Bidder Asymmetries in Procurement Auctions: Efficiency vs. Information*

Evidence from Railway Passenger Services

Christoph Carnehl[†]
Stefan Weiergraeber[‡]

December 2, 2022

Abstract

We estimate a structural model of procurement auctions with private and common value components and asymmetric bidders using detailed contract-level data on the German market for railway passenger services. Exploiting exogenous variation in the procurement design, we disentangle the asymmetries in private costs from asymmetries in information about the common value. While each asymmetry can rationalize a firm's dominance, understanding its source is crucial for evaluating the auction design as welfare and revenue implications depend on the source of dominance. Our results indicate that the incumbent is slightly more cost-efficient and has substantially more precise information about the common value component. If the bidders' strategic response to the common value asymmetry were eliminated, the average probability of selecting the efficient firm would increase by 43%-points.

JEL Classification: H57, L92, D44

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

*We thank two anonymous referees, Yonghong An, John Asker, Michael Baye, Estelle Cantillon, Francesco Decarolis, Matthew Gentry, Elisabetta Iossa, Marc Ivaldi, Gautam Gowrisankaran, Yao Luo, Georgia Kosmopoulou, Andras Niedermayer, Volker Nocke, Martin Pesendorfer, Robert Porter, Bernard Salanié, Armin Schmutzler, Johannes Schneider, Katja Seim, Michelle Sovinsky, André Stenzel, Konrad Stahl, Hidenori Takahashi, Frank Wolak, Ruli Xiao, and Christine Zulehner as well as participants at IIOC 2017, CEPR Applied IO School 2017, EARIE 2018, SITE 2018, ASSA 2019, and Berlin IO Day 2019 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.

[†]Bocconi University, Department of Economics and IGIER; E-mail: `christoph.carnehl[at]unibocconi[dot]it`.
[‡]Department of Economics, Indiana University; E-mail: `sweiergr[at]iu[dot]edu`.

1. Introduction

A substantial part of economic activity is conducted via procurement mechanisms.[1] In many countries and organizations, the procurement of goods and services above a certain threshold value must be awarded competitively. While the advantages of competitive procedures motivate many procurement regulations, concerns have been raised about their effectiveness in several industries. One of the most frequent problems is the existence of incumbency advantages that prevent entrants from submitting competitive bids.[2] Understanding the sources of incumbency advantages and designing procurement mechanisms well is essential not only because of the size of these markets but also because buyers often have much flexibility in the procurement design. If used correctly, this flexibility can help to improve procurement outcomes.[3] Even though incumbency advantages are widely acknowledged, the empirical literature analyzing its sources is scarce.

In this paper, we combine exogenous variation in the procurement design with a structural auction model to empirically study the sources of the dominance of the former state monopolist Deutsche Bahn (*DB Regio*[4]) in the German market for short-haul railway passenger services (SRPS). More than 20 years after the market's liberalization, DB Regio still operates the majority of the traffic volume (67.1% in 2016, Monopolkommission (2019)). The German market for SRPS, with its size of around EUR 8 billion in subsidies for 2016, is an important example of incumbency dominance that shares many features with similar markets in other countries. For example, in the 1990s, many European countries liberalized their telecommunications, retail electricity, and transportation services sectors. In all these markets, asymmetries between firms are prevalent because entrants that became active in the market relatively recently compete with established, often state-owned, incumbents. While the aim of the liberalization was a more efficient provision of publicly subsidized goods through increased competition, the experiences have been mixed.

For the German SRPS market Lalive and Schmutzler (2008) provide evidence using reduced-form regressions that DB has a significantly higher probability of winning auctions than its competitors.

[1]For example, public procurement alone amounts to 13% of GDP in OECD countries (Committee 2016).

[2]A recent overview of the topic is provided in OECD (2019). Iossa (2019) discusses the important role of incumbency advantages in particular. European Commission (2016) provides a discussion of incumbency advantages in the transportation sector, which is the focus of our paper.

[3]For example, Coviello et al. (2018) provide a discussion of the value of flexibility in procurement and show evidence for potential benefits of additional discretion to procurement agencies.

[4]For brevity, we refer to DB Regio, the short-haul distance passenger service subsidiary of Deutsche Bahn, as DB in the remainder of this paper.

Industry experts regularly bring up two potential explanations for the incumbent's dominance: a more efficient cost structure of DB, i.e., a private value advantage, and better information about future ticket revenues, i.e., an informational advantage about a common value.

We show theoretically—in an extension of the model of Goeree and Offerman (2003) to asymmetric firms—that both channels can rationalize a dominant firm. Therefore, to assess the efficiency of the market, disentangling the asymmetries in private and common value components is essential. Most importantly, an informational advantage of a firm creates an amplified winner's curse for the less informed bidders, which induces them to bid overly cautiously. This can potentially have detrimental effects on both auction revenues and the selection of the cost-efficient bidder. To the best of our knowledge, we are the first to empirically disentangle these asymmetries, which allows us to determine the reason underlying the apparent incumbency advantage.

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. In addition, ticket revenues from operating a train line constitute a common value component and DB might have an informational advantage regarding future demand. The reason is that *DB Vertrieb*, the sales and marketing division of the DB holding that owns DB Regio, manages ticket sales even on lines it is not operating itself. Therefore, it has access to comprehensive ticket revenue and passenger data. Entrants—and even procurement agencies—typically do not have access to this information.

Competition authorities have raised concerns about DB's exclusive data access for many years; see, Monopolkommission (2009).[5] Recently, this debate has been reinvigorated by a comprehensive discussion of DB's data monopoly in Monopolkommission (2019).[6] 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.

For our estimation, we use a detailed contract-level data set on German SRPS procurement auctions, covering the period from 1995 to 2011. A key feature of our data is that we observe plausibly

[5] The *Monopolkommission* is an independent advisory council to the federal government of Germany focusing on competition policy.

[6] The fact that the competition authority and the competitors regularly argue about and demand the data to be 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.

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.

We use the gross auctions in a first step to recover the cost distributions of the firms using standard methods following Athey and Haile (2002). The exogeneity of the contract mode implies that lines auctioned with gross contracts are not systematically different from lines auctioned with net contracts; hence, we can extrapolate the cost distribution from gross to net auctions. This allows us to recover the distribution of asymmetric information in net auctions. Intuitively, conditional on the estimated cost distributions, any systematic differences in bidding behavior between DB and the other firms have to derive from differences in the information about common values. Assuming that the choice between net and gross contracts is exogenous may seem restrictive at first sight. Therefore, we provide extensive evidence based on industry reports, statistical tests, and reduced-form regressions in support of this key assumption in Section 2.2.

The results of our structural analysis reveal 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 sense in only 23% of the auctions.[7] 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 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 4.3 times higher than that of the incumbent.

In summary, our results support the concerns of the German competition policy advisory council in Monopolkommission (2009; 2019) that DB's dominance is at least partially due to its informational advantage. This may call for regulatory interventions. For example, a relatively easy measure to increase efficiency could be to award more gross contracts, eliminating the auction's common value

[7] Note that if DB's distribution is dominated in a procurement auction, it has the stronger distribution.

component. We study this intervention in a counterfactual analysis. We find that if the net auctions in our sample were procured as gross auctions, the average ex-ante efficiency, i.e., the probability of selecting the cost-efficient bidder, increases drastically from 17% to 90%. While both the additional noise introduced by the revenue signal and asymmetries in the cost distributions already lead to considerable efficiency losses in net auctions, the most important source of inefficiency is the asymmetric precision of information about the common value component. Finally, our counterfactuals reveal that gross auctions tend to result in higher agency revenues as well.

Auction settings with private and common value asymmetries are pervasive. In principle, our model and estimation strategy can also be applied to other settings. The only requirement is that the data feature some variation in auction modes allowing 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. Other potential applications 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.[8] 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 plausibly symmetrically distributed (Hendricks and Porter 1988).

Related literature. Our work belongs to the literature on 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, which we extend to accommodate bidder asymmetries.

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. De Silva et al. (2009) study a natural experiment in which an information release policy makes uncertainty more symmetric. Both papers consider a setting with private and common values as in Goeree and Offerman (2003).

[8] Often, mineral rights auctions are modeled as pure common value auctions. However, there may be private value considerations as well, for example, due to differences in extraction technologies, see Sant'Anna (2018) for a discussion.

However, their empirical strategy follows a reduced-form approach that does not allow them to distinguish the two asymmetries nor to disentangle which asymmetry induces the observed bidding pattern. In contrast, we explicitly model private and common value asymmetries and quantify each of the asymmetries with a structural empirical model.

For the estimation of our model, we rely on the extensive literature on the structural estimation of auctions; see Athey and Haile (2007) for an overview. Guerre et al. (2000) show how first-price IPV auctions can be nonparametrically identified and estimated based on winning bids only. However, identifying structural parameters in common value auctions is more complicated. Several papers have suggested different modeling assumptions and data requirements to obtain identification. Li et al. (2000) discuss identification and nonparametric estimation of conditionally independent private information auctions. Their arguments rely on a parametric restriction of the value conditional on winning. Février (2008) shows identification based on a parametric restriction of the private signal distribution. He (2015) obtains identification of a symmetric pure common value setting assuming, analogous to our common value model, that the common value is equal to the sum of common value signals. Somaini (2020) shows how common values can be identified in a structural model using 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. Several papers following Hendricks and Porter (1988) have looked at auctions featuring asymmetries in the information about a common value. 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. Hendricks et al. (1994) extend the framework in Engelbrecht-Wiggans et al. (1983) to allow for reservation prices of an informed seller and test the model's predictions on equilibrium bid distributions. In particular, they focus on a pure common value setting with informed bidders and uninformed bidders who do not observe a private signal.

Hong and Shum (2002) estimate a model with both private and common value components and symmetric bidders using procurement data from New Jersey. Their focus is on estimating the relative importance of private and common values for specific types of auctions. In contrast, we have precise information about which parts of the contracts correspond to private and which to common value components. This additional information allows us to focus on quantifying each asymmetry.

Similar to our approach, Athey et al. (2011) compare different auction formats for timber auctions. They estimate a structural model to study entry and bidding behavior when firms are asymmetric in their private value distribution.

Our approach also shares some features with the growing literature on procurement auctions with multi-dimensional signals, see, for example, Luo and Takahashi (2019), who compare different auction formats for highway procurement in Florida and find that carefully considering which party bears the risk of cost overruns can significantly increase the efficiency of the market.

Finally, Hunold and Wolf (2013) study the German market for SRPS using a similar data set. In reduced-form regressions, they find that DB is more likely to win longer and bigger contracts. Moreover, DB has an advantage in net auctions indicating an informational advantage of DB. Lalive et al. (2021) 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.

2. Industry Description and Data

In this section, we provide background information on the SRPS industry in Germany and describe the patterns in our data that motivate our structural model.

2.1. Industry Background

Like many other countries, Germany liberalized its railway sector in the 1990s. One of the main objectives of liberalization was to induce competition in the market. SRPS are part of the government's universal service obligation and are generally not profitable for operators. Therefore, local procurement agencies are assigned the task of choosing an operator that provides this service on behalf of the federal government. As these services require high subsidies (around EUR 6.6 billion per year during our sample period, Monopolkommission (2019)), the procurement agencies aim at competition *for* the market to keep the required subsidies at a reasonably low level.[9]

To date, the Federal Republic of Germany owns the former state monopolist *Deutsche Bahn AG* (DB), which competes with entrants. While the market share of competitors has risen over time, DB still had a market share of 67.1% measured in train-kilometers[10] in 2016 (see Monopolkommission (2019)).

Industry experts agree that DB and entrants differ both in their cost structure and their information about demand conditions. DB's cost of operating a train line is likely different from an entrant's 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, which 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. Therefore, we expect DB to have a cost advantage. Most entrants are large firms 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, we judge it reasonable that systematic cost differences among entrants are negligible.

Systematic differences between DB and its competitors regarding their information about ticket revenues stem from DB Regio (the branch of DB that operates in the SRPS sector) being vertically integrated with DB Vertrieb. Even when DB is not operating the route itself, all tickets are sold through DB Vertrieb. Therefore, it is conceivable that DB possesses an informational advantage about demand conditions, while its competitors cannot access this information (see Monopolkommission (2009; 2019)). Instead, entrants have to rely on their own market research, which is usually less reliable than DB's information. 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 (2019)) and that this can generate a competitive advantage for DB. While technically it would be straightforward to release DB's revenue data, the legal system in Germany sets a high standard to declare data as an *essential facility*, which DB would have to make public. So far, lawyers seem to opine that DB's data does not necessarily fall into this lim-

[9] The subsidies for train operating companies that win auctions account only for a part of the total subsidy budget. Other uses of this budget include subsidies that were awarded non-competitively via direct negotiations with a firm –during our sample, roughly 60% of the procured train kilometers were awarded non-competitively (Hunold and Wolf (2013))–, infrastructure investments, as well as subsidies for local bus services.

[10] The variable *train-km* denotes the number of kilometers one train would have to run 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 line, and the required frequency of service.

ited category (Monopolkommission 2019, p.121). This has sparked a debate about the underlying reasons for DB's dominance, mainly whether there are features in the procurement process that reinforce DB's dominance or whether DB is the efficient firm in the market. Our empirical analysis contributes to this policy debate.

When procuring SRPS, the procurement agencies have a high degree of freedom in designing the contract and the awarding rules. The agencies specify almost all contract components, for example, how frequently a company has to run services on a particular line, the duration of the contract, and the type of vehicles to be used. Moreover, ticket prices are regulated and beyond the control of the train operating company. Therefore, the degree to which train operating companies can affect ticket revenues is limited. While some marginal incentives to improve services may remain, we do not believe that these are substantial relative to the overall cost and the baseline revenues generated independently of marginal improvements of the service. This suggests that the ticket revenues are mainly determined by factors exogenous to the train operating company.

An important additional feature, which is crucial to our empirical approach, 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*.

2.2. Data Description and Reduced-Form Evidence

Our data set consists of almost all procurement contracts from the German market for SRPS from 1995 to 2011, which we obtained from the procurement agencies and a consulting firm. 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. We focus on auctions and discard all contracts awarded non-competitively, i.e., via direct negotiations with only one firm.[11] Moreover, we collected data on the characteristics of each line, including data on track access charges and the frequency of service from additional publicly available sources.[12] To the best of our knowledge, this data set is the most comprehensive one on the German market for SRPS

[11] In addition, we dropped four contracts that are labeled as auctions but recorded only one bidder because our auction model cannot be applied to one-bidder settings.

