

# Bidder Asymmetries in Procurement Auctions: Efficiency vs. Information\*

Evidence from Railway Passenger Services

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December 3, 2018

## Abstract

We develop a structural empirical model of procurement auctions with private and common value components and bidder asymmetries 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 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 median probability of selecting the efficient firm would increase by 61%-points.

**JEL Classification:** H57, C57, L92

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

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\*We thank Yonghong An, Mike Baye, Francesco Decarolis, Xavier d'Haultfoeuille, Marc Ivaldi, Gautam Gowrisankaran, Stephan Laueremann, Tong Li, Georgia Kosmopoulou, Andras Niedermayer, Volker Nocke, Martin Pesendorfer, Daniel Quint, Bernard Salanié, Armin Schmutzler, Johannes Schneider, Michelle Sovinsky, André Stenzel, Xun Tang, Hidenori Takahashi, Frank Wolak, Ruli Xiao, and Christine Zulehner as well as participants at IIOC 2017, CEPR Applied IO School 2017, EARIE 2018, and SITE 2018 for helpful discussions and comments. We thank Marisol Diaz Aspiazu for capable research assistance and Felix Berschin from *Nahverkehrsberatung Südwest* for providing us with the data on procurement prices.

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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 a provided service. In many markets, bidders in procurement auctions are likely to be asymmetric. First, large firms that are active in many projects may differ from small firms 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.<sup>1</sup> Neglecting potential asymmetries in common value components can have severe implications for the results, however. We extend the model of Goeree and Offerman (2003), which assumes symmetric private and symmetric common value components, and allow for asymmetries in both dimensions. In this model, we show that observing a firm that wins systematically more often than its competitors can not only be rationalized by a stronger private value distribution but also by more precise information. It is known from the theory of asymmetric private value auctions that dominance can be attributed to a more efficient cost distribution (see Maskin and Riley (2000a)). However, in a model with asymmetric common value information, the dominance can also be attributed to more precise information about the common value because a more precisely informed firm is less affected by the winner's curse. Under private value asymmetries, the more efficient firm wins too few auctions from an efficiency perspective because its competitors bid too aggressively. Under common value asymmetry, the more precisely informed firm wins too many auctions because its competitors bid too cautiously. Hence, to assess the performance of a procurement mechanism and to provide policy recommendations, it is crucial to quantify the respective importance of private and common value asymmetries.

The contribution of our paper is to develop and to implement an empirical strategy to estimate asymmetries in both the private value distributions and the precision of information about a common value and to disentangle the two. The estimation strategy is based on our theoretical framework which extends the model of Goeree and Offerman (2003). To the best of our knowledge, we are the first to structurally estimate and disentangle these asymmetries which allows us to determine the reason underlying an observed bidding pattern and the dominance of a firm in a particular market.<sup>2</sup> In light of our theoretical result that a firm's dominance can be explained by either asymmetry but with different efficiency implications, the distinction between the sources of asymmetric bidding patterns is important. The structural estimates allow us to compute ex ante efficiency measures for different types of auctions and to conduct counterfactual analyses.

Asymmetries between firms are particularly likely in industries with experienced incumbents

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<sup>1</sup>See for example Athey et al. (2011), Suzuki (2010), Estache and Iimi (2010), and Tas (2017).

<sup>2</sup>While De Silva et al. (2003; 2009) use the model of Goeree and Offerman (2003) to motivate their analysis, their empirical strategy follows a reduced form approach that does not allow them to distinguish the two asymmetries and to disentangle which asymmetry induces the observed bidding pattern.

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 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 EUR 8 billion 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 procure 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*<sup>3</sup>) still operates the majority of the traffic volume (73.6% in 2015, Monopolkommission (2015)). An explicit concern by the Monopolkommission<sup>4</sup> and industry experts is that in many cases entrants do not submit competitive bids. Using reduced form regressions, Lalive and Schmutzler (2008) provide evidence that DB has a significantly higher probability of winning auctions than its competitors.

From 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, it may have advantages in financing expenditures compared to its rivals. These factors may result in a cost advantage of DB over its competitors. In addition, ticket revenues from operating a track constitute a common value component and DB might have an informational advantage regarding future demand: *DB Vertrieb*, which is integrated with the DB holding that owns DB Regio, has access to 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)).<sup>5</sup> Consequently, it is likely that DB has an informational advantage over its competitors. Ticket revenues typically cover about 40% of the total cost of a contract and are equal to approximately 67% of the winning bid on average (Rödl & Partner 2014); therefore, the common value component is a substantial part of the value of a contract in our application, and it should affect firms' bidding behavior significantly. 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.

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<sup>3</sup>For brevity, we refer to DB Regio, the short haul distance passenger subsidiary of Deutsche Bahn, as DB in the remainder of this paper.

<sup>4</sup>The *Monopolkommission* is an independent advisory council to the federal government of Germany focusing on competition policy.

<sup>5</sup>The fact that the competition authority and the competitors regularly argue about and demand the data available to other parties before bidding supports the view that revenues are indeed a common value, i.e., information that other bidders hold is relevant for a bidder's assessment of the ex post value of winning the auction.

Our model of the bidding stage 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 in a model with symmetric bidders that, under certain conditions, the private information of a bidder can be summarized by a scalar sufficient statistic which allows us to use standard auction methods from Milgrom and Weber (1982) and the subsequent literature. We extend the model of Goeree and Offerman (2003) by introducing asymmetries in both the private value distributions and the precision of information about the common value. Furthermore, our model allows for endogenous firm entry. We employ a tractable model of entry in the style of Levin and Smith (1994), which we use to estimate auction-specific bid preparation costs incurred by an entrant firm when participating in the auction.

We take our model to a detailed contract-level data set on German SRPS procurement auctions. A key feature of our data is that we observe plausibly exogenous variation in the auction design which enables us to disentangle the two asymmetries. While some local procurement agencies decide 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 IPV auction. If the train operating company is the claimant of the ticket revenues (*net contract*), the auction is one with a private value (cost) and 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 of using 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)) which documents the importance of agencies' individual preferences for gross or net contracts.<sup>6</sup> 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 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.<sup>7</sup>

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 IPV auctions are identified from the winning bid and the winner's identity only. While, in principle, we could estimate bid distribution nonparametrically, we apply a parametric approach due to our relatively small sample size. We incorporate several controls for track heterogeneity and obtain the cost distributions conditional on observable contract

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<sup>6</sup>Often, the argument is ideological: the operating risk should be borne by the operating firm and not by a public agency.

<sup>7</sup>The interpretability of our counterfactual analyses of changing the contract mode would be more limited if exogeneity with respect to revenue characteristics does not hold, however.

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 contract tracks. Hence, systematic 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 in only 27% of the auctions.<sup>8</sup> 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, i.e., the variance of the unknown ticket revenues after having conditioned on the own revenue signal, is on average 2.7 times higher than that of the incumbent. The estimates from our entry model indicate, that bid preparation costs of entrant firms tend to be higher in net auctions than in gross auctions with median entry costs of EUR 5.8 million and EUR 3.8 million, respectively.<sup>9</sup> These numbers are similar to estimates for railway service tendering procedures in the UK, where estimated entry costs range from GBP 5 million to GBP 10 million (RTM 2016). Observing higher entry costs higher in net auctions than in gross auctions is intuitive: When preparing a bid for a net auction, an entrant not only has to evaluate its costs, but it also has to estimate the future ticket revenues.

In summary, our results support the concerns of the German competition policy advisory council 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 which leads to more symmetric bid functions. As a consequence, if the net auctions in our sample were procured as gross auctions, the median ex ante efficiency, i.e., the probability of selecting the cost-efficient bidder, increases drastically from 19.9% to 80.7%. To illustrate which channels are likely to be the main drivers of the huge efficiency loss in net auctions, we simulate several hypothetical scenarios in which we successively eliminate specific sources of inefficiency. We find that both the noise introduced by the revenue signal and asymmetries in the cost distributions already lead to considerable efficiency losses. By far, the most important source of inefficiency, however, is the asymmetric precision of information about the common value component.

We interpret these numbers as evidence that agencies should evaluate carefully when to use net auctions instead of following their agency-specific, often ideological, preferences about the contract form in all tenders.

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<sup>8</sup>Note that if DB's distribution is dominated in a procurement auction, it has the stronger distribution.

<sup>9</sup>For example, this cost can include market-specific research about vehicle requirements and other cost components as well as demand conditions.

Our counterfactuals reveal that gross auctions tend to result in higher agency revenues as well. Assuming that the expected ticket revenues do not depend on who bears the revenue risk, we find that the required net subsidies<sup>10</sup>, i.e., the paid subsidies minus the expected ticket revenues received by the agencies, are more than 50% lower when net auctions are procured as gross auctions than in the observed net auction sample. The reason for this is that the common value uncertainty leads to additional bid shading in net auctions. As a consequence, the winning bids are not substantially lower than in gross auctions. Instead, agencies pay an additional risk premium to the firms in net auctions which reduces the agency payoff. Overall, our analysis supports the view that too many auctions have been procured as net auctions both from an efficiency and a revenue perspective.

Auction settings in which private and common value asymmetries are present are very common. In principle, our model and estimation strategy can be applied to other settings as well. The only requirement is that some variation in auction modes is observed that allows the researcher to estimate the private value distribution from one sample and use this distribution to extrapolate private values on the sample with additional 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 across bidders 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 (see the seminal paper by 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 bidders' valuations are determined by both idiosyncratic preferences for an object and its potential resale value, which some bidders may have superior knowledge about.

**Related literature** The SRPS industry is characterized by bidder asymmetries because a former state monopolist, that is the incumbent on many tracks (DB) competes with new and relatively inexperienced entrants. Therefore, we build on the theory of asymmetric first-price auctions. In a seminal paper, Maskin and Riley (2000a) 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 that involve 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, the private information of each bidder can be summarized by a scalar suf-

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<sup>10</sup>Note that in all of our auctions, the procurement agency pays the winning bid to the winning firm as a subsidy to fulfill the contract. Therefore, we use the terms *subsidy* and *winning bid* interchangeably.

ficient statistic which allows for applying standard auction methods. The essential assumptions in their model are that, first, the signals are independently drawn from logconcave distributions, and, second, that the average of the common value signals is equal to the true common value. Our theory relies on their framework and extends their symmetric model to a model in which bidders have asymmetric private value distributions and have asymmetrically precise information about the common value.

De Silva et al. (2003) analyze data on highway procurement in Oklahoma with reduced form regressions and find that entrants win with lower bids than incumbents. In De Silva et al. (2009) a natural experiment in the same application with more recent data is studied in which an information release policy makes uncertainty more symmetric. In this paper, the authors find that bidding becomes more symmetric after the information release. In both papers, a setting with private and common values as in Goeree and Offerman (2003) is considered and asymmetries in bidding are explained by differences in the distribution of the compound private signal. However, the private and common value distributions are not modeled separately and therefore the authors cannot disentangle which of the asymmetries induces the observed bidding behavior. A key contribution of our paper is that we model private and common value asymmetries explicitly and that the variation in our data allows us to disentangle and quantify each of the asymmetries. We theoretically show that it is crucial to understand the relative importance of the asymmetries as they have opposite welfare implications. Moreover, our structural empirical results allow us to study the efficiency properties of the auctions and to conduct counterfactual analyses.

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 non-parametrically identified and estimated based on winning bids only. Li et al. (2000) discuss identification and nonparametric estimation of 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 the common value signals. 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. 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 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 well-known difficulties with the nonparametric identification of these models in general settings (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.

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 firms, that are better informed, are 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. Moreover, we 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 versus open auctions) exploiting exogenous variation in the auction mode across different auctions similar to our analysis of gross versus 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 nonparametric 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 (2018) 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.<sup>11</sup>

Hunold and Wolf (2013) study the German market for SRPS using a similar data set. They use reduced form regressions to understand how the auction design affects the likelihood that

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<sup>11</sup> Our application is also reminiscent of the theoretical literature on auctions of fixed price versus 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.

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 are larger as measured by the number of train-kilometers. Moreover, they find that DB has an advantage in net auctions which supports our hypothesis of an informational advantages of DB. Their results on the subsidies, i.e., the winning bids, are 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.

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 the 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 Effects of Asymmetries

In this section, we present our model of procurement auctions for gross and net contracts and study the effects of two asymmetries on bidding behavior: first, the effect of asymmetric private value (cost) distributions, and second, 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 cost of fulfilling 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 first develop our model of the bidding stage, in which the number of actual bidders is fixed and known to all firms. Afterwards, we present an entry model based on Levin and Smith (1994) so that ultimately the number of bidders is endogenous. Throughout, we index bidding firms by  $i$ ,  $i$ 's bid by  $b_i$ , and we denote the number of bidders by  $N$ . 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 systematic cost differences across incumbent and entrants. The differential information about expected revenues comes from the precision of the revenue signals which we discuss 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  $b_i$ , which is the subsidy that bidder  $i$  requests for fulfilling the contract. 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 IPV first-price procurement auction

$$(1) \quad \pi_i = b_i - c_i$$

$$(2) \quad E[\pi_i(b_i)] = (b_i - c_i) \cdot \Pr(\min_{i \neq j} b_j \geq b_i | c_i, b_i).$$

For technical reasons discussed below, we assume that each  $F_{c_i}$  is logconcave.<sup>12</sup> We assume that there are two bidder groups: the incumbent and the entrants.<sup>13</sup> 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 (2000a).

In a gross contract, there is only ex ante uncertainty about the operating costs  $c_i$ . Before bidding, a firm receives private information about its cost, which is distributed according to  $F_{c_i}$  with strictly positive density,  $f_{c_i}$ , on support  $[c_L, c_H]$ . Each firm  $i$  chooses  $b_i$  to maximize its expected profit

$$(3) \quad \pi_i(b_i, c_i) = (b_i - c_i) \prod_{j \neq i} (1 - F_{c_j}(\phi_j(b_i))),$$

where  $\phi_j(b_i)$  is bidder  $j$ 's inverse bid function evaluated at  $i$ 's bid. From Maskin and Riley (2000b) it is known that an equilibrium in pure and monotonic 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 with the standard 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  $N$ , i.e.,  $1 - G_{i, M_i | B_i}^{gr}(m_i | b_i, N) \equiv \Pr(m_i \leq \min_{j \neq i} B_j | B_i = b_i, N)$ , 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

$$(4) \quad b_i = c_i + \frac{1 - G_{i, M_i | B_i}^{gr}(b_i | b_i, N)}{g_{i, M_i | B_i}^{gr}(b_i | b_i, N)}.$$

We borrow the definition of conditional stochastic dominance<sup>14</sup> and the following Lemma from Maskin and Riley (2000a), both adapted to the procurement setting.

