Bidder Asymmetries in Procurement Auctions: Efficiency vs. Information
Evidence from Railway Passenger Services

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Abstract
We develop a structural empirical model of procurement auctions with private and common value components and asymmetric bidders in both dimensions. While each asymmetry can explain the dominance of a firm, they have opposite welfare implications. We propose a novel empirical strategy to disentangle and to quantify the two asymmetries using detailed contract-level data on the German market for railway passenger services. Our results indicate that the incumbent is slightly more cost-efficient and has substantially more information about future ticket revenues than its competitors. If bidders’ common value asymmetry was eliminated, the average probability of selecting the efficient firm would increase by 40%-points.

JEL Classification: H57, C57, L92
Keywords: procurement with asymmetric bidders, structural estimation of auctions, railway passenger services

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1. Introduction

Many procurement auctions involve both a private and a common value component. While private value components typically consist of bidder-specific costs, common values can comprise common costs or potential revenues from the provided service. In many markets, bidders in procurement auctions are likely to be asymmetric. First, large firms active in many projects may differ from entrants in their cost efficiency, for example, due to economies of scale or capacity constraints. Second, established firms may have access to superior information about a common value component, for example, due to experiences from similar services they have been involved in.

Empirical studies of asymmetric auctions predominantly employ private value models. Neglecting potential asymmetries in common value components can have substantial implications for the results, however. If a firm wins systematically more often, the theory of asymmetric private value auctions attributes this to a more efficient cost distribution (see Maskin and Riley (2000)). From an efficiency perspective the more efficient firm even wins too few auctions because its competitors bid overly aggressive. We show in a theoretical model with private and common value components that the dominance of a firm can also be explained by asymmetrically precise common value signals. In this case, the more precisely informed firm wins too many auctions from an efficiency perspective. Therefore, the two channels have very different policy implications. Hence, to assess the performance of a procurement mechanism it is crucial to distinguish and quantify the respective importance of private and common value asymmetries. In this paper, we build on and extend the theoretical framework of Goeree and Offerman (2003) to develop a structural empirical auction model with private and common value components that allows for bidder asymmetries in both dimensions.

Asymmetries between firms are particularly likely in industries with experienced incumbents and entrants that recently became active in the market. In the 1990s, many European countries started to liberalize several network industries that used to be controlled by state monopolists (for example telecommunications, retail electricity and transportation services). The aim was a more efficient provision of publicly subsidized goods through to increased competition. In many markets experiences with privatization have been mixed, however. The German market for short-haul railway passenger services (SRPS), with its size of around 8 billion EUR in subsidies for 2016, is an important example that shares many features with similar markets in other countries.

We exploit a detailed data set on procurement awardings in the German market for SRPS from 1995 to 2011. Since SRPS are generally not profitable, state governments procures the tracks and subsidize the train operating companies for the provision of the service. While the aim of the liberalization was to attract competitors, the former state monopolist (DB Regio) could be more efficient because it has a more precise information on the demand.

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2 For brevity, we refer to DB Regio, the short haul distance passenger subsidiary of Deutsche Bahn, as DB in the remainder of this paper.
still operates the majority of the traffic volume (73.6% in 2015, Monopolkommission (2015)). An explicit concern by procurement agencies and industry experts is that entrants bid very cautiously.

By looking at the aggregate market structure it is not clear whether DB’s dominance is justified by an efficient cost structure or whether DB can defend its position due to strong informational advantages. As the former state monopolist, DB has more experience in providing services and as a publicly held firm may have advantages in financing compared to its rivals. These factors may result in a cost advantage of DB over its competitors. In addition, DB Vertrieb, which is integrated with the DB holding that owns DB Regio, has access to all the ticket revenue and passenger data even on tracks which it is not operating itself. Entrants and even procurement agencies typically do not have access to this information (Monopolkommission 2013). As ticket revenues amount to about 40% of the total cost of a contract on average (see Rödl & Partner (2014)), the common value component is a substantial part of the value of a contract and should affect firms’ bidding behavior significantly. Consequently, it is likely that DB has an informational advantage over its competitors. Hence, to assess the market’s efficiency, disentangling the asymmetries in private and common value components is essential. While this is in general a difficult task, we provide a novel empirical strategy that allows us to quantify the cost distributions and the precision of the bidders’ common value signals.

Our model builds on the theoretical work of Goeree and Offerman (2003) who provide a tractable framework to study auctions with private and common value components. They show that if signals about private and common values are independently drawn from logconcave distributions, the private information of a bidder can be summarized in a scalar sufficient statistic which allows us to apply standard methods from auction theory. We extend their model by introducing asymmetries in both the private value distributions and the precision of information about the common value.

We take our model to a detailed contract-level data set on German short-haul railway passenger service (SRPS) procurement auctions. A key feature of our data is that we observe plausibly exogenous variation in the auction design enabling us to disentangle the two asymmetries. While some local procurement agencies prefer to have the train operating firms bear the revenue risk from ticket sales, other agencies decide to bear the risk themselves. 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.

Assuming that the choice between net and gross contracts is exogenous seems to be restrictive at first sight. However, this choice is strongly agency-dependent and there is only very little variation within an agency over time, while track characteristics differ within and across agencies. When comparing track characteristics between the two different contract modes, we find no significant difference in either of the observed contract characteristics. Moreover, we regress
the agency’s choice to use a net contract on a series of observable track characteristics and find no significant effect of any of the regressors. Finally, anecdotal evidence and industry experts support our exogeneity assumption (see in particular Bahn-Report (2007)) highlighting the importance of agencies’ individual, mostly political, preferences for gross or net contracts. Typically, agencies do not differentiate between tracks for which the risk can be assessed easily and those on which it is difficult to do so; instead they simply offer their preferred contract form. For the estimation, we require exogeneity only with respect to the cost characteristics. If the contract mode was chosen based on revenue risk characteristics that are unrelated to the cost structure of the track, our parameter estimates would not be affected.³

Our estimation strategy proceeds in two steps. First, we estimate the cost distribution for each firm from the observed winning bids in gross auctions. Athey and Haile (2002) show that asymmetric independent private value auctions are identified from the winning bid and the winner’s identity only. We incorporate several controls for track heterogeneity and obtain the cost distribution conditional on contract characteristics. In the second step, we exploit the net auction data. Given the first-step results, we can predict the cost distribution for each of the awarded net tracks. Hence, differences in bidding behavior that are not explained by cost differences have to be attributed to the common value component which allows us to estimate the parameters describing the informational asymmetry and the revenue signal distribution.

The results of our structural analysis show a systematic cost advantage of DB over its entrant rivals. Importantly though, it is not as large as one may initially expect given DB’s dominance in the market for SRPS. When comparing the cost distributions across bidder types, we find that DB’s cost distribution is dominated in a first-order stochastic dominance (FOSD) sense on its lower tail for only 25% of the auctions.⁴ When testing for FOSD on the full support, we find that DB’s distribution is dominated in 50% of the auctions. This implies that on the lower tail, the distributions are relatively similar with a slight advantage for DB on average while the entrants’ distributions have more mass on the right tail. The estimation of the informational advantage of DB over its competitors reveals that indeed in most auctions DB has significantly more precise information about future ticket revenues. For example, our estimates imply that on average an entrant’s residual uncertainty (after having conditioned on its own revenue signal) is 2 to 5 times higher than that of the incumbent.

In summary, our results support the concerns of the German antitrust authority in Monopolkommission (2015) that DB’s dominance is at least partially due to its informational advantage which may call for regulatory interventions, for example to symmetrize information across all 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 auctions, making bid functions

³However, the interpretability of our counterfactual analyses of changing the contract mode is limited, if exogeneity with respect to revenue characteristics does not hold.
⁴Note that if DB’s distribution is dominated in a procurement auction, it has the stronger distribution. We define the lower tail from the lower bound of the distribution to twice the winning bid.
more symmetric. As a consequence the average ex ante efficiency, i.e. the probability of selecting the most cost-efficient bidder, of the auctions increases massively from 37.1% to 78.4%. Moreover, by moving from gross to net auctions the ex ante efficiency can be increased in about 90% of the auctions. Most notably, the gains in efficiency probability are on average 54%-points while the efficiency losses amount to only 21%-points on average. We interpret this as evidence that agencies should evaluate carefully when to use net auctions instead of following their political preferences in all tenders. In particular, our analysis supports the view that too many auctions in our data set have been procured as net auctions from an efficiency perspective. Note that it is not obvious that the common value asymmetry decreases efficiency. DB is on average more efficient and the informational advantage increases the probability that DB wins. However, we find that entrants shade their bid too much, so that they even lose auctions they should win from an efficiency perspective.

Auction settings in which private and common value asymmetries interact are very common. In principle, our model and estimation strategy can be applied to different settings. The only requirement is that we observe some variation in auction modes that allows us to estimate the private value distribution from one sample and use this distribution to extrapolate private values on the sample with common value uncertainty. Specific examples include oil drilling auctions, procurement auctions with subcontracting requirements, and auctions of objects with resale value. Oil drilling auctions are sometimes in the form of drainage lease auctions next to an existing tract and sometimes in the form of wildcat auctions. While the private value component is likely to be asymmetric in both settings due to the use of different technologies, in drainage lease auctions one firm tends to have more precise information about its value than its rivals while in wildcat auctions information is likely to be symmetrically distributed (Hendricks and Porter 1988). Some procurement agencies, for example the New Mexico DOT, require firms to use specific subcontractors for certain projects. If firms possess private information about the value of these subcontractors, a model with both asymmetric private and common value components is likely to be appropriate. Finally, auctions of objects that can be traded in a resale market can fit into our model framework if a bidders’ valuations are determined by both idiosyncratic preferences of an object and its potential resale value which some bidders may have superior knowledge about.

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, that competes with new entrants. Therefore, we build on the theory of asymmetric first-price auctions. In a seminal paper, Maskin and Riley (2000) show that stochastically weaker firms bid more aggressively and stronger firms win with higher profits. Goeree and Offerman (2003) provide a tractable framework to study auctions involving both private and common value components. Having two-dimensional private information is generally a complicated problem when the strategic variable is one-dimensional. Their key contribution is to show that under certain assumptions, that

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we discuss in Section 2, the private information can be summarized by a scalar sufficient statistic which allows us to apply standard auction methods. Our theory relies on their modeling framework and extends their analysis of the symmetric case to a model in which bidders have asymmetric private value distributions and are asymmetrically informed about the common value.

De Silva et al. (2003) analyze an asymmetric procurement model and confirm the theoretical predictions of Maskin and Riley (2000) with reduced form regressions using data on highway procurement in Oklahoma. In particular, they find that entrants tend to bid more aggressively than incumbents. 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 and show that the release of information helps entrants in assessing the value of a procurement project. However, their application and empirical methods differ from ours in several important dimensions. Most importantly, they assume a setting in which all bidders have identical cost distributions, and only differ in their information about a common value. In contrast, we analyze a setting in which the incumbent is potentially more cost-efficient, but also faces less uncertainty about the common value (ticket revenues) than the entrants. Furthermore, De Silva et al. (2009) employs a reduced-form quantile-regression approach while we aim at estimating cost distributions and informational asymmetry structurally which enables us to assess the ex ante efficiency of an auction and to perform counterfactual analyses.

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.

For the estimation of our model, we rely on the large literature on the structural estimation of asymmetric auctions. Guerre et al. (2000) show how first-price IPV auctions can be nonparametrically identified and estimated based on winning bids only without having to solve for the auction equilibrium. Li et al. (2000) discuss identification and nonparametric estimation of CIPI (conditionally independent private information) auctions which comprise IPV and common value auctions as a special case. Their arguments rely on measurement error techniques and require observing all bids and that bidders’ signals are a multiplicative function of the private and common value signal. Since we only observe winning bids we cannot use their methodology. Therefore, we develop an empirical strategy that relies only on winning bid data and exogenous variation in the contract design.

