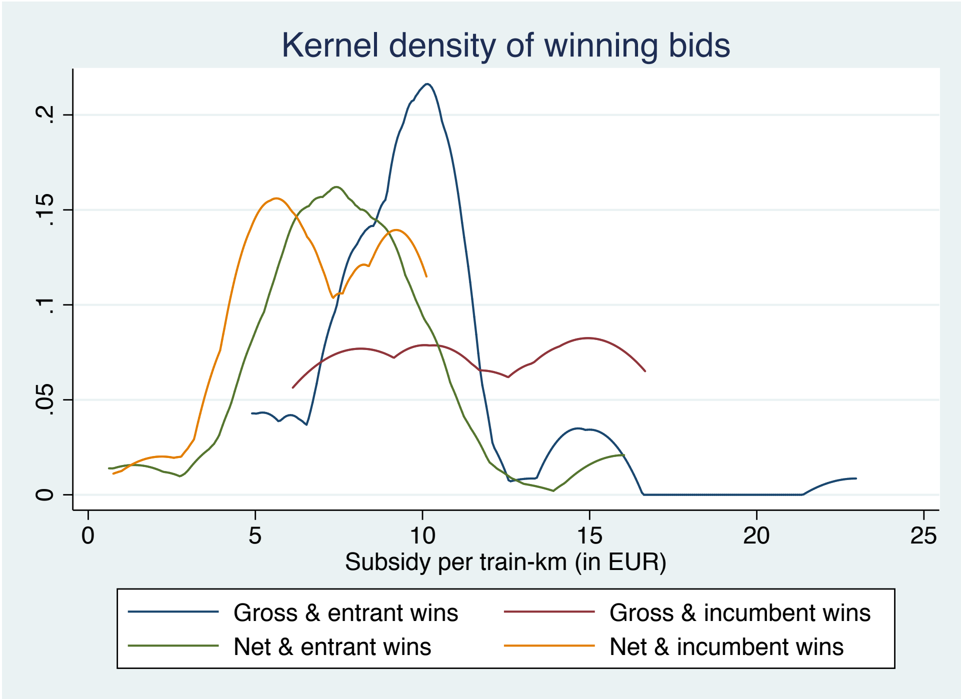
4 Identification & Estimation

4.1 Identification arguments

The cost distributions in an asymmetric IPV model are non-parametrically identified from the winning bid, the number of bidders and the identity of the winner (Athey and Haile 2002). In contrast, the non-parametric identification of a common value component is much more complicated. Identification of the joint distribution of the common value and all the signals requires observing the full bid distribution and either exogenous variation in the number of bidders or the ex post value of the auctioned object. In principle, the realized ticket revenues are observable. Unfortunately, currently we do not have access to it. Identification of just the joint distribution of all common value signals fails if some bids are not observed. In principle, the full bid distribution is recorded by the agencies. Unfortunately, we do not have access to these data at this point. Therefore, we cannot provide a formal identification argument for our common value component. Similarly to Hong and Shum (2002), we rely on an intuitive argument to identify the distribution of the common value.

α_I to be much larger than the entrants' α_E. Since the incumbent bids in all auctions, variation in N across auctions comes only from a different number of less informed entrants. Second, increased uncertainty about ticket revenues could well be consistent with our data. Tracks that attract more bidders are usually contracts with a higher expected profit, but higher expected profits usually come also with higher demand risk. While we are aware of the shortcomings of this model, we believe it nevertheless provides a framework that fits our application well. With a sufficiently large sample, we could avoid this problem, by simply estimating the asymmetry parameters separately for each N.

Figure 1: Kernel density of winning bids



Intuitively, identification of the revenue risk parameters comes from comparing differences between the incumbent's and the entrants' bidding strategies across gross and net auctions. Our key idea is to compare similar tracks under different procurement mechanisms (net vs. gross). Since the procurement mode is assumed to be orthogonal to unobserved contract characteristics, any systematic difference in bidding behavior should be attributed to the revenue uncertainty in net auctions. In addition, we exploit some arguably mild functional form assumptions that help us in identifying the common value component. For example, we assume independence of bidders' revenue signals instead of trying to identify their joint distribution from the data.

4.2 Estimation strategy

Our estimation proceeds in two steps. First, we estimate the asymmetric IPV model using data on auctions of gross contracts. This allows us to compute the distribution of costs for a track with given characteristics. Second, we estimate or model with private (cost) and common value (ticket revenue) components using data on net auctions. Since we extrapolate the cost distributions from the first step, we can isolate the effect of the common value signal in the second step.

As in Athey et al. (2011) we assume that there are two types of bidders: DB as the incumbent who participates in all auctions and $N-1$ symmetric entrants. Asymmetry complicates the estimation since in general the differential equations in the first order conditions do not have a closed-form solution anymore. An additional complication is that under asymmetry

the markup term has to be computed for each bidder configuration, i.e. for each number of bidders, separately.[9] With a sufficiently large sample, we can follow the non-parametric approach of Brendstrup and Paarsch (2003) who generalize Guerre et al. (2000) to asymmetric IPV auctions.

Since the total number of procured tracks is still relatively small, a fully non-parametric estimation will be very imprecise. Therefore, we employ a parametric approach. As in Lalive et al. (2015) and Athey et al. (2011), we assume that the bid functions $G()$ follow a Weibull distribution:

$$G(b_i|X,N) = 1 - \exp\left[-\left(\frac{b_i}{\lambda(X,N)}\right)^{\nu(X,N)}\right] \tag{9}$$

where λ and ν are the scale and shape parameters. Both vary across incumbent and entrants and are modeled as a function of observed contract characteristics:

$$\begin{aligned}
\log(\lambda^I(X,N)) &= \lambda_0^I + \lambda_X^I X + \lambda_N^I N \\
\log(\lambda^E(X,N)) &= \lambda_0^E + \lambda_X^E X + \lambda_N^E N \\
\log(\nu^I(X,N)) &= \nu_0^I + \nu_X^I X + \nu_N^I N \\
\log(\nu^E(X,N)) &= \nu_0^E + \nu_X^E X + \nu_N^E N
\end{aligned}$$

where I and E denote the incumbent and entrants respectively. In order to keep the number of parameters reasonably low, we include only the number of train kilometers and the infrastructure access costs associated with using the corresponding track sections in the contract characteristics X. We believe, that the admission costs charged by DB Netz are a good proxy for the type of track that is procured. Moreover, the total number of train kilometers is a good proxy for the complexity of a project. Finally, we include the contract's specified frequency-of-service as an additional regressor as a proxy for demand conditions.[10]

Since we only observe the winning bids, our estimation relies on the first order statistic, i.e. the lowest realization of N random variables where $N-1$ bids are drawn from the entrants' distribution and one is drawn from the incumbent's distribution. With one incumbent and $N-1$ entrants, the density of the first order statistic conditional on the incumbent or an entrant winning are given by (see Appendix 8.3 for the derivation):

$$h(x^{(1:N)}, I) = g^I(x)(1-G^E(x))^{N-1} \tag{10}$$

$$h(x^{(1:N)}, E) = (N-1)g^E(x)(1-G^E(x))^{N-2}(1-G^I(x)). \tag{11}$$

[9]Campo et al. (2003) develop a non-parametric estimation technique that is appropriate for this setting.
[10]Experimenting with different regressors yields qualitatively similar results which are available upon request.

The likelihood function is then based on equations (10) and (11):

$$LL(\lambda,\nu)=\sum_{j=1}^{T_G}\log(h_{b^{1:N}}(b_j)) \tag{12}$$

where b_j denotes the winning bid in auction j and T_G is the total number of gross auctions in our sample. Given the estimated parameters of the bid distributions, we can back out the cost distribution of each track with characteristics X by inverting bidders' FOCs. Following Athey et al. (2011), we compute the cost distribution for a given track without imposing any additional parametric assumptions as follows:

1. Draw a pseudo-sample of bids for both incumbent and entrant from the estimated bid distributions. $G^I(b|X,N)$ and $G^E(b|X,N)$.

2. The pseudo-sample of bids has to satisfy the the first-order conditions 13 and 14:

$$\hat{c}^I=b_i^I-\frac{1-\hat{G}^I_{M,B}(b_i^I,b_i^I,N)}{\hat{g}^I_{M,B}(b_i^I,b_i^I,N)} \tag{13}$$

$$\hat{c}^E=b_i^E-\frac{1-\hat{G}^E_{M,B}(b_i^E,b_i^E,N)}{\hat{g}^E_{M,B}(b_i^E,b_i^E,N)} \tag{14}$$

   In our procurement application, the markup terms can be computed as follows:

$$\begin{aligned}\hat{G}(b_i)&=G_{M_i|B_i}(b_i|b_i,X,N)\\&=Pr(\min_{j\neq i}B_j\geq b_i|b_i,X,N)\\&=(1-G^E(b_i))^{N-2}(1-G^I(b_i))\text{ (for an entrant)}\\&=(1-G^E(b_i))^{N-1}\text{ (for the incumbent)}\end{aligned} \tag{15}$$

   where in the last 2 lines G^E and G^I denote the estimated bid distributions for incumbent and entrants. Intuitively, $\hat{G}(b_i)$ describes the CDF of the lowest rival bid evaluated at the actual winning bid b_i, i.e. conditioning on the event that bid b_i was pivotal. The denominator of the markup term $\hat{g}$, is simply the derivative of $\hat{G}$:

$$\begin{aligned}\hat{g}&=\frac{\partial\hat{G}(b_i)}{\partial b_i}\\&=-(N-1)(1-G^E(b_i|X,N))^{N-2}g^E(b_i|X,N)\text{ (for the incumbent)}\\&=-(N-2)(1-G^E(b_i|X,N))^{N-3}g^E(b_i|X,N)(1-G^I(b_i|X,N))\\&-g^I(b_i|X,N)(1-G^E(b_i|X,N))^{N-1}\text{ (for entrants)}\end{aligned} \tag{16}$$

3. This results in a pseudo-sample of cost realizations for each track. Now, kernel smoothing treating $\hat{c}$ as a draw from the cost distribution can be used to compute the cost distribution non-parametrically.