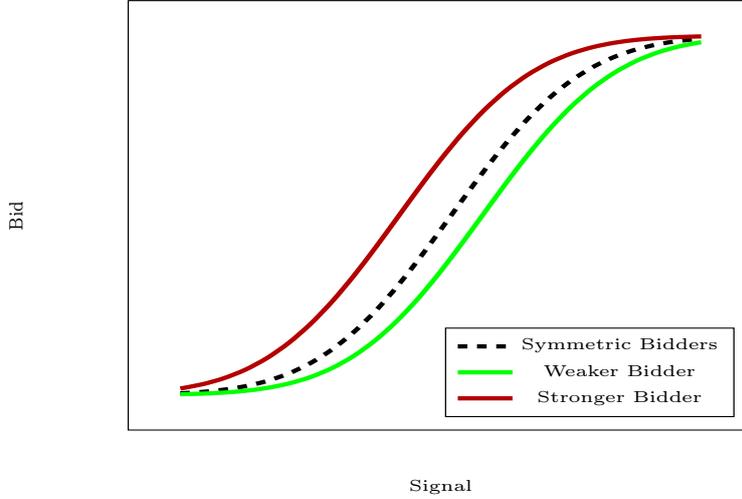
**Lemma 1** (Maskin and Riley (2000a), Proposition 3.3 and Proposition 3.5.). *If the private value distribution of bidder  $i$  conditionally stochastically dominates the private value distribution of*

<sup>12</sup>Many commonly used distributions satisfy logconcavity, for example, the normal distribution, the log-normal distribution, and the beta distribution (see Bagnoli and Bergstrom (2005) for an overview). The vast majority of our estimated cost distributions are logconcave as well.

<sup>13</sup>We use DB and incumbent synonymously because it is the historic incumbent and we rarely observe the same track procured twice.

<sup>14</sup>Conditional stochastic dominance is defined as follows. There exists  $\lambda \in (0, 1)$  and  $\gamma \in [c_L, c_H]$  such that  $1 - F_i(x) = \lambda(1 - F_j(x))$  for all  $x \in [\gamma, c_H]$  and  $\frac{d}{dx} \frac{1 - F_i(x)}{1 - F_j(x)} > 0$  for all  $x \in [c_L, \gamma]$ .

Figure 1: Private value bidder asymmetry: Illustration of bid functions



*Notes:* When bidders are symmetric, their bid functions coincide. When bidders are asymmetric, the weaker bidder will bid systematically lower markups to compensate for its cost disadvantage.

*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 Figure 1 for an illustration). As a result, the auction may be inefficient and the strong bidder wins too few auctions from an efficiency perspective. This result has been generalized by De Silva et al. (2003) to hold also in the Goeree and Offerman (2003) setup, i.e., in the presence of an additional (symmetric) common value component. Therefore, it will hold for net auctions if firms have 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 (revenue) component. Therefore, we develop an asymmetric first-price auction model with both private and common values. The private cost of fulfilling the contract,  $c_i$ , is drawn from distribution  $F_{c_i}$ , and we denote the common value component, the ticket revenues, by  $R$ . In addition to their private value signal,  $c_i$ , firms receive a private signal about  $R$ ,  $r_i$ , which is drawn from distribution  $F_r$  with mean  $\bar{R}$  and variance  $\sigma_r$  on support  $[\underline{r}, \bar{r}]$ . All signals are drawn independently within and across bidders. For technical reasons discussed below, we assume that  $F_{c_i}$  and  $F_r$  are logconcave.

Our model of net auctions builds 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 both the private and the common value signal. The strategic variable, the bid, is only one-dimensional. In general, there is no straightforward mapping from two-dimensional signals into a one-dimensional strategic variable such that the expected value of winning is monotonic in the private information. However, under the assumptions that the common value equals the sum of the signals, i.e.,  $R = \sum_{i=1}^N r_i$ , and that the revenue signal distribution is logconcave, Goeree and Offerman (2003) show that such a mapping exists. In this case, the expected value of winning can be written as a linear combination 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. Therefore, standard auction theory methods following Milgrom and Weber (1982) can be applied. In 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.

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, i.e.,  $R = \sum_{i=1}^N \alpha_i r_i$ . If  $R = \sum_{i=1}^N \alpha_i r_i$  with the normalization  $\sum_{i=1}^N \alpha_i = 1$ , it follows directly from their analysis that the expected value of winning the auction is monotonic in  $\rho_i \equiv c_i - \alpha_i r_i$ , 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

$$(5) \quad \pi_i = R - c_i + b_i$$

$$(6) \quad \mathbb{E}[\pi_i(b_i)|b_i, c_i, r_i] = \left( b_i - c_i + \alpha_i r_i + \sum_{j \neq i} \alpha_j \mathbb{E}[r_j | \rho_j \geq \phi_j(b_i)] \right) \Pr(b_i \leq \min_{i \neq j} b_j | c_i, r_i, b_i)$$

where  $\phi_j(b_i)$  is bidder  $j$ 's inverse bid function.<sup>15</sup>

This model allows us to study the effect of differential precision of common value signals. While every firm draws its signal  $r_i$  from the same distribution, the asymmetry between incumbent and entrants is captured by their weights  $\alpha_i$ . We denote the incumbent's and the entrants' weights by  $\alpha_I$  and  $\alpha_E$ , respectively. We treat  $\alpha_i$  as a structural model parameter that measures the informational value of  $i$ 's signal. Intuitively, 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

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

due to independence of the revenue signals  $\{r_j\}_{j=1}^N$ . The conditional variance can be written as

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

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<sup>15</sup>Note that inverse bid functions differ between gross and net auctions. For notational convenience, we omit this additional dependency.

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

$$(7) \quad \text{var}[R|r_E = r] = ((N - 2)\alpha_E^2 + \alpha_I^2) \sigma_r \text{ for the entrant}$$

$$(8) \quad \text{var}[R|r_I = r] = (N - 1)\alpha_E^2 \sigma_r \text{ for the incumbent,}$$

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, without loss of generality, we can normalize  $\alpha_I + (N - 1)\alpha_E = 1$ .

Bidding behavior is monotonic and characterized by a system of differential equations as shown in the following Lemma (see Appendix A.1 for the derivation).

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

$$(9) \quad b_i = c_i - \alpha_i r_i - \sum_{j \neq i} \alpha_j \mathbb{E}[r_j | \rho_j = \phi_j(b_i)] + \frac{1 - G_{i, M_i | B_i}^{\text{net}}(b_i | b_i, N)}{g_{i, M_i | B_i}^{\text{net}}(b_i | b_i, N)},$$

where  $G_{i, M_i | B_i}^{\text{net}}(b_i | b_i; N) = \Pr(b_i \leq \min_{j \neq i} B_j | B_i = b_i, N)$  and  $g_{i, M_i | B_i}^{\text{net}}$  denotes the corresponding density function.  $\phi_j(\cdot)$  denotes the inverse bid function of bidder  $j$ .

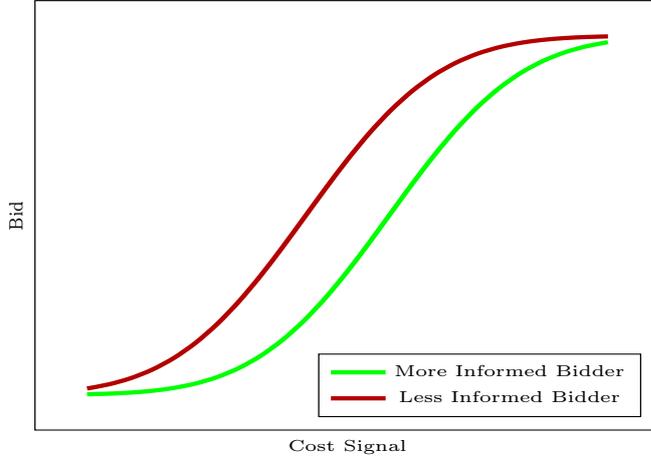
The intuition is analogous to bidding in the gross auction. Players bid their expected valuation of winning the auction plus a bid shading term. In the net auction, however, the value of winning also depends on the other players' revenue signals and the bidder therefore faces a winner's curse motive. This can be seen in the conditioning set of the expectation of the other players' revenue signals  $\mathbb{E}[r_j | \rho_j = \phi_j(b)]$ . If bidder  $i$  wins with bid  $b$ , then it must be the case that the compound signals of the other players,  $\rho_j$ , were not too good. Hence, when computing that expectation, the players have to take the winner's curse into account.

While theory gives strong predictions about how bidding behavior differs across asymmetric participants in private value auctions, this is less clear in our net auction setting due to the additional asymmetric common revenue component. We give an intuition for the effect of the asymmetric precision in the following Lemma that assumes a symmetric and known cost component (see Appendix A.2 for the proof).

**Lemma 3.** *Assume there are  $N \geq 2$  bidders with one bidder having precision parameter  $\alpha_I$  and the remaining  $N - 1$  bidders having precision parameter  $\alpha_E$ . Moreover, assume that all bidders have the same cost  $c$ . If  $\alpha_I > \alpha_E$ , then,  $H_I(b) \geq H_E(b)$ , i.e., the bid distribution of bidder  $I$  is stochastically dominated by the bid distributions of bidders with  $\alpha_E$ , with strict inequality for all interior bids  $b$  when  $N > 2$ .*

Lemma 3 shows that less precisely informed bidders are affected more by the winner's curse and will shade the equilibrium bid more than the more precisely informed bidder. As a consequence, if all 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).

Figure 2: Common value bidder asymmetry: Illustration of bid functions



*Notes:* If costs are symmetric, the less precisely informed bidder (red curve) shades the bid more than the more precisely informed bidder for the same cost and revenue realization.

Net auctions are likely to be inefficient for several reasons. First, even if the common value precision is the same for all bidders and private value distributions are identical, the bidder with the lowest private value realization does not necessarily win the auction: the bidder with the lowest private value realization might have received an unfavorable common value signal and, therefore, might bid very cautiously. Hence, a high-cost bidder can win if she has received a high common value signal. Second, even if both bidders have the same private and common value signal realization, they will not submit the same bid, if the precision of the common value signals is asymmetric. The less precisely informed bidder will shade the bid more than the more precisely informed one and the bidder with more precise information is more likely to win with high cost realizations than the other bidders. Finally, as in gross auctions, cost asymmetries across bidder types introduce a source of inefficiency.

**Entry model.** Our entry model fits into the framework introduced by Levin and Smith (1994) and is only played among entrants, i.e., DB enters with probability 1 in all auctions. Denote the set of potential bidders by  $\mathcal{N}$  and the set of actual bidders by  $N$ .<sup>16</sup> Denote the cost of entry to an auction by  $e$ . When deciding about entry, all potential entrants have symmetric expected profits of entering an auction with  $N$  bidders, denoted by  $\pi_e(N)$ , because the equilibrium strategies of entrants are symmetric. In this setup, Assumption 1 to 5 in Levin and Smith (1994) are satisfied and a symmetric Nash equilibrium in mixed entry strategies exists and it is unique: Each bidder decides to enter the auction with probability  $q \in (0, 1)$  such that the expected profit from entering the auction is zero for any potential bidder. We summarize the

<sup>16</sup>Note that when there are  $N$  bidders,  $N - 1$  firms have entered through the entry game and the additional firm, that always enters, is DB.

equilibrium of the entry game in the following lemma.

**Lemma 4.** *In the entry game played by  $\mathcal{N} - 1$  potential entrant bidders, there exists a unique symmetric equilibrium in mixed strategies. Each entrant bidder enters the auction with probability  $q$  such that*

$$(10) \quad \sum_{N=2}^{\mathcal{N}} \left( \binom{\mathcal{N}-2}{N-2} q^{N-2} (1-q)^{\mathcal{N}-N} \pi_e(N) \right) = \kappa.$$

The left hand side of Equation (10) describes the expected profit (net of the entry cost) of an entrant firm before entering the auction while the right hand side is the entry cost. The summation is taken over all potential bidder configurations that can occur if the entrant under consideration has decided to enter.

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

#### 3.1. Industry Description and Relation to Auction Model

As many other countries, Germany liberalized its railway sector in the 1990s. This liberalization implemented the EU Directive 91/440 *Development of the Community's Railways* through the *Eisenbahnneuordnungsgesetz* in 1993. One of the main objectives of this legislation was to induce competition in the railway sector. SRPS are part of the universal service obligation of the government and are generally not profitable for operators. Therefore, local procurement agencies are assigned the task to choose an operator that provides this service on behalf of the federal government.<sup>17</sup> As these services require high subsidies (around EUR 8 billion in 2016, Monopolkommission (2015)), the procurement agencies aim at competition *for* the tracks to keep the required subsidies at a reasonably low level.

As part of the reform, the former state monopolists *Deutsche Bundesbahn* in West Germany and *Deutsche Reichsbahn* in East Germany were 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 SRPS, the procurement agencies have a high degree of freedom in designing the contract and 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 regulated and beyond the control of the train operating company.

An important additional feature is that the agency also specifies who obtains the ticket revenues: either 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

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<sup>17</sup>For our sample period, there were 27 different local procurement agencies.

between net and gross contracts is exogenous to a tracks' cost distribution, i.e., conditional on observed track characteristics, the cost distribution should be independent of the choice of contract mode. In general, one might be worried that the choice between gross and net contracts is driven by selection and endogenous procurement decisions of the agencies. In our application, this would be problematic if agencies decide on the contract mode (net versus gross) based on unobservable cost characteristics. We argue that the role of endogenous contract mode is negligible in our setting 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 characteristics 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 almost exclusively 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 the two groups of auctions; therefore, we conclude that the two sets of tracks are not systematically different (see Table 1 and Table 2 in Section 3.2).

From a model 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 vehicles to be used or the ticket prices. Consequently, we consider the level of demand by passengers to be independent of the firm operating the service and as a common value to all firms and do not consider a model with price and quality as in Asker and Cantillon (2010).