In the same multiplicative framework as Li et al. (2000), Hong and Shum (2002) estimate a parametric model with both private and common value components and symmetric bidders using procurement data from New Jersey. They argue that the winner’s curse effect can outweigh the competition effect so that more bidders can result in less aggressive bidding. Therefore, their focus is on estimating the relative importance of private and common values for specific types
of auctions. They find that highway work and bridge repairs contain a substantial common value component while paving services are mostly private values auctions. In contrast to their study, we have 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. These features allow us to focus on separating the effects of asymmetric cost distributions and asymmetric information about the common value across different bidder types.

There is relatively little empirical research on asymmetric common value auctions due to known difficulties with nonparametric identification in common value auctions, see for example the discussion in 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 neighboring firms in drainage lease auctions. In recent work, Somaini (2015) shows how common values can be identified in a structural model from the full bid distribution and observable variation in bidder-specific cost shifters. In a seminal paper, Hendricks and Porter (1988) demonstrate that informational asymmetries across bidders have important implications for bidding behavior in offshore drainage lease auctions. Similarly to our application, they analyze a setting in which one firm is more precisely informed about a common value than its rivals. They find that on drainage tracts that are adjacent to a firm’s existing tract, competition seems to be less and profits of participating informed firms are much higher than in auctions in which information is more likely to be symmetric, for example tracts with no neighboring firm or wildcat auctions. In contrast to their study, we aim at structurally quantifying the informational asymmetry without prespecifying which firm is more precisely informed and also allow for an additional private value asymmetry across bidder types.

Several papers analyze and compare different auction formats for public procurement. Athey et al. (2011) estimate a structural model of timber auctions to study entry and bidding behavior when firms are asymmetric in their private value distribution. They analyze the effect of different auction formats (sealed bid vs. open auctions) exploiting exogenous variation in the auction mode across different auctions similar to our analysis of gross vs. net auctions. While Athey et al. (2011) focus on an asymmetric private value model, we study a model with both private value and common value asymmetries. Flambard and Perrigne (2006) employ a non-parametric estimation strategy exploiting the full bid distribution to quantify bidder asymmetries in snow removal auctions in Montreal. As in Athey et al. (2011), they focus on a pure private value model and evaluate various bid preference experiments such as discriminatory reserve prices. Decarolis (forthcoming) compares first price auctions with bid screening to average bid auctions in Italian procurement auctions. In a similar framework as Krasnokutskaya (2011) he applies a deconvolution estimator to separate common and idiosyncratic cost components and to compare the efficiency under first-price and average bid auctions. These auction formats are not used in our application and bidder default which is one of the key elements in his paper, has not been an important issue in the German market for SRPS.
Hunold and Wolf (2013) study the German market for SRPS using a similar data set, but use reduced-form regressions to understand how the auction design affects the likelihood that DB wins an auction, the number of bidders and the resulting subsidy. Their results indicate that DB is more likely to win longer contracts and contracts that require more train kilometers. Moreover, they find initial support for our hypothesis that DB has an advantage when a track is awarded as a net contract. Their results on the resulting subsidy are very weak and rely on a lower number of observations than our analysis. The only effect they find is that net contracts yield lower subsidies which is intuitive as the winning firm receives the ticket revenues in addition to the subsidy.

In a recent working paper, Lalive et al. (2015) analyze the respective benefits of auctions and negotiations in the context of our application. While they focus on the trade-off between competitive auctions and non-competitive negotiations with one firm, we focus on the specific contract design, once the agency has decided to run a competitive procurement auction. To the best of our knowledge, we are the first to analyze the effects of multidimensional bidder asymmetry and the role of gross and net contracts in this industry using structural econometric methods.

The remainder of the paper is structured as follows. We develop the theoretical auction model in Section 2 and provide detailed information about our application, the data and reduced form evidence in Section 3. The identification arguments and estimation strategy are outlined in Section 4. We discuss our estimation results and counterfactuals in Sections 5 and 6 respectively. Section 7 concludes.

2. Auction Model and the Effect of Asymmetries

In this section, we present our model of procurement auctions for gross and net contracts and study the effect of two asymmetries on bidding behavior: (i) the effect of asymmetric private value (cost) distributions, and (ii) the effect of asymmetric precision of the common value (revenue) signals. All auctions are first-price sealed-bid auctions. The value of a contract and the bidding behavior 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 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 \( N \). Since our data is not rich enough to model entry, we assume \( N \) to be exogenous and abstract from bidder participation decisions as for example modeled in Bhattacharya et al. (2014), Decarolis (forthcoming), Krasnokutskaya and Seim (2011) or Sweeting and Bhattacharya (2015). The cost
component, \( c_i \), is drawn from distribution \( F_{c_i} \) and is privately observed. The ticket revenue, \( R \), is an unknown common value for which firms observe only a private signal, \( r_i \), which is drawn from distribution \( F_r \). We allow \( F_{c_i} \) to differ across firms to model cost differences across incumbent and entrants. The differential information about expected revenues comes from the precision of the revenue signals as discussed below. All signals are independent across firms and cost signals are independent of revenue signals for each firm. We assume that bidders are risk neutral.

**Gross contract auctions**  Firms compete for a single indivisible item (a contract for one track) by submitting bids \( b_i \) (the requested subsidy). Firm \( i \)'s ex post value of winning (\( \pi_i \)) and the expected value of winning with a particular bid are given by the formulas for an independent private values (IPV) first-price procurement auction

\[
\begin{align*}
\pi_i &= b_i - c_i \\
E[\pi_i(b_i)] &= (b_i - c_i) \cdot \Pr(b_i \leq \min_{i \neq j} b_j | c_i, b_i)
\end{align*}
\]

For technical reasons discussed in the next subsection, we assume that each \( F_{c_i} \) is logconcave. As the incumbent, DB, is vertically integrated with the network operator, DB Netz, and as it is the former state monopolist, as well as owned by the Federal Republic of Germany, we assume that the incumbent draws its costs from a different distribution than the entrants. To keep the estimation tractable, we treat all entrants symmetrically. This yields an asymmetric auction with two bidder types and we build on the theoretical work on asymmetric IPV auctions, in particular Maskin and Riley (2000).

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 \( F_{c_i} \) with strictly positive density, \( f_{c_i} \), on support \([c_{i,L}, c_{i,H}]\). Each 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. From Reny and Zamir (2004) we know that an equilibrium in pure and monotone strategies with almost everywhere differentiable bid functions exists in our setup. The equilibrium is implicitly defined by the first-order conditions which constitute a system of differential equations in inverse bid functions together with boundary conditions. Denote by \( 1 - G_{i,M_i|B_i}^{gr}(m_i|b_i, N) \) the distribution of the opponents’ minimum bid given own bid \( b_i \) and a set of bidders \( N \), and by \( g_{i,M_i|B_i}^{gr}(m_i|b_i, N) \) the corresponding density in
a gross auction. Then, bid functions have to satisfy:

\[
    b_i = c_i + \frac{1 - G_{\text{gr},M_i|B_i}(b_i|b_i, N)}{g_{\text{gr},M_i|B_i}(b_i|b_i, N)}.
\]

We borrow the definition of conditional stochastic dominance\(^6\) and the following Lemma from Maskin and Riley (2000), both adapted to the procurement setting.

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

Lemma 1 shows that a bidder with a stronger cost distribution will also have a stronger bid distribution and therefore win the majority of auctions. Hence, observing a dominant bidder in an IPV auction is an indicator for a bidder with a stronger value distribution. However, the weaker bidder will bid more aggressively (see Section 2 for an illustration). As a result, the auction may be inefficient and the strong bidder wins too few auctions from an efficiency perspective. For our application, this model suggests that if the incumbent, DB, wins the majority of the gross auctions, it is on average the more efficient firm. This result has been generalized by De Silva et al. (2003) to hold also in the presence of an additional common value component and therefore also in the net auctions if firms had equally precise information about the common value component.

**Net contract auctions** When net contracts are procured, the bidders’ values of a contract consist of a private cost and a common value component. Therefore, we develop an asymmetric first-price auction model with both private and common values. The value of the contract differs across bidders and consists of: (i) a private component, which is the cost of fulfilling the contract, \(c_i\), drawn from distribution \(F_{c_i}\), and (ii) a common component, the ticket revenues, \(R\). In addition to their private value signal, \(c_i\), firms receive a private signal about \(R\), \(r_i\), drawn from distribution \(F_r\) with mean \(\bar{R}\) and variance \(\sigma_r\). Revenue signals are conditionally independent given \(R\). For technical reasons, we assume that \(F_{c_i}\) and \(F_r\) are log-concave.

To model net auctions, we build on Goeree and Offerman (2003). A key problem in auctions with private and common values is that each bidder’s private information is two-dimensional, consisting of the private and the common value signal. The strategic variable, the bid, is only one-dimensional. Generically, there is no straightforward mapping from two-dimensional signals into a one-dimensional strategic variable. However, under the assumption that the common value is equal to the sum of the signals, i.e., \(R = \sum_{i=1}^{N} r_i\), and a log-concave revenue signal

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\(^6\)Conditional stochastic dominance is defined as follows: There exists \(\lambda \in (0, 1)\) and \(\gamma \in [c_{j,L}, c_{i,H}]\) such that

\[
1 - F_i(x) = \lambda(1 - F_j(x)) \quad \text{for all} \quad x \in [\gamma, c_{i,H}] \quad \text{and} \quad \frac{d}{dx} \frac{1 - F_i(x)}{1 - F_j(x)} > 0 \quad \text{for all} \quad x \in [c_{j,L}, \gamma].
\]
Figure 1: Private value bidder asymmetry: Illustration of bid functions

The weaker bidder will bid systematically lower markups to compensate for its cost disadvantage. Please update!

distribution Goeree and Offerman (2003) show that such a mapping is possible. In this case, the expected value of winning can be rewritten as a linear composition of the private signals, $r_i$ and $c_i$ as $\rho_i \equiv c_i - r_i$, and terms independent of a bidder’s private information. Our application, this scalar statistic, $\rho_i$, can be interpreted as a net cost signal (costs minus revenue) and is sufficient to capture all of bidder $i$’s private information in one dimension. Therefore, standard auction theory methods following Milgrom and Weber (1982) can be applied.

We extend the model by Goeree and Offerman (2003) to accommodate asymmetric precision of the common value signal of different bidder types. Instead of taking the sum of revenue signals, we model the common value signal as the weighted sum of signals: $R = \sum_{i=1}^{N} \alpha_i r_i$. It follows directly from their analysis that if $R = \sum_{i=1}^{N} \alpha_i r_i$ with $\sum_{i=1}^{N} \alpha_i = 1$, there exist a mapping from revenue and cost signals to a sufficient statistic, $\rho_i \equiv c_i - \alpha_i r_i$, and $\alpha_i$ can be interpreted as a measure of bidder $i$’s revenue signal precision. The ex post value of winning $(\pi_i)$ and the expected value of a bid are then given by

\[ \pi_i = R - c_i + b_i \]

\[ \mathbb{E}[\pi_i(b)|h, c_i, r_i] = \left( b - c_i + \alpha_i r_i + \sum_{j\neq i} \alpha_j \mathbb{E}\left[r_j|\rho_j \geq B_j^{-1}(b)\right] \right) \Pr(b_i \leq \min_{i\neq j} b_j|c_i, r_i, b_i) \]
bidders signal and a higher \( \alpha_i \) indicates a more reliable revenue signal for bidder \( i \). Conditional on a private revenue signal \( r_i \), the expected value of the common value is given by

\[
E[R| r_i = r] = \alpha_i r + \sum_{j \neq i} \alpha_j E[r_j] = \alpha_i r + \sum_{j \neq i} \alpha_j \bar{R}
\]
due to independence of the revenue signals \( \{r_j\}_{j=1}^N \) and the conditional variance can be written as

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

As \( \alpha_i = \alpha_E \) for all entrants and \( \alpha_i = \alpha_I \) for the incumbent, we can simplify this to

\[
\text{var}[R| r_E = r] = (\frac{N-2}{N-1} \alpha_E^2 + \alpha_I^2) \sigma_r \quad \text{for the entrant}
\]

(6)

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

(7)

and hence \( \text{var}[R| r_E = r] > \text{var}[R| r_I = r] \) if \( \alpha_I > \alpha_E \). Note that the vector \( \alpha = (\alpha_I, \alpha_E) \) effectively consists only of one parameter since we can normalize \( \alpha_I + (N-1) \alpha_E = 1 \). Moreover, the \( \alpha \) parameters can be used to compute by how much the residual revenue uncertainty differs across bidder types, for example by computing the difference \( \text{var}[R| r_E = r] - \text{var}[R| r_I = r] = \sigma_r (\alpha_I^2 - \alpha_E^2) \) or the ratio of conditional variances

\[
\frac{\text{var}(R| r_E)}{\text{var}(R| r_I)} = \frac{[(N-2)\alpha_E^2 + \alpha_I^2] \sigma_r}{[(N-1)\alpha_E^2] \sigma_r} = \frac{N-2}{N-1} + \frac{\alpha_I^2}{(N-1)\alpha_E^2}
\]

Bidding behavior is characterized by a system of differential equations as derived in the following Lemma (see Appendix A.3 for the derivation).