[12] The *track access charge* is the (regulated) fee that is charged to the train operating company for running a vehicle on a specific railway track.

available and contains information on 81 and 75 gross and net auctions, respectively. Table 1 displays descriptive statistics for our sample split up by gross and net auctions.

Table 1: Descriptive statistics by auction mode

	Gross (N=81)				**Net** (N=75)				**p-value**
	Mean	SD	Min	Max	Mean	SD	Min	Max	
Winning bid (10 Mio. EUR)	6.91	5.07	0.68	26.59	6.61	6.27	0.35	29.99	0.75
No. bidders	4.85	1.99	2.00	11.00	3.45	1.61	2.00	8.00	0.00
Access charges (EUR)	3.39	0.44	2.29	4.64	3.32	0.82	1.23	6.10	0.51
Volume (Mio. train-km)	0.76	0.51	0.13	2.53	0.86	0.74	0.09	4.17	0.34
Train frequency (per day)	33.11	15.84	14.59	112.57	31.07	10.76	14.49	67.26	0.35
Size of network (km)	67.00	39.39	8.85	167.97	79.83	64.55	10.44	317.17	0.14
Duration (Years)	10.22	2.63	2.00	16.00	10.43	4.07	2.00	22.00	0.71
Used vehicles (Dummy)	0.58	0.50	0.00	1.00	0.59	0.50	0.00	1.00	0.94

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,* Train frequency *indicates how often a train has to serve the track per day,* Size of network *describes the size of the physical track network to be covered (in km),* 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. The last column displays the p-values associated with testing the equality of the means of the most important track characteristics across different auction modes (gross vs. net).*

In the following, we provide descriptive and reduced-form evidence about the patterns in our data to motivate the structural model that we develop in Section 3. Table 6 in Appendix B summarizes the results from several reduced-form regressions. Overall, the regressions confirm the descriptive patterns in Table 1. Winning bids tend to be slightly lower in net auctions, which is not surprising because bidders factor in the additional revenues from ticket sales in a net contract, see Column (1) in Table 6. Moreover, the larger the contract (in terms of duration or volume), the larger the winning bid. Gross auctions generally attract significantly more bidders than net auctions (on average 4.9 and 3.5, respectively; see Table 1 and Column (2) of Table 6). 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.

Column (3) in Table 6 presents the results of a reduced-form logit regression of a dummy indicating whether the incumbent won the auction on various contract characteristics. While most structural characteristics, such as contract size or track access charges, do not affect the probability of the incumbent winning, procuring a line 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. An important point is that the net auction coefficient in Column (3) captures two effects: a potential winner's curse effect from the asymmetric information about a common value in the bidding stage and the fact that net auctions typically attract fewer bidders in the entry stage. When we control for the number of bidders explicitly, see Column (4) of Table 6, the net auction coefficient becomes smaller and, due to our relatively small sample size and a relatively high standard error, insignificant. To better disentangle the entry from the bidding channel, we develop a structural model that features both a bidding stage and an entry stage in which the number of participating bidders is endogenously determined.

One might be concerned that differences in the observed bidding patterns are driven by differences in the type of bidders participating in the respective auction modes. For example, net auctions may attract larger and less risk-averse firms. To mitigate this concern, we provide evidence that the set of entrant firms is similar across auction modes. Table 7 in Appendix B provides several statistics of the winning entrant firms across gross and net auctions. Throughout, we do not find a significant difference in the set of winning entrants across the two auction formats.

A key assumption for our empirical strategy is that the procurement agency's choice between net and gross contracts is exogenous to a line's cost distribution. In general, one might be worried that procurement agencies endogenously choose the auction mode. We argue that endogeneity concerns regarding the contract mode are 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 uncorrelated with the structural cost and revenue characteristics of the contract (see, in particular, the extensive discussion in Bahn-Report (2007)). Most agencies have a preferred auction mode and procure routes almost exclusively under this regime. In Bahn-Report (2007) it is argued that even on lines for which it is apparent that the revenue risk is high, agencies with a preference for net contracts do not switch to gross auctions.[13]

Second, we do not find a significant difference in the contract characteristics between the gross and the net sample. The last column in Table 1 displays the p-values from t-tests for the equality

[13] We provide additional references on this topic in Appendix B.

of the means of the most important contract characteristics (rows 3 to 8). None of the differences in means is statistically significant, which further supports our exogeneity assumption.

To support our assumption of an exogenous procurement mode even further, we regress a dummy for net auctions on our standard set of contract characteristics. None of the included regressors is statistically significant (see last column of Table 6 in Appendix B).

3. Auction Model and the Effects of Asymmetries

In this section, we present our structural procurement auction model to analyze the differential effects of cost and informational asymmetries on bidding behavior. All auctions are first-price sealed-bid auctions. The value of winning an auction depends 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, a private value. For a *net contract* the valuation consists of the firm-specific cost of the contract c_i, a private value, and the ticket revenues R, a common value.

Throughout, we index firms by i, i's bid by b_i, and we denote the number of bidders by N. We assume that N is common knowledge among the firms.[14] We allow the number of bidders to be endogenous by incorporating an entry model based on Levin and Smith (1994). We discuss the entry model and its estimation in Appendix G. We distinguish between two types of bidders: DB (incumbent) and $N-1$ entrants.[15] In both gross and net auctions, firms privately draw a cost realization, c_i, from distribution F_{c_i} which has a strictly positive density f_{c_i} on its support $[c_L, c_H]$. For the reasons discussed in Section 2.2, we allow the cost distribution to differ between DB and the entrants, i.e., we assume that DB draws its cost from a distribution F_{c_I} and that entrants draw it from a, potentially different, distribution F_{c_E}. In net auctions, firms additionally draw a common value signal from a common distribution F_r. For technical reasons discussed below, we assume that F_{c_I}, F_{c_E}, and F_r are logconcave.[16] All signals are drawn independently across firms and cost signals

[14] We believe that for our application, the assumption of a known number of competitors is reasonable. For example, before the auction, there tend to be media reports about train operating companies signaling their interest in particular networks.

[15] We use DB and incumbent synonymously because it is the historic incumbent and we rarely observe the same line procured twice.

[16] Many commonly used distributions satisfy logconcavity, for example, the normal distribution, the exponential distribution, the extreme value distribution, and the beta-distribution. In addition, we empirically find that the vast majority of our estimated cost distributions are logconcave.

are independent of revenue signals. Both our theoretical model and our empirical methodology rely crucially on the independence of all signals. We discuss the implications of the independence assumption for the interpretation of our results in Section 5. Moreover, we assume that bidders are risk neutral.[17]

In our setting, gross auctions are standard first-price asymmetric IPV procurement auctions and we build on the theoretical work on asymmetric IPV auctions, in particular, Maskin and Riley (2000a). Each firm submits a bid b_i, which is the subsidy that bidder i requests for fulfilling the contract. Firm i chooses its bid b_i to maximize its expected payoff[18]

$$E[\pi_i(b_i, c_i)] = (b_i - c_i) \cdot \Pr(b_i \leq \min_{i \neq j} b_j). \tag{1}$$

From Maskin and Riley (2000b) we know that an equilibrium in pure and monotonic strategies with almost everywhere differentiable bid functions exists in this setup. The equilibrium is implicitly defined by the first-order conditions, which constitute a system of differential equations. Denote by $G^{gr}_{i,M_i}(m_i|N)$ the distribution of the opponents' minimum bid m_i given a set of bidders N, i.e., $1 - G^{gr}_{i,M_i}(m_i|N) \equiv \Pr(\min_{j \neq i} B_j \geq m_i|N)$, and by $g^{gr}_{i,M_i}(m_i|N)$ the corresponding density in a gross auction. Then, equilibrium bid functions satisfy

$$b_i = c_i + \frac{1 - G^{gr}_{i,M_i}(b_i|N)}{g^{gr}_{i,M_i}(b_i|N)}. \tag{2}$$

We borrow the definition of conditional stochastic dominance[19] and the following result from Maskin and Riley (2000a) 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 bidder j, then i is the weak bidder and bids more aggressively than bidder j; i.e, the bid distribution of i*

[17]We believe that risk-neutrality is plausible in our setting as almost all active firms in the industry are large and often internationally operating companies (see Section 2).

[18]Since all cost signals are independent, so are the bids. Hence, the probability that bidder i wins the auction does not condition on bidder i's signal realization.

[19]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 $x \in [c_L, \gamma]$. Note that conditional stochastic dominance is slightly stronger than FOSD so that if a distribution conditionally stochastically dominates another it also first-order stochastically dominates it but not vice versa.

first-order stochastically dominates the bid distribution of j.

Lemma 1 shows that a bidder with a stronger cost distribution has a stronger bid distribution and therefore wins the majority of auctions. Hence, observing a dominant bidder in an IPV auction indicates a bidder with a stronger private value distribution. However, the weaker bidder bids more aggressively, resulting in a potential inefficiency when the weaker bidder outbids the stronger bidder despite a higher cost realization.

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 that, as we argue below, fits our application well. A firm's payoff conditional on winning an auction consists of the subsidy (the winning bid b_i), the private cost (c_i drawn from F_{c_i}), and the common value R. In addition to the private cost component, firms draw a private signal, r_i, about the common value from a distribution F_r. We assume that the common value equals the weighted average of the firms' revenue signals, i.e., $R = \sum_{i=1}^{N} \alpha_i r_i$, where $\alpha_I \in (0,1)$ for DB and $\alpha_E = (1-\alpha_I)/N \in (0,1)$ for the entrants.[20] Together with the assumption of F_{c_i} and F_r being log-concave, this formulation allows us to map the two-dimensional private information of bidders, (c_i, r_i), into a one-dimensional strategic variable $\rho_i := c_i - \alpha_i r_i$. Goeree and Offerman (2003) show that such an additive structure of the common value allows for this reduction in a symmetric setting with $\alpha_i = 1/N$ and this result extends to our asymmetric setting.[21] With this simplification, we can apply standard auction theory methods following Milgrom and Weber (1982). In our application, the scalar statistic ρ_i can be interpreted as a *net cost signal*.

The expected value of bidding b_i for firm i is

$$\mathbb{E}[\pi_i(b_i,c_i)|b_i,c_i,r_i] = \left(b_i - c_i + \alpha_i r_i + \sum_{j\neq i} \alpha_j \mathbb{E}\left[r_j|\rho_j \geq \phi_j(b_i)\right]\right) \Pr(b_i \leq min_{i\neq j} b_j), \tag{3}$$

where $\phi_j(b_i)$ is bidder j's inverse bid function evaluated at the bid b_i.

The parameter α_i captures the differential precision of the bidders' information about the common value. While every firm draws its signal r_i from the same distribution, the asymmetry between

[20] The particular formulation of α_E is chosen to ensure that the weights add up to one.

[21] Their results hold in our asymmetric framework because the statistic ρ_i has a log-concave density following from c_i and r_i having a log-concave density which allows us to directly apply Lemma 1 in Goeree and Offerman (2003), which does not rely on the symmetric structure assumed in their paper.

incumbent and entrants is captured by their weights α_i in the common value R. Intuitively, a higher α_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 of the revenue given bidder i's information at the time of bidding is

$$var[R|r_i = r] = \sum_{j\neq i} \alpha_j^2 \sigma_r^2, \tag{4}$$

and hence $var[R|r_E = r] > var[R|r_I = r]$ if $\alpha_I > \alpha_E$.[22]

In this framework, equilibrium bids are monotonic in the net cost signal ρ_i and characterized by a system of differential equations as shown in the following Lemma (see Appendix A.1 for the proof).

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*

$$b_i = c_i - \alpha_i r_i - \mathbb{E}[\sum_{j\neq i} \alpha_j r_j | \min_{j\neq i} \phi_j^{-1}(\rho_j) = b_i] + \frac{1 - G_{i,M_i}^{net}(b_i|N)}{g_{i,M_i}^{net}(b_i|N)}, \tag{5}$$

where $G_{i,M_i}^{net}(b_i|N) = \Pr(b_i \leq \min_{j\neq i} B_j | B_i = b_i, N)$ *and* g_{i,M_i}^{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. Bidders bid their expected valuation of winning the auction plus a bid shading term. In a net auction the expected value of winning also depends on the losing bidders' expected revenue signals so that bidders face a winner's curse motive.

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

[22] This model is equivalent to a model in which all firms have the same $\alpha = \frac{1}{N}$ but draw their signals r from asymmetric revenue signal distributions F_{r_i}, but with a parametric restriction on how the distributions of the incumbent and the entrants are related.

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 α_I and the remaining $N-1$ bidders having precision parameter α_E. Moreover, assume that all bidders have the same cost c. Denote by $H_i(b)$ the equilibrium bid distribution of bidder group i. If $\alpha_I > \alpha_E$, then $H_I(b) \geq H_E(b)$, i.e., the bid distribution of bidder I is first-order stochastically dominated by the bid distributions of bidders with α_E, with strict inequality for all interior bids b when $N > 2$.*

Lemma 3 shows that less precisely informed bidders are affected more severely by the winner's curse and will shade their equilibrium bids more than the more precisely informed bidder. Consequently, if all bidders have the same cost, the better-informed bidder will have the stronger bid distribution and will win the majority of the auctions.

While our asymmetric version of the model in Goeree and Offerman (2003) is not the standard common value model, we believe that it is the best framework for our purposes for several reasons. The revenue and cost components relate to different sides of the market, future demand and costs, and it seems plausible that firms receive two distinct, independent signals about them. In general, such a setting leads to the difficult problem of mapping two-dimensional private information into a one-dimensional strategic variable, the bid. To the best of our knowledge, the framework by Goeree and Offerman (2003) is the only one that allows for a suitable signal dimensionality reduction in our setting. The additive structure of the common value can also be economically interpreted in our application: Each contract refers to providing a service on a specific line, for example, from city A to city C via city B. The revenue generated by providing this service is the sum of the revenues generated by running the service between cities A and B and between cities B and C. Bidders in the German SRPS market typically obtain information about revenues by conducting surveys. If each bidder conducts a reliable survey on a particular subroute of the procured line, their individual revenue information aggregates to the ticket revenues on the entire line.