Using the gross auction estimates, we can compute the cost distribution for each track and each bidder type. In our second step we use these to extrapolate costs to the net auction contracts. This allows us to focus on the effects of the common value signals on incumbent's and entrants' bidding behavior.

Recall that we assume that firms receive a pair of signals (c_i, r_i) for private costs and common revenues respectively. We assume that revenue signals r_i are drawn from a logconcave distribution $F(R, \sigma_r)$ with mean R and variance σ_r. As discussed in Section 2 the structure of our net auction model allows us to combine the two signals into one *net cost* signal: $\rho_i = c_i - \alpha_i r_i$ that completely determines bidding behavior. Moreover, we denote the expected valuation of the contract conditional on winning the auction with bid b by $\mathcal{P}_i \equiv c_i - \alpha_i r_i - \sum_{j \neq i} \alpha_j \mathbb{E}\left[r_j | \rho_i = B_j^{-1}(b)\right]$ given inverse bid functions B_j^{-1}. Then, according to Lemma 2 bidding behavior is determined by the system

$$\mathcal{P}^I = b^I - \frac{1 - G^I_{M,B}(b^I, b^I, N)}{g^I_{M,B}(b^I, b^I, N)} \tag{17}$$

$$\mathcal{P}^E = b^E - \frac{1 - G^E_{M,B}(b^E, b^E, N)}{g^E_{M,B}(b^E, b^E, N)}. \tag{18}$$

Our goal in this section is to estimate the additional parameters contained in the common value component. In particular, we are interested in the parameter vector α that describes the different precision of the players' information. Our net auction estimation proceeds in two steps:

1. Since we have relatively few observations, we continue to follow a parametric estimation approach. We assume that bid functions follow a Weibull distribution whose parameters are functions of track and contract characteristics (analogous to the gross auction estimation). After having estimated the net bid function parameters, we can back out the combined cost-revenue signal (net cost signal) $\mathcal{P}$ based on the first-order conditions 17.

2. Afterwards, we can treat $\mathcal{P}_i$ as known and transform the sample of winning bids into a sample of (winner's) expected valuations given the winning bid b. Moreover, from the gross auction step we know the cost distributions from which c is drawn. This allows us to isolate the revenue signal part of $\mathcal{P}$ via

$$\mathcal{P}^i \equiv \rho_i - \sum_{j \neq i} \alpha_j \mathbb{E}\left[r_j | \rho_i = B_j^{-1}(b)\right] \tag{19}$$

$$\mathcal{P}^i - c_i = -\alpha_i r_i - \sum_{j \neq i} \alpha_j \mathbb{E}\left[r_j | \rho_i = B_j^{-1}(b)\right] \tag{20}$$

We know $\mathcal{P}$ from the first step and the distribution of c from the gross auction step. Therefore, the LHS "is known" (in expectation). The distribution of the RHS is based on $r \sim F(R, \sigma_r)$ and can be computed up to a vector of parameters (R, σ, α). Thus, we can estimate the parameters using maximum likelihood.

Derivation of the conditional expectation. To carry out the second step, we need to compute the conditional expectation in the expected valuation of winning the line with bid b. The expectation term conditions on the bid being pivotal, i.e. $\rho_i = B_j^{-1}(b)$. However, from the first step we only know the compound expected valuation conditional on winning with bid b. As a consequence, we have to decompose $\mathcal{P}^i$ into ρ_i (i's own signal) and the expectation about rivals' revenue signals. This is a non-trivial exercise as we have to do this consistently with the first-order conditions for equilibrium bidding. We make use of the fact that in equilibrium given the signal ρ_i, the conditional expectation term is a deterministic number. Intuitively, it describes i's expectation about the opponents' revenue signal conditioning on the event that i won with bid b and that b was a pivotal bid.

Given the first step of the estimation procedure we can compute for every winning bid b_w the corresponding (compound) signal that induces opponents to bid b_w, i.e. the opponents' signal that makes b_w pivotal. If i is the winning bidder, denote this signal by $\bar{\mathcal{P}}_{-i}(b_w)$ and note that if an entrant wins, this is immediately given by the winning $\mathcal{P}$ of this line for the other entrants. For any arbitrary player $-i$ this can be computed by inverting bidder $-i$'s bid function at the observed winning bid:

$$\bar{\mathcal{P}}_{-i}(b_w) = b_w - \frac{1 - G^{-i}_{M,B}(b_w, b_w, N)}{g^{-i}_{M,B}(b_w, b_w, N)}. \tag{21}$$

This gives us for every line with corresponding winning bid a sample of N expected valuations conditional on winning with a bid b_w. These have to be consistent with each other due to the following observation: In the expected value of i's opponents' signals, the conditional expectation of i's revenue signal appears again. Hence, we have for each auction N equations in N unknowns conditional on the corresponding ρ_i. The equation system is given by assuming that i wins the auction with bid b

$$\bar{\mathcal{P}}^i(b) = c_i - \alpha_i r_i - \sum_{j \neq i} \alpha_j \mathbb{E}\left[r_j | \mathcal{P}^i = \bar{\mathcal{P}}^j(b)\right] \text{ (for winner)} \tag{22}$$

$$\bar{\mathcal{P}}^j(b) = c_j - \alpha_j r_j - \sum_{k \neq j} \alpha_k \mathbb{E}\left[r_k | \bar{\mathcal{P}}^j(b) = \bar{\mathcal{P}}^k(b)\right] \text{ (for } N-1 \text{ rival bidders)} \tag{23}$$

with $\bar{\mathcal{P}}^i(b) = \mathcal{P}^i(b)$. This is a fixed-point problem in N unknowns conditional on a set of parameters α, R, σ_r. These unknowns are the conditional expectations about the opponents' revenue signals. $\bar{\mathcal{P}}^j(b)$ can be computed from our estimation in the first step. Then, the expectation term for every j is, observing that r_j has to satisfy (by simply rearranging the FOC)

$$r_j(c_j) = \frac{1}{\alpha_j}\left(c_j - \bar{\mathcal{P}}^j(b) - \sum_{k \neq j} \alpha_k \mathbb{E}\left[r_k | \bar{\mathcal{P}}_j(b) = \bar{\mathcal{P}}^k(b)\right]\right), \tag{24}$$

which we can use to compute

$$\mathbb{E}\left[r_j|\bar{\mathcal{P}}_j(b)=\bar{\mathcal{P}}^j(b)\right]=\int_{\underline{c}}^{\overline{c}} r_j(c)f_r(r_j(c))f_{c,j}(c)dc \tag{25}$$

where the joint density $f(c_j,r_j)=f_{c,j}(c_j)f_r(r_j(c_j))$ follows from the independence of the revenue and cost signals. Then, applying (24) in (25) and using this in (22) delivers us a system of N equations in N unknowns for any combination of parameters ρ_i, c_i, α_i for every i. However, as entrants are symmetric this reduces to a two-dimensional system with unknowns X^I and X_E[11]

(26)

$$\bar{\mathcal{P}}^I(b)=c_I-\alpha_I r_I-(N-1)\alpha_E\int_{\underline{c}}^{\overline{c}}\frac{1}{\alpha_E}\left(c-\bar{\mathcal{P}}^E(b)-\underbrace{\sum_{k\neq j}\alpha_k\mathbb{E}\left[r_k|\bar{\mathcal{P}}_j(b)=\bar{\mathcal{P}}^k(b)\right]}_{X_E}\right)f_r(r_E(c))f_{c,E}(c)dc$$

(27)

$$\bar{\mathcal{P}}^E(b)=c_E-\alpha_E r_E-(N-2)\alpha_E\int_{\underline{c}}^{\overline{c}}\frac{1}{\alpha_E}\left(c-\bar{\mathcal{P}}^E(b)-\underbrace{\sum_{k\neq j}\alpha_k\mathbb{E}\left[r_k|\bar{\mathcal{P}}_j(b)=\bar{\mathcal{P}}^k(b)\right]}_{X_E}\right)f_r(r_E(c))f_{c,E}(c)dc$$
$$-\alpha_I\int_{\underline{c}}^{\overline{c}}\frac{1}{\alpha_I}\left(c-\bar{\mathcal{P}}^I(b)-\underbrace{\sum_{k\neq j}\alpha_k\mathbb{E}\left[r_k|\bar{\mathcal{P}}_j(b)=\bar{\mathcal{P}}^k(b)\right]}_{X_I}\right)f_r(r_I(c))f_{c,I}(c)dc$$

For now, we are only interested in the conditional expectation terms and hence, we can reduce this system using $X_i=\sum_{j\neq i}\alpha_j\mathbb{E}[r_j|\overline{\mathcal{P}}^j(b)=\overline{\mathcal{P}}^j(b)]$ further to:

$$X_I=(N-1)\int_{\underline{c}}^{\overline{c}}\left(c-\bar{\mathcal{P}}^E(b)-(N-2)\alpha_E X_E-\alpha_I X_I\right) \tag{28}$$

$$f_r(\frac{1}{\alpha_E}\left(c-\bar{\mathcal{P}}^E(b)-(N-2)\alpha_E X_E-\alpha_I X_I\right))f_{E,c}(c)dc \tag{29}$$

$$X_E=(N-2)\int_{\underline{c}}^{\overline{c}}\left(c-\bar{\mathcal{P}}^E(b)-(N-2)\alpha_E X_E-\alpha_I X_I\right) \tag{30}$$

$$f_r(\frac{1}{\alpha_E}\left(c-\bar{\mathcal{P}}^E(b)-(N-2)\alpha_E X_E-\alpha_I X_I\right))f_{E,c}(c)dc \tag{31}$$
$$+\int_{\underline{c}}^{\overline{c}}\left(c-\bar{\mathcal{P}}^I(b)-(N-1)\alpha_E X_E\right)f_r(\frac{1}{\alpha_I}\left(c-\bar{\mathcal{P}}^I(b)-c-(N-1)\alpha_E X_E\right))f_{I,c}(c)dc.$$