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

(8) \[
b = \left(c_i - \alpha_i r_i - \sum_{j \neq i} \alpha_j E[r_j| r_j = B_j^{-1}(b)] \right) + \frac{1 - G_{i,M_i|B_i}^{\text{net}}(b_i|b_i, N)}{g_{i,M_i|B_i}^{\text{net}}(b_i|b_i, N)}
\]

where \( G_{i,M_i|B_i}^{\text{net}} \) and \( g_{i,M_i|B_i}^{\text{net}} \) denote the distribution and density function of the minimum opponent bid given the own bid being pivotal. \( B_j^{-1}(\cdot) \) 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 value of winning also depends on the other players’ revenue signals and the bidder therefore faces a winner’s curse motif. This can be seen in the conditioning set of the expectation of the other players’ revenue signals \( E[r_j| r_j = B_j^{-1}(b)] \). If bidder \( i \) wins with bid \( b \), then it must be the
case that other players’ compound signals, \( \rho_j \), were not too good. Hence, when computing that expectation, the player has to take this into account.

While theory gives strong predictions about how bidding behavior differs across asymmetric participants in private value auctions, this is much less clear in our net auctions due to the additional asymmetric common revenue component. We give an intuition on the effect of the asymmetric precision in the following Lemma that assumes a symmetric and known cost component (see Appendix A.4 for the proof).

**Lemma 3.** Assume there are two firms that have the same cost \( c \). Then, if \( \alpha_1 > \alpha_2 \) and the induced signal distributions satisfy likelihood ratio dominance, bidder 2 shades her bid more than bidder 1 given any interior revenue signal \( r \). Moreover, bidder 1’s bid distribution is stochastically dominated by bidder 2’s bid distribution.

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. As a consequence, if both bidders have the same costs, the more informed bidder will have the stronger bid distribution and will win the majority of the auctions, see Figure 2 for an illustration. If the firms have symmetric costs, the dominant firm will be the one with the more precise information. For our application, this model implies that DB is dominant in the net auctions because it is better informed about ticket revenues if the cost distributions of DB and its competitors are symmetric. Therefore, if the cost realizations of the participants are different, the outcome can be inefficient because the less informed bidders shade their bids more than the more informed bidder. Industry evidence suggests that DB is more precisely informed about the ticket revenues in our application because it is integrated with DB Vertrieb which organizes the ticket sales even on lines that are not operated by DB. This information is not made public and therefore private information of DB. Its competitors have to rely on other less reliable sources of data that provide them with a potentially very imprecise estimate of future ticket revenues.

**Figure 2: Common value bidder asymmetry: Illustration**

In a pure CV auction, the less informed bidder shades his bid more than the more informed bidder (left graph). If a bidder type is both less cost-efficient and less informed, the two asymmetries can offset each other (right graph).
**Empirical implications of the theory** In our application, two asymmetries crucially affect bidding behavior. First, one bidder, DB, is potentially more efficient than the other bidders on average. Second, the same bidder, DB, is potentially more precisely informed about the common value. We briefly summarize the implications of the theory for our application in the following paragraph.

Both asymmetries in isolation can explain the dominant position of DB Regio in the market for SRPS in Germany. However, the assessment of the market structure depends on which of the asymmetries is mainly driving DB’s dominance. If it is dominant due to a better cost distribution, the outcome is desirable and from an efficiency perspective DB even wins too few auctions. If it is dominant due to more precise information, the outcome can be undesirable, as DB might win the auction although it is not expected to be the most cost-efficient firm. When both asymmetries are present, they can potentially offset each other. If DB Regio is both more efficient and more precisely informed, as many industry experts suggest, the aggressiveness of the entrants due to the weaker private-value distribution is (partially or more than) offset by the reduced aggressiveness due to the winner’s curse as illustrated in Figure 3. The overall effect on the efficiency of the auction is therefore an important empirical question.

One crucial implication of the theory is that if one neglects the common value component from the analysis, the assessment of the observed market outcome can be misleading. Seeing a dominant firm can be rationalized by a dominating bid distribution of this firm. If one assumes an IPV model, this observation leads to the conclusion that the dominant firm has a better cost distribution and following Lemma 1 the dominant firm wins too few auctions from an efficiency perspective. Hence, the dominance would not call for regulatory intervention. However, as we have illustrated, the dominance can also be due to more precise information about a common value, which in turn may call for a market intervention favoring entrants.

### 3. Short Haul Railway Passenger Services in Germany

#### 3.1. Industry description

As many other countries, Germany liberalized its railway sector in the 1990s. This liberalization followed the EU Directive 91/440 *Development of the community’s railways* implemented through the *Eisenbahnneuordnungsgesetz* in 1993. One of the main objectives was to induce competition in the railway sector. Short haul railway passenger services are part of the universal service obligation of the government and are generally not profitable for operators. Therefore, local procurement agencies were assigned the task to choose an operator that provides this service on behalf of the federal government.\(^7\) As these services require high subsidies (around 8 billion EUR in 2016, Monopolkommission (2015)), the procurement agencies aim at competition for the tracks to keep the required subsidies at a low level.

\(^{7}\)For our sample period, there were 27 different local procurement agencies.
As part of the reform, the former state monopolists Deutsche Bundesbahn in West Germany and Deutsche Reichsbahn in East Germany merged into Deutsche Bahn AG which to date remains publicly owned by the Federal Republic of Germany. As a consequence, new entrants in the market for German SRPS compete with a publicly held operator, DB, that formerly was the state monopolist.

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 precisely specify almost all 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. Moreover, ticket prices are usually beyond the control of the train operating company.

An important additional feature is that the agency also chooses who obtains the ticket revenues: the agency itself or the train-operating company. When the agency receives the ticket revenues, the contract is called a *gross contract*. When the operating company receives the ticket revenues, the contract is called a *net contract*. We assume that the agency’s choice between net and gross contracts is exogenous to a tracks’ cost distribution, i.e. conditional on observed track characteristics, tracks that are procured as gross or net contract should have identical cost distributions for both bidder types. In general, one might be worried that the choice between gross and net contracts is driven by selection and endogenous procurement decisions by the agencies. This is a potential problem if agencies decide the contract mode (net vs. gross) based on unobservable cost 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, industry experts proclaim that the main procurement features are mostly determined by agency preferences that generally are orthogonal to the structural cost and revenue character-
istics of a track, see in particular the extensive discussion in Bahn-Report (2007). Agencies have a preferred auction mode (gross or net auctions), and procure tracks predominantly under this regime. In Bahn-Report (2007) it is argued that even on tracks for which it is apparent that the revenue risk is high, agencies with a preference for net contracts do not switch to gross auctions. Second, we do not find statistically significant 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 (see ?? and Table 2).

From a theory perspective, the only difference between net and gross contracts is the presence of a common value component, the ticket revenues. 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 or the ticket prices. Consequently, we consider the demand to be independent of the firm operating the service and therefore as a common value to all firms.

Furthermore, we consider the costs to be a private value as the firms have different access to vehicles, funding opportunities, and can pay different wages. Naturally, there are common cost components like electricity and infrastructure charges. However, these can typically be anticipated by all firms in advance resulting in very little cost uncertainty. 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’ costs. 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 (2011)).

In light of 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.

While the market share of competitors has been rising over the years since the liberalization, DB still had a market share of 73.6% measured in train-kilometers in 2013 (see Monopolkommission (2015)). The German antitrust authority has explicitly raised the concern that DB Vertrieb does not make reliable demand data accessible for the agencies and its competitors (see

\(^8\)Note that common value components only result in winner’s curse problems if bidders possess private information about these factors. Common cost or revenue characteristics that are public information do not create a winner’s curse.
This has led to a debate about the underlying reasons for DB’s dominance, in particular whether there are features in the procurement process that reinforce the dominance of DB or whether DB is simply the efficient firm in the market. We assess this question empirically by taking our auction model to a detailed data set on SRPS auctions in Germany from 1995 to 2011.

3.2. Data and descriptive statistics

Our data set consists of almost all procurement contracts from the German market for SRPS from 1995 to 2011.9 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. Moreover, we collected data on characteristics of the track regions and data on track access charges and the frequency of service from the German Federal Statistical Office and additional publicly available sources.

Table 1: Descriptive statistics by auction mode

<table>
<thead>
<tr>
<th></th>
<th>Gross (N=82)</th>
<th></th>
<th>Net (N=75)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Min</td>
<td>Max</td>
</tr>
<tr>
<td>Winning bid (Mio. EUR)</td>
<td>7.50</td>
<td>7.33</td>
<td>0.68</td>
<td>55.16</td>
</tr>
<tr>
<td>No. bidders</td>
<td>4.82</td>
<td>2.01</td>
<td>2.00</td>
<td>11.00</td>
</tr>
<tr>
<td>Train-km (Mio.)</td>
<td>0.80</td>
<td>0.61</td>
<td>0.13</td>
<td>3.79</td>
</tr>
<tr>
<td>Duration (Years)</td>
<td>10.23</td>
<td>2.61</td>
<td>2.00</td>
<td>16.00</td>
</tr>
<tr>
<td>Used vehicles (Dummy)</td>
<td>0.59</td>
<td>0.50</td>
<td>0.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Notes: This table compares descriptive statistics of the most important auction characteristics across different auction modes (gross vs. net). For used vehicles, 1 indicates that used vehicles are allowed, while 0 indicates that new vehicles are required to fulfill the contract.

Table 1 displays descriptive statistics for our sample split up by gross and net auctions. Throughout, the data is consistent with our model and its predictions. Not surprisingly, net auction bids tend to be lower since bidders factor in the additional revenue from the ticket sales. Gross auctions generally attract more bidders (on average 4.8) than net auctions (on average 3.5). Since the incumbent (DB) participates in all auctions, variation in the number of bidders is purely driven by variation in the number of entrants. Observing systematically fewer entrants in net auctions, can be interpreted as additional evidence that this auction format is more problematic for entrants than the incumbent. Interestingly, there does not seem to be a significant difference in the track and contract characteristics between gross and net samples which we interpret as initial support for our assumption that the auction mode is exogenous to a track’s cost characteristics. Table 2 displays the results of t-tests on the equality of the means.

---

9For a few tenderings conducted during our sample period we do not have access to the relevant data, in particular, the winning bid.
of the most important track and contract characteristics: contract duration (in ten-years), track access charges (in EUR per net-km), size of the contract (in million train-km) and an indicator whether used vehicles are permitted for operating the track. None of the differences in means is statistically significant further supporting our exogeneity assumption.