While the market share of competitors has risen over time, DB still had a market share of 73.6% measured in train-kilometers in 2013 (see Monopolkommission (2015)). The competitors of DB consist of many firms all of which are small in terms of market share in the German market for SRPS. *Transdev* is the competitor with the highest market share serving 6% of the market followed by *Netinera* with 4% and *BeNEX* with 3%. The German Monopolkommission, has explicitly raised the concern that *DB Vertrieb* does not make reliable demand data accessible for the agencies and DB's competitors (see Monopolkommission (2011)). 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.

**Relating the theory model to the application.** In the following, we argue that our model developed in Section 2 is appropriate to study the German SRPS industry. First, we consider costs to be a private value because firms have different access to vehicles, funding opportunities, and they can pay different wages. Naturally, there are common cost components like electricity and infrastructure charges. However, these factors can typically be anticipated by all firms

in advance and, therefore, do not result in significant cost uncertainty.<sup>18</sup> While we expect entrants to be symmetric with respect to their cost distribution, we expect the cost of DB to be 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. Expenditures for vehicles are a substantial component of the costs of serving a contract. Also, DB is likely to have cheaper access to funding as it is a publicly held firm. Altogether, we expect DB to have a cost advantage. Most entrants are large firms that are active in several markets and have similar capital structures, infrastructure networks, and technological equipment. Therefore, and given that DB is 14 times larger than its biggest competitor (*Veolia Transdev*, see mofair and Netzwerk-Privatbahnen (2011)), we judge it reasonable that differences among entrants are negligible; therefore, we treat all entrants symmetrically.

Second, we assume that future ticket revenues constitute a common value because there is a substantial debate by both the competing firms and competition authorities that DB should make its private revenue data public (see, for example, Monopolkommission (2013)). This discussion provides strong evidence that private signals about future revenues are valuable to other firms. Moreover, we find in reduced form regressions that in net auctions the number of bidders tends to increase the subsidy paid, while in gross auctions the winning bid tends to decrease in the number of bidders. In line with the findings in Hong and Shum (2002), we take this as further evidence for a common value setting in our net auction sample. Both of these features are typically not present in a setting with known revenue streams or ex post uncertainty about revenues as, for example, analyzed in Luo et al. (2018). Regarding the information about the revenue stream, we expect systematic differences between DB and its competitors as well. DB Regio (the branch of DB that operates in the SRPS sector) is vertically integrated with DB Vertrieb GmbH. Almost all tickets, even when DB is not operating the track itself, are sold through DB Vertrieb GmbH. Therefore, DB possesses an informational advantage about demand conditions, while its competitors cannot access the information that DB Vertrieb GmbH has (see Monopolkommission (2011)). Instead, entrants have to rely on their own market research which is usually much less reliable than the information of DB and often prohibitively costly to obtain.

In our entry model, only entrants decide about entering the auction. We assume that DB is not active in the entry game because industry experts agree that DB is participating in all auctions (see Frankfurter Allgemeine Zeitung (2011)). Moreover, we do not consider selective entry as, for example, in Sweeting and Bhattacharya (2015). In the German SRPS market, it seems plausible that competitors of DB do not hold private information before deciding to invest into entry. Firms have to make considerable investments into learning about auction-specific information. For example, they hire specialized consultants to acquire information about the details of their cost structure, including garages, schedules, and specific vehicle financing. Moreover, these consultancies support firms in estimating the future revenues. Hence, firms incur a considerable amount of sunk entry cost before they know about their cost and the

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<sup>18</sup>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.

expected future revenues.

**Empirical implications of the theory.** In our application, two asymmetries crucially affect bidding behavior. First, on average, DB is potentially more efficient than the other bidders. Second, DB is potentially also 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 according to Lemma 1 and Lemma 3 (see Figure 3 for an illustration). However, the assessment of the market structure depends on the relative importance of the asymmetries and hence on which of the two 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, because DB might win the auction although it is not the most cost-efficient firm.<sup>19</sup> 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 can be partially offset or even overturned 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, as is often done in empirical studies, 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 market interventions that symmetrize information.

### 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.<sup>20</sup> 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 including data on track access charges and the frequency of service from additional publicly available sources.<sup>21</sup>

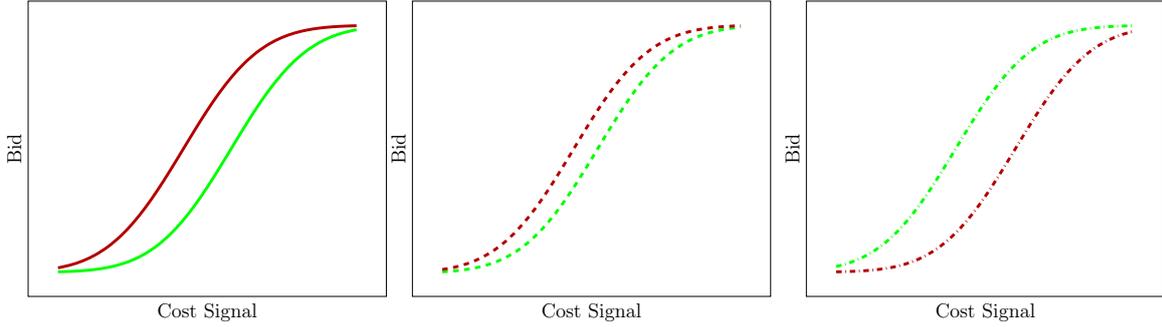
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<sup>19</sup>Note that also in this case entrants might win the auction even if DB is more cost-efficient because of the additional noise introduced by the revenue signal. However, the more precisely informed bidder will win the auction more often when she is not the efficient bidder than the less precisely informed bidder.

<sup>20</sup>For a few tenderings conducted during our sample period we do not have access to the relevant data, in particular, the winning bid.

<sup>21</sup>In particular, we used the *Trassenpreisprogramm* software of DB that allows us to compute statistics, such as the length and the regulated access charges, for each track in our sample.

Figure 3: Both asymmetries: Illustration of bid functions



*Notes:* Left panel: Under symmetric cost distributions, a bidder with substantially less precise information (red curve) shades her bid more than a more informed bidder (green curve) and might lose even when the less precisely informed bidder has a lower cost realization. Middle panel: If a bidder has a weaker cost distribution and is less precisely informed (red curve), the two asymmetries can partially offset each other moving bid functions closer to symmetry. Right panel: When a bidder has a weaker cost distribution and is only slightly less precisely informed (red curve), the bid functions may reverse their relative positions and yield the opposite inefficiency than in the previous panels. Note that the horizontal axis only depicts the cost signal and assumes the same revenue signal for both bidders.

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 revenues from 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 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 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 of the most important track and contract characteristics: contract duration (in years), track access charges (the costs for using a 1-km long stretch of a specific track network), size of the contract (in million train-km<sup>22</sup>) and an indicator whether used vehicles are permitted for operating the track. None of the differences in means is statistically significant which further supports our exogeneity assumption. 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 dropping a few awardings with unreliable or missing 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.

<sup>22</sup>The variable *train-km* denotes the number of kilometers one train would have to run in order to fulfill the total required volume of the contract. It is often used as a summary statistic of the overall size of the contract and is a function of contract duration, size of the respective track, and the required frequency of service.

Table 1: Descriptive statistics by auction mode

	<b>Gross</b> (N=82)				<b>Net</b> (N=75)			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Winning bid (10 Mio. EUR)	7.50	7.33	0.68	55.16	6.61	6.27	0.35	29.99
No. bidders	4.82	2.01	2.00	11.00	3.45	1.61	2.00	8.00
Access charges (EUR)	3.39	0.44	2.29	4.64	3.32	0.82	1.23	6.10
Volume (Mio. train-km)	0.80	0.61	0.13	3.79	0.86	0.74	0.09	4.17
Duration (Years)	10.23	2.61	2.00	16.00	10.43	4.07	2.00	22.00
Used vehicles (Dummy)	0.59	0.50	0.00	1.00	0.59	0.50	0.00	1.00

*Notes: This table compares descriptive statistics of the most important auction characteristics across different auction modes (gross vs. net). Volume captures the size of the contract in million train-km, i.e., the total number of km that one train would have to drive to fulfill the contract, Duration is the length of the contract, Used vehicles indicates whether the contract requires new vehicles to be used on the track with 1 indicating that used vehicles are permitted. Access charges denotes the regulated price (in EUR) that a firm has to pay every time a train operates on a one km long stretch of a specific track.*

Table 2: Statistical comparison of contract characteristics across gross and net auctions

	<b>Gross</b>	<b>Net</b>	Difference	p-value
	(N=82) Mean	(N=75) Mean		
Access charges (EUR per net-km)	3.3949	3.3164	0.0785	0.4620
Volume (Mio. train-km)	0.7985	0.8587	-0.0602	0.5785
Duration (Years)	10.2317	10.4267	-0.1950	0.7243
Used vehicles (Dummy)	0.5854	0.5867	-0.0013	0.9869

*Notes: This table summarizes the results from testing the equality of the means of the most important track characteristics across different auction modes (gross vs. net). Variable definitions are as in Table 1.*

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. As different tracks are often geographically separated and have different technological features, for example, different vehicles, urban versus rural areas, etc., we argue that the scope for network effects or learning across lines is limited. Therefore, we treat bidding behavior as time-invariant. With a substantially longer time dimension, panel methods can allow for the analysis of additional aspects such as the effects of entrants' learning about the market. Given that there are usually less than 25 awardings per year and the contract duration is on average 10 years, we suspect that a reasonable panel analysis requires at least 15 to 20 additional years of data.

### 3.3. Reduced Form Evidence

In this section, we provide reduced form evidence to support our hypotheses and to guide the specification of the structural model that we estimate in the next section.

Table 3: Reduced form regressions: Winning bids and number of bidders

	(1)	(2)	(3)
	Winning bid	No. of bidders	No. of bidders
Net auction	-2.9421*	-1.7284***	-0.4363***
	(1.5396)	(0.2435)	(0.0575)
No. bidders-gross	-0.1745		
	(0.2270)		
No. bidders-net	0.2741		
	(0.3197)		
Access charges	14.1498***	-4.8861***	-1.4178***
	(5.0204)	(1.7575)	(0.4504)
Contract volume	8.1860***	-0.2400	-0.0473
	(1.3761)	(0.1842)	(0.0437)
Contract duration	4.7269***	0.6498**	0.1386*
	(0.7278)	(0.3166)	(0.0776)
Used vehicles	0.4257	-0.4361**	-0.1042**
	(0.6495)	(0.2083)	(0.0459)
Frequency (log)	-0.2462	0.9827**	0.1618**
	(0.6663)	(0.4925)	(0.0746)
Adjusted $R^2$	0.759	0.535	

*Notes:* Heteroskedasticity-robust standard errors in parentheses. Models (1) and (2) are estimated by OLS. Column (3) is a negative binomial count data regression.

*No. bidders-gross* and *No. bidders-net* denote the number of bidders in the auction interacted with dummies for gross and net auctions, respectively.

*Net auction* is a dummy for net auctions. *Frequency (log)* is the logged average number of times the train has to operate on the line per day. All other variable definitions are as in Table 1. Number of observations: 157.

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 3 displays the results from OLS and count data 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, a linear-quadratic time trend is generally insignificant which supports 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 notable 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 could be a winner’s curse effect in net auctions that outweighs the competition effect

associated with more bidders.<sup>23</sup>

Column (1) in Table 4 presents the results of a reduced form logit regression of a dummy indicating whether the incumbent won the auction on various track characteristics. While most structural track characteristics, such as contract size or track access charges, do not have an effect on the probability of the incumbent winning, procuring a track in a net auction has a large, positive, and significant effect. We interpret these estimates as further evidence that the net auction format favors DB.

To support our assumption of exogenous procurement mode (gross versus 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. In line with our assumption of time-invariant bidding behavior, these variables have no significant effect.

Table 4: Reduced form logit regressions: Incumbent winning and net auction choice

	(1)	(2)
	DB wins	Net auction
Net auction	5.1355** (2.5312)	
Access charges	-3.2533 (4.1045)	-1.5853 (2.8356)
Contract volume	0.2424 (0.3551)	-0.3729 (0.6523)
Contract duration	2.2152** (1.1105)	0.3444 (0.4946)
Frequency (log)	0.5300 (0.8019)	-0.0388 (0.6872)

*Notes:* Heteroskedasticity-robust standard errors in parentheses.  
Both models are estimated using binary logit regressions. *DB wins* denotes a dummy indicating whether the incumbent won the auction. *Net auction* is 1 (0) if the auction is a net (gross) auction. All other variable definitions are as in Table 3.  
Number of observations: 157. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## 4. Identification and Estimation

In this section, we discuss our identification strategy and how we estimate the model.

<sup>23</sup>Pinkse and Tan (2005) show that this observation is not necessarily indicative of a common value setting. Instead, an *affiliation effect* can result in winning bids that are increasing in the number of bidders.

## 4.1. Identification

The cost distributions in an asymmetric IPV model are nonparametrically 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 identification of a common value component is more complicated. In general, 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, 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 parameters characterizing the distribution of the common value component.

Intuitively, identification of the parameters of the net auction model comes from contrasting 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 versus gross). If the procurement mode is orthogonal to a track's cost characteristics, any systematic differences in bidding behavior that are not explained by differences in the cost distributions can be attributed to differences in the revenue uncertainty in net auctions.

For our identification strategy to work several assumptions need to be satisfied. First and most importantly, we require that the procurement mode is orthogonal to a track's cost characteristics. This allows us to use the gross auction sample, in which there is no revenue risk, to estimate the cost distributions and extrapolate them to the net auction sample. While we cannot directly test this assumption, we provide extensive evidence from both industry reports and our data in support of this orthogonality assumption in Section 3.

Second, we have to impose several arguably mild functional form assumptions on the distribution of the cost and revenue signals. Specifically, we assume that the revenue signals  $r$  and the cost signals  $c$  are drawn from logconcave distributions and are independent across bidders and each bidder's revenue signal is independent of her cost signal. Furthermore, we maintain the assumption of the model of Goeree and Offerman (2003) that the common value equals the (weighted) sum of the revenue signals.

Finally, we implicitly assume that firms value the same revenue stream identically. This assumption could be violated, for example, if some bidder types value money differently than others or if they exhibit different degrees of risk aversion. Unfortunately, our data is not rich enough to allow us to distinguish between the effects of risk aversion and those of asymmetric information about the common value. While in principle both channels could rationalize the observed data, all industry evidence supports that the asymmetric information problem is much more relevant than issues related to pure revenue risk. In particular, even the small entrants in our application often belong to large international conglomerates that are active in many markets, and often other industries as well, so that it is plausible that entrants value a given

revenue stream in the same way as the incumbent (see also our discussion in Section 3).