This system can be solved (numerically) for (X_I, X_E) for any given set of parameters (α, R, σ_r)

[11] X_E and X_I differ only in the composition of the firms over which the summation is taken.

using the estimated distributions f_{c_i} from the gross auctions and the distributional assumptions on f_{r_i} being a truncated normal distribution with mean R, variance σ_r and truncation thresholds $\underline{r}$ and $\overline{r}$. Existence of a solution to the system follows directly from Brouwer's fixed point theorem as it is a continuous mapping from a convex and compact set to itself. Formally proving uniqueness of the fixed point is much harder. Therefore, we rely on extensive robustness checks in which we initiate the solver at different starting values to check that the results are likely to constitute the unique fixed point.

Derivation of the Likelihood Function. Given the values of the conditional expectation terms, X_I, X_E, for any vector of parameters (R, σ_r, α), we can construct a likelihood function from the first-order conditions for equilibrium bidding using the estimated values $\mathcal{P}^i$:

$$\mathcal{P}^I = c_I - \alpha_I r_I - \underbrace{(N-1)\alpha_E X_E(R, \sigma_r, \alpha)}_{E_I} \tag{32}$$

$$\mathcal{P}^E = c_E - \alpha_E r_E - \underbrace{(N-2)\alpha_E X_E(R, \sigma_r, \alpha) - \alpha_I X_I(R, \sigma_r, \alpha)}_{E_E} \tag{33}$$

where the left-hand side is the "dependent variable" $\mathcal{P}^i$ that we back out in the first stage. The right-hand side depends on the parameters (R, σ_r, α) and is the sum of two independent random variables. We can compute their density using the convolution of their distributions. The pdf of $\alpha_i r_i$ is $f_{\alpha_i r_i} = \frac{1}{\alpha_i}\mathcal{N}(r_i/\alpha_i; R, \sigma_r, \underline{r}, \overline{r})$. c_i is distributed according to $f_c(c_i)$. Hence, the density of $c_i - \alpha_i r_i$ is:

$$f_{c_i - \alpha_i r_i}(x) = \int_{-\infty}^{\infty} f_{-(\alpha_i r_i)}(y - x) f_c(y) dy \tag{34}$$

where x is the right-hand side of Equation (32).

Finally to capture revenue heterogeneity across tracks, we model the mean of the revenue distribution (R) as a function of the frequency of service and the total number of train kilometers as a sufficient statistic for demand, so that $R = \gamma_0 + \gamma_1 fs + \gamma_2 tkm$. Similarly, we model the variance of the revenue signal distribution as a function of the contract length: $\sigma_r = \bar{\sigma}_r + \gamma_3 cl$. In principle, one can also parametrize α in a variety of ways. For example, we could estimate the asymmetry parameters as a continuous function of the number of bidders or a function of time which would enable us to allow for entrants learning about the common value over time.

5 Estimation results

Table 5 displays the results for the estimation of bid functions in gross and net auctions for the incumbent and the entrants. In a highly non-linear model it is difficult to interpret the

magnitude of the coefficients.[12] Therefore, we focus on the shape of the implied bid functions and cost distribution estimates. We provide graphs for bid functions and cost distributions for both incumbent an entrant for several representative gross and net auction lines in Appendix (8).

Generally bid functions in gross auctions are close for incumbent and entrants and entrants' dominate the incumbent's bid function in the lower tail. This is consistent with the theory of asymmetric auctions which prescribes weaker bidders to bid more aggressively. Our cost distribution estimates are mostly as expected: Generally, the incumbent's cost distribution dominates the entrants' distribution, i.e. incumbents cost are shifted to the left. However, for most lines this difference is smaller than what one would expect and on a several lines entrants even seem to have a cost advantage.

When comparing a typical bid function in a gross auction with one in a net auctions, we find striking differences. Overall, in net auctions the incumbent is much more aggressive compared to the entrants. This is line with our theoretical model that prescribes that entrants who are at a higher risk of the winner's curse will shade their bids more.

Having estimated bidding behavior in both gross and net auctions allows us to predict firms' hypothetical bids if net auction tracks would have been procured in a gross auction. Moving from net to gross contracts makes the bidding functions for the two types much more similar and often results in the familiar picture of the entrants bidding more aggressively than the incumbent in the left tail of the distribution. Analogously, estimating the cost distributions associated with our net contracts reveals positive but only small cost advantages for the incumbent.

Table 3 displays the estimation results for the revenue signal and asymmetry parameters. As expected the expected revenue is increasing in the size of the contract with a highly significant coefficient. The expected revenue is also increasing in the specified frequency of service although, due to a high standard error, not significant. The variance of the revenue distribution is highly significant and positive and, not surprisingly, increasing in the length of the contract.

Most importantly, our estimates for the asymmetry parameters reveal that the incumbent has a substantial information advantage. In our main specification, we estimate α_I separately for auctions with 2 bidders and 3 or more bidders. For $N = 2$, we get an estimated α_2^I of 0.62 implying $\alpha_2^E = 0.38$. Put differently, in auctions with only 2 bidders the incumbent typically has almost 66% more information about the ticket revenues than an entrant. An even more asymmetric pattern persists for auctions with more than 2 bidders. For example, in auctions with 3 bidders, we get $\alpha_3^I = 0.55$ implying $\alpha_3^E = 0.23$.

[12] One striking feature of our estimates are the high standard errors which are mostly due to our small sample size. This problem is well-known in the literature and shared with many other studies estimating parametric bid functions, for example Athey et al. (2011). One explanation is that the asymptotic MLE formula provides a bad description of the behavior of the estimator in small finite samples. In future versions, we plan to compute bootstrap standard errors instead of the currently provided asymptotic MLE standard errors.

Table 2: Estimation results: Bid function parameters

	Gross auctions	Net auctions
λ_0^I	0.8107	-1.5602***
	(0.9570)	(0.3893)
λ_X^I	2.5096***	23.5200
	(0.3706)	(29.2770)
	0.0121	0.6044
	(2.8902)	(5.0368)
	0.8513	-2.9337
	(4.0425)	(5.9271)
λ_N^I	0.1554	1.5298
	(0.7100)	(2.2238)
λ_0^E	2.2926**	-3.2925**
	(1.0765)	(1.4675)
λ_X^E	2.8809	66.7780
	(2.7107)	(100.6200)
	-0.7412	-3.2713
	(10.5870)	(27.6500)
	-1.1131	2.5225
	(11.1180)	(11.1990)
λ_N^E	-0.3706	0.5490
	(2.1102)	(2.8292)
ν_0^I	10.4300***	-2.8274
	(0.3564)	(19.0480)
ν_X^I	0.2138	-32.4190
	(4.3872)	(74.5280)
	0.8138	-1.7658
	(31.6310)	(42.4940)
	-13.2610	18.7310
	(43.7320)	(31.6820)
ν_N^I	-2.8742	-0.4042
	(13.3170)	(16.2530)
ν_0^E	-0.3185	2.4473
	(6.2125)	(13.6530)
ν_X^E	0.1677	-22.5010
	(4.6607)	(64.9760)
	1.1258	4.1126
	(23.2190)	(21.5850)
	2.0834	-0.7447
	(14.1550)	(36.1390)
ν_N^E	0.6701	-0.7632
	(5.2758)	(3.3997)

Table 3: Estimation results: Revenue parameters and asymmetry parameters

	Parameter estimates
α_2^I	0.6224***
	(0.0140)
α_{3+}^I	0.5480***
	(0.1943)
σ_{r0}	2.8665***
	(0.2855)
σ_{r1}	0.8292***
	(0.1441)
β_{R0}	2.0355
	(1.5010)
β_{R1}	8.1742
	(6.0590)
β_{R2}	4.9362***
	(0.7209)

6 Counterfactuals

In this section, we consider a series of counterfactuals and analyze the effects of procurement design on efficiency and agency revenues. First, we define an ex ante efficiency measure in our setup and then compare the ex ante probability of selecting the efficient bidder for three scenarios: first, the actual gross auction sample, second the actual net auction sample and finally we analyze the efficiency effects of procuring the net auction sample as gross auctions. Afterwards, we propose several additional counterfactuals for future research. In particular, we plan to consider the symmetrization of the information between incumbent and entrants in net auctions; that is, enforcing an $\alpha = \frac{1}{N}$, as could be obtained by requiring DB to make its information public.