Table 2: Comparison of contract characteristics across gross and net auctions

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>net N</th>
<th>gross N</th>
<th>Difference</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contract duration</td>
<td>1.02</td>
<td>82</td>
<td>1.04</td>
<td>75</td>
</tr>
<tr>
<td>Access charges</td>
<td>0.34</td>
<td>82</td>
<td>0.33</td>
<td>75</td>
</tr>
<tr>
<td>Train-km</td>
<td>0.80</td>
<td>82</td>
<td>0.86</td>
<td>75</td>
</tr>
<tr>
<td>Used vehicles</td>
<td>0.59</td>
<td>82</td>
<td>0.59</td>
<td>75</td>
</tr>
<tr>
<td>Observations</td>
<td>157</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: This table compares the means of key track characteristics across gross and net sample. The last columns corresponds to the p-value for testing equality of the mean across gross and net sample.

While this data set contains relatively few observations, it is to our knowledge the most comprehensive data on the German market for SRPS available. After having dropped a few awardings with unreliable information for some variables, the estimation of gross (net) auctions is based on 82 (75) awardings respectively. A limitation of our data is that we do not observe all bids, but only the winning bids.

Since tracks are typically procured for a very long time (on average 10 years) we rarely observe the same track being procured twice. Therefore, panel data methods cannot be applied and we treat our data as a pure cross-section. Since often different tracks are geographically separated, we argue that the scope for network effects or learning across lines is limited. Therefore, we treat bidding behavior as independent of time. With a substantially longer time dimension, panel methods can allow for the analysis of additional aspects such as unobserved auction heterogeneity in the style of Krasnokutskaya (2011) or the effects of entrants’ learning about the market. However, we suspect that for a reasonable panel analysis we require at least 10 to 15 additional years of data.

3.3. Reduced-form evidence

In this section, we provide reduced-form evidence to support our initial hypotheses and to guide the specification of the structural model estimated in the next section. Table 3 displays the results from OLS regressions of the winning bid and the number of bidders on various contract characteristics. The regressions confirm the patterns observed in the raw data. Winning bids are significantly lower in net auctions and the larger the contract (in terms of duration or volume), the larger the winning bid. For both dependent variables, winning bid and number of bidders, a
linear-quadratic time trend is statistically insignificant supporting our conjecture that during our sample learning is not very important. While net auctions attract significantly fewer entrants, longer contracts increase the number of participants. A striking difference between gross and net auctions is that the number of bidders has a negative effect on the winning bid in gross auctions (-0.17), but a positive effect in net auctions (0.27) although both coefficients are insignificant. In line with Hong and Shum (2002), these estimates suggest that there is a winner’s curse effect in net auctions that outweighs the competition effect associated with more bidders.

Table 3: Reduced-form OLS regressions: winning bids and number of bidders

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Winning bid</td>
<td>No. of bidders</td>
</tr>
<tr>
<td>Time trend</td>
<td>0.10</td>
<td>-0.12</td>
</tr>
<tr>
<td></td>
<td>(0.29)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>Time Trend²</td>
<td>-0.00</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>No. bidders-gross</td>
<td>-0.17</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
<td></td>
</tr>
<tr>
<td>No. bidders-net</td>
<td>0.27</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.32)</td>
<td></td>
</tr>
<tr>
<td>Net auction</td>
<td>-2.94*</td>
<td>-1.73***</td>
</tr>
<tr>
<td></td>
<td>(1.54)</td>
<td>(0.24)</td>
</tr>
<tr>
<td>Contract duration</td>
<td>4.73***</td>
<td>0.65**</td>
</tr>
<tr>
<td></td>
<td>(0.73)</td>
<td>(0.32)</td>
</tr>
<tr>
<td>Frequency (log)</td>
<td>-0.25</td>
<td>0.98**</td>
</tr>
<tr>
<td></td>
<td>(0.67)</td>
<td>(0.49)</td>
</tr>
<tr>
<td>Train-km</td>
<td>8.19***</td>
<td>-0.24</td>
</tr>
<tr>
<td></td>
<td>(1.38)</td>
<td>(0.18)</td>
</tr>
<tr>
<td>Access charges</td>
<td>14.15***</td>
<td>-4.89***</td>
</tr>
<tr>
<td></td>
<td>(5.02)</td>
<td>(1.76)</td>
</tr>
<tr>
<td>Used vehicles</td>
<td>0.43</td>
<td>-0.44**</td>
</tr>
<tr>
<td></td>
<td>(0.65)</td>
<td>(0.21)</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.759</td>
<td>0.535</td>
</tr>
</tbody>
</table>

Notes: Heteroskedasticity-robust standard errors in parentheses.
* p < 0.1, ** p < 0.05, *** p < 0.01
Number of observations: 157

Column (1) in Table 4 presents the results of a reduced-form logit regression of DB winning on various track characteristics. While structural track characteristics such as contract size or track access charges, do not seem to have an effect on the probability of the incumbent winning, procuring a track in a net auction has a large and significant effect. We interpret these estimates as evidence that net auctions per se favor DB.

To support our assumption of exogenous procurement mode (gross vs. net) further, we regress a dummy for net auctions on our standard set of contract characteristics. None of the included
regressors is statistically significant, see Column (2) of Table 4. In both regressions, we control for time trends or year fixed effects none of which are significant supporting our assumption of time-invariant bidding behavior.

Table 4: Reduced-form Logit regressions: incumbent winning and net auction choice

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DB wins Frequency (log)</td>
<td>0.53 (0.80)</td>
<td>-0.04 (0.69)</td>
</tr>
<tr>
<td>Net auction</td>
<td>5.14** (2.53)</td>
<td></td>
</tr>
<tr>
<td>Train-km</td>
<td>0.24 (0.36)</td>
<td>-0.37 (0.65)</td>
</tr>
<tr>
<td>Contract duration</td>
<td>2.22** (1.11)</td>
<td>0.34 (0.49)</td>
</tr>
<tr>
<td>Access charges</td>
<td>-3.25 (4.10)</td>
<td>-1.59 (2.84)</td>
</tr>
</tbody>
</table>

Notes: Heteroskedasticity-robust standard errors in parentheses. 
* p < 0.1, ** p < 0.05, *** p < 0.01  
Number of observations: 157

4. Identification and 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 (see for example the discussion in Athey and Haile (2002)). The non-parametric identification of a common value component is 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. Identification of just the joint distribution of all common value signals fails if some bids are not observed. In principle, both the realized ticket revenues are observable and the full bid distribution is recorded by the agencies. Unfortunately, we do not have access to these data. 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.

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). As illustrated in the previous section, the procurement mode is plausibly orthogonal to a track’s
cost characteristics. Therefore, any systematic differences in bidding behavior that are not explained by differences in the cost distributions should be attributed to differences in 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 gross auctions. This allows us to compute the distribution of costs for a track with given characteristics. Second, we estimate our 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.

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. 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. With a sufficiently large sample, we could follow a non-parametric approach such as in Brendstrup and Paarsch (2003).

Since the total number of procured tracks is still relatively small, a fully non-parametric estimation is not feasible in our application. Therefore, we employ a parametric approach. As in Athey et al. (2011) and Lalive et al. (2015) we assume that the bid distributions for contract type \( j \) of bidder type \( i \), \( G^j_i \), follow a Weibull distribution with distribution function

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

(9)

where \( \lambda^j_i \) and \( \nu^j_i \) are the bidder-specific scale and shape parameters. Both vary across incumbent and entrants as well as the contract mode and are modeled as a log-linear function of observed contract characteristics and the number of bidders \( N \)

\[
\begin{align*}
\log(\lambda^j_i(X,N)) & = \lambda^j_{i,0} + \lambda^j_{i,X} X + \lambda^j_{i,N} N \\
\log(\lambda^j_E(X,N)) & = \lambda^j_{E,0} + \lambda^j_{E,X} X + \lambda^j_{E,N} N \\
\log(\nu^j_i(X,N)) & = \nu^j_{i,0} + \nu^j_{i,X} X + \nu^j_{i,N} N \\
\log(\nu^j_E(X,N)) & = \nu^j_{E,0} + \nu^j_{E,X} X + \nu^j_{E,N} N
\end{align*}
\]

where \( I \) and \( E \) denote the incumbent and entrants respectively. In order to keep the number
of parameters reasonably low, we include only the most relevant contract characteristics based on the reduced-from regressions presented in the previous section: the total size of the contract measured by the total number of train-km, the track access costs and a dummy for whether the auction requires new instead of used train vehicles. The track access costs are likely to be very informative about the type of track that is procured. Moreover, the total number of train kilometers is a good proxy for the complexity of a project. Furthermore, we include the contract’s specified frequency-of-service as an additional regressor to capture demand conditions.

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 bid 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 A.2 for the derivation)

\[
G_{I}^{(1:N)}(x) = g_{I}(x)(1 - G_{E}^{(N-1)}(x))^{N-1} \tag{10}
\]
\[
G_{E}^{(1:N)}(x) = (N - 1)g_{E}(x)(1 - G_{E}^{(N-2)}(x))^{N-2}(1 - G_{I}(x)) \tag{11}
\]

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

\[
LL(\lambda, \nu) = \sum_{t=1}^{T^J} \log \left( G_{E}^{(1:N)}(b_t)(1 - I_{DB wins}) + G_{I}^{(1:N)}(b_t)I_{DB wins} \right) \tag{12}
\]

where \(b_t\) denotes the winning bid in auction \(t\), \(j\) the auction mode \((j \in \{gross, net\}) and \(T^J\) is the total number of auctions of type \(j\) in our sample. Given the estimated parameters of the bid distributions, we can back out the cost distribution of each bidder on each track with characteristics \(X\) by inverting bidders’ FOCs. Following Athey and Haile (2007), 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, \(G_{I}^{gr}(b|X, N)\) and \(G_{E}^{gr}(b|X, N)\).

2. The pseudo-sample of bids has to satisfy the first-order conditions

\[
\hat{c}^{I} = b^{I} - \frac{1 - \hat{G}_{I,M|B}^{gr}(b^{I}|b^{I}, X, N)}{\hat{g}_{I,M|B}^{gr}(b^{I}|b^{I}, X, N)} \tag{13}
\]
\[
\hat{c}^{E} = b^{E} - \frac{1 - \hat{G}_{E,M|B}^{gr}(b^{E}|b^{E}, X, N)}{\hat{g}_{E,M|B}^{gr}(b^{E}|b^{E}, X, N)} \tag{14}
\]

\(^{10}\)We experimented with additional regressors, in particular including dummies for electrified tracks. These larger specifications yielded qualitatively similar results, but much larger standard errors. Results are available upon request.
In our procurement application, the markup terms can be computed as follows

\begin{align}
1 - G_{i,M|B}(b_i|b_i, X, N) &= P_r(\min_{j \neq i} B_j \geq b_i|b_i, X, N) \\
1 - G_{E,M|B}(b_i|b_i, X, N) &= (1 - G_{E}^{gr}(b_i|X, N))^{N-2}(1 - G_{I}^{gr}(b_i|X, N)) \quad \text{(for an entrant)} \\
1 - G_{I,M|B}(b_i|b_i, X, N) &= (1 - G_{E}^{gr}(b_i|X, N))^{N-1} \quad \text{(for the incumbent)}
\end{align}

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

\begin{align}
\hat{g}_{i,M|B}(b_i|b_i, X, N) &= \frac{\partial \hat{G}_{i,M|B}(b_i|b_i, X, N)}{\partial b_i} \\
\hat{g}_{E,M|B}(b_i|b_i, X, N) &= -(N-1)(1 - G_{E}^{gr}(b_i|X, N))^{N-2}g_{E}^{gr}(b_i|X, N) \quad \text{(for the incumbent)} \\
\hat{g}_{E,M|B}(b_i|b_i, X, N) &= -(N-2)(1 - G_{E}^{gr}(b_i|X, N))^{N-3}g_{E}^{gr}(b_i|X, N)(1 - G_{I}^{gr}(b_i|X, N)) \\
&\quad - g_{E}^{gr}(b_i|X, N)(1 - G_{E}^{gr}(b_i|X, N))^{N-1} \quad \text{(for entrants)}
\end{align}