## 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 common value parameters in the second step.

We assume that there are two types of bidders: DB as the incumbent, that 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 nonparametric approach.

Since the total number of procured tracks is still relatively small, a fully nonparametric 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 estimate the parameters of the bid distribution using maximum likelihood assuming that the bid distributions for contract type  $j$  of bidder type  $i$ ,  $H_i^j$ , follow a Weibull distribution with distribution function

$$(11) \quad H_i^j(b_i|X, N) = 1 - \exp \left[ - \left( \frac{b_i}{\lambda_i^j(X, N)} \right)^{\nu_i^j(X, N)} \right],$$

where  $\lambda_i^j$  and  $\nu_i^j$  are the bidder-specific scale and shape parameters. Both vary across incumbent and entrants and the contract mode (gross or net). We model these parameters as a log-linear function of observed contract characteristics and the number of bidders  $N$

$$\begin{aligned} \log(\lambda_I^j(X, N)) &= \lambda_{I,0}^j + \lambda_{I,X}^j X + \lambda_{I,N}^j N \\ \log(\lambda_E^j(X, N)) &= \lambda_{E,0}^j + \lambda_{E,X}^j X + \lambda_{E,N}^j N \\ \log(\nu_I^j(X, N)) &= \nu_{I,0}^j + \nu_{I,X}^j X + \nu_{I,N}^j N \\ \log(\nu_E^j(X, N)) &= \nu_{E,0}^j + \nu_{E,X}^j X + \nu_{E,N}^j N, \end{aligned}$$

where  $I$  and  $E$  denote the incumbent and the entrants, respectively. To keep the number of parameters reasonably low, we include only the most relevant contract characteristics based on the reduced form regressions presented in the previous section: the track access costs, a dummy for whether the auction requires new instead of used vehicles, and three measures of contract size and complexity (contract duration in years, contract volume as measured by the number of total train-kilometers, and the size of the track network serviced). The track access costs are not only a direct measure of an important cost component but also informative about

the type of track that is procured. The contract duration captures that firms might value relatively short-term contracts differently than long-term contracts. Finally, the total volume of the contract and the size of the track network that the train has to cover are plausible proxies for the overall size and complexity of a contract.<sup>24</sup>

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 B.1 for the derivation)

$$(12) \quad H_I^{j,(1:N)}(x) = h_I^j(x)(1 - H_E^j(x))^{N-1}$$

$$(13) \quad H_E^{j,(1:N)}(x) = (N - 1)h_E^j(x)(1 - H_E^j(x))^{N-2}(1 - H_I^j(x)),$$

where  $h_i^j(\cdot)$  denotes the derivative of  $H_i^j(\cdot)$ .

The likelihood function is then based on Equations (12) and (13)

$$(14) \quad LL(\lambda^j, \nu^j) = \sum_{t=1}^{T^j} \log \left( H_E^{j,(1:N)}(b_t)(1 - \mathbf{I}_{\text{DB wins}}) + H_I^{j,(1:N)}(b_t)\mathbf{I}_{\text{DB wins}} \right),$$

where  $b_t$  denotes the winning bid in auction  $t$ ,  $j$  the auction mode ( $j \in \{gross, net\}$ ),  $T^j$  is the total number of auctions of type  $j$  in our sample, and  $\mathbf{I}_{\text{DB wins}}$  is an indicator variable for auctions that DB wins. Given the estimated parameters of the bid distributions, we can back out the cost distribution of each bidder on each gross auction track with characteristics  $X$  by inverting the bidding FOCs. We follow the suggestion of Athey and Haile (2007) and compute the cost distribution for a given track and bidder type without imposing any additional parametric assumptions (see Appendix B.2 for the details).

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 the bidding behavior of the entrants and the incumbent in the net auction sample.

Recall that in our net auction model, 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  $F(\bar{R}, \sigma_r)$  with mean  $\bar{R}$  and variance  $\sigma_r$ . As discussed in Section 2, the structure of our net auction model allows us to combine the two signals into one *net cost* signal,  $\rho_i = c_i - \alpha_i r_i$ , that completely summarizes bidder  $i$ 's private information. Moreover, we denote the expected valuation of the contract conditional on winning the auction with bid  $b$  by  $\mathcal{P}_i(b) \equiv c_i - \alpha_i r_i - \sum_{j \neq i} \alpha_j \mathbb{E}[r_j | \rho_j = \phi_j(b)]$  given inverse bid functions  $\phi_j$ . According to

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<sup>24</sup>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.

Lemma 2, bidding behavior is determined by the system

$$(15) \quad \mathcal{P}^I(b^I) = b^I - \frac{1 - G_{I,M|B}^{net}(b^I|b^I, X, N)}{g_{I,M|B}^{net}(b^I|b^I, X, N)}$$

$$(16) \quad \mathcal{P}^E(b^E) = b^E - \frac{1 - G_{E,M|B}^{net}(b^E|b^E, X, N)}{g_{E,M|B}^{net}(b^E|b^E, X, N)}.$$

In the remainder of this section, we develop the estimation procedure for the parameters characterizing the common value component. 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.

Since we have relatively few observations, we continue to follow a parametric estimation approach. We assume that bid distributions in net auctions follow a Weibull distribution whose parameters are functions of track and contract characteristics (analogous to the gross auction estimation). After having estimated the bid distribution parameters for the net auction sample, we can back out the combined cost-revenue signal  $\mathcal{P}^i$  based on the FOCs in Equations (15) and (16).

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  $\mathcal{P}$  by

$$(17) \quad \mathcal{P}^i - c_i = -\alpha_i r_i - \sum_{j \neq i} \alpha_j \mathbb{E}[r_j | \rho_j = \phi_j(b)].$$

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 left hand side is known from the data and the gross auction step. The distribution of the right hand side is only a function of  $r \sim F_r(\bar{R}, \sigma_r)$  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 of other bidders' revenue signals in the expected valuation of winning the line with bid  $b$  in Equation (6). The expectation term conditions on the bid being pivotal, i.e.,  $\rho_j = \phi_j(b)$ . From the first step we only know the compound expected valuation conditional on winning with bid  $b$ . Therefore, 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 FOCs 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  $\bar{\mathcal{P}}^{-i}(b)$  and note that if an entrant wins, this is immediately given by the winning  $\mathcal{P}$  of this track for the other entrants. For any arbitrary bidder  $-i$ , we can compute it by inverting  $-i$ 's bid function at the observed winning bid

$$(18) \quad \bar{\mathcal{P}}^{-i}(b) = b - \frac{1 - G_{-i,M|B}^{net}(b|b, X, N)}{g_{-i,M|B}^{net}(b|b, X, N)}.$$

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

$$(19) \quad \bar{\mathcal{P}}^i(b) = c_i - \alpha_i r_i - \sum_{j \neq i} \alpha_j \mathbb{E} [r_j | \mathcal{P}^i = \bar{\mathcal{P}}^j(b)] \quad (\text{for winner})$$

$$(20) \quad \bar{\mathcal{P}}^j(b) = c_j - \alpha_j r_j - \sum_{k \neq j} \alpha_k \mathbb{E} [r_k | \bar{\mathcal{P}}^j(b) = \bar{\mathcal{P}}^k(b)] \quad (\text{for } N - 1 \text{ rival bidders}),$$

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

$$(21) \quad r_j(c_j) = \frac{1}{\alpha_j} \left( c_j - \bar{\mathcal{P}}^j(b) - \sum_{k \neq j} \alpha_k \mathbb{E} [r_k | \bar{\mathcal{P}}^j(b) = \bar{\mathcal{P}}^k(b)] \right),$$

we can compute the conditional expectation for each firm  $j$ 's signal as

$$(22) \quad \mathbb{E} [r_j | \bar{\mathcal{P}}^j(b) = \bar{\mathcal{P}}^j(b)] = \int_{\underline{c}}^{\bar{c}} r_j(c) \frac{f_{c,j}(c) f_r(r_j(c))}{\int_{\underline{c}}^{\bar{c}} f_{c,j}(x) f_r(r_j(x)) dx} dc,$$

where the joint density  $f(c_j, r_j) = \frac{f_{c,j}(c_j) f_r(r_j(c_j))}{\int_{\underline{c}}^{\bar{c}} f_{c,j}(x) f_r(r_j(x)) dx}$  follows from the independence of the revenue and cost signals. Plugging (21) into (22) 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

$X_I \equiv \mathbb{E} [r_I | \bar{\mathcal{P}}^I(b) = \bar{\mathcal{P}}^j(b)]$  and  $X_E \equiv \mathbb{E} [r_E | \bar{\mathcal{P}}^E(b) = \bar{\mathcal{P}}^I(b)]$

$$(23) \quad X_I = \frac{\int_{\underline{c}}^{\bar{c}} \frac{1}{\alpha_I} (c - \bar{\mathcal{P}}^I(b) - (N-1)\alpha_E X_E) f_r \left( \frac{1}{\alpha_I} (c - \bar{\mathcal{P}}^I(b) - (N-1)\alpha_E X_E) \right) f_{I,c}(c) dc}{\int_{\underline{c}}^{\bar{c}} f_r \left( \frac{1}{\alpha_I} (x - \bar{\mathcal{P}}^I(b) - (N-1)\alpha_E X_E) \right) f_{I,c}(x) dx}$$

$$(24) \quad X_E = \frac{\int_{\underline{c}}^{\bar{c}} (c - \bar{\mathcal{P}}^E(b) - (N-2)\alpha_E X_E - \alpha_I X_I) f_r \left( \frac{1}{\alpha_E} (c - \bar{\mathcal{P}}^E(b) - (N-2)\alpha_E X_E - \alpha_I X_I) \right) f_{E,c}(c) dc}{\int_{\underline{c}}^{\bar{c}} f_r \left( \frac{1}{\alpha_E} (x - \bar{\mathcal{P}}^E(b) - (N-2)\alpha_E X_E - \alpha_I X_I) \right) f_{E,c}(x) dx}$$

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  $f_{c_i}$  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.

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 distribution at zero allows us to accommodate that revenues cannot be negative while preserving the logconcavity of the revenue signal distribution. To capture revenue heterogeneity across tracks, we model the mean of  $F_r$  as a linear function of a constant and the total number of train-kilometers as a sufficient statistic for demand on a given track. In order to keep the number of parameters reasonably low, we model the variance of  $F_r$  ( $\sigma_r$ ) as constant across tracks.<sup>25</sup>

Moreover, we specify the asymmetry parameter  $\alpha$  as a function of the number of bidders  $N$ . Generally, it is not clear that the structural revenue uncertainty should be a function of the number of bidders. However, an artifact of the model of Goeree and Offerman (2003) is that the residual revenue uncertainty is increasing in the number of bidders.<sup>26</sup> To address this issue, one ideally estimates the  $\alpha$ -parameters separately for each set of bidders, and potentially separately for different track covariates. Given our small data set such a nonparametric specification of  $\alpha$  is infeasible. To simultaneously keep the number of model parameters low enough and prevent the residual revenue uncertainty from increasing in the number of bidders by construction, we parametrize  $\alpha_I$  as a linear function of  $N$ , and we restrict it to lie between zero and one using a logit transformation such that  $\alpha_I = \frac{\exp(\gamma_0 + \gamma_1 N)}{1 + \exp(\gamma_0 + \gamma_1 N)}$  implying that  $\alpha_E = \frac{1}{N-1}(1 - \alpha_I)$ , and the actual parameters that we estimate are  $\gamma_0$  and  $\gamma_1$ .

Given the values of the conditional expectation terms,  $X_I$  and  $X_E$ , for any vector of parameter

<sup>25</sup>In robustness checks, we experimented with both having  $\sigma_r$  and additional revenue shifters entering the mean  $\bar{R}$ . These specifications generally led to similar estimates of the asymmetry parameters but considerably higher standard errors.

<sup>26</sup>Note that Hong and Shum (2002) also find that the winner's curse is increasing in the number of bidders.

guesses for  $(\bar{R}, \sigma_r, \alpha)$ , we can construct the likelihood function from the first-order conditions for equilibrium bidding using the estimated values  $\mathcal{P}^i$

$$(25) \quad \mathcal{P}^I = c_I - \alpha_I r_I - (N - 1)\alpha_E X_E(R, \sigma_r, \alpha)$$

$$(26) \quad \mathcal{P}^E = c_E - \alpha_E r_E - (N - 2)\alpha_E X_E(R, \sigma_r, \alpha) - \alpha_I X_I(R, \sigma_r, \alpha).$$

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 density function of  $\alpha_i r_i$  is  $f_{\alpha_i r_i} = \frac{1}{\alpha_i} \mathcal{N}(r_i/\alpha_i; \bar{R}, \sigma_r, 0, \bar{r})$ .  $c_i$  is distributed according to  $f_c(c_i)$ . Hence, the density of  $c_i - \alpha_i r_i$  is

$$(27) \quad f_{c_i - \alpha_i r_i}(x) = \int_{-\infty}^{\infty} f_{-(\alpha_i r_i)}(y - x) f_c(y) dy,$$

where  $x$  is the right hand side of Equation (25), if the incumbent wins the auctions, and the right hand side of Equation (26) if the entrant wins the auction. Finally, the likelihood function for our second net auction step, that we use to estimate the parameter of the revenue signal distribution  $(\bar{R}, \sigma_r)$  and the informational asymmetry parameters  $\alpha$  is given by

$$(28) \quad LL(\bar{R}, \sigma_r, \alpha) = \sum_{t=1}^{T^{net}} \log(f_{c_i - \alpha_i r_i}(\mathcal{P}^i)),$$

where  $T^{net}$  denotes the number of net auctions in our sample.

### 4.3. Entry Stage

Our estimation of the entry cost closely follows Athey et al. (2011) and is facilitated by the fact that the entry game is played only among symmetric players which results in a unique symmetric entry equilibrium. In this equilibrium, each entrant decides to enter the auction with a probability  $q \in (0, 1)$ , while DB participates in each auction with probability 1. As discussed in Section 3, DB can safely be assumed to be active in all auctions (see Frankfurter Allgemeine Zeitung (2011)).