6.1 Efficiency

Consider bidder i winning with bid b resulting from cost realization c. The probability that bidder i winning with bid b is the efficient bidder is given by

$$\Pr(c \leq \min_{j \neq i} c_j | b \leq \min_{j \neq i} b_j). \tag{35}$$

According to the definition of conditional probabilities this is given by

$$\Pr(c \leq \min_{j \neq i} c_j | b \leq \min_{j \neq i} b_j) = \frac{\Pr(b \leq \min_{j \neq i} b_j \cap c \leq \min_{j \neq i} c_j)}{\Pr(b \leq \min_{j \neq i} b_j)}. \tag{36}$$

We can rewrite the second event in terms of the bids as follows: the cost $c = b_i^{-1}(b)$ of bidder

i corresponding to the winning bid b is lower than the minimum cost of all opponents, $\min_{j\neq i} c_j$, then, the every other bidder j has to have bid more than the bid that corresponds to the same cost realization, i.e. $b_j(c) = b_j(b_i^{-1}(b))$. That is, the second event corresponds to the condition

$$b_j \geq b_j(b_i^{-1}(b)) \; \forall j \neq i. \tag{37}$$

Therefore, we get the new condition

$$\Pr(c \leq \min_{j\neq i} c_j | b \leq \min_{j\neq i} b_j) = \frac{\Pr(b \leq b_j \; \forall j \neq i \cap b_j \geq b_j(b_i^{-1}(b)) \; \forall j \neq i)}{\Pr(b \leq \min_{j\neq i} b_j)} \tag{38}$$

that only depends on the bid functions. Note that if bidders were symmetric, the first event trivially implies the second event and the ex ante probability of selecting the efficient bidder is equal to one. We can rewrite this condition further to

$$\Pr(c \leq \min_{j\neq i} c_j | b \leq \min_{j\neq i} b_j) = \frac{\Pr(b_j \geq b \cap b_j \geq b_j(b_i^{-1}(b)) \; \forall \neq i)}{\Pr(b \leq \min_{j\neq i} b_j)} \tag{39}$$

$$= \frac{\Pr(b_j \geq \max\{b, b_j(b_i^{-1}(b))\} \; \forall j \neq i)}{\Pr(b \leq \min_{j\neq i} b_j)}. \tag{40}$$

The max operator can be solved for each of the bidders directly from the bid functions for each b. Then, we can compute this probability directly from the bid functions estimated in the previous sections. The denominator is again given by the first-order statistics of the bid functions.

What remains to be done is to aggregate over all possible cases that can occur: all winning bids and the corresponding winner's identity. Therefore, the ex ante probability of selecting the efficient bidder is given by

$$\int_{\underline{b}}^{\bar{b}} \Pr(\text{incumbent } i \text{ wins with bid } b) \frac{\Pr(b_j \geq b \cap b_j \geq b_j(b_i^{-1}(b)) \; \forall j \neq i)}{\Pr(b \leq \min_{j\neq i} b_j)} \tag{41}$$

$$+ \Pr(\text{entrant } i \text{ wins with bid } b) \frac{\Pr(b_j \geq b \cap b_j \geq b_j(b_i^{-1}(b)) \; \forall j \neq i)}{\Pr(b \leq \min_{j\neq i} b_j)} dF(b) \tag{42}$$

where $F(b)$ is the distribution of the winning bid. The probability of the incumbent and an entrant winning given bid b is given by

$$\Pr(\text{incumbent wins with } b) = \Pr(\text{incumbent bids } b \text{ and all entrants bid } b_e \geq b) \tag{43}$$

$$= g_I(b)(1 - G_E(b))^{N-1} \tag{44}$$

$$\Pr(\text{incumbent wins with } b) = \Pr(\text{an entrant bids } b \text{ and all other bidders bid } b_i \geq b) \tag{45}$$

$$= (N-1) g_E(b)(1 - G_E(b))^{N-2}(1 - G_I(b)). \tag{46}$$

This yields the following ex ante probability of selecting the efficient bidder:

$$\int_{\underline{b}}^{\bar{b}} g_I(b)(1-G_E(b))^{N-1}\frac{\Pr(b_j \geq b \cap b_j \geq b_j(b_i^{-1}(b))\ \forall j \neq i)}{\Pr(b \leq \min_{j\neq i} b_j)} + \tag{47}$$

$$(N-1)g_E(b)(1-G_E(b))^{N-2}(1-G_I(b))\frac{\Pr(b_j \geq b \cap b_j \geq b_j(b_i^{-1}(b))\ \forall j \neq i)}{\Pr(b \leq \min_{j\neq i} b_j)} db \tag{48}$$

Table 4: Efficiency comparison for different auction formats

	Gross Auctions	Net Auctions	Net → Gross
Pr(selecting efficient firm)	0.7984	0.6363	0.7528

Table 4 displays the computed probabilities of selecting the efficient firm for various procurement modes. All auction modes are fairly efficient with average probabilities of selecting the efficient firm between 64% and 80%. Our gross auction sample exhibits the highest efficiency measure with an average probability of almost 80%. In contrast, the efficiency probability is substantially lower in our net auction sample (around 64%). One interpretation of this large difference is that the gross auction sample consists of lines that are somewhat easier to procure efficiently than the lines in the net auction sample. However, the difference could also be a direct effect of the different procurement modes. In order to investigate the latter effect, we compute the counterfactual efficiency probability when procuring the net auction sample as gross auctions.

We find a significant increase in the probability of selecting the efficient bidder (from 64% to 75%) brining the efficiency of the net auction sample almost to the efficiency level of the gross auction sample. One take-away message from this exercise is that in our application, the asymmetry introduced by potential cost asymmetries is relatively small compared to the inefficiency introduced by asymmetric information about the common value. Our policy implications are somewhat similar to the ones by Hong and Shum (2002): More competition, which is often put forward as an argument for net auctions, need not always be desirable, especially if the winner's curse is strong. In our application, letting train operating companies bear the revenue risks can be detrimental for procurement efficiency since net auctions are likely to put the incumbent at a large advantage.

6.2 Additional counterfactuals

Resulting subsidies While looking at efficiency probabilities is arguably the most important property of an auction design, the procurer might also care about the expected subsidy to be paid. Our estimates allow us to predict the subsidy that the agency has to pay to the winning firm. Since we have estimated the bid functions for all bidder types and all auction formats, we

can compute the expected winning bid via:

$$\int_{\underline{b}}^{\overline{b}} b(g_I(b)(1-G_I(b))^{N-1} + (N-1)g_E(b)(1-G_E(b))^{N-2}(1-G_I(b))db. \tag{49}$$

When comparing the expected subsidy from gross and net auctions it has to be kept in mind that in gross auctions, the agency also obtains the ticket revenues and, therefore, this has to be substracted from the subsidy paid to the winning firm.

Gross as net auctions A straightforward extension is to analyze the effects for efficiency and revenues when procuring the gross auction sample as net auctions. In light of the above results for procuring net as gross auctions, we expect average efficiency to decrease.

Eliminating the informational asymmetry Completely abandoning net contracts might not be desirable. Therefore, we simulate how procurement outcomes would change if entrants and incumbents had the same information on the common value component, i.e. if their revenue signals have equal weight. In our setting this is done by setting α_i equal for every firm and appropriately adjusting the expected value of the signal. For example, one could simulate auction outcomes when the entrants and incumbent become equally informed by setting $\alpha_I = \alpha_E$. This will not affect the variance of the incumbent's signal, but will decrease the uncertainty for the entrants (see the theoretical discussion above). In practice, this could be easily achieved by mandating the incumbent to share its information on ticket sales with the procurement agencies and rival bidders. We expect that going all the way from net to gross auctions is not necessary to increase the ex ante efficiency and suspect that information-symmetric net auctions could well result in the highest efficiency probability.

7 Conclusion

We develop and study a model of procurement auctions that allows for asymmetries in the private value component and asymmetrically precise information on the common value component. Theory predicts that if a bidder is on average more efficient than his competitors, he will bid less agressively while the less efficient bidders bid more aggressively. Moreover, if a bidder is more precisely informed about the common value component, he is less affected by the winner's curse than the competitor and will shade his bid less than the competitors. Observing a dominant firm in the market can be explained by both asymmetries: the dominant firm can have on average lower costs than the competitors or be more precisely informed both allowing it to submit on average lower bids than the competitors.

We take this model to a data set on short haul railway passenger auctions in Germany. With this data set we can disentangle the two asymmetries by making use of a variation in the contract

design: local state agencies that procure these services can choose who bears the revenue risk from ticket sales. If the ticket revenues remain with the agency (*gross contract*) the auction is a standard asymmetric independent private values auction. If the train operating company is the claimant of the ticket revenues (*net contract*), the auction is one with a private value (cost) as well as a common value (ticket revenues) component. In a first step, we estimate the cost distributions of DB and the entrants from the winning bids in gross auctions. Given the first-step results, differences in bidding behavior that are not explained by the differences in cost distributions can be attributed to the common value component.

The results of our structural analysis show no systematic cost advantage of DB over its rivals. Importantly, they are not as large as one may initially expect - under a pure private value assumption - given DB's dominance in the market for SRPS. The estimation of the informational advantage over its competitors reveals that indeed in most auctions DB holds significantly more precise information about future ticket revenues. This highlights the concerns in Monopolkommission (2015) that DB's dominance is at least partially due to its informational advantage which may call for regulatory interventions that symmetrize the information across the bidders. Alternatively, efficiency could be increased by awarding more gross contracts which eliminates the common value component from the auction. We study this intervention in a counterfactual analysis and find that entrants shade their bids less than in net contract auctions, making bid distributions more symmetric. This increases ex ante efficiency of the auctions from 64% to 75%.

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8 Appendix

In this appendix, we provide bid functions and estimated cost distributions for several representative lines for both gross and net auctions.

8.1 Exemplary bid and cost distributions

8.1.1 Bid distributions in gross auctions

The following graphs display a comparison of incumbent and entrant bid functions for gross auction, i.e. auctions in which the bidders do not face any revenue risk.