3. Inverting the FOCs for all simulated bids results in a pseudo-sample of cost realizations for each track. Finally, we use kernel smoothing treating $\hat{c}$ as draws from the cost distribution to compute the cost distribution non-parametrically. Using the gross auction estimates, we can compute the cost distribution for any contract and each bidder type. In our second step we use the estimates 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 in a net auction 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 $\bar{R}$ and variance $\sigma_r$. For our main specification, we assume that $r$ is drawn from a normal distribution truncated at zero. 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 summarizes bidder $i$’s private information. Moreover, we denote the expected valuation of the contract conditional on winning the auction with bid $b$ by $P_i(b) \equiv c_i - \alpha_i r_i - \sum_{j \neq i} \alpha_j \mathbb{E}[r_j|\rho_i = B_j^{-1}(b)]$ given inverse bid functions $B_j^{-1}$. According to
Lemma 2 bidding behavior is determined by the system

\begin{align}
\mathcal{P}_i(b^i) &= b^i - \frac{1 - \hat{G}_{I,M|B}^\text{net}(b^i|b^i, X, N)}{\hat{g}_{I,M|B}^\text{net}(b^i|b^i, X, N)} \\
\mathcal{P}_E(b^E) &= b^E - \frac{1 - \hat{G}_{E,M|B}^\text{net}(b^E|b^E, X, N)}{\hat{g}_{E,M|B}^\text{net}(b^E|b^E, X, N)}.
\end{align}

In the remainder of this section we develop the estimation procedure for the parameters characterizing the common value distribution. In particular, we are interested in the parameter vector \( \alpha \) that describes the precision of 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 distributions 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 \( \mathcal{P}_i \) based on the FOCs (17) and (18).

2. Afterwards, we can treat \( \mathcal{P}_i \) as known and transform the sample of winning bids into a sample of (winners’) expected valuations given the winning bid \( b^i \). Moreover, from the gross auction step we know the cost distributions from which \( c_i \) is drawn. Therefore, we can isolate the revenue signal part of \( \mathcal{P} \) via

\begin{align}
\mathcal{P}_i &\equiv \rho_i - \sum_{j \neq i} \alpha_j \mathbb{E}_j \left[ r_j | \rho_j = B_j^{-1}(b) \right] \\
\mathcal{P}_i - c_i &= -\alpha_i r_i - \sum_{j \neq i} \alpha_j \mathbb{E}_j \left[ r_j | \rho_j = B_j^{-1}(b) \right] 
\end{align}

We know \( \mathcal{P}_i \) from the first step and the distribution of \( c_i \) from the gross auction step. Consequently, the distribution of the LHS is known from the data and the gross auction step. The distribution of the RHS is only a function of \( r \sim \mathcal{N}(\bar{R}, \sigma_r) \) and can be computed up to a vector of parameters \((\bar{R}, \sigma_r, \alpha)\). Thus, we can estimate the parameters using maximum likelihood.

To implement the second step, we need to compute the conditional expectation in the expected valuation of winning the line with bid \( b \) in Equation (5). The expectation term conditions on the bid being pivotal, i.e. \( \rho_j = B_j^{-1}(b) \). 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 \( \rho_i \) (i’s private 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 \( \rho_i \), the conditional expectation term is a deterministic number that describes \( i \)’s expectation about the opponents’ revenue signals 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 and for every winning bid \( b \) we can compute the corresponding (compound) signal that induces opponents to bid \( b \), i.e. the opponents’ signal that makes \( b \) pivotal. If \( i \) is the winning bidder, denote this signal by \( \bar{P}^{-i}(b) \) and note that if an entrant wins, this is immediately given by the winning \( P \) of this line for the other entrants. For any arbitrary bidder \(-i\), this can be computed by inverting \(-i\)’s bid function at the observed winning bid

\[
\bar{P}^{-i}(b) = b - \frac{1 - C_{\text{net},M|B}(b|b, X, N)}{g_{\text{net},M|B}(b|b, X, N)}.
\]

Applying this logic to every bidder for a given track, yields a sample of \( N \) expected valuations conditional on winning bid \( b \) and the winner’s identity. These equations 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 for each auction, we have \( N \) equations in \( N \) unknowns. If bidder \( i \) wins the auction with bid \( b \), the equation system is given by

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

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

with \( \bar{P}^{i}(b) = \mathcal{P}^{i}(b) \). This system is a fixed-point problem in \( N \) unknowns conditional on a set of parameters \( \alpha, R, \sigma_r \). These unknowns are the conditional expectations about the opponents’ revenue signals. \( \bar{P}^{j}(b) \) can be computed from our estimation in the first step. Observing from the bidding FOCs that \( r_j \) has to satisfy

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

we can compute the conditional expectation for each firm \( j \)’s signal as

\[
\mathbb{E} [r_j | \bar{P}^{j}(b) = \bar{P}^{j}(b)] = \int_{\mathbb{R}} r_j(c) \frac{f_{c,j}(c) f_r(r_j(c))}{\int_{\mathbb{R}} f_{c,j}(x) f_r(r_j(x)) dx} dc,
\]

where the joint density \( f(c_j, r_j) = \frac{f_{c,j}(c_j) f_r(r_j(c_j))}{\int_{\mathbb{R}} f_{c,j}(x) f_r(r_j(x)) dx} \) follows from the independence of the revenue and cost signals. Plugging (24) into (25) transforms the system into a one-dimensional integral over the cost distributions for given parameter values for \( \rho_i, c_i, \alpha_i \) for every \( i \). As entrants are symmetric, our equations reduce to a two-dimensional system with unknowns
\[ X_I \equiv \mathbb{E} [r_I | \bar{P}^I(b) = \bar{P}^I(b)] \quad \text{and} \quad X_E \equiv \mathbb{E} [r_E | \bar{P}^E(b) = \bar{P}^I(b)] \]

\begin{align}
(26) \quad X_I &= \int_{\gamma}^{\tau} \frac{1}{\alpha_I} \left( c - \bar{P}^I(b) - (N - 1)\alpha_E X_E \right) \\
&\quad \cdot \int_{\gamma}^{\tau} \frac{f_r}{\alpha_I} \left( x - \bar{P}^I(b) - (N - 1)\alpha_E X_E \right) f_{I,c}(x) dx \\
(27) \quad X_E &= \int_{\gamma}^{\tau} (c - \bar{P}^E(b) - (N - 2)\alpha_E X_E - \alpha_I X_I) \\
&\quad \cdot \int_{\gamma}^{\tau} \frac{f_r}{\alpha_E} (x - \bar{P}^E(b) - (N - 2)\alpha_E X_E - \alpha_I X_I) f_{E,c}(x) dx
\end{align}

This system can be solved numerically for \((X_I, X_E)\) for any given set of parameters \((\alpha, \bar{R}, \sigma_r)\) using the estimated distributions \(f_r\) from the gross auctions and the distributional assumptions on \(f_r\). 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 empirical robustness checks in which we initiate the solver at different starting values to check that the results are likely to constitute a unique fixed point.

In order to compute the likelihood, we need to specify a distribution for the common value signals. We choose a truncated Normal distribution for \(F_r\). Truncating the Normal distribution at zero allows us to accommodate that revenues cannot be negative while preserving the log-concavity of the revenue signal distribution. To capture revenue heterogeneity across tracks, we model the mean of \(F_r\) as a function of the frequency of service and the total number of train kilometers as a sufficient statistic for demand, so that \(\bar{R} = \gamma_0 + \gamma_1 f_s + \gamma_2 tkm\). Similarly, we model the variance of \(F_r\) as a linear function of the contract length: \(\sigma_r = \sigma_r + \gamma_3 c_l\). Moreover, we specify the asymmetry parameter \(\alpha\) as a function of the number of bidders \(N\). To keep the number of parameters to estimate reasonably small, we parametrize \(\alpha_I\) as a linear function of \(N\): \(\alpha_I = \gamma_0 + \gamma_1 N\) implying \(\alpha_E = \frac{1}{N-1}(1 - \alpha_I)\). With a sufficiently large sample, we could allow for much more flexible specifications, such as higher order polynomials or estimating the asymmetry parameters separately for each \(N\) and different values for contract characteristics.

Given the values of the conditional expectation terms, \(X_I, X_E\), for any vector of parameters \((\bar{R}, \sigma_r, \alpha)\), we can construct the likelihood function from the first-order conditions for equilibrium bidding using the estimated values \(\bar{P}^i\):

\begin{align}
(28) \quad \bar{P}^I &= c_I - \alpha_I \gamma I - (N - 1)\alpha_E X_E(R, \sigma_r, \alpha) \\
(29) \quad \bar{P}^E &= c_E - \alpha_E \gamma E - (N - 2)\alpha_E X_E(R, \sigma_r, \alpha) - \alpha_I X_I(R, \sigma_r, \alpha)
\end{align}

where the left-hand side is the “dependent variable” \(\bar{P}^i\) that we back out in the first stage. The right-hand side depends on the parameters \((\bar{R}, \sigma_r, \alpha)\) and is the sum of two independent random variables. We can compute their density using the convolution of their distributions. The pdf
of $\alpha r_i$ is $f_{\alpha r_i} = \frac{1}{\alpha_i} \mathcal{N}(r_i/\alpha_i; \bar{R}, \sigma_r, 0)$. $c_i$ is distributed according to $f_c(c_i)$. Hence, the density of $c_i - \alpha r_i$ is:

$$f_{c_i - \alpha r_i}(x) = \int_{-\infty}^{\infty} f_{-(\alpha r_i)}(y - x) f_c(y) dy$$  \hspace{1cm} (30)$$

where $x$ is the right-hand side of Equation (28).

### 5. Estimation results

Table 10 in Appendix A.5 displays the estimates for the bid distribution parameters in gross and net auctions for both the incumbent and the entrants. In a highly non-linear auction model it is difficult to interpret the magnitude of the coefficients. Therefore, we focus on the shape of the implied bid functions and the cost distribution estimates. One representative example of bid functions and cost densities for a gross auction contract is displayed in Figure 4. We provide graphs for several additional gross and net auctions in Appendix A.6.

**Cost estimates** Generally, bid functions in gross auctions are relatively close for DB and entrants, suggesting only a small, but potentially significant systematic difference in cost distributions. Figure 5 displays the histogram of the incumbent’s relative cost advantage measured by the median cost for different tracks. A negative number indicates that the entrant has a lower median cost for fulfilling the contract. On the positive axis, for example a value of 0.5 indicates that the entrant has a 50% higher median cost than DB this specific contract. For many lines, DB has a significant, but small cost advantage although there is substantial heterogeneity. On the one hand, there are numerous lines on which entrants seem to have a cost advantage and for the majority of tracks the incumbent’s cost advantage is modest. On the other hand, there is a significant number of tracks that seem to be prohibitively costly for the entrants to operate when compared to the incumbent’s cost distribution.

In a procurement setting, comparing global statistics or the full distribution might not be very relevant for efficiency and revenue properties of the auction. To compare the cost distributions of different bidder types better, we investigate the lower tail of DB’s and entrants’ cost distributions in more detail. In particular, we test for first-order stochastic dominance (FOSD) using the non-parametric test by Davidson and Duclos (2000).