The common value component in net auctions introduces the potential for inefficiencies beyond those in gross auctions.[23] Bidding now depends also on the common value signals and strategic

[23]The result in Lemma 1 has been generalized by De Silva et al. (2003) to the private and common value setup of Goeree and Offerman (2003). Hence, it holds for net auctions if firms have equally precise information about the common value component.

considerations, which are unrelated to the efficiency-determining cost realizations.

Both the private and the common value asymmetry in isolation can explain the dominant position of DB in the market for SRPS in Germany according to Lemma 1 and Lemma 3. However, the final assessment of the market structure depends on the relative importance of the two asymmetries. If DB is dominant because of a better cost distribution, DB may even win too few auctions from an efficiency perspective. If it is dominant due to more precise information, DB likely wins many auctions without being the cost-efficient firm.[24] When both asymmetries are present, they can potentially offset each other. Suppose DB is both more efficient and more precisely informed, as many industry experts suggest. In that case, the entrant's aggressiveness due to the weaker private-value distribution can be partially offset (or even overturned) by the bid shading due to the winner's curse. Therefore, the overall effect on the efficiency of the auction is an important empirical question.

4. Empirical Strategy

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

4.1. Identification

The cost distributions in our gross auction sample, which we model as an asymmetric IPV model, are nonparametrically identified from the winning bid, the number of bidders by bidder type, and the identity of the winner (see, for example, Athey and Haile (2002)). Identification of our net auction model is more complicated. In this section, we provide an intuitive argument why the asymmetry parameters α and the revenue signal distribution F_r are identified from our data. We discuss the challenges associated with a formal identification proof in Appendix C.

Our intuitive identification argument for the net auction model consists of four steps. First, recall that we observe the number of bidders, the winning bids, and the winners' identities in the data. The structure of our model based on Goeree and Offerman (2003), which implies the independence of the bidders' signals and consequently their bids, allows us to estimate the full bid distribution

[24] 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.

from these data.[25] Therefore, we can build on the equilibrium first-order conditions from Lemma 2 and recover the distribution of the expected value of winning the auction with bid b for bidder i

$$\mathcal{P}_i = c_i - \alpha_i r_i - \mathbb{E}\left[\sum_{j \neq i} \alpha_j r_j | \min_{j \neq i} b_j = b; F_r, \alpha\right]$$

similarly as in an IPV auction.

Second, the cost (private value) distributions are formally identified from the gross auctions and –because of our exogeneity assumption on the auction mode– can be extrapolated to the net auction sample. Hence, we can condition all identification arguments on the cost distributions and treat them as known.

Third, many of the standard identification issues associated with the more standard common value model setups, such as the often used mineral rights model, do not occur in our setup. One important difficulty in identifying a standard common value setting (where the common value is drawn from a given distribution and bidders' signals are conditionally independent draws from a signal distribution conditional on the realized common value) is that there are $N + 1$ unknowns to be identified in an N-bidder auctions –the joint signal distribution of N bidders and the distribution of the common value itself. Thus, even when all N bids are observed, a standard common value auction is underidentified. Several ways of dealing with this issue have been proposed in the literature (see, for example, Li et al. (2000); Février (2008)). Our modeling framework based on Goeree and Offerman (2003) takes an alternative approach to the problem: We assume that the common value is equal to the (weighted) sum of the revenue signals. Hence, the revenue signal distribution directly determines the distribution of the common value, which reduces the dimensionality of the problem by not requiring the common value distribution to be identified separately. He (2015) makes use of this feature and, in a symmetric and pure common value version of the additive formulation of the common value, provides a non-parametric identification proof based on a quantile function approach.

It is hard to show formally that the proof of He (2015) extends to our setting with private and common values. With the additional private value signal the integral equation associated with our

[25] Recall that the key assumptions of Goeree and Offerman (2003) are that the common value equals the (weighted) sum of the revenue signals and 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.

first-order condition in net auctions becomes much more complicated. We are unable to prove that for a general cost distribution the integral equation always has a unique solution (see our discussion in Appendix C).

In our fourth step, we, therefore, argue intuitively that the variation in our data allows us to separately identify the asymmetry parameter α_I, which fully captures the informational asymmetry across bidder types,[26] and the revenue signal distribution F_r –which is symmetric and common to all bidders.[27] Specifically, we exploit that we can compare the bid distributions in net auctions across bidder groups, i.e., the separate bid distributions for the incumbent and entrants. Variation in winning bids *within* the same bidder group, controlling for the cost distributions, can be attributed to changes in the revenue signals and, hence, the revenue signal distribution, which is *common* for all bidder groups. Differences in the bid distributions *across* bidder groups, controlling again for the differences in the cost distributions, can then only be attributed to differences in the informativeness of the revenue signals, α_I. Put differently, the spread between the (winning) bid distributions for the two bidder groups will identify the asymmetry parameter α_I and the overall level of the two conditional and the unconditional bid distributions in net auctions will identify the common revenue signal distribution F_r.

4.2. Estimation Strategy

In the following, we describe our estimation algorithm and the model specification that we take to the data. 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 contract 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 using a convolution approach.

Since the total number of procured lines is still relatively small, a fully nonparametric estimation is not feasible in our application; therefore, we employ a parametric approach similar to Athey et al.

[26] Recall that α_E is a deterministic function of α_I: $\alpha_I + (N-1)\alpha_E = 1$.

[27] Note that α_I needs to be identified for every number of bidders N, because we estimate it for each bidder configuration separately (see our discussion below in Section 4.2). Therefore, we cannot exploit variation in the number of bidders for identification.

(2011) and Lalive et al. (2021). We estimate the parameters of the bid distribution separately for each auction mode and bidder type using maximum likelihood. We assume that the bid distribution for contract type j of bidder type i, H_i^j, follows a Weibull distribution with auction- and bidder type-specific scale and shape parameters, λ_i^j and ν_i^j, that we model as a log-linear function of the number of participating bidders N and several observed contract characteristics, namely, 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 network). The track access costs are a direct measure of an important cost component. The contract duration captures that firms might value short-term contracts differently than long-term contracts.

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. Given the estimated parameters of the bid distributions, we can back out the cost distribution of each bidder on each gross auction contract with characteristics X by inverting the equilibrium first-order conditions. We follow the suggestion of Athey and Haile (2007) and compute the cost distribution for a given line and bidder type without imposing any additional parametric assumptions (see Appendix D.2 for the details).

In our second step, we use the cost distribution estimates from the gross auction sample to extrapolate the private cost distributions to each net auction. This allows us to treat the cost distributions as known and 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 firms receive a pair of signals for private costs and common revenues (c_i, r_i) in our net auction model. We assume that revenue signals r_i are drawn from a logconcave distribution $F_r(\bar{R}, \sigma_r^2)$ with mean $\bar{R}$ and variance σ_r^2. As discussed in Section 3, 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 $\mathcal{P}_i(b) \equiv c_i - \alpha_i r_i - \mathbb{E}\left[\sum_{j \neq i} \alpha_j r_j | \min_{j \neq i} b_j = b\right]$. According to Lemma 2, bidding behavior is determined by the system

$$\mathcal{P}^I(b^I) = b^I - \frac{1 - G^{net}_{I,M}(b^I|X,N)}{g^{net}_{I,M}(b^I|X,N)} \tag{6}$$

$$\mathcal{P}^E(b^E) = b^E - \frac{1 - G^{net}_{E,M}(b^E|X,N)}{g^{net}_{E,M}(b^E|X,N)}. \tag{7}$$

The key parameter of interest in the net auction sample is the vector α, which captures the precision of players' information. Our net auction estimation proceeds in two steps. Analogous to the gross auction estimation, we assume that the bid distributions in net auctions follow a Weibull distribution whose parameters are functions of contract characteristics. Afterwards, we can back out the combined cost-revenue signal $\mathcal{P}^i$ based on the first-order conditions in Equations (6) and (7).

$$\mathcal{P}^i = c_i - \alpha_i r_i - \underbrace{\mathbb{E}\left[\sum_{j\neq i} \alpha_j r_j | \min_{j\neq i} \phi_j^{-1}(\rho_j) = b_i\right]}_{\chi_i}. \tag{8}$$

The distribution of the left-hand side is estimated in the first step from our winning bid data. The distribution of the right-hand side, given the estimated distributions of c_i, is only a function of $F_r(\bar{R}, \sigma_r^2)$ and can be computed up to a vector of parameters $(\bar{R}, \sigma_r^2, \alpha)$.[28] Therefore, we estimate the parameters using maximum likelihood.

The most involved step in constructing the likelihood is the computation of the conditional expectation terms χ_i. Here we exploit that in equilibrium, given the signal ρ_i, these terms are deterministic numbers that describe a bidder's expectation about the opponents' revenue signals conditioning on the event that the bidder wins with bid b and that b is a pivotal bid. Consequently, for each parameter guess, each winning bid, and each winner's identity, χ is determined by the equilibrium bidding strategies. Therefore, we obtain χ_I and χ_E by solving a fixed-point problem of consistent first-order conditions. We relegate the technical details of the computation of the likelihood function to Appendix D.3.

We specify a parametric distribution for the common value signals to take the likelihood function to our data. 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

[28]Note, however, that this distribution involves a convolution of two random variables.

revenue signal distribution. To capture revenue heterogeneity across lines, we model the mean of the parent normal distribution of F_r as a linear function of a constant and the frequency of train service as a sufficient statistic for demand on a given route. To keep the number of parameters reasonably low, we model the variance of the parent distribution of F_r as constant across lines.[29]

We estimate separate α-parameters for auctions with 2, 3, 4, and 5 or more bidders, respectively. This is because, in our model setup, in which the α-parameters are the weights that determine the informational content of a bidder's revenue signal, we have to ensure that for different bidder configurations, the economic properties of the common value do not change mechanically.

First, note that to ensure that the expected value of the revenue does not mechanically increase in the number of bidders –which would be an undesirable feature– we need to normalize the revenue weights such that they sum up to one in every auction. Second, note that if we would only estimate a single α_I-parameter that is common across all auctions with potentially different bidder configurations, only the effective $\alpha_E = (1 - \alpha_I)/(N - 1)$ for each entrant would adjust. This would change the relative informational advantage of DB over entrants as a function of the number of bidders, even if the auctions are otherwise identical. To prevent this undesirable property, our estimates of α_I need to vary across N.[30] Finally, we restrict all α-parameters to lie between zero and one using a logit transformation. Our estimation of the entry cost is relatively standard and closely follows Athey et al. (2011). We relegate the details to Appendix G.2.

5. Estimation Results

In this section, we discuss our structural estimation results. Table 8 in Appendix E displays the maximum likelihood estimates for the bid distribution parameters in gross and net auctions for both

[29] Note that, even though we estimate only one variance parameter for all lines, the actual variance of the (truncated normal) revenue distribution σ_r^2 will differ across lines because the variance of a truncated normal distribution is a function of both the mean and the variance of the parent normal distribution.

[30] An alternative would be to estimate directly the relative informational advantage of the incumbent relative to the entrants as one structural parameter that should not change with N. A problem with this approach is that we do not have clear guidance on how to define the relative informational advantage of the incumbent. On the one hand, a natural candidate might be to estimate a parameter $\gamma := \alpha_I/\alpha_E$ and translate this parameter, together with the restriction that $\alpha_I + (N - 1)\alpha_E = 1$, into the implied parameters for α_I and α_E in our model terminology. On the other hand, the "structural informational advantage" could also take very different forms, such as a linear relationship, for example, $\gamma = \alpha_I - \alpha_E$. We opt for a more general approach that does not take a stance on the exact parametric form of the relative informational advantage of the incumbent and estimate a separate α-parameter for each bidder configuration.

the incumbent and the entrants. In a highly 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 2 in Appendix E. This contract exhibits characteristics that are close to the mean contract characteristics of our gross auction sample, as summarized in Table 1.

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 4 in Appendix E displays the histogram of the incumbent's relative cost advantage as measured by the estimated median cost for different lines. DB has a significant but small cost advantage for many lines, although there is substantial heterogeneity. On the one hand, there are several lines on which entrants seem to have a cost advantage, and for the majority of lines, the incumbent's cost advantage is modest. On the other hand, a considerable number of contracts (roughly 25% of our sample) are much more costly for the entrants to operate when compared to the incumbent's cost distribution.[31]

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 D.4. Although some of our graphs suggest some systematic cost asymmetries, we cannot reject the null hypothesis of equal cost distributions for most contracts. We reject the null hypothesis in favor of the alternative of the entrants' cost distribution dominating DB's cost distribution for only 23% of our observations.[32] 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 might have expected given the raw data.

We find striking differences when comparing a typical bid function in a gross auction with one

[31] Consistent with our hypothesis that entrants are somewhat less cost-efficient than the incumbent and Lemma 1, we find that in gross auctions the entrants charge a significantly lower markup (on average 10% of the winning bid) than the incumbent (on average 34% over the winning bid).

[32] Recall that if the entrants' cost distribution dominates DB's cost distribution, DB has more mass on low cost realizations. Moreover, note that the result from Maskin and Riley (2000a) requires conditional stochastic dominance, while we only test for first-order stochastic dominance. This implies that the 23% is an upper bound for the number of observations in which conditional stochastic dominance cannot be rejected as first-order stochastic dominance is weaker.

in net auctions. Overall entrants shade their bids substantially more in net auctions than in gross auctions. For example, the median markup of an entrant is EUR 5.5 million in gross auctions and EUR 12.6 million in net auctions.[33] This behavior is in line with our theoretical model that prescribes that bidders who have less precise information will shade their bids more. To quantify the informational advantage, we estimate the precision parameters (α_I, α_E) of our theoretical model.