Figure 2: Bid distribution for gross auction line 18

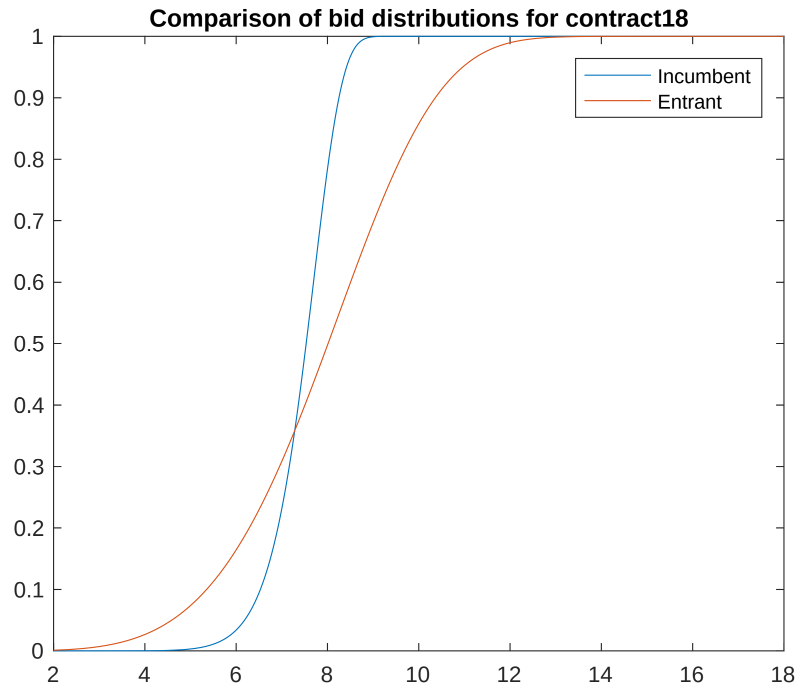


Figure 3: Bid distribution in gross auction line 20

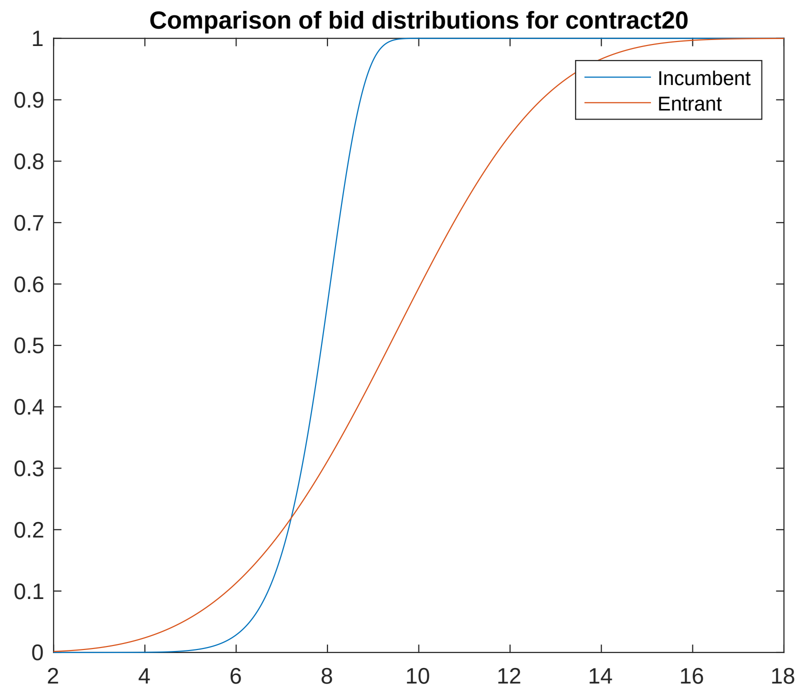
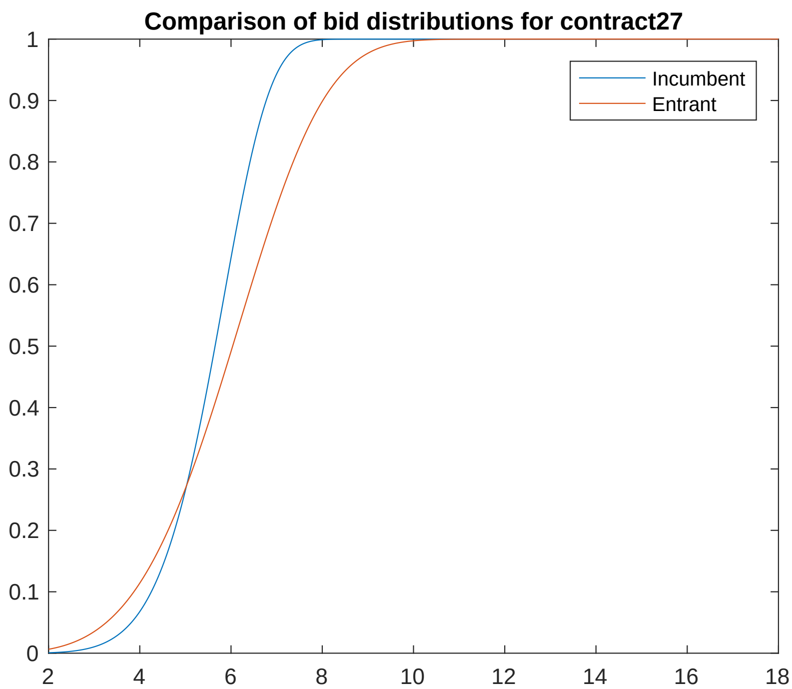


Figure 4: Bid distribution in gross auction line 27



8.1.2 Estimated cost distributions in gross auctions

In this section, we graph our estimates of the cost distributions associated with the bid functions provided in the previous section.

Figure 5: Cost distribution for gross auction line 18

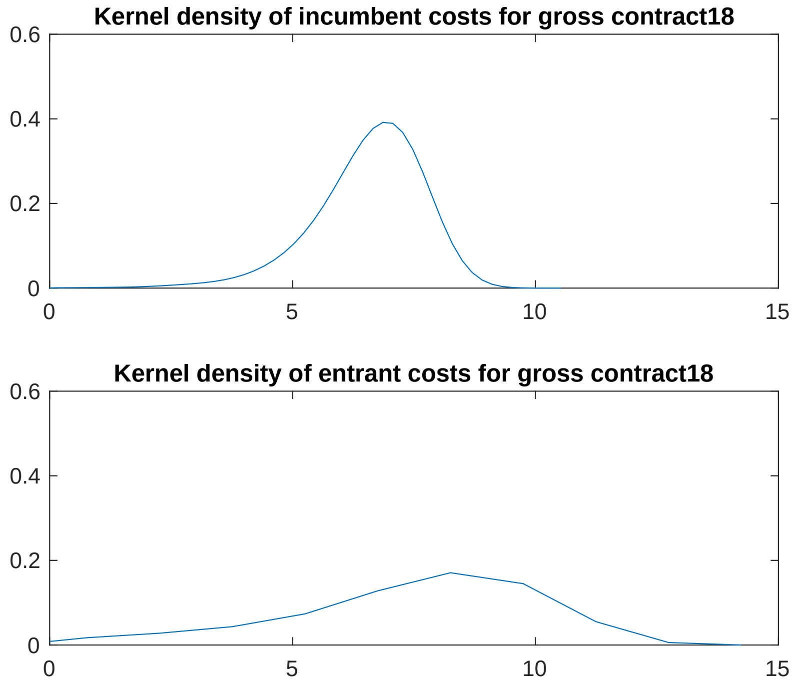


Figure 6: Cost distribution for gross auction line 20

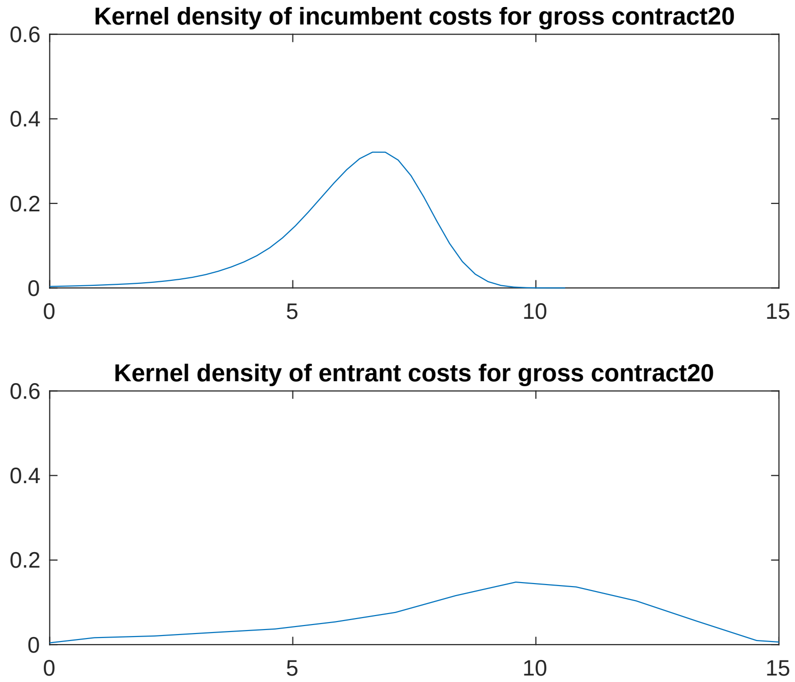
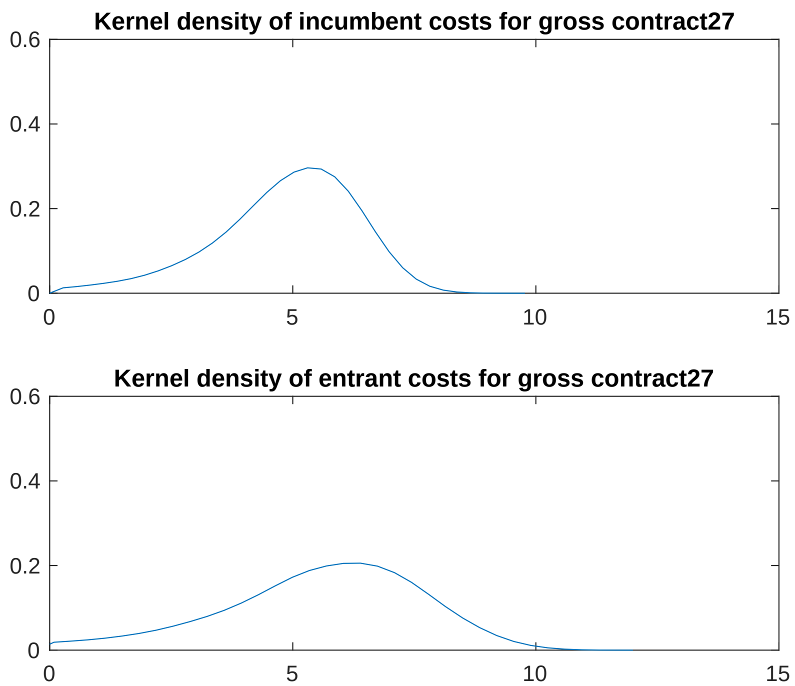