Even though Figure 5 might suggest strong cost asymmetries we cannot reject the null hypothesis of equal cost distributions in the lower tail for the majority of contracts. Only for 25% of our auctions, we can reject the null hypothesis in favor of the alternative of the entrants’

---

11In our main specification we define the lower tail as the cost range from 0 to twice the winning bid observed in our data. Defining the lower tail based on the percentiles of the cost distribution, for example the lowest quartile leads to qualitatively similar results.
cost distribution dominating DB’s cost distribution.\textsuperscript{12} Details on how we test for FOSD of the cost distributions are provided in Appendix A.7. When testing for FOSD on the full support of the cost distributions, we find that the entrants’ dominates DB’s cost distribution in almost 50% of the auctions. The higher share of FOSD relations results from the estimated cost distribution of the entrant having a higher share of mass in the right tail than DB. In conclusion, while entrant and DB generally seem to have more or less equal cost distributions in the lower tail, the entrant generally has a fatter right tail. These results indicate that DB’s dominance can at least partially justified by it being on average more efficient than its competitors.

\textbf{Revenue and asymmetry estimates} When comparing a typical bid function in a gross auction with one in a net auctions, we find striking differences. Overall, in net auctions entrants seem to shade their bids substantially more than DB. This behavior is in line with our theoretical model that prescribes that entrants who have less precise information will shade their bids more. To quantify the informational advantage, we estimate the precision parameters $(\alpha_I, \alpha_E)$ of our theoretical model.

In our main specification, we estimate $\alpha_I$ as a linear function of the number of bidders. This specification fits auctions with 3 or more bidders well. Tracks with only 2 bidders are arguably

\textsuperscript{12}Note that if the entrants’ cost distribution dominates DB cost distribution, DB has more mass on low cost realizations.
Figure 5: Comparison of median and mean costs across bidder types

This graph summarizes the distribution of the incumbent’s cost advantage measured by the median cost across all auctions in our sample. 0 indicates that both bidder types have the same median cost for a contract. Positive (negative) values denote a cost advantage of the incumbent (entrant).

special.\textsuperscript{13} Therefore, we estimate a separate $\alpha$-parameter for the subset of auctions with only 2 bidders and model $\alpha_I$ as a linear function of $N$ for auctions with more than 2 bidders.

Table 5 summarizes our estimated asymmetry parameters for several bidder configurations $N$. Most importantly, our estimates reveal that the incumbent has a substantial informational advantage on lines with three or more bidders. Our $\alpha$-estimates imply that the incumbent has roughly 2.5 to 5 times more information about the ticket revenues than an entrant on the majority of tracks. For auctions with 2 bidders, we get an estimated $\alpha_I$ of 0.52 implying that incumbent and entrants on these lines have basically equal information on the common value.

6. Counterfactuals

In this section, we analyze the effects of procurement design on efficiency and agency revenues in more detail. First, we define an ex ante efficiency measure in our setup for gross as well as net auctions 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

\textsuperscript{13}Often these tracks were procured under special circumstances or comprise tracks on which an entrant has been providing services for a longer time. Unfortunately, our data is not rich enough to incorporate this aspect rigorously.
finally we analyze the efficiency effects of procuring the net auction sample as gross auctions. In addition, we compute the expected winning bids for each track under both net and gross procurement.

6.1. Efficiency

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

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

(31)

Efficiency in gross auctions  We begin by deriving the relevant formulas for computing ex ante efficiency probabilities in gross auctions. Using the definition of conditional probabilities we get

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

(32)

We can rewrite the second event in terms of the bids. The cost $c_i = b_i^{-1}(b)$ of bidder $i$ corresponding to the winning bid $b$ has to be lower than the minimum cost of all opponents, $\min_{j \neq i} c_j$, for an efficient outcome. If this is the case, every other bidder $j$ has to have bid more than the bid that corresponds to the same cost realization, i.e. $b_j(c) = b_j(b_i^{-1}(b))$. Consequently, the second event corresponds to the condition

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

(33)

For notational convenience, we suppress covariate dependency of the bid functions in this section.
Therefore, we can rewrite

\begin{equation}
\Pr(c_i \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_j^{-1}(b)) \forall j \neq i)}{\Pr(b \leq \min_{j \neq i} b_j)}
\end{equation}

which only depends on the bid functions. Note that if bidders were symmetric, the first event 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

\begin{equation}
\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_j^{-1}(b)) \forall j \neq i)}{\Pr(b \leq \min_{j \neq i} b_j)} = \frac{\Pr(b_j \geq \max\{b, b_j(b_j^{-1}(b))\} \forall j \neq i)}{\Pr(b \leq \min_{j \neq i} b_j)}.
\end{equation}

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 given by the first-order statistics of the bid functions.

In the last step, we have to aggregate over all possible winning bids and the winner’s identity so that the ex ante probability of selecting the efficient bidder is given by

\begin{equation}
\int_b^\infty \Pr(\text{incumbent } i \text{ wins with bid } b) \frac{\Pr(b_j \geq b \cap b_j \geq b_j(b_j^{-1}(b)) \forall j \neq i)}{\Pr(b \leq \min_{j \neq i} b_j)}
\end{equation}

\begin{equation}
+ \Pr(\text{entrant } i \text{ wins with bid } b) \frac{\Pr(b_j \geq b \cap b_j \geq b_j(b_j^{-1}(b)) \forall j \neq i)}{\Pr(b \leq \min_{j \neq i} b_j)} dG(b)
\end{equation}

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

\begin{equation}
\Pr(\text{incumbent wins with } b) = \Pr(\text{incumbent bids } b \text{ and all entrants bid } b \leq b) = g^i_I(b)(1 - G^i_E(b))^{N-1}
\end{equation}

\begin{equation}
\Pr(\text{entrant wins with } b) = \Pr(\text{an entrant bids } b \text{ and all other bidders bid } b \geq b) = (N - 1)g^e_E(b)(1 - G^i_E(b))^{N-2}(1 - G^i_I(b))
\end{equation}

and the resulting ex ante probability of selecting the efficient bidder is

\begin{equation}
\int_b^\infty g^i_I(b)(1 - G^i_E(b))^{N-1} \frac{\Pr(b_j \geq b \cap b_j \geq b_j(b_j^{-1}(b)) \forall j \neq i)}{\Pr(b \leq \min_{j \neq i} b_j)}
\end{equation}

\begin{equation}
+ (N - 1)g^e_E(b)(1 - G^i_E(b))^{N-2}(1 - G^i_I(b)) \frac{\Pr(b_j \geq b \cap b_j \geq b_j(b_j^{-1}(b)) \forall j \neq i)}{\Pr(b \leq \min_{j \neq i} b_j)} db.
\end{equation}

**Efficiency in net auctions**  Next, we derive the formulas for the ex ante efficiency probabilities of net auctions. In net auctions, computing the efficiency measure is slightly more involved as the bidders’ compound net cost signal that determines the bid contains both a cost realization
and a revenue signal. As before, we are interested in determining the conditional probability

\[
\Pr(c_i \leq \min_{j \neq i} c_j \mid b \leq \min_{j \neq i} b_j).
\]

(45)

When computing these probabilities, we have to take into account that each bidder’s signal consists of a private (cost) and a common value (revenue) signal. Determining the probability of having the lowest compound signal is not the relevant statistic for efficiency evaluations since only the cost realization characterizes the efficient firm, while the revenue signal per se is irrelevant. To compute the ex ante probability of selecting the efficient firm, we proceed in several steps. First, we invert each possible winning bid to get the corresponding winning net cost signal for each bidder type. Second, we integrate over all winner’s cost signals that can rationalize a specific net cost signal and compute the probability that for any net cost signal, with which each of the competitors could have lost, the losing bidder had a cost realization above the winning bidder’s cost under consideration. In summary, we get to the following expression

\[
\int_b A^I(b)g_{\text{net}}^i(b)(1 - G_E^i(b))^{N-1} + A^E(b)(N - 1)g_{\text{net}}^E(b)(1 - G_E^E(b))(1 - G_E^i(b))^{N-2}db
\]

(46)

which integrates over all potential winning bids and winner identities weighted by the respective efficiency probabilities, where

\[
A^I(b) = \int_c (B^E(c))^{N-1} f_{\rho I}(c)f_{c I}(c)dc
\]

(47)

\[
A^E(b) = \int_c B^I(c)(B^E(c))^{N-2} f_{\rho E}(c)f_{c E}(c)dx
\]

(48)

denote the probabilities of the incumbent \((A^I)\) and the entrant \((A^E)\) being the efficient firm when winning with bid \(b\). Both terms integrate over all potential winner’s costs that rationalize the compound signal inducing winning bid \(b\) with

\[
B^E(c) = \int_{\rho E(\rho I(b))}^{\rho I} C^E(\rho)f_{\rho E}(\rho)\frac{f_{\rho I}(\rho)}{\int_{\rho I(\rho E(b))}^{\rho I} f_{\rho I}(\rho)dx}d\rho
\]

(49)

\[
B^I(c) = \int_{\rho I(\rho E(b))}^{\rho I} C^I(\rho)f_{\rho I}(\rho)\frac{f_{\rho E}(\rho)}{\int_{\rho E(\rho I(b))}^{\rho I} f_{\rho E}(\rho)dx}d\rho
\]

(50)

and \(B^i(c)\) being the probability that the cost realization for competitor \(i\), integrated over all net cost signals that lose against the winning bid \(b\), is higher than the currently fixed (winner’s) cost \(c\). Here, \(f_{\rho I}(\rho) = \int_{-\infty}^{\infty} f_{c I}(x)f_{-\alpha I'}(x - \rho)dx\) denotes the density of the net cost signal \(\rho_i\) based on the convolution of the cost and revenue signals. Finally, \(C^E(\rho)\) and \(C^I(\rho)\) integrate
over all potential costs of the losing bidder

\[ C^E(\rho) = \int_c^{\infty} f_r(\tilde{c}) f_{cE}(\tilde{c}) d\tilde{c} \]  

(51)  

\[ C^I(\rho) = \int_c^{\infty} f_r(\tilde{c}) f_{cI}(\tilde{c}) d\tilde{c} \]  

(52)

where the lower bound of integration \( c \) is the winner’s cost signal currently fixed, and \( r_i(c) \) is the corresponding revenue signal that rationalizes \( \rho_i \) given a cost realization \( c \) and is determined by \( r_i(c) = \frac{1}{\alpha_i} (c - \rho_i(b) - c) \).

<table>
<thead>
<tr>
<th>Table 6: Efficiency comparison for different auction formats</th>
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<tr>
<td>Pr(selecting efficient firm)</td>
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**Ex ante efficiency results**  Table 6 displays the probabilities of selecting the efficient firm for the different procurement modes averaged across all tracks in our gross and net sample respectively. Gross auctions are very efficient with average probabilities of selecting the efficient firm above 80%. In contrast, the probability of selecting the efficient firm is substantially lower in our net auction sample (37% on average).

In light of our empirical analysis comparing gross and net auctions in Section 3, the most likely explanation for the efficiency difference between gross and net auctions, is a direct effect of the procurement modes. In particular, the strong bid shading of entrants in net auctions due to their informational disadvantage can reduce the efficiency of net auctions. To investigate this channel in more detail, we compute the counterfactual efficiency probabilities if our net auction sample was procured as gross auctions.

We find a substantial increase in the probability of selecting the efficient bidder (from 37.1% to 78.4%) bringing the efficiency of the net auction sample almost to the level of the gross auction sample. When testing the equality of the average efficiency of gross auctions and net auctions procured as gross, we are not able to reject the null hypothesis at the 5%-level.

We interpret these results as evidence for the informational asymmetry to be much more severe than the private value (cost) asymmetry. If the common value asymmetry was relatively smaller, it could well be that net auctions exhibit higher efficiency than gross auctions by offsetting asymmetries in bidder type’s cost distribution as discussed in Section 2. One policy implication from this exercise is that letting train operating companies bear the revenue risks can be detrimental for procurement efficiency since net auctions are likely to put the former state monopolist at a large advantage.