Table 2: Estimation results: Informational asymmetry and revenue estimates

	$N=2$	$N=3$	$N=4$	$N=5$
α_I	0.6770	0.5874**	0.4907***	0.5041***
	(0.2878)	(0.1087)	(0.0404)	(0.0025)
α_E	0.3230	0.2063**	0.1698***	0.1240***
	(0.2878)	(0.0544)	(0.0135)	(0.0006)
$var_E\left[R \mid r_E = r\right] / var_I\left[R \mid r_I = r\right]$	4.3928	4.5520	3.4520	4.8841
Mean & SD rev. signal, gross	3.1253	2.6712		
Mean & SD rev. signal, net	3.0495	2.6304		

*Notes: The table displays the estimated asymmetry parameters for the incumbent (row α_I) and the entrants (row α_E) 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. Row 4 and 5 display the estimated mean and standard deviation (SD) of the revenue signal distribution (in 10-million euros). Row 5 averages the estimated statistics across all net auctions. Row 4 computes the analogous hyothetical revenue signal statistics for the gross auction sample based on the estimated revenue signal parameters from the net auction estimation and the observed contract characteristics of the gross auction sample.*

Table 2 summarizes our estimated asymmetry parameters as well as the parameter estimates for the revenue signal distribution. Most importantly, our estimates reveal that the incumbent has a substantial informational advantage on all lines, even though for auctions with two bidders, the asymmetry parameters are not statistically different from 0.5. Our estimates for α imply that the relative residual revenue variance –as measured by the ratio of Equation (4) for entrant and incumbent– is on average four times higher for the entrant than the incumbent (see row 3 of Table 2). Moreover, the ratio of the residual revenue variance for incumbent and entrants is relatively constant

[33] For our net auctions, we find that both bidder types charge roughly identical markups over their net cost signal (around 24% over the winning bid). That is, the common value uncertainty compensates fully for the additional aggressiveness of the entrant bidders due to a weaker private value distribution. Note that the similarity of markups of DB and the entrants in net auctions does not indicate that net auctions are efficient, see our discussion in Section 6. First, the common value signals affect bidding behavior but are orthogonal to the cost-efficiency of a bidder. Second, conditional on the same cost signal and revenue signal, entrants are more prone to the winner's curse (captured by the expectation about other bidders' signals) and will therefore bid more cautiously than DB.

across bidder configurations.[34]

The average expected revenue signal is close across the gross and net auction samples. The estimated standard deviation of the revenue signal is relatively large (2.6 compared to a mean of roughly 3, see row 4 and 5 of Table 2). These estimates imply an average and median revenue per train-km of EUR 8 and EUR 4.50, respectively, which is roughly in line with the revenue statistics reported in Hartwig and Pollmeier (2012). When comparing our revenue estimates to the observed winning bids or the estimated cost distributions, we find plausible patterns in line with other industry reports, too. For example, the median of the ratio of the winning bid and 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.

We would like to point out that both our model and our estimation strategy rely on the assumption that revenue signals are drawn independently across bidders.[35] If, in practice, revenue signals are positively correlated across bidders, our estimates provide an upper bound, i.e., a worst case scenario, for the intensity of the winner's curse in our application. This is because –among all possible correlation structures of the revenue signals– assuming independence results in the largest residual uncertainty about the realized common value conditional on a bidder's own signal and, hence, a maximal winner's curse.

With strictly positively correlated revenue signals the winner's curse and overall bid shading would likely be lower, and our net auction efficiency probabilities discussed in the next section would be higher. In the extreme case of perfectly correlated revenue signals, bidders would face minimal—in fact, zero—residual uncertainty about the realized common value and, therefore, no winner's curse at all.[36] This important implication of the independence assumption should be kept in mind when

[34] Our interpretation of α as a measure of a purely informational asymmetry requires the assumption that all firms value a given revenue stream identically, which is consistent with our model assumption of risk-neutrality. An alternative interpretation of the patterns in the data and our asymmetry parameters is that they capture heterogeneous levels of risk aversion across incumbent and entrants. Even though most industry evidence indicates that heterogeneous risk aversion is of only minor relevance in our application, it is in principle possible that entrants exhibit a higher level of risk aversion than DB. Unfortunately, our data do not allow us to incorporate this channel formally. It seems reasonable to us that the policy implications are similar no matter whether the asymmetry in α captures pure informational asymmetry, different levels of risk aversion or a combination of both.

[35] Note that this independence assumption differs from the standard setup in common value auctions, in which signals are conditionally independent given the realized common value. Unfortunately, we cannot test the independence of signals and bids, because we only observe winning bids.

[36] In our application, we believe that revenue signals are not too strongly correlated, in particular, across DB and the entrants. While DB has access to detailed revenue data from actual ticket sales, entrants hire consulting agencies to conduct surveys for a limited amount of time to forecast ticket revenues. Therefore, we conjecture that on small

interpreting our results in this section and our efficiency counterfactuals below.

6. Counterfactuals

In this section, we compute the probability of selecting the efficient bidder for the observed gross auction sample, the observed net auction sample, and a counterfactual in which the net auction sample is procured using gross auctions. In addition, we compute the expected winning bids and the expected agency payoff for each contract observed in our sample and our net-as-gross counterfactual.

We start by defining an ex ante efficiency measure in our setup for gross and net auctions. For any auction, consider bidder i winning with bid b resulting from cost realization c. The probability that this outcome is efficient is[37]

$$\Pr(c_i \leq \min_{j \neq i} c_j | b \leq \min_{j \neq i} b_j). \tag{9}$$

For the observed gross auction sample and the net-as-gross counterfactual we can rewrite this equation in terms of the estimated bid distributions only. For the observed net auction sample we need to combine the estimated bid distributions with our estimates of the primitives for cost and revenue distributions, as well as the estimated asymmetry parameters α. For all three scenarios, we can compute efficiency probabilities and expected winning bids without having to solve the system of bidding FOCs numerically for a new equilibrium.[38] We relegate the details of the efficiency calculation to Appendix F.

Table 3 displays the average of the probabilities of selecting the efficient firm for the different procurement modes across all contracts in our gross and net sample, respectively. We compute our efficiency measure for two cases: first, integrating over the distribution of all potential bidder configurations (*Endogenous N* in Table 3) and second, holding the number of bidders fixed at the observed number of bidders in our sample (*Observed N* in Table 3). Since the two rows are generally similar, we focus our discussion on the computation with endogenous entry as predicted by our entry

lines with little variation in demand over time our estimation results more strongly overstate the importance of the uncertainty about the common value than on larger lines with more variation in demand over time.

[37] For notational convenience, we suppress covariate dependency of the bid functions in this section.

[38] This approach avoids the numerical intricacies often encountered when solving numerically for equilibria in asymmetric first-price auctions, see, for example, Hubbard et al. (2013); Hubbard and Paarsch (2014).

model discussed in Appendix G.

Gross auctions exhibit an average probability of selecting the efficient firm of 87%. However, the probability of selecting the efficient firm in net auctions is substantially lower and only 17% on average.

Table 3: Efficiency comparison for different auction formats

	Gross auctions	Net auctions	Net $\rightarrow$ Gross
Endogenous N	0.8690	0.1658	0.9027
Observed N	0.8747	0.0916	0.9105

Notes: The table displays the mean (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. The first row indicates efficiency probabilities when the number of bidders is endogenous and determined by our entry model. The second row indicates efficiency probabilities when the number of bidders is fixed and as observed in the data.

Finally, we compute the counterfactual efficiency probabilities assuming that our net auction sample is procured as gross auctions. We find a substantial increase in the average probability of selecting the efficient bidder from 17% to 90% (see the last column of Table 3). When testing the equality of the mean efficiency of gross auctions and net auctions procured as gross, we cannot reject the null hypothesis of equal means at the 5%-level.

Table 4: Illustration of efficiency loss in net auctions

	Net auctions (non-strategic)	Net auctions (w/ gross markups)	Net auctions (observed)
Pr(selecting efficient firm)	0.7707	0.5995	0.1658

Notes: The table displays the mean (across auctions) of the ex ante probabilities of selecting the efficient firm in the net auction sample for different hypothetical scenarios. For the simulations in this table, we assume that the number of bidders is fixed at the observed level.

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 due to 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.

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 4 summarizes the associated results.[39]

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. Even though these numbers do not constitute equilibrium efficiency measures, we consider them a useful benchmark to assess the role of the additional noise from the revenue signal, which is the only source of inefficiency in this setting. The efficiency loss induced by the second signal is considerable but arguably modest, resulting in an average efficiency of 77% (see column *non-strategic* of Table 4).

In the second column (*w/ gross markups*) of Table 4, we present the average 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 absolute markup (measured in EUR) as in a gross auction. This scenario captures the combined efficiency loss from the revenue signal noise and strategic bidding due to cost asymmetries. The average efficiency level is 60%, i.e., the strategic behavior due to cost asymmetries induces another 17%-points loss in efficiency. This number is roughly in line with the efficiency loss of 13%-points observed in our gross auction sample.

The key difference between the previous scenario and the actual net auction sample is that in the latter the common value asymmetry affects bidding behavior, whereas the informational asymmetry is irrelevant in the former settings. Comparing the three efficiency statistics in Table 4 reveals that the most substantial efficiency loss –an additional 43%-points compared to the scenario with revenue signal noise and gross markup bidding– occurs when we allow the common value asymmetry to affect bidding strategies.

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. Overall, our counterfactual suggests a substantial potential for efficiency gains when agencies choose procurement modes more carefully rather than basing it predominantly

[39] We provide details on the computation of these statistics in Appendix F.

on the preferences of the agency officials.

Next, we use our estimates to predict the subsidy that the agency has to pay to the winning firm.[40] Table 5 compares the winning bids predicted by our model for the three different scenarios

Table 5: Revenue comparison for different auction formats (in 10-Mio EUR)

	Predicted winning bid	E(ticket revenues)	E(agency payoff)
Gross auctions (endo. N)	6.8775	3.1253	-3.7522
Net auctions (endo. N)	6.4644	3.0495	-6.4644
Net → Gross auctions (endo. N)	7.3305	3.0495	-4.2810
Net → Gross auctions (fixed N)	8.0292	3.0495	-4.9797

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. The upper panel displays statistics when the number of bidders is endgenous as predicted by our entry model. The lower panels displays statistics when the number of bidders is fixed at the values observed in the data. For the gross auction sample, the net auction sample, and the net auctions procured as gross counterfactual we predict on average 4.2, 3.3, and 4.4 bidders, respectively, when the number of bidders is endogenous.

(observed gross auction sample, observed net auctions sample, and the counterfactual where net auctions are procured as gross auctions).[41] The winning bid, i.e., the subsidy that the winning firm receives for fulfilling the contract, is larger in gross auctions than in the observed net auctions. This is not surprising since the winning firm in a gross auction has to be compensated for not receiving the ticket revenues. However, the difference between gross and net auctions is relatively small (6.88 in gross versus 6.46 in net auctions, see Column 1 of Table 5). Given that net and gross auctions are similar in terms of their contract characteristics and ticket revenues are of non-negligible magnitude in our application,[42] the small difference seems striking.

Several points are worth noting here. First, the predicted difference in winning bids of roughly 0.4 is close to the one we observe in our data (0.3, see Table 1). We interpret this as evidence that

[40] 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. However, the expected agency payoff should 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.

[41] For Table 5 we focus on the results with endogenous bidders, i.e., we integrate over the number of entrant bidders as predicted by our entry model. The results assuming that entry is fixed at the level observed in the data are very similar and available upon request.

[42] On average ticket revenues cover roughly 40% of the total costs of a contract, see Rödl & Partner (2014).

our model fits the data reasonably well. Second, net auctions tend to attract on average 1.4 fewer bidders than a comparable gross auction. Less competition is likely to increase the winning bid in net auctions.[43] Third, the small difference in the winning bids can be due to the large winner's curse in net auctions, which can cause substantial bid shading that offsets the effects of the additional revenues from ticket sales.

To separate these two channels, we decompose the total change in the predicted winning bid into a bidding effect and an entry effect. To isolate the effect on the bidding stage, we simulate the counterfactual assuming that the number of bidders stays constant; see row 4 of Table 5 for the results. The average counterfactual winning bid is 8.0. This implies that if a net auction would be procured as a gross auction, in which the train company keeps the ticket revenues, we predict that roughly 50% of the expected ticket revenues[44] would be passed through to the procurement agency if the number of bidders is held constant.

To assess the effect of entry, we simulate our counterfactual endogenizing the number of bidders so that the expected winning bid is averaged over all potential bidder configurations predicted by our entry model. In this scenario, the average predicted winning bid is 7.3 (see row 3 of Table 5). This smaller increase in counterfactual bids is plausible since gross auctions attract more bidders than net auctions and the additional competition is likely to decrease the winning bid.

The increase in the winning bid when going from a net to a gross format is only half as large when the number of bidders is endogenous compared to when the number of bidders is held fixed at the observed net auction level. This implies a "revenue pass-through" of 29% in our counterfactual where the number of bidders is allowed to adjust in response to the auction format. Considering the strong informational asymmetries that we find in our estimation, we judge these counterfactual bidding patterns to be plausible.

In light of our counterfactual findings, it is somewhat appalling that despite the large costs of net auctions in terms of efficiency and revenues, almost 50% of the contracts are procured as net auctions. Our analysis does not necessarily imply that one should always use gross auctions instead

[43] We can obtain first insights on the effect of the net auction mode on winning bids when holding the number of bidders constant from our reduced-form regression in column (1) of Table 6 in Appendix B. The coefficient on *Net* indicates that, holding everything else (including the number of bidders) fixed, net auctions lead to a decrease in the winning bid by 2.56. However, one should keep in mind that the coefficient has a large standard error so that the 90%-confidence interval ranges from -5.0 to -0.1.

[44] Recall that the average expected revenue is around 3, see Column 2 of Table 5.

of net auctions because there can be other factors that we cannot model formally with our setup and our data.[45]

For example, an agency may place intrinsic value on minimizing firm risk for political reasons or the agency may put much weight on providing incentives for the firm to increase the quality of the provided service, even though there is no empirical evidence suggesting that quality is significantly higher in net auctions and procurement agencies use fines to enforce the pre-specified quality levels.[46]

The main contribution of our counterfactuals is to quantify the costs of the informational asymmetry associated with the net auction format both in terms of both efficiency and subsidy levels. Such quantifications are important for policymakers to make informed decisions about whether the benefits of net auctions as perceived by the procurement agency outweigh the significant costs that our empirical analysis quantifies.

7. Conclusion

While many public and private organizations have adopted competitive procurement mechanisms, the experiences with such auctions have often been mixed and the expected benefits have often not been realized (see, for example, OECD (2019)). A key concern with competitive awarding procedures is the existence of incumbency advantages.