We define the set of potential bidders in the entry game for a particular track to consist of two types of firms: first, all firms that are active in the federal state in which the auction under consideration takes place; second, all firms that submit a winning bid in this federal state within the 12 months following the auction under consideration. We consider the entrant firms to be symmetric and not to hold private information before entering an auction as argued in Section 3.

The condition for optimal entry prescribes that each entrant has to be indifferent between entering and not entering the auction. Denote the expected profit of an entrant from entering

an auction with covariates  $X$  and  $\mathcal{N}$  potential bidders by<sup>27</sup>

$$(29) \quad \Pi_e(X, \mathcal{N}) = \sum_{N=2}^{\mathcal{N}} \pi_e(X, N) Pr(N|X, \mathcal{N}, i \in N),$$

where  $\pi_e(\cdot)$  denotes the expected profit from participating in the auction (net of the entry cost) when  $N$  bidders participate and  $Pr(\cdot)$  is the probability that  $N$  bidders enter conditional on one entrant and DB having already entered. Based on our estimates for cost and revenue distributions from the bidding stage, we can compute  $\pi_e(\cdot)$  for each auction and a given number of bidders. Recall that in equilibrium, DB enters the auction with certainty while entrants independently randomize and enter with a probability  $q(X, \mathcal{N})$ ; therefore, the belief of an entrant about the other entrants' entry behavior is binomial and given by

$$(30) \quad Pr(N|X, \mathcal{N}, i \in N) = \binom{\mathcal{N}-2}{N-2} q^{N-2} (1-q)^{(\mathcal{N}-N)}.$$

We follow Athey et al. (2011) and estimate the entrants' probability of entering the auction parametrically, such that

$$(31) \quad q(X, \mathcal{N}) = \frac{\exp(\alpha_X X + \alpha_N \mathcal{N})}{1 + \exp(\alpha_X X + \alpha_N \mathcal{N})}.$$

We estimate the parameters  $(\alpha_X, \alpha_N)$  by maximum likelihood separately for the gross and net auction sample using the observed bidder entry in the two respective samples. For the auction covariates  $X$ , we included the same variables as in the estimation of the bid distributions, i.e., the track access charges, a dummy for whether used vehicles are permitted, the contract duration, the total contract volume in train-kilometers, and the length of the track network served.

Afterwards, we combine the estimated entry beliefs  $Pr(N|X, \mathcal{N}, i \in N)$  with our estimates for the expected profits  $\pi_e(X, N)$  to compute the expected profit from entering the auction  $\Pi_e(X, \mathcal{N})$ . Finally, for each auction, we compute the entry cost  $\kappa(\cdot)$  using the condition for optimal entry

$$(32) \quad \kappa(X, \mathcal{N}) = \Pi_e(X, \mathcal{N}).$$

## 5. Estimation Results

In this section, we discuss our main estimation results. We start by presenting our estimated cost distributions and the estimates of the informational asymmetry parameters. Afterwards, we summarize our estimates of the bid preparation costs of the entrants.

Table 10 in Appendix C displays the maximum likelihood estimates for the bid distribution parameters in gross and net auctions for both the incumbent and the entrants. In a highly

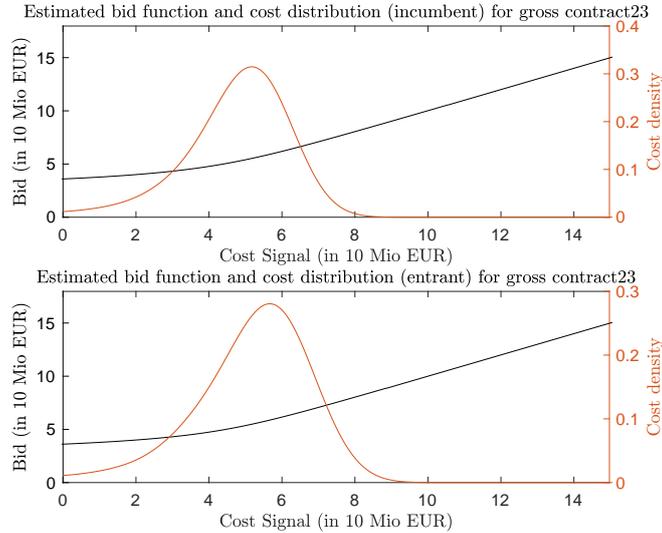
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<sup>27</sup>Recall that  $\mathcal{N}$  includes DB, so that there are only  $\mathcal{N} - 1$  potential entrant firms.

nonlinear auction model it is difficult to interpret the magnitude of the coefficients directly. Therefore, we focus on the shape of the implied bid functions and the cost distribution estimates. One representative example of the bid functions and the cost densities for a gross auction contract is displayed in Figure 4. We provide graphs for several additional gross auctions in Appendix C.

**Cost estimates.** Generally, bid functions in gross auctions are relatively close for the incumbent and the entrants, which suggests only small, but potentially significant, systematic differences in cost distributions. Figure 8 in Appendix C displays the histogram of the incumbent’s relative cost advantage as measured by the estimated 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 for 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 several lines (about 15% of our sample) 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 considerable number of tracks (roughly 25% of our sample) that seem to be prohibitively costly for the entrants to operate when compared to the incumbent’s cost distribution.

Figure 4: Cost density and bid function for gross auction 23



*Notes:* This graph compares the estimated bid functions and cost distributions for the incumbent (top panel) and entrants (bottom panel) for a representative gross auction in our sample.

To compare the cost distributions of different bidder types more formally, we test for first-order stochastic dominance (FOSD) using the nonparametric test by Davidson and Duclos (2000). Details on how we test for FOSD of the cost distributions are provided in Appendix B.3. Although some of our graphs suggest some systematic cost asymmetries, we cannot reject

the null hypothesis of equal cost distributions for the majority of contracts. We reject the null in favor of the alternative of the entrants’ cost distribution dominating DB’s cost distribution for only 27% of our observations.<sup>28</sup> In summary, our cost estimates indicate that DB’s dominance can at least partially be justified by its better cost distribution. However, this cost advantage seems smaller than what one would have expected given the raw data.

**Informational asymmetry estimates.** When comparing a typical bid function in a gross auction with one in a net auctions, we find striking differences. Overall, entrants seem to shade their bids substantially more than DB in net auctions. 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.

Table 5: Estimation results: Informational asymmetry

	$N = 2$	$N = 3$	$N = 4$	$N = 5$
$\alpha_I$	0.5003 (0.1245)	0.6010*** (0.0538)	0.5279*** (0.0473)	0.4535*** (0.0599)
$\alpha_E$	0.4997 (0.1245)	0.2280*** (0.0107)	0.1889*** (0.0053)	0.1682*** (0.0095)

*Notes: The table displays the estimated asymmetry parameters for the incumbent (top row) and the entrants (bottom row) for different numbers of participating bidders. Parameters are estimated using maximum likelihood. Standard errors are computed using the delta method. \*, \*\*, \*\*\* denote significance at the 10, 5 and 1 percent-level for testing  $H_0 : \alpha = \frac{1}{N}$ , respectively.*

As discussed in Section 4.2, we estimate  $\alpha_I$  as a linear function of the number of bidders. This specification fits auctions with three or more bidders well. Tracks with only two bidders are arguably special.<sup>29</sup> Therefore, we estimate a separate  $\alpha$ -parameter for the subset of auctions with only two bidders and model  $\alpha_I$  as a linear function of  $N$  for auctions with more than two bidders.<sup>30</sup>

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 estimates for  $\alpha$  imply that the residual revenue variance –as measured by the ratio of Equation (7) and (8)– is on average 2.7 times higher for the entrant than the incumbent. For auctions with two bidders we obtain an estimated

<sup>28</sup>Note that if the entrants’ cost distribution dominates DB cost distribution, DB has more mass on low cost realizations.

<sup>29</sup>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.

<sup>30</sup>Recall that we do not suggest, that the structural informational asymmetry has to systematically vary with the number of bidders. Instead, we allow  $\alpha$  to be a function of  $N$  in order to mitigate the artifact of the model by Goeree and Offerman (2003) that residual uncertainty about the revenue increases in  $N$  by construction.

$\alpha_I$  of 0.5003 which implies that the incumbent and the entrants on these lines have basically equal information on the common value and we cannot reject the null hypothesis that  $\alpha_I = \alpha_E = 0.5$  on these lines.

Table 6: Estimation results: Entry costs

	Gross auctions	Net auctions
Mean (in million EUR)	5.9142	5.9916
Median (in million EUR)	3.7899	5.7899
SD (in million EUR)	6.4660	3.5015

*Notes: The table displays summary statistics of the distribution of the estimated entry costs of entrant firms in the gross and net auction sample, respectively.*

**Entry cost estimates.** Table 6 summarizes the results from our entry cost estimation. The bid preparation costs of entrants are large for both auction modes.<sup>31</sup> While the mean is very similar across gross and net auctions, entry costs for gross auctions exhibit a substantially larger standard deviation. This is most likely driven by a few very large gross contracts in our sample. The median entry cost is considerably smaller for gross auctions than for net auctions (EUR 3.8 million versus EUR 5.8 million). These results indicate that entry into the median net auction is roughly 50% more expensive than preparing a bid for the median gross auction. This result is intuitive because for net auctions bidders have to learn about both their costs and the estimates of future ticket revenues before placing a bid, which raises the cost of bid preparation. Overall, our entry cost estimates are roughly in line with industry data on bid preparation costs from other countries. For example, RTM (2016) estimates that for railway service procurement in the UK entry costs range from GBP 5 million to GBP 10 million.

## 6. Counterfactuals

In this section, we analyze the effects of procurement design on efficiency and agency revenues in more detail. We start by defining an ex ante efficiency measure in our setup for gross and net auctions and then compare the probability of selecting the efficient bidder for three scenarios: first, the actual gross auction sample, second the actual net auction sample, and finally, we analyze the efficiency effects of procuring the net auction sample using gross auctions. In addition, we compute the expected winning bids and the expected agency payoff for each track under both net and gross contracts.

Naturally, there are several different reasons why net auctions are potentially less efficient than gross auctions. To shed more light on the relative importance of the different channels, we show how the efficiency of the net auction sample changes under different hypothetical

<sup>31</sup>Recall that, consistent with industry evidence, we assume that DB participates in all auctions so that we cannot identify its entry cost.

assignment scenarios. Specifically, we compute the probability of selecting the cost-efficient firm when each firm bids its combined net cost signal without any strategic considerations. Afterwards, we simulate the efficiency probability if bidders interpret their net cost signal as a pure IPV signal on which they add the same markup term as in a gross auction. While the first exercise allows us to isolate how the additional noise of the revenue signal affects efficiency, the second one illustrates the combined effect of cost asymmetries and revenue signal noise without accounting for the winner's curse effect. Comparing these efficiency probabilities with the efficiency measure of the full net auction model sheds light on the magnitude of the various sources of inefficiencies in net auctions.

## 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<sup>32</sup>

$$(33) \quad \Pr(c_i \leq \min_{j \neq i} c_j | b \leq \min_{j \neq i} b_j).$$

**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

$$(34) \quad \Pr(c_i \leq \min_{j \neq i} c_j | b \leq \min_{j \neq i} b_j) = \frac{\Pr(b \leq \min_{j \neq i} b_j \cap c_i \leq \min_{j \neq i} c_j)}{\Pr(b \leq \min_{j \neq i} b_j)}.$$

We can rewrite this equation in terms of the bids. The cost  $c_i = b_i^{-1}(b) \equiv \phi_i(b)$  of bidder  $i$  that corresponds 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.,  $b_j(c) = b_j(\phi_i(b))$ . Consequently, the second event in the numerator of Equation (34) corresponds to the condition

$$(35) \quad b_j \geq b_j(\phi_i(b)) \quad \forall j \neq i.$$

Therefore, we can rewrite

$$(36) \quad \Pr(c_i \leq \min_{j \neq i} c_j | b \leq \min_{j \neq i} b_j) = \frac{\Pr(b \leq b_j \quad \forall j \neq i \cap b_j \geq b_j(\phi_i(b)) \quad \forall j \neq i)}{\Pr(b \leq \min_{j \neq i} b_j)},$$

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

$$(37) \quad \Pr(c \leq \min_{j \neq i} c_j | b \leq \min_{j \neq i} b_j) = \frac{\Pr(b_j \geq b \cap b_j \geq b_j(\phi_i(b)) \quad \forall j \neq i)}{\Pr(b \leq \min_{j \neq i} b_j)}.$$

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<sup>32</sup>For notational convenience, we suppress covariate dependency of the bid functions in this section.

The numerator can be solved for each of the bidders directly from the bid functions for each  $b$ . We can then compute this probability directly from the bid functions estimated previously. 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. The probability of the incumbent and entrant winning with bid  $b$  is given by

$$(38) \quad \Pr(\text{incumbent wins with } b) = \Pr(\text{incumbent bids } b \text{ and all entrants bid } b_e \geq b) \\ = h_I^{gr}(b) (1 - H_E^{gr}(b))^{N-1}$$

$$(39) \quad \Pr(\text{incumbent wins with } b) = \Pr(\text{an entrant bids } b \text{ and all other bidders bid } b_i \geq b) \\ = (N-1)h_E^{gr}(b) (1 - H_E^{gr}(b))^{N-2} (1 - H_I^{gr}(b)),$$

respectively, where  $H_i^{gr}(b)$  are the bid distributions estimated in Section 4.2 and  $h_i^{gr}$  the corresponding densities. The resulting ex ante probability of selecting the efficient bidder is

$$(40) \quad \int_{\underline{b}}^{\bar{b}} \left( h_I^{gr}(b) (1 - H_E^{gr}(b))^{N-1} \frac{\Pr(b_j \geq b \cap b_j \geq b_j(\phi_I(b)) \forall j \neq I)}{\Pr(b \leq \min_{j \neq I} b_j)} + \right. \\ \left. (N-1)h_E^{gr}(b) (1 - H_E^{gr}(b))^{N-2} (1 - H_I^{gr}(b)) \frac{\Pr(b_j \geq b \cap b_j \geq b_j(\phi_E(b)) \forall j \neq E_w)}{\Pr(b \leq \min_{j \neq I} b_j)} \right) db,$$

where  $E_w$  denotes the winning entrant.