Figure 7: Cost distribution for gross auction line 27



8.1.3 Bid distributions in net auctions

In this section, we provide graphs of bid functions for the incumbent and the entrants for several representative net auctions, i.e. auctions in which the firm bears the revenue risk.

Figure 8: Bid distribution for net auction line 26

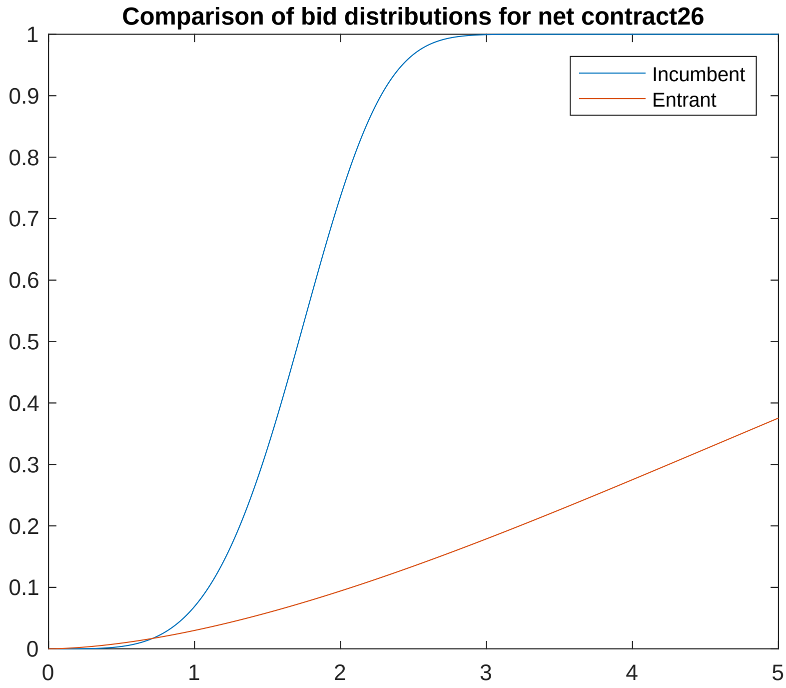


Figure 9: Bid distribution for net auction line 46

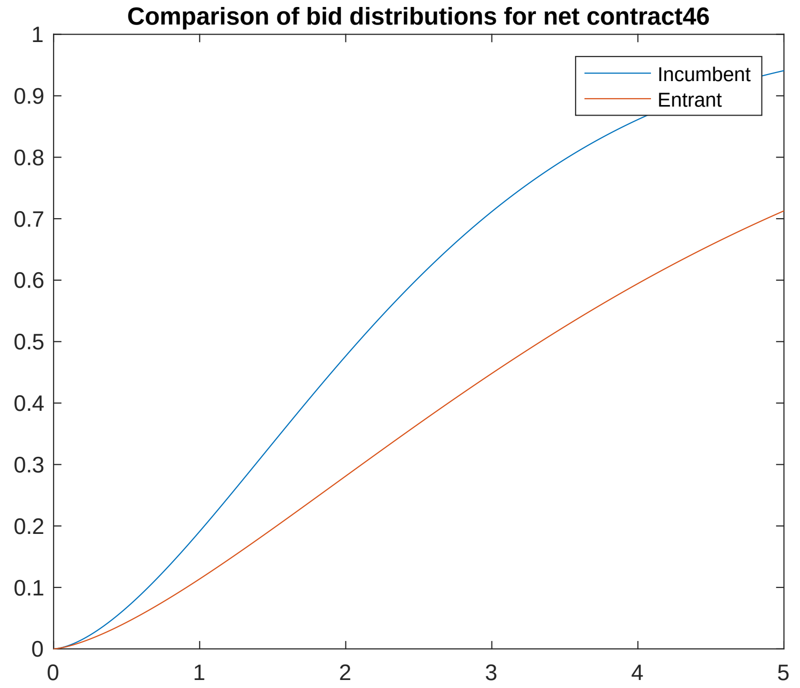
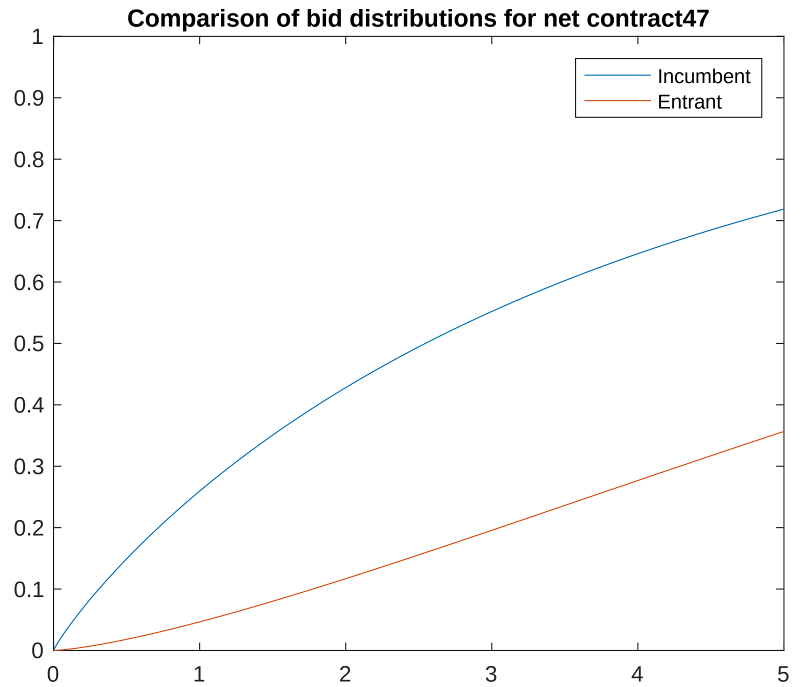


Figure 10: Bid distribution for net auction line 47



8.1.4 Hypothetical bid distributions in net auctions

In this section, we display hypothetical bid functions for the three net auctions presented previously. They illustrate how incumbent and entrant would have bid if the same train track would have been awarded as a gross instead of a net contract.