In this paper, we exploit exogenous variation in the procurement design combined with a structural auction model to quantify the sources of the dominance of the former state monopolist DB in the German market for SRPS. Our structural estimates imply that DB differs from entrants in two dimensions. First, it has a moderately more efficient cost structure. Second, it benefits from a large informational advantage about future ticket revenues. We demonstrate theoretically that both characteristics may explain DB's dominance, but the two channels have opposite implications for the efficiency of the procurement market.

Our counterfactuals indicate that DB's informational advantage can explain the biggest part of the inefficiency in the market. We illustrate that eliminating the common value component

[45] In addition, it is theoretically not clear that net auctions are always less efficient than gross auctions, see our theoretical discussion in Section 3. Therefore, empirical findings for other markets could be qualitatively different.

[46] For example, in 2017, the train operating companies paid a total of EUR 107 million to the agencies in fines due to insufficient quality performance (Monopolkommission (2019)).

from the auction leads to substantially more efficient auction outcomes and higher revenues for the procurement agencies.

While determining the best auction format comprehensively requires careful consideration not only of bidding behavior but also of the procurement agencies' objective function, our empirical analysis highlights significant potential for improving the efficiency of procurement auctions by eliminating informational asymmetries among bidders. The market studied in this paper is of substantial size and therefore of interest in itself. In addition, our industry is comparable to many procurement markets in other countries and industries. Hence, our insights can potentially be informative for designing awarding mechanisms in a wide variety of public and private procurement settings where entrant sellers compete with established incumbents.

References

Athey, S. and P. A. Haile (2002): "Identification of Standard Auction Models," *Econometrica*, 70, 2107–2140.

——— (2007): "Nonparametric Approaches to Auctions," *Handbook of Econometrics*, 6, 3847–3965.

Athey, S., J. Levin, and E. Seira (2011): "Comparing Open and Sealed Bid Auctions: Evidence from Timber Auctions," *The Quarterly Journal of Economics*, 126, 207–257.

Bahn-Report (2007): "Licht und Schatten im Bestellerdschungel," *Bahn-Report*, 2007, 24–29.

Committee, O. P. G. (2016): "Survey on Public Procurement," *Public Governance Committee.*

Coviello, D., A. Guglielmo, and G. Spagnolo (2018): "The effect of discretion on procurement performance," *Management Science*, 64, 715–738.

Davidson, R. and J.-Y. Duclos (2000): "Statistical Inference for Stochastic Dominance and for the Measurement of Poverty and Inequality," *Econometrica*, 68, 1435–1464.

De Silva, D. G., T. Dunne, and G. Kosmopoulou (2003): "An Empirical Analysis of Entrant and Incumbent Bidding in Road Construction Auctions," *The Journal of Industrial Economics*, 51, 295–316.

De Silva, D. G., G. Kosmopoulou, and C. Lamarche (2009): "The Effect of Information on the Bidding and Survival of Entrants in Procurement Auctions," *Journal of Public Economics*, 93, 56–72.

Decarolis, F. (2018): "Comparing Public Procurement Auctions," *International Economic Review*, 59, 391–419.

Engelbrecht-Wiggans, R., P. R. Milgrom, and R. J. Weber (1983): "Competitive Bidding and Proprietary Information," *Journal of Mathematical Economics*, 11, 161–169.

European Commission (2016): "Study on economic and financial effects of the implementation of Regulation 1370/2007 on public passenger transport services," .

Frankfurter Allgemeine Zeitung (2011): "Die Ausschreibungswelle wird den Markt verstopfen." .

Février, P. (2008): "Nonparametric Identification and Estimation of a Class of Common Value Auction Models," *Journal of Applied Econometrics*, 23, 949–964.

Goeree, J. K. and T. Offerman (2003): "Competitive Bidding in Auctions with Private and Common Values," *The Economic Journal*, 113, 598–613.

Guerre, E., I. Perrigne, and Q. Vuong (2000): "Optimal Nonparametric Estimation of First-Price Auctions," *Econometrica*, 68, 525–574.

Hartwig, K.-H. and P. Pollmeier (2012): "Ein Ansatz zur Verteilung der Bestellerentgelte im SPNV," .

He, M. (2015): "Nonparametric Identification of Pure Common Value Auction Models with an Application to the US OCS Wildcat Auction," .

Hendricks, K. and R. H. Porter (1988): "An Empirical Study of an Auction with Asymmetric Information," *The American Economic Review*, 78, 865–883.

Hendricks, K., R. H. Porter, and C. A. Wilson (1994): "Auctions for oil and gas leases with an informed bidder and a random reservation price," *Econometrica: Journal of the Econometric Society*, 1415–1444.

Hong, H. and M. Shum (2002): "Increasing Competition and the Winner's Curse: Evidence from Procurement," *The Review of Economic Studies*, 69, 871–898.

Hubbard, T. P., R. Kirkegaard, and H. J. Paarsch (2013): "Using economic theory to guide numerical analysis: Solving for equilibria in models of asymmetric first-price auctions," *Computational Economics*, 42, 241–266.

Hubbard, T. P. and H. J. Paarsch (2014): "On the numerical solution of equilibria in auction models with asymmetries within the private-values paradigm," in *Handbook of computational economics*, Elsevier, vol. 3, 37–115.

Hunold, M. and C. Wolf (2013): "Competitive Procurement Design: Evidence from Regional Passenger Railway Services in Germany," *ZEW-Centre for European Economic Research Discussion Paper.*

Iossa, E. (2019): "Competition for the market: Tackling the incumbency advantage," *OECD, Global Forum on Competition.*

Kress, R. (2013): *Linear Integral Equations*, vol. 82, Springer Science & Business Media.

Lalive, R. and A. Schmutzler (2008): "Entry in Liberalized Railway Markets: The German Experience," *Review of Network Economics*, 7, 36–52.

Lalive, R., A. Schmutzler, and C. Zulehner (2021): "The Benefits of Procurement Auctions: Competitive Pressure vs. Selection of Efficient Suppliers," *mimeo.*

Levin, D. and J. L. Smith (1994): "Equilibrium in Auctions with Entry," *The American Economic Review*, 84, 585–599.

Li, S. and P. Philips (2012): "Construction Procurement Auctions: Do Entrant Bidders Employ More Aggressive Strategies than Incumbent Bidders?" *Review of Industrial Organization*, 40, 191–205.

Li, T., I. Perrigne, and Q. Vuong (2000): "Conditionally Independent Private Information in OCS Wildcat Auctions," *Journal of Econometrics*, 98, 129–161.

Linz, P. (1985): *Analytical and numerical methods for Volterra equations*, SIAM.

Luo, Y. and H. Takahashi (2019): "Bidding for Contracts under Uncertain Demand: Skewed Bidding and Risk Sharing," *Available at SSRN 3364708.*

Maskin, E. and J. Riley (2000a): "Asymmetric Auctions," *Review of Economic Studies*, 413–438.

——— (2000b): "Equilibrium in Sealed High Bid Auctions," *The Review of Economic Studies*, 67, 439–454.

Milgrom, P. R. and R. J. Weber (1982): "A Theory of Auctions and Competitive Bidding," *Econometrica: Journal of the Econometric Society*, 1089–1122.

MONOPOLKOMMISSION (2009): "Sondergutachten 55: Bahn 2009: Wettbewerb erfordert Weichenstellung," Tech. rep.

——— (2019): "7. Sektorgutachten Bahn 2019: Mehr Qualitaet und Wettbewerb auf die Schiene," Tech. rep.

OECD (2019): "Competition for the market. Background note prepared by the Secretariat," .

RÖDL & PARTNER (2014): "Revision der Regionalisierungsmittel," Tech. rep., KCW GmbH and ETC Transport Consultants GmbH and Rödl & Partner.

RTM (2016): "Growing Cost of Franchise Bidding a 'Deterrent' to New Entrants, Says RDG," *Rail Techology Magazine*.

SACHSEN-ANHALT MINISTERIUM FÜR LANDESENTWICKLUNG UND VERKEHR (2011): "ÖPNV-Plan 2010-15/2025," .

SANT'ANNA, M. (2018): "Empirical Analysis of Scoring Auctions for Oil and Gas Leases," *mimeo*.

SOMAINI, P. (2020): "Identification in auction models with interdependent costs," *Journal of Political Economy*, 128, 3820–3871.

STOLINE, M. R. AND H. K. URY (1979): "Tables of the Studentized Maximum Modulus Distribution and an Application to Multiple Comparisons Among Means," *Technometrics*, 21, 87–93.

SWEETING, A. AND V. BHATTACHARYA (2015): "Selective Entry and Auction Design," *International Journal of Industrial Organization*, 43, 189–207.

A. Proofs

A.1. Proof of Lemma 2

The derivation of the first-order conditions 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 $\tilde{v}_i(\rho_i, m_i; N) = \mathbb{E}[c_i - \alpha_i r_i - \sum_{j\neq i} \alpha_j r_j | \rho_i, \min_{j\neq i} B_j = m_i]$ is given by

$$\max_b \int_b^\infty (b - \tilde{v}_i(\rho_i, m_i; N))\, g_{M_i}(m_i|N) dm_i, \tag{10}$$

where $g_{M_i}(m_i|N) = \Pr(m_i = \min_{j\neq i} B_j|N)$. The objective is differentiable almost everywhere and the first-order condition given by

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

Following the notation of Athey and Haile (2007) further

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

so we get

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

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

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

yielding the desired expression where ϕ_j denotes the inverse bid function.

A.2. Proof of Lemma 3

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

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

The boundary conditions are given by $\phi_i(\underline{b}) = \overline{r}$.[47] 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. To see this, note first that the expected revenue signal of other bidders is less than the own revenue signal. This follows from the assumption that $\phi_i(b) = \phi_j(b)$ and from conditioning on the minimum of all other bids being equal to b. Thus, the expected revenue signal for all bidders that bid b is equal to the own revenue signal, while for all other bidders it is lower as they bid higher. The second observation necessary to establish that the left-hand side is larger for bidder I than for bidders E is that $\alpha_I > \alpha_E$ and thus more weight is placed on the own, higher, signal for bidder I.

Next, note that 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., $\phi_i(\underline{b}) = \overline{r}$. 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 $b \in (\underline{b}, \overline{b})$. 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. Additional Descriptive Statistics

Additional evidence for comparable entrants across auction modes. Table 7 provides several statistics of the winning firms other than DB and compares them across the gross and net sample.[48] As we only observe the identity of the winning firm, we can only study differences in the characteristics of the winning firms. First, it could be that net auctions attract more public firms, which

[47] Existence of a unique minimum bid for all bidders follows from Maskin and Riley (2000b). Monotonicity of the bidding strategies, which follows from Lemma 2 then implies that the highest possible ρ_i, $\overline{r}$, induces the minimum bid $\underline{b}$.

[48] Note that industry experts agree that DB participates in all auctions.

Table 6: Reduced-form evidence: Winning bids, number of bidders, DB winning, and net auction choice

	(1) Winning bid	(2) No. of bidders	(3) DB wins	(4) DB wins	(5) DB wins	(6) Net auction
Net auction	-2.5633*	-0.4519***	5.7130**	2.4975	6.5346**	
	(1.5025)	(0.0566)	(2.4005)	(3.3642)	(2.9865)	
Access charges	13.2283**	-1.5633***	-3.4753	-7.2310	-0.1800	-1.5853
	(5.3226)	(0.4836)	(4.4829)	(4.5140)	(4.3611)	(2.8356)
Contract volume	9.4683***	-0.1983**	0.0619	-0.0570	0.2703	-0.3729
	(3.4346)	(0.0879)	(1.1454)	(1.0211)	(1.0621)	(0.6523)
Contract duration	4.5225***	0.2505***	2.1386**	2.3060**	2.1960**	0.3444
	(0.6862)	(0.0784)	(1.0851)	(0.9291)	(0.8587)	(0.4946)
Used vehicles	0.5481	-0.1123**	0.8125	0.6492	1.1823**	-0.0217
	(0.7672)	(0.0477)	(0.5688)	(0.5511)	(0.5931)	(0.3516)
Frequency (log)	-1.3826	0.3302***	1.1711	1.3866	1.0857	-0.0388
	(1.7797)	(0.0774)	(1.2658)	(1.3509)	(1.3912)	(0.6872)
No. bidders-gross	-0.1039			-0.7210***		
	(0.2231)			(0.2774)		
No. bidders-net	0.2863			-0.9090**		
	(0.3060)			(0.4062)		
Network size	-0.0166	0.0026**	0.0025	0.0076	-0.0019	0.0078
	(0.0290)	(0.0011)	(0.0113)	(0.0117)	(0.0122)	(0.0077)
Pot. bidders-gross					0.2443	
					(0.1713)	
Pot. bidders-net					1.0180	
					(0.7472)	

Notes: Heteroskedasticity-robust standard errors in parentheses. Models (1) is estimated by OLS. Column (2) is a negative binomial count data regression. Models (3) to (6) are binary logit models. *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. *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 1. Number of observations: 156. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Summary statistics of characteristics of winning firms (excluding DB) in gross and net auctions

	Gross Mean	**Net** Mean	Difference	p-value
Public company dummy	0.681	0.718	-0.0371	0.663
Revenues (billion EUR)	4.61	4.95	-0.34	0.975
Number of Employees	2690.3	3262.7	-572.4	0.926

Notes: This table summarizes the results from testing the equality of the means of winning firms' characteristics across different auction modes (gross vs. net). Note that we have excluded DB from this analysis.

in our case are held by federal states, large cities, or foreign countries, because these might be less sensitive to revenue uncertainty compared to private companies. Table 7 shows that our data cannot reject the equality of the share of public firms winning net and gross contracts, respectively. Second, it is conceivable that net auctions attract larger firms. We use two proxies for the size of a firm (yearly revenues and number of employees) and, again, find no significant differences in these firm characteristics across the contract modes. In conclusion, we interpret these test results as evidence that gross and net contracts do not attract a different set of entrant firms.