**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 more involved as the bidders' compound signal, that determines the bid, contains both a cost realization and a revenue signal. As before, we are interested in determining the conditional probability

$$(41) \quad \Pr(c_i \leq \min_{j \neq i} c_j | b \leq \min_{j \neq i} b_j).$$

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

$$(42) \quad \int_{\underline{b}}^{\bar{b}} A^I(b) h_I^{net}(b) (1 - H_E^{net}(b))^{N-1} + A^E(b) (N-1) h_E^{net}(b) (1 - H_I^{net}(b)) (1 - H_E^{net}(b))^{N-2} db,$$

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

$$(43) \quad A^I(b) = \int_{\underline{c}}^{\bar{c}} (B^E(c))^{N-1} \frac{f_r(r_I(c)) f_{c_I}(c)}{\int_{\underline{c}}^{\bar{c}} f_r(r_I(x)) f_{c_I}(x) dx} dc$$

$$(44) \quad A^E(b) = \int_{\underline{c}}^{\bar{c}} B^I(c) (B^E(c))^{N-2} \frac{f_r(r_E(c)) f_{c_E}(c)}{\int_{\underline{c}}^{\bar{c}} f_r(r_E(x)) f_{c_E}(x) dx} dc$$

denote the probabilities that the incumbent ( $A_I$ ) and an entrant ( $A_E$ ) is the efficient firm when winning with bid  $b$ . Both terms integrate over all potential winner's costs that rationalize the compound signal that induces winning bid  $b$  with

$$(45) \quad B^E(c) = \int_{\rho_E(\rho_I(b))}^{\bar{\rho}} C^E(\rho) \frac{f_{\rho_E}(\rho)}{\int_{\rho_E(\rho_I(b))}^{\bar{\rho}} f_{\rho_E}(x) dx} d\rho$$

$$(46) \quad B^I(c) = \int_{\rho_I(\rho_E(b))}^{\bar{\rho}} C^I(\rho) \frac{f_{\rho_I}(\rho)}{\int_{\rho_I(\rho_E(b))}^{\bar{\rho}} f_{\rho_I}(x) dx} d\rho,$$

where  $B^i(c)$  denotes the probability that the cost realization for a competitor of type  $i$ , integrated over all net cost signals that lose against the winning bid  $b$ , is higher than the currently fixed (winner's) cost  $c$ . Here,  $f_{\rho_i}(\rho) = \int_{-\infty}^{\infty} f_{c_i}(x) f_{-\alpha_i r}(x - \rho) dx$  denotes the density of the compound signal  $\rho_i$ , which is 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

$$(47) \quad C^E(\rho) = \int_c^{\bar{c}} f_r(r_E(\tilde{c})) f_{c_E}(\tilde{c}) d\tilde{c}$$

$$(48) \quad C^I(\rho) = \int_c^{\bar{c}} f_r(r_I(\tilde{c})) f_{c_I}(\tilde{c}) d\tilde{c},$$

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  $r_i(c) = \frac{1}{\alpha_i} (c - \rho_i(b))$ .

**Efficiency results.** Table 7 displays summary statistics of the distribution of the probabilities of selecting the efficient firm for the different procurement modes across all tracks in our gross and net sample, respectively. Gross auctions exhibit a median probability of selecting the efficient firm of 85%. The probability of selecting the efficient firm in net auctions, however, is substantially lower and only 20% in the median. In light of our empirical analysis comparing gross and net auctions in Section 3, a potential explanation for the efficiency difference between

Table 7: Efficiency comparison for different auction formats

	Gross auctions	Net auctions	Net $\rightarrow$ Gross
Pr(selecting efficient firm)	0.8503	0.1985	0.8071

*Notes: The table displays the median (across auctions) of the ex ante probabilities of selecting the efficient firm in our two different samples (gross and net) and a counterfactual scenario in which the net auction sample is procured using gross auctions.*

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.

Table 7 summarizes the corresponding results. We find a substantial increase in the median probability of selecting the efficient bidder (from 20% to 81%) that brings the efficiency of the net auction sample almost to the level of the gross auction sample. When testing the equality of the median efficiency of gross auctions and net auctions procured as gross using a Wilcoxon rank-sum test, we are not able to reject the null hypothesis of equal medians at the 5%-level.

Table 8: Illustration of efficiency loss in net auctions

	Net auctions (non-strategic)	Net auctions (w/ gross markups)	Net auctions (observed)
Pr(selecting efficient firm)	0.7952	0.6036	0.1985

*Notes: The table displays the median (across auctions) of the ex ante probabilities of selecting the efficient firm in the net auction sample for different hypothetical scenarios.*

While in a gross auction, the only source of inefficiency is the cost asymmetry between the incumbent and the entrants, the severe efficiency loss in net auctions is likely to be due to a combination of several reasons. First, cost asymmetries still prevail. Second, the revenue signal introduces additional noise that might prevent the cost-efficient firm from submitting the lowest bid. Third, asymmetric precision of information about the common value component will affect bidding strategies.

In order to illustrate which of these channels is likely to be the most significant source of the efficiency loss in net auctions, we conduct several simulations in which we successively eliminate different channels to disentangle the different effects. Table 8 summarizes the associated results.

To isolate the efficiency loss from pure noise caused by the revenue signal, we simulate the efficiency measure for each auction when each firm truthfully bids its combined signal, i.e., its cost signal minus its revenue signal, without any strategic considerations. In this setting, the only source of inefficiency is the additional noise from the revenue signal. The efficiency loss induced by the second signal is considerable but arguably modest resulting in a median

efficiency of roughly 80% (see column *non-strategic* of Table 8).

In the second column (*w/ gross markups*) of Table 8, we present the median efficiency probability for a setting in which each firm considers the sum of its signals as a pure IPV signal, i.e., it bids  $c_i - r_i$  and adds the same markup as in a gross auction.<sup>33</sup> This scenario captures the combined efficiency loss from the revenue signal noise and strategic bidding due to cost asymmetries. The median efficiency level is 60%, i.e., the strategic behavior due to cost asymmetries induces another 20%-points loss in efficiency. This number is roughly in line with the efficiency loss of 15%-points that we observe in our gross auction sample.

The key difference between the previous scenario and the actual net auction sample efficiency is that, while in the latter the common value asymmetry affects bidding behavior, it does not in the former settings. Comparing the three efficiency statistics in Table 8 reveals that the biggest efficiency loss –an additional 40%-points compared to the scenario with revenue signal noise and gross markup bidding– occurs when we allow the common value asymmetry to affect bidding behavior.

In conclusion, we interpret these numbers as evidence that, while several factors contribute to the massive efficiency loss in net auctions, the informational asymmetry about the common value has by far the biggest effect. One potential policy implication from these simulations is that letting train operating companies bear the revenue risk 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 median efficiency across potentially very different auctions can be misleading. Figure 11 in Appendix D displays histograms of the efficiency probabilities for the two samples (gross and net) and the counterfactual in which net auctions are procured as gross contracts. The general picture is consistent with our discussion above. In addition, Figure 11 reveals that moving from net to gross auctions results in auctions that were very inefficient before, i.e., auctions that had a probability of selecting the efficient firm of less than 40%, to benefit most. Generally, the distribution of efficiency probabilities is shifted to the right when moving from net to gross.

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

## 6.2. Counterfactual Winning Bids

While efficiency probabilities are an important indicator of the performance of a government procurement auction, the procurer might also care about the winning bid, which determines the subsidy to be paid. Our estimates allow us to predict the subsidy that the agency has to

<sup>33</sup>Specifically, we use the markup function,  $MU_i^{ngr}(c_i)$ , that we obtained from our counterfactual in which net auctions are procured as gross auctions for each bidder type  $i$ . We apply this markup function to each bidder’s sum of the signals, so that  $b_i = c_i - r_i + MU_i^{ngr}(c_i - r_i)$ . For realizations of the sum of the signals that lie outside the estimated cost distribution support, we approximate the hypothetical markups using linear extrapolation. We compute the efficiency measures for each auction by simulating the outcome of the auction 5000 times.

pay to the winning firm.<sup>34</sup> Since we have estimated the bid functions for all bidder types and all auction formats, we can compute the expected winning bid in auction  $j$  using

$$(49) \quad \int_b^{\bar{b}} b \left( h_I^j(b)(1 - H_I^j(b))^{N-1} + (N-1)h_E^j(b)(1 - H_E^j(b))^{N-2}(1 - H_I^j(b)) \right) db,$$

where  $H_i^j$  ( $h_i^j$ ) denote the distribution (density) function of the bid distribution of bidder type  $i$  in auction  $j$ . Table 9 compares the winning bids predicted by our model for the three different

Table 9: Revenue comparison for different auction formats

	Predicted winning bid	E(ticket revenues)	E(agency payoff)
Gross auctions	6.5061	4.4623	-2.0437
Net auctions	6.2760	4.4731	-6.2760
Net → Gross auctions	7.0107	4.4731	-2.5376

*Notes: The table summarizes the predicted winning bids along with the mean of the expected ticket revenues and expected procurement agency payoff for our two different samples (net and gross) and a counterfactual scenario in which the net auction sample is procured using gross auctions. Means are calculated over all auctions within the respective samples, i.e., gross and net.*

auction formats. Not surprisingly, the winning bid, i.e., the subsidy that the winning firm receives for fulfilling the contract, increases when moving from net to gross auctions, since the winning firm has to be compensated for the foregone revenues. Interestingly, the difference between gross and net auctions in terms of the average winning bid is not that large, however. One explanation for the relatively small difference in the winning bids is that net auctions involve a large winner’s curse risk causing substantial bid shading which offsets the additional revenues from ticket sales in net auctions.

In addition, Table 9 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. When comparing our revenue estimates to the observed winning bids or the estimated cost distributions, we find plausible patterns, that are in line with industry reports. For example, the median (across all auctions) of the ratio of the winning bid over the expected revenue is approximately 1.4 in our sample. Rödl & Partner (2014) document that this ratio is around 1.5 for a typical SRPS auction in Germany.

Figure 12 in Appendix D 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 slightly decreases when

<sup>34</sup>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.

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 about a common value component. Our theoretical model can rationalize a dominant firm with either asymmetry: a more efficient cost distribution or more precise information about the common value or a combination of both. Empirically quantifying the importance of each asymmetry is crucial for evaluating the efficiency of the market: If the dominant firm is on average more efficient than its competitors, it wins too few auctions. If the dominant firm is only more precisely informed, it wins too many auctions.

While most of the empirical literature on asymmetric auctions focuses 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 the incumbent and the entrants. We take our model to a data set on procurement for SRPS in Germany, an important example for a deregulated industry in which the former state monopolist, DB, is still dominant even 20 years after the liberalization. In principle, our model and our estimation strategy can be applied to other settings as well. The only requirement is that we observe some variation in the procurement mode that allows us to estimate the private value distribution from one sample and use this distribution to extrapolate private values to the sample with common value uncertainty. Specific examples for such markets 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 contrast the bidding behavior for different tracks that have comparable cost characteristics; but some tracks are procured with revenue risk, some without such risk. If the ticket revenues remain with the agency (*gross contract*), the auction is a standard asymmetric IPV auction. If the train operating company is the claimant of the ticket revenues (*net contract*), the auction features both a private value (cost) and a common value (ticket revenues) component.

Our estimation proceeds in two steps. First, we estimate the cost distributions of the incumbent and the entrants from the winning bids in gross auctions. These estimates allow us to predict the cost distributions for each net contract. Therefore, systematic differences in bidding behavior that are not explained by differences in cost distributions must be attributed

to the common value component. This allows us to estimate the parameters of the revenue distribution and the informational asymmetry in a second step.

The results from our structural estimation 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 FOSD sense in only 27% of the auctions. The estimation of the informational advantage of DB reveals that in most auctions DB possesses 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.

Our structural model allows us to compute ex ante efficiency probabilities for different auction formats. In our gross auction sample, the median probability of selecting the efficient firm is high (85%). Net auctions, however, tend to perform very poorly with a median efficiency probability of 20%. In a series of counterfactuals, we illustrate which characteristics of net auctions are the most severe sources of inefficiencies. These simulations reveal that both the additional noise of the revenue signal and the cost asymmetries among bidders already cause a non-negligible efficiency loss. By far the biggest source of inefficiency, however, is the informational asymmetry about the future ticket revenues.

Therefore, it is likely that efficiency can be increased by awarding more gross contracts instead of net contracts, which eliminates the common value component from the auction. We simulate this change in procurement mode and find that entrants shade their bids considerably less than in net auctions which results in much more symmetric bid functions across different bidder types. As a consequence, the median probability of selecting the efficient firm increases substantially from 20% to 81%. In addition, agency payoffs increase significantly when moving from net to gross auctions.

While determining the best auction format in a comprehensive way requires a careful consideration not only of bidding behavior but also of the procurement agencies' objective function, our empirical analysis highlights a significant potential for improving the efficiency of procurement auctions by eliminating informational asymmetries among bidders.

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## A. Proofs

### A.1. Proof of Lemma 2

The derivation of the FOC is standard given the insights of Goeree and Offerman (2003) for the mapping of the two-dimensional private information into one dimension. Combining this insight with the conditions (monotonic preferences in the signal, independence of signals across bidders and supermodularity of preferences, which are all straightforwardly satisfied in our setup) in Maskin and Riley (2000b) we know that a monotonic equilibrium in pure strategies exists. The maximization problem of bidder  $i$  given signal  $\rho_i = c_i - \alpha_i r_i$  and letting the expected net cost of winning be denoted by  $\tilde{v}_i(\rho_i, m_i; N) = \mathbb{E}[c_i - \alpha_i r_i - \sum_{j \neq i} \alpha_j r_j | \rho_i, \max_{j \neq i} B_j = m_i]$  is given by

$$(50) \quad \max_b \int_b^\infty (b - \tilde{v}_i(\rho_i, m_i; N)) g_{M_i|B_i}(m_i | \beta_i(\rho_i; N); N) dm_i,$$

where  $g_{M_i|B_i}(m_i | \beta_i(\rho_i; N); N) = \Pr(m_i = \min_{j \neq i} B_j | B_i = \beta_i(\rho_i; N), N)$  and  $\beta_i(\cdot)$  is bidder  $i$ 's bidding function. The objective is differentiable almost everywhere and the first-order condition given by

$$0 = -(b_i - \tilde{v}_i(\rho_i, b; N)) g_{M_i|B_i}(b_i | \beta_i(\rho_i; N); N) + (1 - G_{M_i|B_i}(b_i | \beta_i(\rho_i; N); N)).$$

Following the notation of Athey and Haile (2007) further

$$v_i(\rho_i, \tilde{\rho}_i; N) = \mathbb{E}[c_i - \alpha_i r_i - \sum_{j \neq i} \alpha_j r_j | \rho_i, \max_{j \neq i} B_j = \beta_i(\tilde{\rho}_i; N); N],$$

so we get

$$b_i = v_i(\rho_i, \rho_i; N) + \frac{1 - G_{M_i|B_i}(b_i | b_i; N)}{g_{M_i|B_i}(b_i | b_i; N)},$$

which is using the expected net cost of winning in our setting

$$b_i = c_i - \alpha_i r_i - \sum_{j \neq i} \alpha_j \mathbb{E}[r_j | \rho_j = \phi_j(b_i)] + \frac{1 - G_{M_i|B_i}(b_i | b_i; N)}{g_{M_i|B_i}(b_i | b_i; N)},$$

yielding the desired expression where  $\phi_j$  denotes the inverse bid function.