Figure 11: Hypothetical bid distribution for net auction line 26

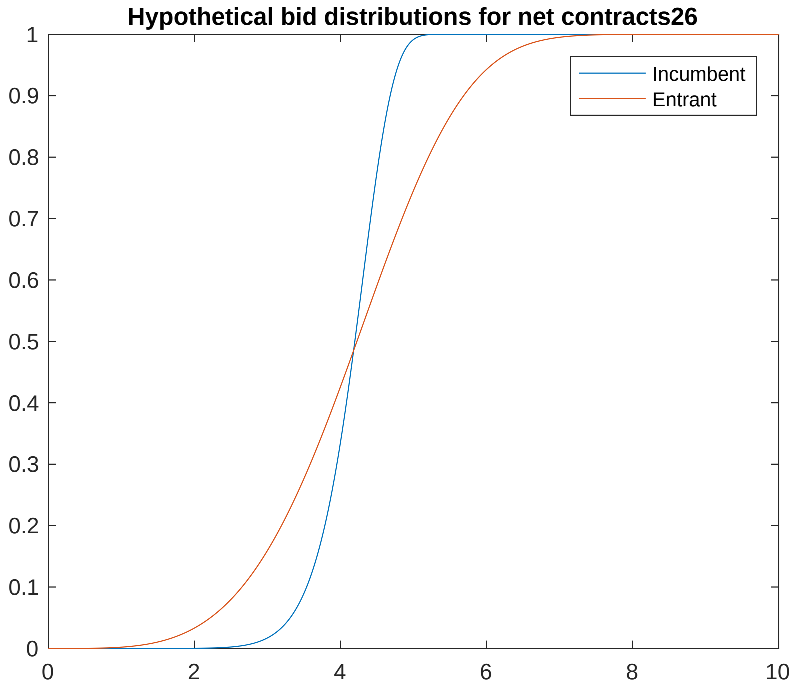


Figure 12: Hypothetical bid distribution for net auction line 46

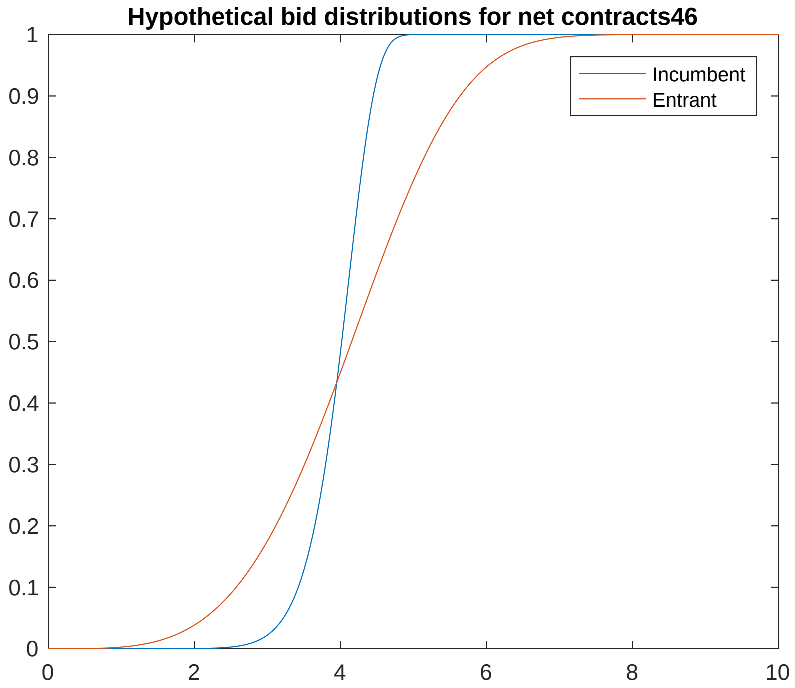
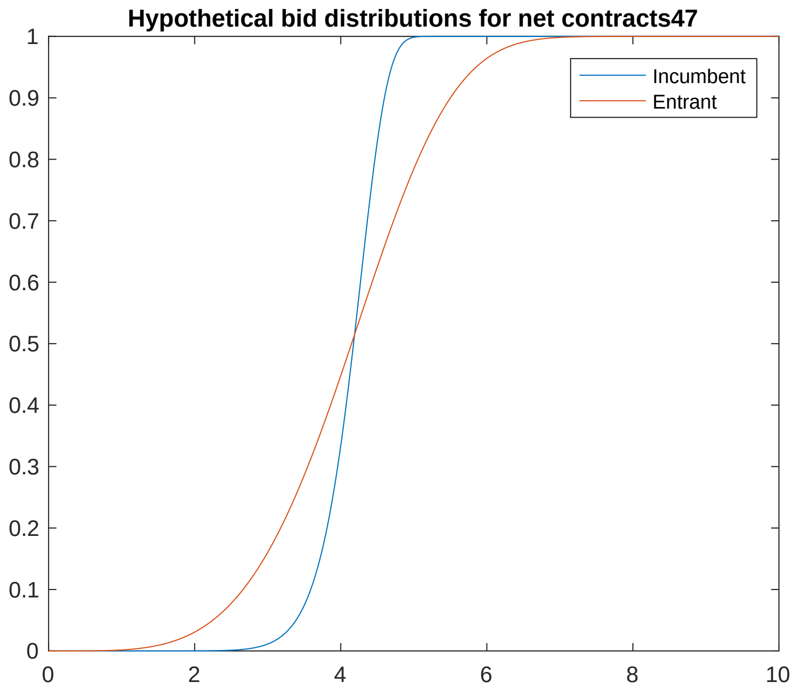


Figure 13: Hypothetical bid distribution for net auction line 47



8.1.5 Estimated cost distributions in net auctions

In this section, we present our estimates for the cost distributions for the three net auction tracks displayed previously.

Figure 14: Cost distribution for net auction line 26

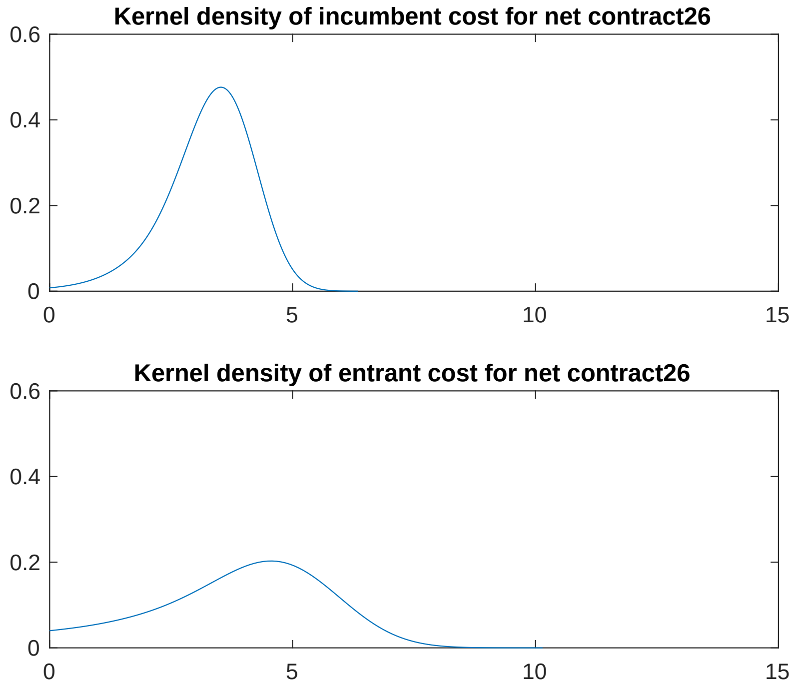


Figure 15: Cost distribution for net auction line 46

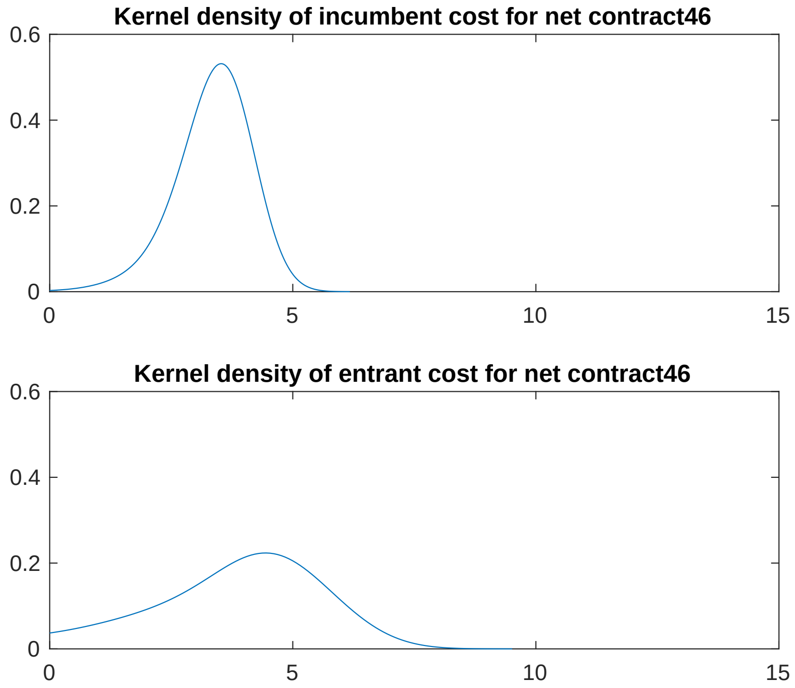
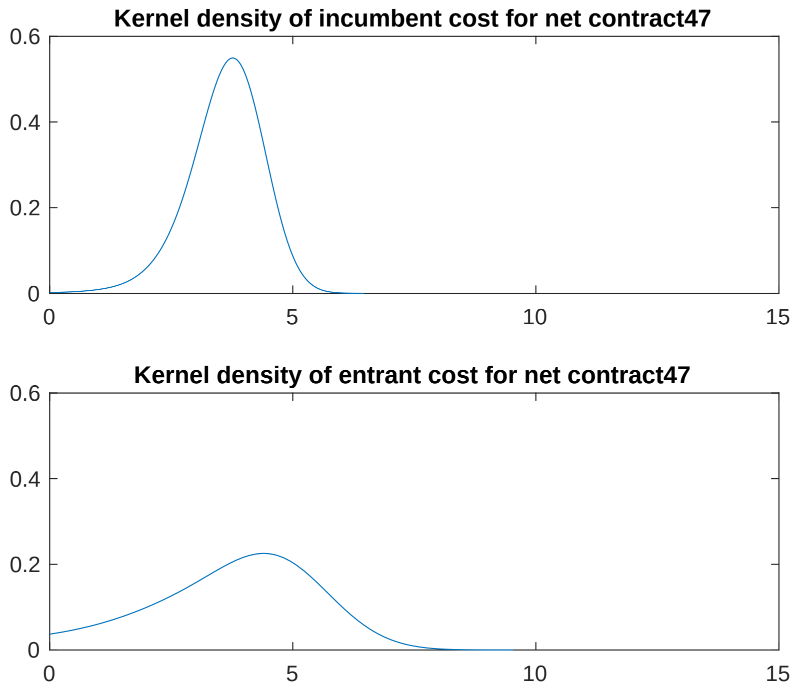


Figure 16: Cost distribution for net auction line 47



8.2 Detailed estimation results

Table 5: Estimation results: bid functions in gross auctions

	Point Estimates	Standard Errors	t-Statistics	p-Values
λ_0^I	0.8107	0.9570	0.8472	0.3969
λ_X^I	2.5096	0.3706	6.7722	0.0000
	0.0121	2.8902	0.0042	0.9966
	0.8513	4.0425	0.2106	0.8332
λ_N^I	0.1554	0.7100	0.2189	0.8267
λ_0^E	2.2926	1.0765	2.1296	0.0332
λ_X^E	2.8809	2.7107	1.0628	0.2879
	-0.7412	10.5867	-0.0700	0.9442
	-1.1131	11.1176	-0.1001	0.9203
λ_N^E	-0.3706	2.1102	-0.1756	0.8606
ν_0^I	10.4298	0.3564	29.2657	0.0000
ν_X^I	0.2138	4.3872	0.0487	0.9611
	0.8138	31.6314	0.0257	0.9795
	-13.2611	43.7319	-0.3032	0.7617
ν_N^I	-2.8742	13.3168	-0.2158	0.8291
ν_0^E	-0.3185	6.2125	-0.0513	0.9591
ν_X^E	0.1677	4.6607	0.0360	0.9713
	1.1258	23.2194	0.0485	0.9613
	2.0834	14.1552	0.1472	0.8830
ν_N^E	0.6701	5.2758	0.1270	0.8989

.