Additional evidence for exogeneity of auction mode. In the following, we present additional industry evidence that supports our assumption of an exogenous auction mode choice. Regarding a procurement agency's inflexibility to adjust the auction mode, Bahn-Report (2007) explicitly states: *"The individual preferences of individual agencies are so pronounced that experienced bidders could sort anonymized tenders without problems to the agencies based on their corresponding ideologies. At the BEG [the Bavarian agency], there is an irrefutable net principle, i.e., there are absolutely only contracts in which the train operating company carries the entire revenue risk. (...) In contrast, in Hessen and Brandenburg, there is an irrefutable gross principle just like that (...). Many activities like these have the character of lighthouse projects in which agencies try this or that because they like it. Economic rationality is rarely involved, however."* In other cases, the decision is not even made at the agency level but at a higher political level that can span several regional agencies. For example, the planning document for regional transportation services in the state of Sachsen-Anhalt (Sachsen-Anhalt Ministerium für Landesentwicklung und Verkehr (2011)) mentions explicitly that for *all* SRPS contracts, gross auctions should be used. In such cases, the contract mode cannot even be adjusted to the line under consideration.

C. Details on Identification

In this section, we outline the steps for a formal identification proof for our net auction model and discuss the associated challenges.

The identification of the cost distributions is standard in the gross auctions. Moreover, the bid distributions in the net auctions are identified in our setting due to the structure of the Goeree and Offerman (2003)-setup that implies the independence assumptions that we impose on the bidders' signals. What remains to be identified in the net auctions are (i) the revenue distribution, F_r, and (ii) the signal weights, α_i. Note that there is only one asymmetry parameter, α_I, to be identified.[49] However, it needs to be identified for every number of bidders N, as we estimate it for each bidder configuration separately.

As is well known, formal identification of common value auctions is a non-trivial problem (see Athey and Haile (2007) for an overview). We face additional difficulties in our application. Specifically, we study a setting with private and common values that need to be disentangled, and we have asymmetric bidders.

One important difficulty in identifying a standard common value setting (where the common value is drawn from a given distribution and bidders' signals are conditionally independent draws from a signal distribution conditional on the realized common value) is that there are $N+1$ unknowns to be identified in an N-bidder auctions - the joint signal distribution of N bidders and the distribution of the common value itself. Thus, even when all N bids are observed, a standard common value auction is underidentified. Several ways of dealing with these issues have been proposed in the literature (see, for example, Li et al. (2000); Février (2008)).

Our modeling framework based on Goeree and Offerman (2003) takes an alternative approach to the problem: We assume that the common value is equal to the (weighted) sum of the revenue signals. Hence, the revenue signal distribution determines the distribution of the common value,

[49] Once α_I is identified, identification of α_E follows straightforwardly from the normalization equation $\alpha_I+(N-1)\alpha_E = 1$.

which reduces the dimensionality of the problem by not requiring an additional distribution, the common value distribution, to be identified. He (2015) makes use of this feature and, in a symmetric and pure common value version of the additive formulation of the common value, provides a non-parametric identification proof based on a quantile function approach. The identification result is obtained by rewriting the first-order conditions as a linear integral equation in the unknown common value signal distribution for which uniqueness results are readily available (see, for example, Chapter 3.3 in Kress (2013) for a textbook treatment of linear Volterra equations).

Note that He (2015) assumes that all bids are observed. However, observing only winning bids together with the winner's identity is sufficient to recover the full bid distribution. Hence, his identification result extends to the case of observing only winning bids. It is important to note that this is an additional advantage of the additive formulation of the common value component. In a standard common value setting with an unknown common value realization and *conditionally independent* signals –and therefore only *conditionally independent* bids– observing the winning bid alone does not suffice to identify all bid functions as the order statistics are correlated through the realized common value (see Section 7.1 in Athey and Haile (2007) for a discussion). In the additive framework, all signals and thus bids are *independent*, and therefore, the order statistics are independent as well. This allows us to follow the same approach that is common for IPV auctions in which only winning bids and the winning bidder's identity are observed (see Section 3.3.1 in Athey and Haile (2007)). Thus, the same proof as in He (2015) applies to the case of observing only winning bids and winners' identities.

Additionally, we need to overcome the difficulty of disentangling private and common values and incorporating asymmetry among bidders. We conjecture that the asymmetry could be incorporated into the approach of He (2015). The integral equation in He (2015) is one-dimensional. In the asymmetric case with two bidder groups the problem can be written as an analogous two-dimensional integral equation, for which similar uniqueness results have been established (see, for example, Theorem 3.5 in Linz (1985)). Therefore, we are confident that our model would be formally identified in the absence of private values based on a relatively straightforward extension of He (2015) to asymmetric bidders.

The key problem, which prevents us from providing a complete formal identification proof for our net auction model is the presence of the additional private value component. One can rewrite the first-order conditions in a net auction in the same way as He (2015). The first-order condition is

$$b_i - \frac{1 - G_i^{net}(b_i)}{g_i^{net}(b_i)} = \rho_i - \mathbb{E}\Big[\sum_{j \neq i} \alpha_j r_j | \min_{j \neq i} b_j = b_i\Big]. \tag{11}$$

Unfortunately, the integral equation associated with this first-order condition (see below) is substantially more complicated than in He (2015) and, to the best of our knowledge, there does not exist a generally tractable solution to this equation that we could use for a formal identification proof.

The difficulties arise because the first term on the right-hand side in Equation 11 is the combined signal, ρ_i, while the expectation term contains the deconvolution of ρ_j into only the revenue signal conditioning on all potential signal realizations giving rise to ρ_j that induces the observed bid for bidder j, $c_j - \alpha_j r_j = \rho_j(b_i)$. If the distribution of the compound signal ρ were known, isolating the distribution of the revenue signals—and thus, the expected revenue signal—would be a standard deconvolution step. However, that step requires knowledge of the distribution of ρ, which in turn would need to be identified separately first. We illustrate the consequences below by contrasting our first-order condition with the one in He (2015).

We can write the right-hand side of Equation 11 for the incumbent[50] I and bid b as

$$\rho_I(b) - \frac{1-\alpha_I}{N}\left(\int_0^\infty r\frac{f_{c_E}(\rho_E(b)-r)f_r(r)}{\int_{-\infty}^\infty f_{c_E}(\rho_E(b)-\tilde{r})f_r(\tilde{r})d\tilde{r}}dr + \int_{\rho_E(b)}^\infty \int_0^\infty r\frac{f_{c_E}(\rho - r)f_r(r)}{\int_{-\infty}^\infty f_{c_E}(\rho-\tilde{r})f_r(\tilde{r})d\tilde{r}}drd\rho\right),$$

where $\rho_I(b)$ and $\rho_E(b)$ correspond to the compound signal realizations of the incumbent and entrant, respectively, that give rise to bid b. The corresponding first-order condition in He (2015) which features symmetric bidders and no private value component is

$$b_i - \frac{1 - G_i(b_i)}{g_i(b_i)} = 2\rho_i(b_i) + (N-2)\int_{\rho_i(b_i)}^\infty \tilde{\rho} f(\tilde{\rho})d\tilde{\rho},$$

which is linear in ρ and $f(\rho)$ giving rise to a linear Volterra equation of the second kind when rewriting it in quantile form.[51]

In contrast to the setting in He (2015), the distribution to be identified, $f_r(r)$, appears non-linearly

[50] The corresponding equation for the entrant bidders is analogous.

[51] Using quantile functions requires a straightforward rewriting using the change of variables $F(\rho) = \tau$ and $\rho = Q(\tau)$ for the quantile function $Q(\cdot)$ and $F(\cdot)$ being the cumulative distribution function of ρ.

in our integrand and it is interacted with the cost distribution. This prevents us from following the analogous steps in rewriting this equation using quantile functions and applying existing uniqueness results for the resulting integral equation. For a formal identification proof, we require that the system of integral equations in $f_r(r)$ has a unique solution. To the best of our knowledge, this is a complicated mathematical problem.

D. Details of the Estimation Routine

In this appendix, we discuss the details of our estimation routine.

D.1. Estimation of Bid Distributions

We estimate the parameters of the bid distributions 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

$$H_i^j(b_i|X,N) = 1 - \exp\left[-\left(\frac{b_i}{\lambda_i^j(X,N)}\right)^{\nu_i^j(X,N)}\right], \tag{12}$$

where λ_i^j and ν_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 network serviced).[52] The track access costs are a direct measure of an important cost component. The contract duration captures that firms might value short-term contracts differently than long-term contracts.

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

$$h_I^{j,(1:N)}(x) = h_I^j(x)(1 - H_E^j(x))^{N-1} \tag{13}$$

$$h_E^{j,(1:N)}(x) = (N-1)h_E^j(x)(1 - H_E^j(x))^{N-2}(1 - H_I^j(x)), \tag{14}$$

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

The likelihood function is then given by

$$LL(\lambda^j, \nu^j) = \sum_{t=1}^{T^j} \log\left(h_E^{j,(1:N)}(b_t)(1 - \mathbf{I}_{\text{DB wins}}) + h_I^{j,(1:N)}(b_t)\mathbf{I}_{\text{DB wins}}\right), \tag{15}$$

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.

Plugging in the functional form of the Weibull distribution, we obtain the following terms. 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

[52]In light of the substantial increase in computational burden from incorporating unobserved contract heterogeneity we opt for a model with only observed auction covariates. In principle, we could introduce unobserved heterogeneity parametrically as suggested in Decarolis (2018) using track access charges as a cost shifter that is common to all firms. However, we do not believe that unobserved heterogeneity is of significant relevance in our setting given the industry evidence provided in Section 2.

assumption on the bid distribution

$$\exp_U = \exp\left(-\left(\frac{x}{\lambda_U}\right)^{\rho_U}\right) \tag{16}$$

$$h_U = \exp\left(-\left(\frac{x}{\lambda_U}\right)^{\rho_U}\right)\left(\frac{x}{\lambda^U}\right)^{\rho^U-1} = \exp_U\left(\frac{x}{\lambda^U}\right)^{\rho^U-1} \tag{17}$$

$$H_U = 1-\exp\left(-\left(\frac{x}{\lambda_U}\right)^{\rho_U}\right) = 1-\exp_U . \tag{18}$$

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

$$h_I^{j,(1:N)}(x) = \Pr(b^I = x, b^{E_1} \geq x, \dots, b^{E_{N-1}} \geq x) \tag{19}$$

$$= \Pr(b^I = x)\Pr(b^{E_1}, \dots, b^{E_{N-1}} \geq x) \tag{20}$$

$$= h_I^j(x)(1-H_E^j(x))^{N-1}. \tag{21}$$

For a winning entrant it is given by

$$h_E^{j,(1:N)}(x) = (N-1)\Pr(b_i^E = x, b_{j\neq i}^E \geq x, b^I \geq x) \tag{22}$$

$$= (N-1)\Pr(b_i^E = x)\Pr(b_{j\neq i}^E \geq x, b^I \geq x) \tag{23}$$

$$= (N-1)h_E^j(x)(1-H_E^j(x))^{N-2}(1-H_I^j(x)). \tag{24}$$

D.2. Estimation of Cost Distributions

In this appendix, we provide 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 first-order conditions

$$\hat{c}^I = b^I - \frac{1 - G^{gr}_{I,M}(b^I|X,N)}{g^{gr}_{I,M}(b^I|X,N)} \tag{25}$$

$$\hat{c}^E = b^E - \frac{1 - G^{gr}_{E,M}(b^E|X,N)}{g^{gr}_{I,M}(b^E|X,N)}. \tag{26}$$

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

$$\begin{aligned} 1 - G^{gr}_{i,M}(b_i|X,N) &= Pr(b_i \le \min_{j \neq i} B_j|X,N) \\ 1 - G^{gr}_{E,M}(b_i|X,N) &= (1 - H^{gr}_E(b_i|X,N))^{N-2}(1 - H^{gr}_I(b_i|X,N)) \text{ (for an entrant)} \\ 1 - G^{gr}_{I,M}(b_i|X,N) &= (1 - H^{gr}_E(b_i|X,N))^{N-1} \text{ (for the incumbent),} \end{aligned} \tag{27}$$

where in the last two lines H^{gr}_E and H^{gr}_I denote the estimated bid distributions in gross auctions for entrants and the incumbent, respectively. $G^{gr}_{i,M}(b_i)$ 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

$$\begin{aligned} g^{gr}_{i,M}(b_i|X,N) &= \frac{\partial H^{gr}_i(b_i|X,N)}{\partial b_i} \\ g^{gr}_{I,M}(b_i|X,N) &= -(N-1)(1 - H^{gr}_E(b_i|X,N))^{N-2} h^{gr}_E(b_i|X,N) \text{ (for the incumbent)} \\ g^{gr}_{E,M}(b_i|X,N) &= -(N-2)(1 - H^{gr}_E(b_i|X,N))^{N-3} h^{gr}_E(b_i|X,N)(1 - H^{gr}_I(b_i|X,N)) \\ &\quad - g^{gr}_I(b_i|X,N)(1 - H^{gr}_E(b_i|X,N))^{N-1} \text{ (for entrants).} \end{aligned} \tag{28}$$

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

D.3. Derivation of the Second Step Net Likelihood

To evaluate the second step net likelihood, we need to compute the conditional expectation of other bidders' revenue signals in the expected valuation of winning the auction with bid b in Equation (3). The expectation term conditions on the bid being pivotal, i.e., $\min_{j \neq i} b_j = b$. From the first step, we only know the compound expected valuation conditional on winning with a bid b. Therefore, we have to decompose $\mathcal{P}^i$ into ρ_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 all bidders' first-order conditions for equilibrium bidding. We make use of the fact that in equilibrium, given the signal ρ_i, the conditional expectation term is a deterministic number 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 $\bar{\mathcal{P}}^{-i}(b)$. For any bidder $-i$, we can compute this compound signal by inverting $-i$'s bid function at the observed winning bid

$$\bar{\mathcal{P}}^{-i}(b) = b - \frac{1 - G^{net}_{-i,M}(b|X,N)}{g^{net}_{-i,M}(b|X,N)}. \tag{29}$$

Applying this logic to every bidder for a given line yields a sample of N expected valuations conditional on the winning bid b and the winner's identity. These equations have to be consistent 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

$$\mathcal{P}^i(b) = c_i - \alpha_i r_i - \mathbb{E}\left[\sum_{j \neq i} \alpha_j r_j | \min_{j \neq i} b_j = b\right] \text{ (for winner)} \tag{30}$$

$$\bar{\mathcal{P}}^j(b) = c_j - \alpha_j r_j - \mathbb{E}\left[\sum_{k \neq j} \alpha_k r_k | \min_{k \neq j} b_k = b\right] \text{ (for } N-1 \text{ rival bidders).} \tag{31}$$

This system is a fixed-point problem in N unknowns conditional on a set of parameters $(\alpha, \bar{R}, \sigma_r^2)$. The unknowns are the conditional expectations about the opponents' revenue signals and $\bar{\mathcal{P}}^j(b)$ can be computed from our estimation in the first step.