Looking only at the mean efficiency averaged across potentially very different auctions can be
misleading. Figure 6 displays histograms of efficiency probabilities for the two samples (gross and net) and the counterfactual in which net auctions are instead procured as gross contracts. The general picture is consistent with our discussion above. In addition, Figure 6 reveals that moving from net to gross auctions results in auctions that were very inefficient before (probability of selecting the most efficient firm less than 50%) to benefit most. Generally, the distribution of efficiency probabilities is shifted to the right when moving from net to gross. For 89% of the net auctions, the ex ante efficiency increases when they are procured as gross auctions. While efficiency decreases on several lines, the efficiency losses are relatively modest (on average 21%-points). In contrast, the efficiency gains are much more pronounced (on average 54%-points).

Even though in practice, it is very hard to argue that one auction mode is strictly better, our counterfactual exercise suggests that there is a substantial efficiency potential when agencies choose procurement modes carefully based on track characteristics instead of basing it on the political preferences of the agency officials.

6.2. Counterfactual winning bids

While efficiency probabilities are arguably the most important indicator of the performance of a government procurement auction, 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.\textsuperscript{15} Since we have estimated the bid functions for all bidder types and all auction formats, we can compute the expected winning bid via

\begin{equation}
\int_{b}^{\tilde{b}} b(g_j^i(b)(1 - G_j^i(b))^{-1} + (N - 1)g_E^i(b)(1 - G_E^i(b))^{N-2}(1 - G_j^i(b))db.
\end{equation}

Table 7: Revenue comparison for different auction formats

<table>
<thead>
<tr>
<th>Auction Format</th>
<th>Observed bid</th>
<th>Predicted bid</th>
<th>E(ticket revenue)</th>
<th>E(agency payoff)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gross auctions</td>
<td>6.9096</td>
<td>6.7935</td>
<td>22.8475</td>
<td>16.0540</td>
</tr>
<tr>
<td>Net auctions</td>
<td>6.4556</td>
<td>6.5835</td>
<td>23.6491</td>
<td>-6.5835</td>
</tr>
<tr>
<td>Net $\rightarrow$ Gross auctions</td>
<td>6.4556</td>
<td>7.2760</td>
<td>23.6491</td>
<td>16.3732</td>
</tr>
</tbody>
</table>

Table 7 compares averages of actual winning bids and winning bids predicted by our model for the three different auction formats. Interestingly, the difference between gross and net auctions in terms of average subsidy is not statistically significant. One explanation for the relatively small difference in subsidies is that net auctions involve a potentially large winner’s curse risk which offsets the additional revenues from ticket sales in net auctions. Although not statistically significant, the winning bids tend to rise when moving from net to gross auctions since the winning firm has to be compensated for the foregone revenues. Moving from net to gross auctions does not seem to have a substantial impact on the expected subsidy payments on average.

In addition, Table 7 displays our estimates for mean ticket revenues and the expected agency payoff defined as the expected subsidy to be paid minus the expected ticket revenues if gross contracts are procured. A striking feature is that the estimated revenues are consistently higher than expected costs. This can be interpreted as empirical evidence that the revenue component in our industry is substantial, highlighting that asymmetric information about it can be a severe problem. The high ticket revenues seem to contradict the idea that operating regional passenger train services is not profitable in general. However, one should be careful in interpreting these numbers literally to make statements about a track’s profitability. For example, sunk costs or fixed costs associated with a preexisting fleet of train vehicles are substantial in our industry (BSL Transportation Consultants (2016) estimate the cost of vehicles to be around 29% of total costs). The average depreciation duration of vehicles is 15 to 20 years while the average contract duration is only around 9 years. Hence, expenditures for past vehicle purchases still have to be recovered in follow-up contracts. These types of costs can typically not be recovered from bid

\textsuperscript{15}Naturally, 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 which can offset the subsidy increase the agency has to pay to the winning firm. The expected agency payoff should however be interpreted with caution since we remain agnostic about many features of the agency’s objective function. In particular, it is not clear whether the agencies maximize their revenues, try to minimize or maximize explicit subsidy payments or maximize efficiency.
data. Therefore, directly comparing cost and revenue magnitudes backed out from our model can be misleading.

Figure 7: Distribution of winning bids for different auction formats

This graph compares the distribution of the predicted winning bids in the actual net auction sample (upper panel), the predicted winning bids when the net auction sample is procured as gross contracts (middle panel) as well as the relative change in winning bids when going from net to gross auctions (lower panel). For the lower panel, 0 indicates no change in the predicted winning bid. Positive (negative) numbers indicate that the winning bid increases (decreases) in our counterfactual simulation compared to the actual net auction sample.

Figure 7 displays histograms of the expected winning bids for different procurement modes. It reveals substantial heterogeneity across tracks. While there is a modest increase in the winning bid for the majority of tracks when moving from net to gross contracts, there is a significant number of contracts for which the required subsidy decreases when bidder’s revenue risk is eliminated. In conclusion, our counterfactuals provide evidence that in many cases gross auctions can easily outperform net auctions in terms of both efficiency and expected subsidy levels.

7. Conclusion

We develop and study a model of procurement auctions that allows for bidder asymmetries in the private values and asymmetrically precise information on a common value component. Theory predicts that if a bidder is on average more efficient than his competitors, his bid distribution will be dominated by the opponents’ bid distribution. Moreover, if a bidder is more precisely
informed about the common value component, he is less affected by the winner’s curse than the competitors and will shade his bid less. Observing a dominant firm in a market can therefore be explained by both asymmetries. It may have lower costs than the competitors or it may be more precisely informed; both allowing it to submit on average lower bids than its competitors. However, the two explanations have different welfare implications. The more efficient firm being dominant is not problematic - it actually wins too few auctions. In contrast, the more precisely informed firm is not necessarily the most cost-efficient and procurement auctions may perform very poorly in selecting the best firm to provide the service. Hence, disentangling the two asymmetries is key for a correct assessment of the auction outcomes.

While most of the empirical literature on asymmetric auctions has focused on pure private value settings, we propose a novel empirical strategy that allows us to separately quantify private and common value asymmetries. For our model, we extend the framework by Goeree and Offerman (2003) to bidders with asymmetrically precise information about the common value and asymmetric private value distributions. We develop an empirical model analogue to structurally estimate the parameters capturing the informational asymmetry between incumbent and entrants. We take our model to a data set on procurement for short haul railway passenger services (SRPS) in Germany, an important example for an industry in which the former state monopolist is still dominant even 20 years after the liberalization.

In principle our model and estimation strategy can be applied to different settings. The only requirement is that we observe some variation in auction modes that allows us to estimate the private value distribution from one sample and use this distribution to extrapolate private values on the sample with common value uncertainty. Specific examples include oil drilling auctions, procurement auctions with subcontracting requirements, and auctions of objects with resale value.

For the estimation strategy, we exploit exogenous variation in the contract design. Local state agencies that procure railway services choose mostly based on their political preferences, which are orthogonal to track characteristics, who bears the revenue risk from ticket sales. This feature allows us to observe comparable tracks in terms of cost characteristics sometimes being procured with revenue risk and sometimes without. 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. Our estimation proceeds in two steps. First, we estimate the cost distributions of the incumbent (DB) and the entrants from the winning bids in gross auctions. The first-step results allow us to predict the cost distributions for each net track. Therefore, systematic differences in bidding behavior that are not explained by differences in cost distributions can be attributed to the common value component which allows us to estimate the parameters of the revenue distribution and the informational asymmetry parameters in the second step.

The results of our structural analysis suggest only a slight systematic cost advantage of DB
over its rivals. Notably, they are not as large as one may initially expect given DB’s dominance in the market for SRPS. We find that DB’s cost distribution is dominated by the entrant’s cost distribution in a first-order stochastic dominance sense on the lower tail of the distribution in only 25% of the cases. The estimation of the informational advantage of DB reveals that in most auctions DB holds significantly more precise information about future ticket revenues than its competitors. Our results support the concerns of the German antitrust authority in Monopolkommission (2015) that DB’s dominance is at least partially due to its informational advantage which may call for regulatory interventions. For example, efficiency could be increased by awarding more gross instead of net contracts which eliminate 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 auctions, making bid distributions more symmetric. As a consequence, the average probability of selecting the efficient firm in an auction increases from 37.1% to 78.4% on average. This massive increase highlights significant potential to improve procurement efficiency by eliminating informational asymmetries.
References


Guerre, E., I. Perrigne, and Q. Vuong (2000): “Optimal Nonparametric Estimation of


A. Appendix

A.1. Additional descriptive statistics

Table 8 displays summary statistics for our full sample of procurement auctions.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winning bid</td>
<td>157</td>
<td>7.075</td>
<td>6.838</td>
<td>0.347</td>
<td>55.16</td>
</tr>
<tr>
<td>No. of bidders</td>
<td>157</td>
<td>4.166</td>
<td>1.948</td>
<td>2</td>
<td>11</td>
</tr>
<tr>
<td>Train-km</td>
<td>157</td>
<td>0.827</td>
<td>0.669</td>
<td>0.0871</td>
<td>4.170</td>
</tr>
<tr>
<td>Contract duration</td>
<td>157</td>
<td>1.032</td>
<td>0.338</td>
<td>0.200</td>
<td>2.200</td>
</tr>
<tr>
<td>Used vehicles</td>
<td>157</td>
<td>0.586</td>
<td>0.494</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Notes: The table presents summary statistics of

Table 9 displays an overview of our sample size for different subset of awardings.
### Table 9: Number of observed train line awardings by winning firm and auction mode

<table>
<thead>
<tr>
<th>Auctions</th>
<th>Gross contracts</th>
<th>Net contracts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Incumbent wins</td>
<td>30</td>
<td>28</td>
</tr>
<tr>
<td>Entrant wins</td>
<td>52</td>
<td>47</td>
</tr>
<tr>
<td>∑</td>
<td>82</td>
<td>75</td>
</tr>
</tbody>
</table>

#### A.2. Derivation of the 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 $N$. We introduce the following notation for bidder type $U$ given our parametric Weibull assumption on the bid distribution:

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

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

Denote the density function of the first order statistic of winning bid $x$ from winner $U$ given number of bidders $N$ by $h_U^{(1:N)}$. In case the incumbent wins, the likelihood function is derived from

$$
G_I^{(1:N)}(x) = \Pr(b^I = x, b^{E_1} \geq x, \ldots, b^{E_{N-1}} \geq x)
$$

$$
= \Pr(b^I = x) \Pr(b^{E_1}, \ldots, b^{E_{N-1}})
$$

$$
= g_I(x)(1 - G_E(x))^{N-1}
$$

and for an entrant it is given by

$$
G_E^{(1:N)}(x) = (N - 1) \Pr(b_E^I = x, b_{j \neq i}^{E} > x, b^I > x)
$$

$$
= (N - 1) \Pr(b_E^I = x) \Pr(b_{j \neq i}^{E} > x, b^I > x)
$$

$$
= (N - 1) g_E(x)(1 - G_E(x))^{N-2}(1 - G_I(x)).
$$


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

$$
\pi_i(b) = \left(b - c_i + \alpha_i r_i + \sum_{j \neq i} \alpha_j \mathbb{E} \left[ r_j | \rho_j \geq B^{-1}_j(b) \right] \right) \left(1 - F^{1:N-1}_{\rho_j}(B^{-1}_j(b))\right)
$$
where \( F_{ij}^{1:N_i} \) denotes the first order statistic of the opponents’ signals. The FOC is given by

\[
0 = - \left( b - c_i + \alpha_i r_i + \sum_{j \neq i} \alpha_j \mathbb{E} \left[ r_j | \rho_j \geq B_j^{-1}(b) \right] \right) f_{ij}^{1:N_i}(B_j^{-1})(b)B_j^{-1}(b) + (1 - F_j^{1:N_i}(B_j^{-1}))(b)B_j^{-1}(b)
\]

\[
+ (1 - F_j^{1:N_i}(B_j^{-1}))(b) \left( 1 + \sum_{j \neq i} \alpha_j \frac{f_{ij}^{1:N_i}(B_j^{-1})(b)}{1 - F_j^{1:N_i}(B_j^{-1})(b)} B_j^{-1}(n) \right)
\]

\[
\left( \mathbb{E} \left[ r_j | \rho_j = B_j^{-1}(b) \right] - \mathbb{E} \left[ r_j | \rho_j \geq B_j^{-1}(b) \right] \right)
\]

\[
0 = - \left( b - c_i + \alpha_i r_i + \sum_{j \neq i} \alpha_j \mathbb{E} \left[ r_j | \rho_j = B_j^{-1}(b) \right] \right) f_{ij}^{1:N_i}(B_j^{-1})(b)B_j^{-1}(b) + (1 - F_j^{1:N_i}(B_j^{-1}))(b).
\]

Rearranging for \( b \) and replacing the first-order statistic of opponents’ signals with the first-order statistic of opponents’ bid distributions gives the result. Note that again Reny and Zamir (2004) gives us existence of a pure monotone strategy equilibrium.