## A.2. Proof of Lemma 3

Recall the first-order condition for optimal bidding of bidder  $i$

$$\begin{aligned} b - c + \alpha_i r_i + \sum_{j \neq i} \alpha_j \mathbb{E}[r_j | \rho_j = \beta_j^{-1}(b_i)] &= \frac{1 - G_{M_i|B_i}(b|b; N)}{g_{M_i|B_i}(b|b; N)} \\ &= \frac{\prod_{j \neq i} (1 - F_r(\phi_j(b)))}{\left( \prod_{j \neq i} (1 - F_r(\phi_j(b))) \right)'} \end{aligned}$$

The boundary conditions are given by  $\phi_i(\underline{b}) = \bar{r}$ . Note that, whenever  $\phi_i(b) = \phi_j(b)$ , it follows that the left-hand side is larger in the first-order condition for bidder  $I$  than for bidders of group  $E$ . This can be seen because the expected value terms are less than the own revenue signal and the own revenue signal is weighted more by bidder  $I$ . Moreover, the only term that differs on the right-hand side in the first-order condition for bidder  $I$  compared to the one of bidder  $E$ , is that there is no  $\phi'_I(b)$  in the denominator but an additional  $\phi'_E(b)$  compared to the first-order condition of bidder  $E$ . Hence, the slope of  $\phi_E(b)$  has to be flatter whenever  $\phi_I(b) = \phi_E(b)$  and for  $b + \varepsilon$ , with  $\varepsilon > 0$  and small,  $\phi_I(b + \varepsilon) < \phi_E(b + \varepsilon)$  because the bid function is decreasing. Note that the lowest bid is placed by both bidders for the highest revenue signal, i.e.,  $\phi_i(\underline{b}) = \bar{r}$ . Then, for bids slightly above  $\underline{b}$ ,  $\underline{b} + \varepsilon$ , the left-hand side of bidder  $I$ 's first-order condition will exceed the left-hand side of bidder  $E$ 's first-order condition. By the same logic from above,  $\phi_I(\underline{b} + \varepsilon) < \phi_E(\underline{b} + \varepsilon)$ . Taking these two arguments together, it will never occur that  $\phi_I(b) > \phi_E(b)$ . But as revenue signals are drawn from the same distribution it follows that the bid distribution of bidder  $I$  will be first-order stochastically dominated by the bid distribution of bidders in group  $E$  and  $H_I(b) \geq H_E(b)$  with strict inequality for  $b \in (\underline{b}, \bar{b})$ . Note that for two bidders, the left-hand side of the first-order condition is identical and bidders have to have the same bid distribution, i.e., for all  $b$ ,  $H_I(b) = H_E(b)$ .

## B. Details on Estimation Routine

### B.1. Derivation of the Likelihood Function for Bid Distribution Estimation

The likelihood function is derived from the first order statistic of the winning bid, i.e., the probability that the outcome of the auction is that bidder  $U$  wins the auction with bid  $x$  given that  $N$  bidders participate. We introduce the following notation for bidder type  $U$  given our parametric Weibull assumption on the bid distribution

$$(51) \quad \exp_U = \exp\left(-\left(\frac{x}{\lambda_U}\right)^{\rho_U}\right)$$

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

$$(53) \quad H_U = 1 - \exp\left(-\left(\frac{x}{\lambda_U}\right)^{\rho_U}\right) = 1 - \exp_U.$$

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

$$(54) \quad h_I^{j,(1:N)}(x) = \Pr(b^I = x, b^{E_1} \geq x, \dots, b^{E_{N-1}} \geq x)$$

$$(55) \quad = \Pr(b^I = x) \Pr(b^{E_1}, \dots, b^{E_{N-1}} \geq x)$$

$$(56) \quad = h_I^j(x)(1 - H_E^j(x))^{N-1}.$$

For a winning entrant it is given by

$$(57) \quad h_E^{j,(1:N)}(x) = (N-1) \Pr(b_i^E = x, b_{j \neq i}^E \geq x, b^I \geq x)$$

$$(58) \quad = (N-1) \Pr(b_i^E = x) \Pr(b_{j \neq i}^E \geq x, b^I \geq x)$$

$$(59) \quad = (N-1)h_E^j(x)(1 - H_E^j(x))^{N-2}(1 - H_I^j(x)).$$

## B.2. Estimation of Cost Distributions

In this appendix, we provide additional details on how we estimate the cost distributions based on the estimated bid distributions. We follow the procedure outlined in Athey and Haile (2007) and proceed in the following steps.

1. Draw a pseudo-sample of bids for both incumbent and entrant from the estimated bid distributions,  $H_I^{gr}(b|X, N)$  and  $H_E^{gr}(b|X, N)$ .
2. The pseudo-sample of bids has to satisfy the FOCs

$$(60) \quad \hat{c}^I = b^I - \frac{1 - G_{I,M|B}^{gr}(b^I|b^I, X, N)}{g_{I,M|B}^{gr}(b^I|b^I, X, N)}$$

$$(61) \quad \hat{c}^E = b^E - \frac{1 - G_{E,M|B}^{gr}(b^E|b^E, X, N)}{g_{I,M|B}^{gr}(b^E|b^E, X, N)}.$$

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

(62)

$$1 - G_{i,M|B}^{gr}(b_i|b_i, X, N) = \Pr(b_i \leq \min_{j \neq i} B_j | b_i, X, N)$$

$$1 - G_{E,M|B}^{gr}(b_i|b_i, X, N) = (1 - H_E^{gr}(b_i|X, N))^{N-2}(1 - H_I^{gr}(b_i|X, N)) \text{ (for an entrant)}$$

$$1 - G_{I,M|B}^{gr}(b_i|b_i, X, N) = (1 - H_E^{gr}(b_i|X, N))^{N-1} \text{ (for the incumbent),}$$

where in the last two lines  $H_E^{gr}$  and  $H_I^{gr}$  denote the estimated bid distributions in gross auctions for entrants and the incumbent, respectively.  $G_{i,M|B}^{gr}(b_i)$  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  $g$  is the derivative of  $G$  and

given by

$$(63)$$

$$g_{i,M|B}^{gr}(b_i|b_i, X, N) = \frac{\partial H_{i,M|B}^{gr}(b_i|b_i, X, N)}{\partial b_i}$$

$$g_{I,M|B}^{gr}(b_i|b_i, X, N) = -(N-1)(1 - H_E^{gr}(b_i|X, N))^{N-2} h_E^{gr}(b_i|X, N) \text{ (for the incumbent)}$$

$$g_{E,M|B}^{gr}(b_i|b_i, X, N) = -(N-2)(1 - H_E^{gr}(b_i|X, N))^{N-3} h_E^{gr}(b_i|X, N)(1 - H_I^{gr}(b_i|X, N))$$

$$- g_I^{gr}(b_i|X, N)(1 - H_E^{gr}(b_i|X, N))^{N-1} \text{ (for entrants)}.$$

3. Inverting the FOCs for all simulated bids results in a pseudo-sample of cost realizations for each track and bidder type. Finally, we use kernel smoothing treating  $\hat{c}$  as draws from the cost distribution to compute the cost distribution nonparametrically.

### B.3. 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

$$F_{c_E}(x) \leq F_{c_I}(x) \forall x \text{ and}$$

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

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  $F_{c_E} \succ F_{c_I}$ . In our application, we use the pseudo-sample of simulated cost realizations for both bidder types to compute the empirical CDFs  $\hat{F}_{c_I}$  and  $\hat{F}_{c_E}$ . 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

$$\hat{V}(x) = \hat{V}_{c_E}(x) + \hat{V}_{c_I}(x)$$

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

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 the test statistic

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

We construct the grid  $\mathbf{x}$  such that it covers the area from 0 to the 99% percentile of the estimated cost distribution. We evaluate the test statistic at 10 equally spaced grid points. In line with

the definition of FOSD above, we reject the null hypothesis of equal cost distributions in favor of  $F_{c_E} \succ F_{c_I}$  if

$$\begin{aligned} -T(x) &> m_{\alpha, K, \infty} \text{ for some } x, \text{ and} \\ T(x) &< m_{\alpha, K, \infty} \forall x. \end{aligned}$$

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 condition ensures that there is no point at which the entrant's cost CDF is significantly above the one of the incumbent. 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  $NS$ . In our case these are given by  $K = 10$  and  $\infty$  (since  $NS$  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.

## C. Additional Estimation Results

In this appendix, we present additional estimation results of our structural auction model.

### C.1. Bid Distribution Parameter Estimates

Table 10 displays our maximum likelihood estimates for the bid distribution parameters. Column (1) and column (2) contain the estimates for our gross and net auction sample, respectively.

### C.2. Bid Functions and Cost Distribution Estimates

#### C.2.1. Gross Auction Sample

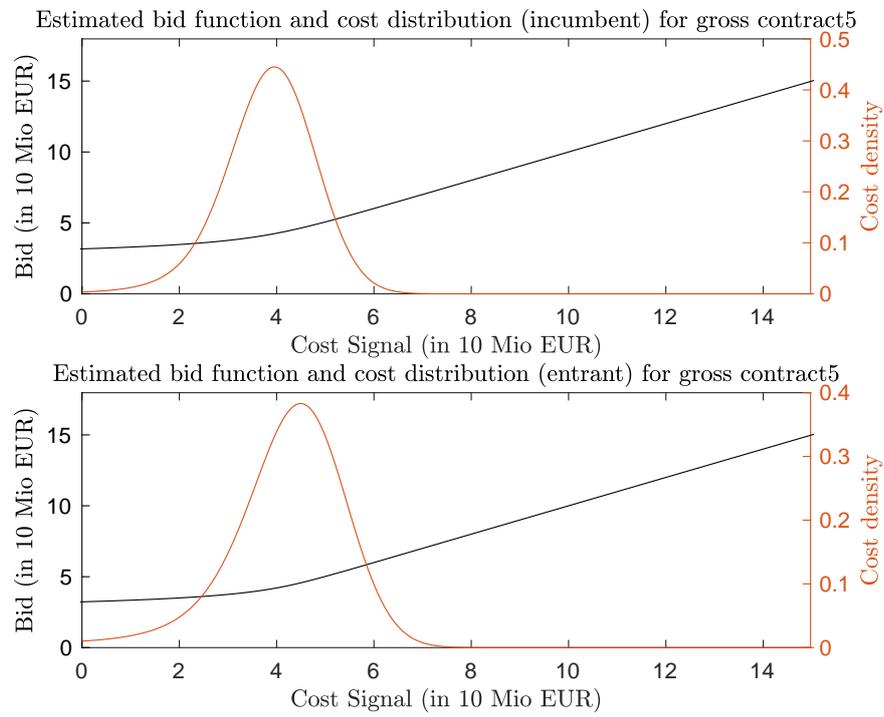
In this appendix, we provide bid functions and estimated cost distributions for several additional representative lines for both gross and net auctions. The following graphs display a comparison of the incumbent and the entrant bid functions and cost distributions for gross auctions, i.e., auctions in which the bidders do not face any revenue risk. Figure 5 and 6 are representative for many lines in our sample and illustrate that generally the incumbent does not have a substantial cost advantage over the entrants resulting in very symmetric bid functions for incumbent and entrants. Figure 7 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

	Gross auctions	Net auctions
$\lambda_X^I$	-0.6428*	1.1620***
	(0.3368)	(0.3849)
	1.7430***	-1.1253*
	(0.6208)	(0.6707)
	1.3521***	0.1724
	(0.2178)	(0.1348)
	0.1728	0.2434
	(0.1191)	(0.2370)
$\lambda_N^I$	1.2837	3.2369***
	(0.9224)	(1.1280)
	-0.2680	10.5870***
	(1.0830)	(2.0029)
	1.1420***	0.9316***
	(0.1886)	(0.2024)
	2.7054***	1.3205
	(0.9474)	(0.9204)
$\lambda_X^E$	1.1296***	1.1206***
	(0.1242)	(0.2282)
	0.1540	-0.4169***
	(0.1013)	(0.1395)
	0.7208	2.3094**
	(0.6264)	(1.1283)
	0.2742	0.6105
	(1.9124)	(1.8694)
$\lambda_N^E$	1.6196**	-0.1089
	(0.7100)	(0.7021)
	-11.5640**	2.5578
	(4.5322)	(1.8910)
	-3.2626***	-0.2547
	(0.8924)	(0.4194)
	-0.7834	-1.2941***
	(0.7292)	(0.4989)
$\nu_X^I$	26.6240***	3.2648
	(6.2998)	(3.5284)
	-14.3580*	-1.4568
	(7.7982)	(8.6910)
	-0.6131	0.7037
	(0.6296)	(0.5876)
	-8.0123**	1.9013
	(3.7136)	(2.3567)
$\nu_X^E$	-1.1937***	-0.5451**
	(0.3906)	(0.2587)
	-0.3281	0.4473
	(0.3478)	(0.4576)
	10.8000***	2.9453
	(2.8143)	(3.1910)
	6.5605	-2.5014
	(5.8253)	(5.4757)

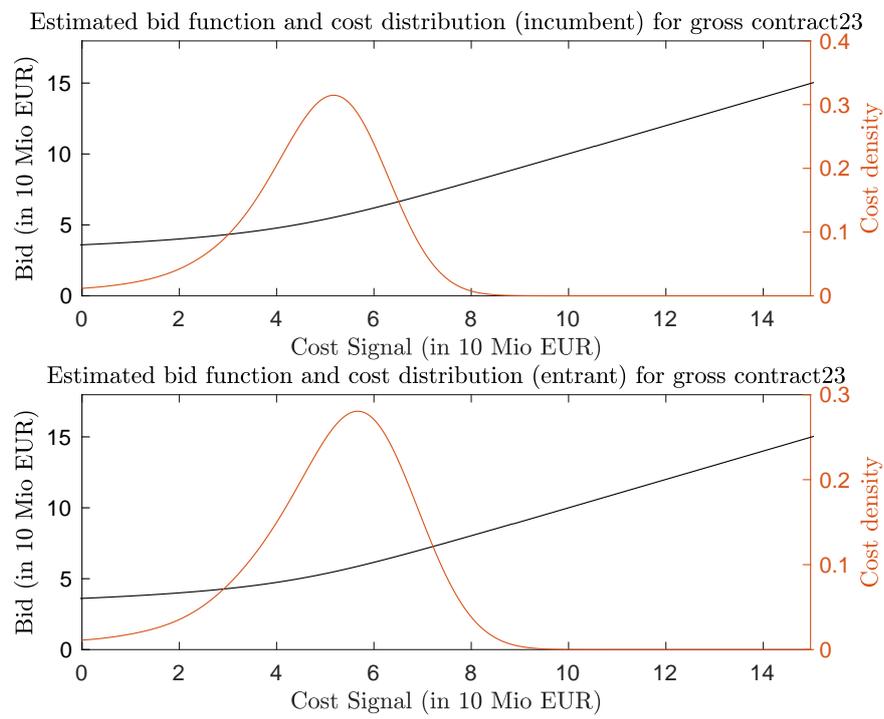
Notes: MLE-SE in parentheses. \*, \*\*, \*\*\* denote significance at the 10%, 5% and 1%-level respectively.