Observing from the bidding first-order conditions that r_j has to satisfy

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

The conditional expectation $\mathbb{E}\left[\sum_{k\neq j}\alpha_k r_k | \min_{k\neq j} b_k = b\right]$ has the following structure: It is computed conditional on the bid being pivotal, i.e., it conditions on at least one bidder placing the exact same bid b and all other bidders bidding no less than b.

Thus, for one opposing bidder, we need to compute the expected revenue signal such that the realized net cost signal induces the bidder to bid b, i.e., for any cost realization, the revenue signal must be equal to $r_j(c)$, which results in

(33) $$X_j^{=} := \mathbb{E}\left[r_j | b_j = b\right] = \int_{\underline{c}}^{\overline{c}} r_j(c)\frac{f_{c,j}(c) f_r\left(r_j(c)\right)}{\int_{\underline{c}}^{\overline{c}} f_{c,j}\left(x\right) f_r\left(r_j(x)\right)dx}dc,$$

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

For the remaining bidders, we need to compute the expected revenue signal such that their bid is not below b, i.e., for any cost realization, the revenue signal must not exceed $r_j(c)$

(34) $$X_j^{\geq} := \mathbb{E}\left[r_j | b_j \geq b\right] = \int_{\underline{c}}^{\overline{c}} \int_0^{r_j(c)} r\frac{f_r(r)}{\int_0^{r_j(c)} f_r(x)dx} dr f_{c,j}(c)dc.$$

For DB's expected revenue signals of other bidders, we obtain

(35) $$\mathbb{E}[\sum_{j\neq I}\alpha_j r_j | \min_{j\neq I} b_j = b] = X_E^{=} + (N-2)X_E^{\geq}.$$

For entrants, the expectation is more complicated, because the expected revenue varies with the identity of the bidder who places the same bid which has to be taken into account in the computation. Thus, we need to compute the probability with which DB places the minimum opposing bid, $P(j = I | b_j = b, \min_{j\neq i} b_j = b)$. We compute this probability using the estimated bid functions for net auctions and Bayes' rule to obtain

$$(36)\qquad P(j=I|b_j=b,\min_{j\neq i} b_j=b)$$
$$=\frac{h_I^{net}(b)(1-H_E^{net}(b))^{(N-2)}}{h_I^{net}(b)(1-H_E^{net}(b))^{(N-2)}+(N-2)h_E^{net}(b)(1-H_I^{net}(b))(1-H_E^{net}(b))^{(N-3)}}.$$

Therefore, the conditional expectation term for entrant bidders is

$$(37)\qquad \sum_{j\neq i}\alpha_j \mathbb{E}[r_j|\min_{j\neq i} b_j=b]=P(j=I|b_j=b,\min_{j\neq i} b_j\geq b)\left(X_I^{=}+(N-2)X_E^{\geq}\right)$$
$$+(1-P(j=I|b_j=b,\min_{j\neq i} b_j\geq b))\left(X_E^{=}+X_I^{\geq}+(N-3)X_E^{\geq}\right).$$

Using $r_i(c)$ from (32), we obtain an equation system with four equations in four unknowns

$$X_E^{=}=\int_{\underline{c}}^{\overline{c}} r_E(c)\frac{f_{c,E}(c)f_r\left(r_E(c)\right)}{\int_{\underline{c}}^{\overline{c}} f_{c,E}\left(x\right)f_r\left(r_E(x)\right)dx}dc$$
$$X_E^{\geq}=\int_{\underline{c}}^{\overline{c}}\int_0^{r_E(c)} r\frac{f_r(r)}{\int_0^{r_E(c)} f_r(r)dr}dr f_{c,E}(c)dc$$
$$X_I^{=}=\int_{\underline{c}}^{\overline{c}} r_I(c)\frac{f_{c,I}(c)f_r\left(r_I(c)\right)}{\int_{\underline{c}}^{\overline{c}} f_{c,I}\left(x\right)f_r\left(r_I(x)\right)dx}dc$$
$$X_I^{\geq}=\int_{\underline{c}}^{\overline{c}}\int_0^{r_I(c)} r\frac{f_r(r)}{\int_0^{r_I(c)} f_r(r)dr}dr f_{c,I}(c)dc$$

with

$$r_E(c)=\frac{1}{\alpha_E}\Big(c_E-\bar{\mathcal{P}}^E(b)-P(j=I|b_j=b,\min_{j\neq i} b_j\geq b)\left(\alpha_I X_I^{=}+(N-2)\alpha_E X_E^{\geq}\right)$$
$$-(1-P(j=I|b_j=b,\min_{j\neq i} b_j\geq b))\left(\alpha_E X_E^{=}+\alpha_I X_I^{\geq}+(N-3)\alpha_E X_E^{\geq}\right)\Big)$$
$$r_I(c)=\frac{1}{\alpha_I}\left(c_I-\bar{\mathcal{P}}^I(b)-(\alpha_E X_E^{=}+(N-2)\alpha_E X_E^{\geq})\right),$$

which follow from plugging in the expectations computed above.

Plugging $r_E(c)$ and $r_I(c)$ into the equations $(X_E^{=}, X_E^{\geq}, X_I^{=}, X_I^{\geq})$ yields an equation system of four equations with four unknowns that can be solved numerically for $(X_E^{=}, X_E^{\geq}, X_I^{=}, X_I^{\geq})$ for any given set of parameters $(\alpha, \bar{R}, \sigma_r^2)$ using the estimated distributions f_{c_i} from the gross auctions and the distributional assumptions on f_r. The 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.

Given the values of the conditional expectation terms, we can construct the likelihood function, for any guess of the parameter vector, from the first-order conditions for equilibrium bidding using the estimated values $\mathcal{P}^i$

$$\mathcal{P}^I = c_I - \alpha_I r_I - X_E^{=}(\theta_r, \alpha) - (N-2) X_E^{\geq}(\theta_r, \alpha) \tag{38}$$

$$\begin{aligned}\mathcal{P}^E = c_E - \alpha_E r_E - P(j = I | b_j = b, \min_{j \neq i} b_j \geq b) \left(X_I^{=}(\theta_r, \alpha) + (N-2) X_E^{\geq}(\theta_r, \alpha) \right) \\ - (1 - P(j = I | b_j = b, \min_{j \neq i} b_j \geq b)) \left(X_E^{=}(\theta_r, \alpha) + X_I^{\geq}(\theta_r, \alpha) + (N-3) X_E^{\geq}(\theta_r, \alpha) \right),\end{aligned} \tag{39}$$

where θ_r denotes the parameters characterizing the revenue signal distribution. In our application, we specify F_r to be truncated-normal (truncated from below at zero), so that $\theta_r = (\bar{R}, \sigma_r^2)$ contains only the mean and variance parameters of the parent normal distribution. The right hand side depends on the parameters $(\bar{R}, \sigma_R^2, \alpha)$ 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 $f_{\alpha_i r_i} = \frac{1}{\alpha_i} \mathcal{N}(r_i / \alpha_i; \bar{R}, \sigma_r^2, 0, \bar{r})$. c_i is distributed according to $f_c(c_i)$. Hence, the density of $c_i - \alpha_i r_i$ is

$$f_{c_i - \alpha_i r_i}(x) = \int_{-\infty}^{\infty} f_{-(\alpha_i r_i)}(y - x) f_c(y) dy, \tag{40}$$

where x is the right hand side of Equation (38), if the incumbent wins the auctions, and the right hand side of Equation (39) if the entrant wins the auction. This implies that we compute each likelihood contribution conditional on the winner's identity (and the winning bid). This conditioning takes into account the truncation issue that we observe $f_{c_i - \alpha_i r_i}$ only for the winner of each auction.[53]

[53] We cannot formally prove that our two functional form assumptions (Weibull for the bid distribution and truncated normal for the revenue signal distribution) are necessarily consistent, i.e., there may be a potential inconsistency from using parametric assumptions in both stages of the estimation. In principle, we could estimate the revenue distribution non-parametrically as follows. First, we estimate the bid distribution in net auctions, which implies a distribution of compound signals $\mathcal{P}$. Second, for each guess of the second-step net parameters, i.e., the asymmetry

Finally, the likelihood function for our second net auction step, that we use to estimate the parameter of the revenue signal distribution $(\bar{R}, \sigma_r^2)$ and the informational asymmetry parameters α is given by

$$LL(\bar{R}, \sigma_r^2, \alpha) = \sum_{t=1}^{T^{net}} \log\left(f_{c_i - \alpha_i r_i}(\mathcal{P}^i)\right), \tag{41}$$

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

D.4. Testing for FOSD

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 of 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

$$\begin{aligned}\widehat{V}(x) &= \widehat{V}_{c_E}(x) + \widehat{V}_{c_I}(x) \\ &= \frac{1}{NS}\left(\hat{F}_{c_E}(x) - \hat{F}^2_{c_E}(x) + \hat{F}_{c_I}(x) - \hat{F}^2_{c_I}(x)\right),\end{aligned}$$

parameters, we back out the implied revenue distribution non-parametrically analogously to the computation of the cost distribution in the gross sample. Finally, we compute the second-step net likelihood based on the parameter guesses, the associated non-parametric revenue distributions, and the cost distributions predicted from the gross sample. While this approach is, in principle, feasible, it results in a more complicated empirical model that is computationally much more intensive to estimate.

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

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

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 ten 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

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

The first condition captures whether, for at least one grid point, the entrant's cost CDF is significantly below the cost CDF of the incumbent. The second 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 ∞ (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.

E. Additional Estimation Results

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

E.1. Bid Distribution Parameter Estimates

Table 8 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.

Table 8: Estimation results: Bid distribution parameters

	Gross auctions	Net auctions
λ_X^I	-0.6426*	1.1619***
	(0.3367)	(0.3846)
	1.7429***	-1.1251*
	(0.6210)	(0.6706)
	1.3521***	0.1726
	(0.2179)	(0.1348)
	0.1727	0.2435
	(0.1191)	(0.2369)
	1.2839	3.2364***
	(0.9224)	(1.1277)
λ_N^I	-0.2682	10.5870***
	(1.0830)	(2.0026)
λ_X^E	1.1420***	0.9314***
	(0.1887)	(0.2025)
	2.7054***	1.3215
	(0.9474)	(0.9202)
	1.1296***	1.1209***
	(0.1242)	(0.2282)
	0.1540	-0.4168***
	(0.1013)	(0.1395)
	0.7209	2.3082**
	(0.6264)	(1.1281)
λ_N^E	0.2742	0.6100
	(1.9124)	(1.8694)
ν_X^I	1.6196**	-0.1086
	(0.7100)	(0.7018)
	-11.5680**	2.5577
	(4.5340)	(1.8910)
	-3.2628***	-0.2547
	(0.8925)	(0.4195)
	-0.7832	-1.2940***
	(0.7294)	(0.4988)
	26.6270***	3.2674
	(6.3005)	(3.5282)
ν_N^I	-14.3550*	-1.4683
	(7.7988)	(8.6893)
ν_X^E	-0.6131	0.7037
	(0.6298)	(0.5880)
	-8.0118**	1.8994
	(3.7140)	(2.3571)
	-1.1936***	-0.5452**
	(0.3906)	(0.2587)
	-0.3281	0.4472
	(0.3478)	(0.4577)
	10.7990***	2.9456
	(2.8146)	(3.1909)
ν_N^E	6.5620	-2.4968
	(5.8253)	(5.4757)

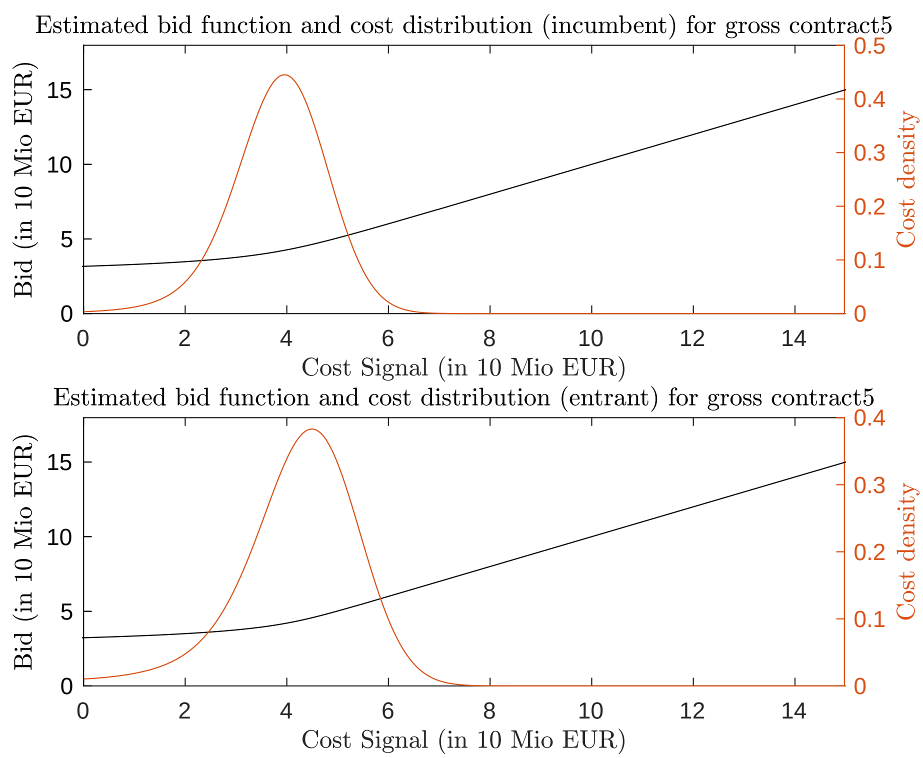
*Notes: MLE-SE in parentheses. *,**,*** denote significance at the 10%, 5% and 1%-level respectively.*

E.2. Bid Functions and Cost Distribution Estimates

E.2.1. Gross Auction Sample

In this appendix, we provide bid functions and estimated cost distributions for several 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 1 and 2 are representative of many lines in our sample and illustrate that generally, the incumbent does not have a substantial cost advantage over the entrants resulting in relatively symmetric bid functions for incumbent and entrants. Figure 3 is representative of the subset of lines in our sample in which the incumbent has a significant cost advantage.