8.3 Derivation of Likelihood Function.

The likelihood function derives from the first-order statistic of the winning bid. That is, the probability that the outcome of the auction is that bidder U wins the auction with bid x given the other bidders $\mathcal{N}$. Introduce the following general notation for bidder type U given our parametric Weibull assumption on the bid function:

$$\text{exp}_U = \exp\left(-(\frac{x}{\lambda_U})^{\rho_U}\right) \tag{50}$$

$$g_U = \exp\left(-(\frac{x}{\lambda_U})^{\rho_U}\right)(\frac{x}{\lambda^U})^{\rho^U-1} = \text{exp}_U(\frac{x}{\lambda^U})^{\rho^U-1} \tag{51}$$

$$G_U = 1 - \exp\left(-(\frac{x}{\lambda_U})^{\rho_U}\right) = 1 - exp_U \tag{52}$$

Denote the density function of the first-order statistic of winning bid x from winner U given number of bidders N by $h^U_{b1:N}$. In case the incumbent wins, the likelihood function is derived

Table 6: Estimation results: bid functions in net auctions

	Point Estimates	Standard Errors	t-Statistics	p-Values
λ_0^I	-1.5602	0.3893	-4.0082	0.0001
λ_X^I	23.5199	29.2769	0.8034	0.4218
	0.6044	5.0368	0.1200	0.9045
	-2.9337	5.9271	-0.4950	0.6206
λ_N^I	1.5298	2.2238	0.6879	0.4915
λ_0^E	-3.2925	1.4675	-2.2437	0.0249
λ_X^E	66.7781	100.6160	0.6637	0.5069
	-3.2713	27.6500	-0.1183	0.9058
	2.5225	11.1989	0.2252	0.8218
λ_N^E	0.5490	2.8292	0.1941	0.8461
ν_0^I	-2.8274	19.0483	-0.1484	0.8820
ν_X^I	-32.4191	74.5279	-0.4350	0.6636
	-1.7658	42.4943	-0.0416	0.9669
	18.7309	31.6825	0.5912	0.5544
ν_N^I	-0.4042	16.2532	-0.0249	0.9802
ν_0^E	2.4473	13.6525	0.1793	0.8577
ν_X^E	-22.5005	64.9759	-0.3463	0.7291
	4.1126	21.5850	0.1905	0.8489
	-0.7447	36.1394	-0.0206	0.9836
ν_N^E	-0.7632	3.3997	-0.2245	0.8224

from

$$
\begin{aligned}
&(53) \qquad h^I_{b^{1:N}}(x, \text{I wins}) = \Pr(b^I = x, b^{E_1} \geq x, \dots, b^{E_{N-1}} \geq x) \\
&(54) \qquad = \Pr(b^I = x)\Pr(b^{E_1}, \dots, b^{E_{N-1}}) \\
&(55) \qquad = g^I(x)(1 - G^E(x))^{N-1}
\end{aligned}
$$

and for an entrant it is given by

$$
\begin{aligned}
&(56) \qquad h^E_{b^{1:N}}(x, \text{ one E wins}) = (N-1)\Pr(b_i^E = x, b^E_{j\neq i} > x, b^I > x) \\
&(57) \qquad = (N-1)\Pr(b_i^E = x)\Pr(b^E_{j\neq i} > x, b^I > x) \\
&(58) \qquad = (N-1)g^E(x)(1 - G^E(x))^{N-2}(1 - G^I(x))
\end{aligned}
$$

8.4 Proof of Lemma 2.

The expected payoff of winning with bid b given signal $-c_i + \alpha_i r_i$ is given by

$$
(59) \qquad \pi_i(b) = \left(b - c_i + \alpha_i r_i + \sum_{j\neq i} \alpha_j \mathbb{E}\left[r_j | \rho_i \geq B_j^{-1}(b) \right] \right) \left(1 - F^{1:N-1}_{\rho_j}(B_j^{-1}(b) \right)
$$

Table 7: Estimation results: asymmetry parameters in net auctions

	Point estimates	Standard errors	t-statistics	p-values
α_2^I	0.6224	0.0140	44.4813	0.0000
α_{3+}^I	0.5480	0.1943	2.8213	0.0048
σ_{r0}	2.8665	0.2855	10.0403	0.0000
σ_{r1}	0.8292	0.1441	5.7530	0.0000
β_{R0}	2.0355	1.5010	1.3561	0.1751
β_{R1}	8.1742	6.0590	1.3491	0.1773
β_{R2}	4.9362	0.7209	6.8476	0.0000

where $F_{\rho_j}^{1:N\backslash i}$ denotes the first-order statistic of opponents' signals. The first-order condition yields

$$0 = -\left(b - c_i + \alpha_i r_i + \sum_{j\neq i} \alpha_j \mathbb{E}\left[r_j|\rho_i \geq B_j^{-1}(b)\right]\right) f_{\rho_j}^{1:N\backslash i}(B_j^{-1})(b) B_j^{\prime -1}(b)$$
$$+ (1 - F_j^{1:N\backslash i}(B_j^{-1}(b))) \left(1 + \sum_{j\neq i} \alpha_j \frac{f_{\rho_j}^{1:N\backslash i}(B_j^{-1})(b)}{1 - F_j^{1:N\backslash i}(B_j^{-1}(b))} B_j^{\prime -1}(n)\right.$$
$$\left.\left(\mathbb{E}\left[r_j|\rho_i = B_j^{-1}(b)\right] - \mathbb{E}\left[r_j|\rho_i \geq B_j^{-1}(b)\right]\right)\right)$$
$$0 = -\left(b - c_i + \alpha_i r_i + \sum_{j\neq i} \alpha_j \mathbb{E}\left[r_j|\rho_i = B_j^{-1}(b)\right]\right) f_{\rho_j}^{1:N\backslash i}(B_j^{-1})(b) B_j^{\prime -1}(b) + (1 - F_j^{1:N\backslash i}(B_j^{-1}(b))).$$

8.5 Proof of Lemma 3.

We assume that both firms have the same cost level c. Thus, the auction is a pure common value auction with asymmetric signal distributions and symmetric value functions. The signal of firm i is $x_i = c - \alpha_i r_i$ where r_i is independently and identically distributed according to a cdf F_r with support $[c - \alpha_i \overline{r}, c]$. Hence, the signals x_i are independently but not identically distributed with $F_{x_i}(x) = \frac{1}{\alpha_i} F_r(\frac{x}{\alpha_i})$ on $[c - \alpha_i \overline{r}, c]$. It follows from the definition of conditional stochastic dominance that $\frac{1-F_{x_2}(x)}{f_{x_2}(x)} > \frac{1-F_{x_1}(x)}{f_{x_1}(x)}$.[13] To simplify notation we write F_j for F_{x_j}.

We now proceed by deriving the tying function for procurement auctions following the proof in Parreiras (2006) for standard first-price common value auctions. The expected value of bidder i conditional on winning with bid b given signal x_i is given by

$$\int_{\phi_j(b)}^{\infty} (b - x_i - \phi_j(b) + c) \; d(1 - F_j(\phi_j(b)))$$

[13] We cannot guarantee that conditional stochastic dominance is satisfied under our parametric assumptions. However, conditional stochastic is sufficient but not necessary for the result in this Lemma to hold, while FOSD is necessary.

where $\phi_j(b)$ is the inverse bid function. As in Parreiras (2006), an equilibrium in monotone strategies exists and therefore the derivate of the inverse bid function is differentiable almost everywhere. Uniqueness of the equilibrium also follows as in Parreiras (2006). The first-order condition implicitly characterizing the equilibrium is given by

$$\frac{1}{\dot{\phi}_j(b)} = (b - x_i - \phi_j(b) + c)\,\frac{f_j(\phi_j(b))}{1 - F_j(\phi_j(b))}. \tag{60}$$

Taking the ratio of the two first-order conditions and applying the function $Q(\phi_1(b)) = \phi_2(b)$ which has derivative $\dot{Q}(\phi_1(b)) = \frac{\dot{\phi}_2(b)}{\dot{\phi}_1(b)}$ yields together with the definition $\phi_1(b) = x$

$$\dot{Q}(x) = \frac{1 - F_2(Q(x))}{f_2(Q(x))} \Big/ \frac{1 - F_1(x)}{f_1(x)} \tag{61}$$

with standard boundary condition $Q(\underline{x}) = \underline{x}$. The interpretation of function $Q(x)$ is that it gives the signal of player 2 that places the same bid as player 1 given signal x. Hence, when $Q(x) \geq x$, bidder 2 shades the bid more than player 1. Given the assumption of conditional stochastic dominance, we have that $\dot{Q}(x)|_{Q(\underline{x})=\underline{x}} > 1$. Moreover, whenever $Q(x)$ approaches x, that is, whenever similar signals yield similar bids, $\dot{Q(x)} > 1$ and pushes $Q(x)$ above x. Formally, $\lim_{Q(x)\searrow x} \dot{Q}(x) > 1$.