**A.4. 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 precisions. 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 \( F_{x_i}(x) = \frac{1}{\alpha_i} F_r \left( \frac{x}{\alpha_i} \right) \) on \([c - \alpha_i \overline{r}, c]\). To simplify notation we write \( F_j \) for \( F_{x_j} \). \( \alpha_1 > \alpha_2 \) implies that \( 1 - F_1(x) \leq 1 - F_2(x) \), i.e. first-order stochastic dominance. However, we have to assume that also likelihood ratio dominance (or weaker hazard rate dominance) holds.

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

\[
\int_{\phi_j(b)}^{\infty} (b - v(x_i, x_j) - \phi_j(b) + c) \; d(1 - F_j(\phi_j(b)))
\]

where \( \phi_j(b) \) is the inverse bid function and \( v(x_i, x_j) \) the common value given signal realizations \( x_i \) and \( x_j \). An equilibrium in monotone strategies exists due to Reny and Zamir (2004) and therefore the derivate of the inverse bid function is differentiable almost everywhere. The first-order condition implicitly characterizing the equilibrium is given by

\[
\frac{1}{\phi_j(b)} = (b - x_i - \phi_j(b) + c) \frac{f_j(\phi_j(b))}{1 - F_j(\phi_j(b))}.
\]
Taking the ratio of the two first-order conditions and applying the function $Q(\phi_1(b)) = \phi_2(b)$ which has derivative $\dot{Q}(\phi_1(b)) = \frac{\phi_2(b)}{\phi_1(b)}$ yields together with the definition $\phi_1(b) = x$

\begin{equation}
\dot{Q}(x) = \frac{1 - F_1(Q(x))}{f_1(Q(x))} \cdot \frac{1 - F_2(x)}{f_2(x)}
\end{equation}

with $Q(\bar{x}) < \bar{x}$ because the signal that yields the most attractive bid is generated by $\bar{r}$ and therefore $-\alpha_1 \bar{r} < -\alpha_2 \bar{r}$. It is straightforward to show that bidder 1 will never submit a bid below the lowest bid of bidder 2. The interpretation of function $Q(x)$ is that it gives the signal of player 1 that places the same bid as player 2 given signal $x$. Hence, when $Q(x) < x$, bidder 1 shades the bid more than player 2. Given the assumption of conditional stochastic dominance, we have that $\dot{Q}(x)_{|Q(x)=x} < 1$. Therefore, because $\alpha_1 > \alpha_2$ and $Q(x) < x$ for all $x$, the revenue signal $r$ that induces the same bid has to be higher for bidder 2 than for bidder 1.

A.5. Additional estimation results

Table 10 displays our bid distribution parameter estimates.

A.6. Bid functions and cost distribution estimates

A.6.1. Gross auction sample

In this appendix, we provide bid functions and estimated cost distributions for several additional representative lines for both gross and net auctions. The following graphs display a comparison of incumbent and entrant bid functions and cost distributions for gross auction, i.e. auctions in which the bidders do not face any revenue risk. Figure 8 and 9 are representative for many lines in our sample illustrating that generally the incumbent does not have a significant cost advantage over the entrants resulting in very symmetric bid functions for incumbent and entrants. Figure 10 is representative for the subset of lines in our sample in which the incumbent has a significant cost advantage.
Table 10: Estimation results: Bid distribution parameters

<table>
<thead>
<tr>
<th>Bid Distribution Parameters</th>
<th>Gross auctions</th>
<th>Net auctions</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda^I_X$</td>
<td>-0.6466*</td>
<td>1.1617***</td>
</tr>
<tr>
<td>(0.3386)</td>
<td>(0.3972)</td>
<td></td>
</tr>
<tr>
<td>$\lambda^I_N$</td>
<td>-0.2631</td>
<td>10.5900***</td>
</tr>
<tr>
<td>(1.0898)</td>
<td>(1.9738)</td>
<td></td>
</tr>
<tr>
<td>$\lambda^E_X$</td>
<td>1.1535***</td>
<td>0.8643***</td>
</tr>
<tr>
<td>(0.1957)</td>
<td>(0.2690)</td>
<td></td>
</tr>
<tr>
<td>$\lambda^E_N$</td>
<td>2.8858***</td>
<td>1.6930*</td>
</tr>
<tr>
<td>(1.0019)</td>
<td>(1.0287)</td>
<td></td>
</tr>
<tr>
<td>$\nu^I_X$</td>
<td>1.6193**</td>
<td>-0.1085</td>
</tr>
<tr>
<td>(0.7112)</td>
<td>(0.6904)</td>
<td></td>
</tr>
<tr>
<td>$\nu^I_N$</td>
<td>-11.4930**</td>
<td>2.5576</td>
</tr>
<tr>
<td>(4.4876)</td>
<td>(1.8841)</td>
<td></td>
</tr>
<tr>
<td>$\nu^E_X$</td>
<td>-3.2588***</td>
<td>-0.2552</td>
</tr>
<tr>
<td>(0.8871)</td>
<td>(0.4172)</td>
<td></td>
</tr>
<tr>
<td>$\nu^E_N$</td>
<td>-0.7875</td>
<td>-1.2945***</td>
</tr>
<tr>
<td>(0.7238)</td>
<td>(0.4872)</td>
<td></td>
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<tr>
<td>26.5780***</td>
<td>3.2700</td>
<td></td>
</tr>
<tr>
<td>(6.2588)</td>
<td>(3.5054)</td>
<td></td>
</tr>
<tr>
<td>$\nu^I_N$</td>
<td>-14.4100*</td>
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<tr>
<td>(7.8018)</td>
<td>(8.6949)</td>
<td></td>
</tr>
<tr>
<td>$\nu^E_X$</td>
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<tr>
<td>(0.5861)</td>
<td>(0.6786)</td>
<td></td>
</tr>
<tr>
<td>$\nu^E_N$</td>
<td>-7.6403**</td>
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</tr>
<tr>
<td>(3.5051)</td>
<td>(2.3931)</td>
<td></td>
</tr>
<tr>
<td>$\nu^I_N$</td>
<td>-1.1561***</td>
<td>-0.5951**</td>
</tr>
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<td>(0.3758)</td>
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<tr>
<td>10.5350***</td>
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<td>(2.6983)</td>
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<td>$\nu^E_N$</td>
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<td>-1.3360</td>
</tr>
<tr>
<td>(5.4409)</td>
<td>(5.4588)</td>
<td></td>
</tr>
</tbody>
</table>

Notes: MLE-SE in parentheses. *,**,*** denote significance at the 10%, 5% and 1%-level respectively.
Figure 8: Cost density and bid function for gross auction 5

Estimated bid function and cost distribution (incumbent) for gross contract 5

Estimated bid function and cost distribution (entrant) for gross contract 5

Figure 9: Cost density and bid function for gross auction 23

Estimated bid function and cost distribution (incumbent) for gross contract 23

Estimated bid function and cost distribution (entrant) for gross contract 23
Figure 10: Cost density and bid function for gross auction 18
A.6.2. Net auction sample

In this appendix, we provide graphs of bid functions for the incumbent and the entrants for several representative net auctions. Finally, we compare how the shape of the bid functions changes if net auctions were procured as gross auctions. Figures 11 and 12 illustrate that in a typical net auctions the entrants bid much more carefully than the incumbent consistent with a strong winner’s curse effect. Figures 13 and 14 depict how the bid functions would change if the same lines were procured as gross auctions. The graphs are in line with the actual gross auction graphs from the previous subsection highlighting that bidding behavior becomes much more symmetric.

Figure 11: Net bid function for net auction 55
Figure 12: Net bid function for net auction 56

Figure 13: Hypothetical gross bid function for net auction 55
Figure 14: Hypothetical gross bid function for net auction 56

Gross bid function and cost distribution (incumbent) for net contract 56

Gross bid function and cost distribution (entrant) for net contract 56
A.7. Testing for FOSD

In order to test whether the estimated cost distributions of different bidder types are equal or exhibit a FOSD relation, we conduct the nonparametric FOSD test proposed by Davidson and Duclos (2000). Consider our two random variables $c_E$ and $c_I$ with associated CDFs $F_{c_E}$ and $F_{c_I}$. The entrants’ cost distribution $F_{c_E}$ dominates the incumbent’s cost distribution $F_{c_I}$ if

$$F_{c_E}(x) \leq F_{c_I}(x) \forall x$$
$$F_{c_E}(x) \neq F_{c_I}(x) \text{ for some } x$$

The test evaluates the empirical CDFs (sample analogues to $F_{c_E}$ and $F_{c_I}$) for incumbent and entrant at several grid points $x$ and checks whether the standardized differences between the two distributions are big enough to reject equality of the two distributions in favor of $c_E \succ c_I$. In our application, we use the pseudo sample of simulated cost realizations for both incumbent and entrant to compute the empirical CDFs $\hat{F}_{c_E}$ and $\hat{F}_{c_I}$. We evaluate the empirical CDFs at a finite set of grid points $x$. Davidson and Duclos (2000) show that under the null of $F_{c_I} = F_{c_E}$, $\hat{F}_{c_E}(x) - \hat{F}_{c_I}(x)$ is asymptotically normal with (estimated) variance given by

$$\hat{V}(x) = \hat{\nu}_{c_E}(x) + \hat{\nu}_{c_I}(x)$$
$$= \frac{1}{NS} \left( \hat{F}_{c_E}(x) - \hat{F}_{c_E}^2(x) + \hat{F}_{c_I}(x) - \hat{F}_{c_I}^2(x) \right)$$

where $NS$ denotes the size of our pseudo sample of cost draws. Standardizing the difference of the empirical CDFs at grid point $x$ results in

$$T(x) = \frac{\hat{F}_{c_E}(x) - \hat{F}_{c_I}(x)}{\sqrt{\hat{V}(x)}}$$

which can be computed for every grid point. When testing for FOSD on the full cost support we construct the grid $x$ such that it covers the area from 0 to the 99% percentile of the estimated cost distribution of the incumbent or the entrant. When testing FOSD in the lower tail, we choose the grid such that it covers the area form 0 to twice the observed winning bid. In both cases, we evaluate the test statistic at 10 equally spaced grid points. In line with the definition of FOSD above, we reject the hypothesis of equal cost distributions in favor of $c_E \succ^{FOSD} c_I$ if

$$-T(x) > m_{\alpha,K,\infty} \text{ for some } x$$
$$T(x) < m_{\alpha,K,\infty} \forall x$$

The first condition captures whether for at least one grid point, the entrant’s cost CDF is significantly below the cost CDF of the incumbent. The second part ensures that there is no point at which the entrant’s cost CDF is significantly above the incumbent’s cost CDF. The critical value $m$ comes from the studentized maximum modulus distribution which is tabulated
in Stoline and Ury (1979). The degrees of freedom are determined by the number of grid points used and the number of observations \( N \). In our case these are given by \( K = 10 \) and \( \infty \) (since \( N \) is much larger than the number of grid points). The critical values \( m_{\alpha,10,\infty} \) for significance levels 10\%, 5\% and 1\% are 2.56, 2.8 and 3.29 respectively.