Figure 5: Cost density and bid function for gross auction 5



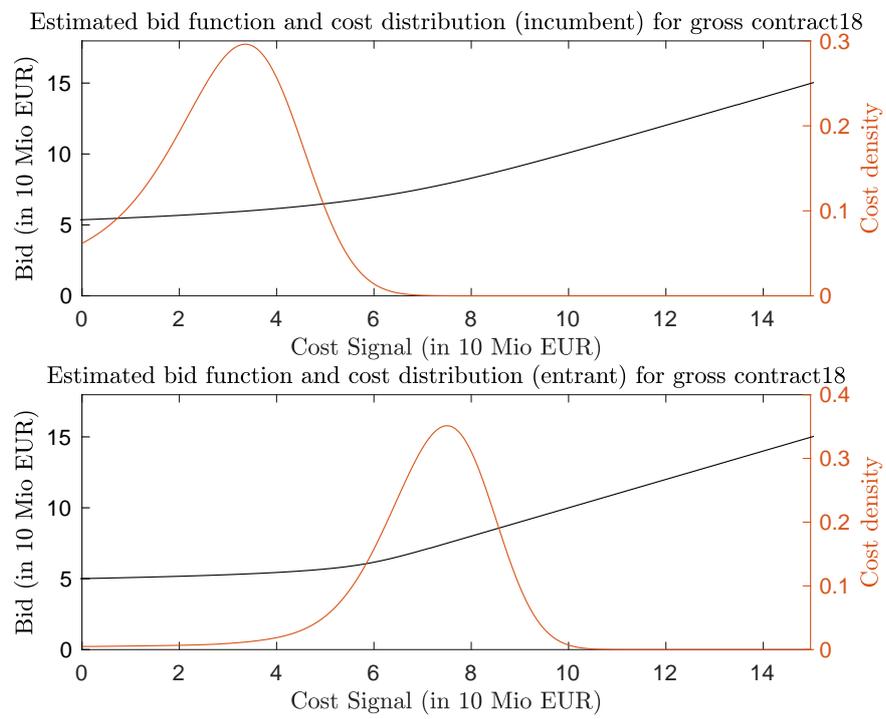
*Notes:* This graph compares the estimated bid functions and cost distributions for the incumbent (top panel) and entrants (bottom panel) for a specific gross auction in our sample.

Figure 6: Cost density and bid function for gross auction 23



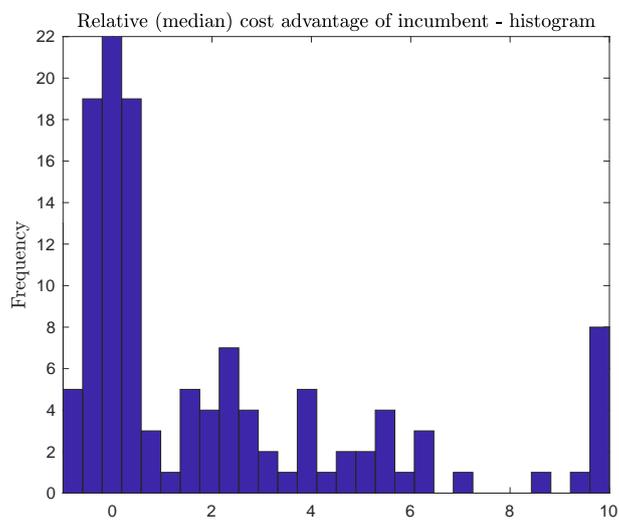
*Notes:* This graph compares the estimated bid functions and cost distributions for the incumbent (top panel) and entrants (bottom panel) for a specific gross auction in our sample.

Figure 7: Cost density and bid function for gross auction 18



*Notes:* This graph compares the estimated bid functions and cost distributions for the incumbent (top panel) and entrants (bottom panel) for a specific gross auction in our sample.

Figure 8: Comparison of median and mean costs across bidder types

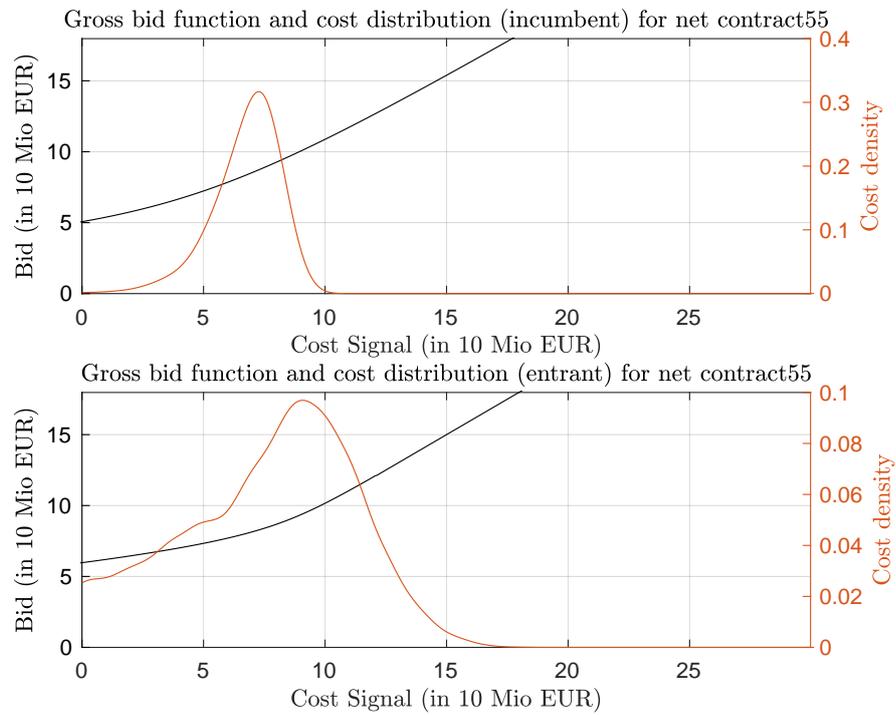


*Notes:* This graph summarizes the distribution of the incumbent's cost advantage measured by the median cost across all auctions in our sample. 0 indicates that both bidder types have the same median cost for a contract. Positive (negative) values denote a cost advantage of the incumbent (entrant).

### C.2.2. Net Auction Sample

In this appendix, we provide several representative graphs of the bid functions for the incumbent and the entrants if net auctions were procured as gross auctions.<sup>35</sup> Figures 9 and 10 are roughly in line with the actual gross auction graphs from the previous subsection.

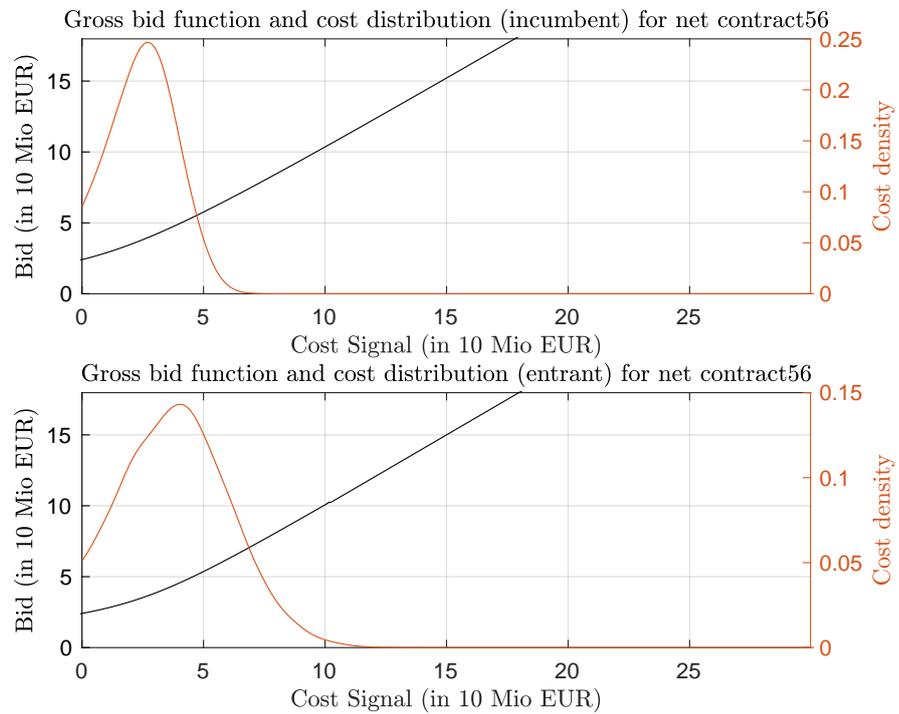
Figure 9: Hypothetical gross bid function for net auction 55



*Notes:* This graph compares the estimated cost distributions and the hypothetical bid functions, if the net auction was procured as a gross auction, for the incumbent (top panel) and entrants (bottom panel) for a specific net auction in our sample.

<sup>35</sup>We do not plot the bid functions for the actual net auctions because it is not possible to decompose the net bid function, that maps from the compound signal  $\rho$  to the bid, into the effect of the cost and the revenue signal in a meaningful way; therefore, it is hard to provide an informative graph that is comparable to the gross auction case.

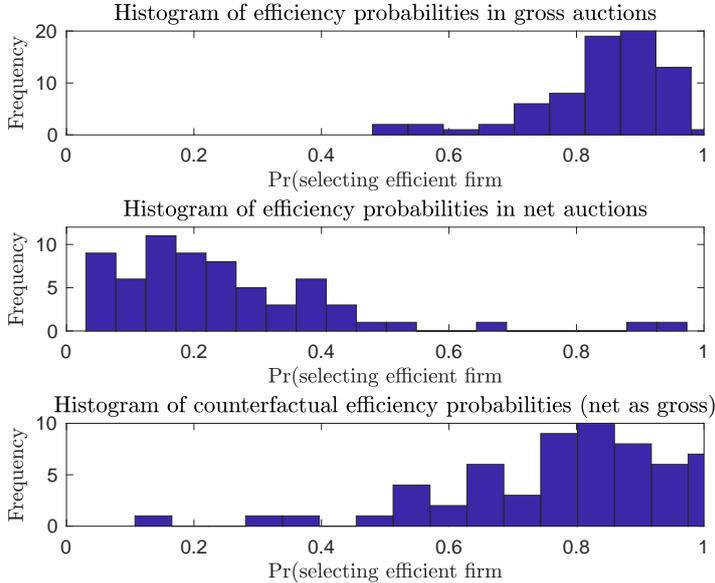
Figure 10: Hypothetical gross bid function for net auction 56



*Notes:* This graph compares the estimated cost distributions and the hypothetical bid functions, if the net auction was procured as a gross auction, for the incumbent (top panel) and entrants (bottom panel) for a specific net auction in our sample.

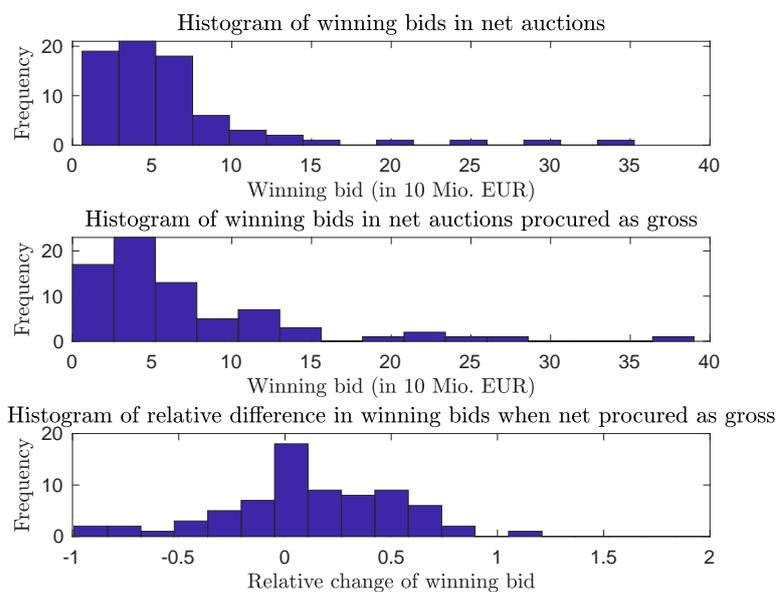
### D. Additional Counterfactual Results

Figure 11: Distribution of efficiency probabilities across different auction formats



*Notes:* This graph compares the distribution of the probabilities of selecting the efficient firm for our gross auction sample (upper panel), our net auction sample (middle panel) and the counterfactual distribution of efficiency probabilities, if our net sample was procured as gross contracts (bottom panel).

Figure 12: Distribution of winning bids for different auction formats



*Notes:* 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.