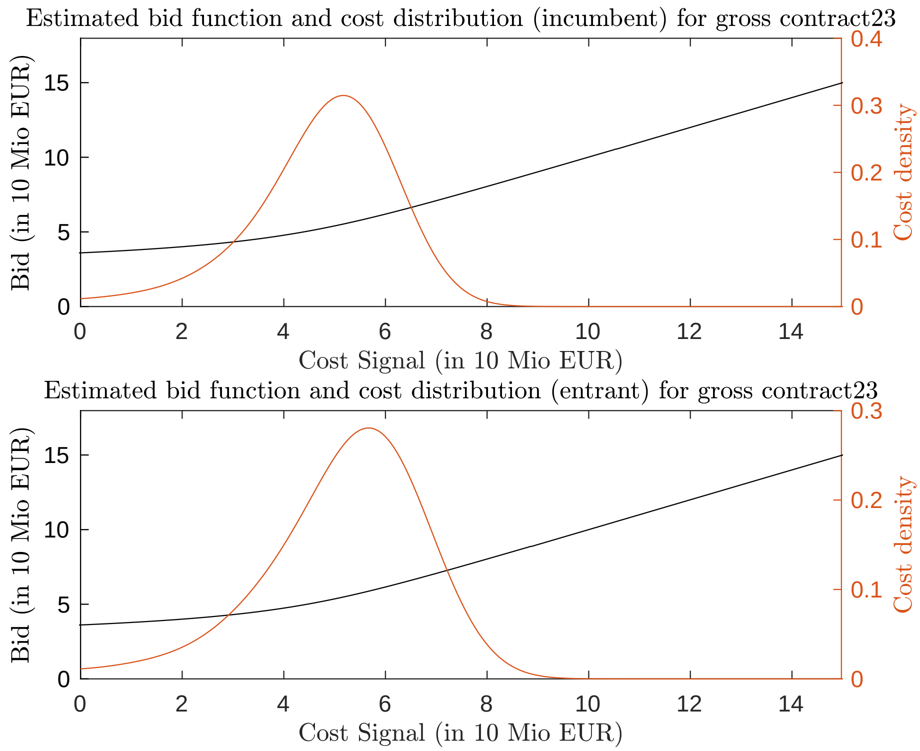
Figure 1: Cost density and bid function for gross auction 5



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.

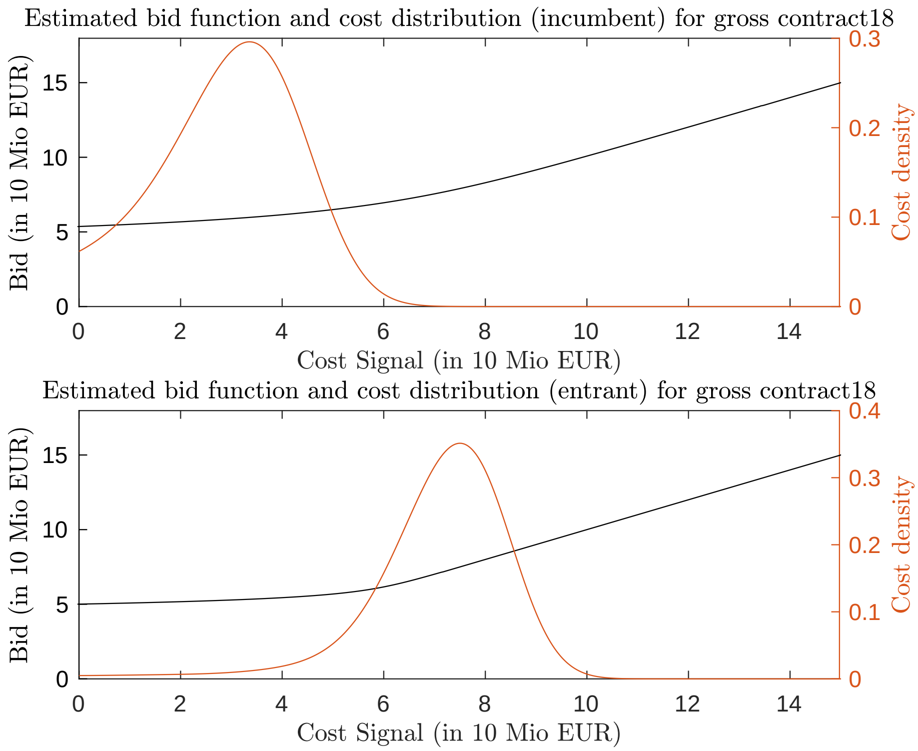
Figure 4 displays the histogram of the incumbent's relative cost advantage as measured by the

Figure 2: Cost density and bid function for gross auction 23



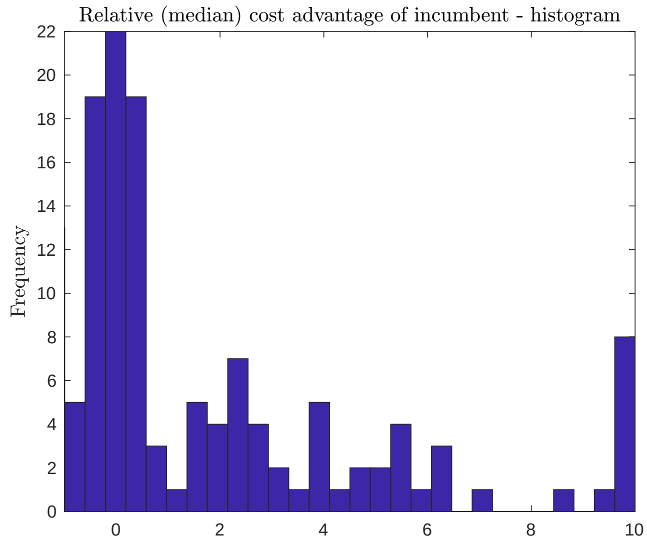
Notes: This graph compares the estimated bid functions and cost distributions for the incumbent (top panel) and entrants (bottom panel) for a specific gross auction in our sample.

Figure 3: 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 4: Comparison of median 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).

estimated median cost for different lines. A negative number indicates that the entrant has a lower median cost for fulfilling the contract. For example, on the positive axis, 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 on which entrants seem to have a cost advantage, and for the majority of lines, the incumbent's cost advantage is modest. On the other hand, a considerable number of contracts (roughly 25% of our sample) are much more costly for the entrants to operate when compared to the incumbent's cost distribution.

F. Computation of Efficiency Measures

In this appendix, we provide additional details about how we compute efficiency probabilities and expected winning bids for both the observed gross and net auction sample and the counterfactual in which net auctions are procured as gross auctions. An important advantage of our counterfactuals is that we can use the estimated bid distributions and primitives for cost distributions, revenue distributions, and asymmetry parameters to compute efficiency probabilities and predicted winning bids in closed form without having to solve numerically for the counterfactual bidding strategies. In light of the substantial computational difficulties in solving numerically for equilibria in asymmetric auctions –see, for example, Hubbard et al. (2013); Hubbard and Paarsch (2014)– we consider this a significant advantage of our counterfactual, in which we only change the auction mode from net to gross auctions. This is possible because our gross sample estimation results allow us to compute the counterfactual bid distributions of the net auction sample when it is procured under a gross auction format. We discuss the details about how we compute the implied efficiency probabilities and expected winning bids analytically in Appendix F.1 and F.3 below.

F.1. Gross Auctions

In this appendix, we detail how the probability in Equation (9) can be rewritten in terms of the bid distributions exclusively. 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 (9) corresponds to the condition

$$b_j \geq b_j(\phi_i(b)) \, \forall j \neq i. \tag{42}$$

Therefore, we can rewrite

$$\Pr(c_i \leq \min_{j \neq i} c_j | b \leq \min_{j \neq i} b_j) = \frac{\Pr\left(b \leq b_j \, \forall j \neq i \cap b_j \geq b_j\left(\phi_i(b)\right) \, \forall j \neq i\right)}{\Pr(b \leq \min_{j \neq i} b_j)}, \tag{43}$$

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

$$\Pr(c \leq \min_{j \neq i} c_j | b \leq \min_{j \neq i} b_j) = \frac{\Pr\left(b_j \geq b \cap b_j \geq b_j\left(\phi_i(b)\right)\ \forall j \neq i\right)}{\Pr(b \leq \min_{j \neq i} b_j)}. \tag{44}$$

The numerator can be solved for each bidder 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

$$\begin{aligned}
\Pr(\text{the incumbent wins with } b) &= \Pr(\text{incumbent bids } b \text{ and all entrants bid } b_e \geq b) \\
&= h_I^{gr}(b)\left(1 - H_E^{gr}(b)\right)^{N-1} \qquad (45)\\
\Pr(\text{an entrant wins with } b) &= \Pr(\text{an entrant bids } b \text{ and all other bidders bid } b_i \geq b) \\
&= (N-1) h_E^{gr}(b)\left(1 - H_E^{gr}(b)\right)^{N-2}\left(1 - H_I^{gr}(b)\right), \qquad (46)
\end{aligned}$$

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

$$\begin{aligned}
&\int_{\underline{b}}^{\bar{b}} \Bigg(h_I^{gr}(b)\left(1 - H_E^{gr}(b)\right)^{N-1} \frac{\Pr\left(b_j \geq b \cap b_j \geq b_j\left(\phi_I(b)\right)\ \forall j \neq I\right)}{\Pr(b \leq \min_{j \neq i} b_j)} + \\
&(N-1) h_E^{gr}(b)\left(1 - H_E^{gr}(b)\right)^{N-2}\left(1 - H_I^{gr}(b)\right) \frac{\Pr\left(b_j \geq b \cap b_j \geq b_j\left(\phi_E(b)\right)\ \forall j \neq E_w\right)}{\Pr(b \leq \min_{j \neq i} b_j)} \Bigg)\, db, \qquad (47)
\end{aligned}$$

where E_w denotes the winning entrant.

F.2. Net Auctions

In net auctions calculating the efficiency measure is more involved because we have to consider 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; the revenue signal per se is irrelevant. Therefore, we cannot rely on the estimated bid distributions only. Instead, we have to combine them with the estimated primitives, i.e., cost distributions f_c, revenue distributions f_r, and asymmetry parameters α.

We proceed in several steps to compute the efficiency measure. 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. Formally, the efficiency probability in Equation (9) can be written as

$$\int_{\underline{b}}^{\overline{b}} A^I(b)h_I^{net}(b)\left(1-H_E^{net}(b)\right)^{N-1}+A^E(b)(N-1)h_E^{net}(b)\left(1-H_I^{net}(b)\right)\left(1-H_E^{net}(b)\right)^{N-2}db, \tag{48}$$

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

$$A^I(b)=\int_{\underline{c}}^{\overline{c}}\left(B^E(c)\right)^{N-1}\frac{f_r\left(r_I(c)\right)f_{c_I}(c)}{\int_{\underline{c}}^{\overline{c}}f_r\left(r_I(x)\right)f_{c_I}(x)dx}dc \tag{49}$$

$$A^E(b)=\int_{\underline{c}}^{\overline{c}}B^I(c)\left(B^E(c)\right)^{N-2}\frac{f_r\left(r_E(c)\right)f_{c_E}(c)}{\int_{\underline{c}}^{\overline{c}}f_r\left(r_E(x)\right)f_{c_E}(x)dx}dc \tag{50}$$

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

$$B^E(c)=\int_{\rho_E(\rho_I(b))}^{\overline{\rho}}C^E(\rho)\frac{f_{\rho_E}(\rho)}{\int_{\rho_E(\rho_I(b))}^{\overline{\rho}}f_{\rho_E}(x)dx}d\rho \tag{51}$$

$$B^I(c)=\int_{\rho_I(\rho_E(b))}^{\overline{\rho}}C^I(\rho)\frac{f_{\rho_I}(\rho)}{\int_{\rho_I(\rho_E(b))}^{\overline{\rho}}f_{\rho_I}(x)dx}d\rho, \tag{52}$$

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 ρ_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

$$C^E(\rho) = \int_c^{\bar{c}} f_r(r_E(\tilde{c})) f_{c_E}(\tilde{c}) d\tilde{c} \tag{53}$$

$$C^I(\rho) = \int_c^{\bar{c}} f_r(r_I(\tilde{c})) f_{c_I}(\tilde{c}) d\tilde{c}, \tag{54}$$

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 ρ_i given a cost realization c and is determined by $r_i(c) = \frac{1}{\alpha_i}(c - \rho_i(b))$.

F.3. Computation of Expected Winning Bids

We compute the expected winning bid in auction j based only on the estimated bid distributions for each auction mode and each bidder type using

$$\int_{\underline{b}}^{\bar{b}} b \left(h_I^j(b)(1 - H_I^j(b))^{N-1} + (N-1) h_E^j(b)(1 - H_E^j(b))^{N-2}(1 - H_I^j(b) \right) db, \tag{55}$$

where H_i^j and h_i^j denote the (estimated) distribution and density function of the bid of bidder type i in auction j, respectively.

F.4. Decomposing the Efficiency Loss in Net Auctions

In this appendix, we provide additional details about how we decompose the efficiency loss in net auctions and obtain the statistics reported in Table 4. As for the main counterfactual described in Section 6, we avoid the numerical intricacies associated with solving explicitly for equilibria in asymmetric first-price auctions. The purpose of the table is not to compute equilibrium efficiency probabilities but rather to disentangle the total difference in the auctions' ex-ante efficiencies between gross and net auctions into its distinct sources. For column *non-strategic*, we calculate the probability that the firm with the lowest cost signal wins the auction conditional on reporting *truthfully* the realized compound signal, i.e., the sum of the revenue signal r_i and the cost signal c_i. This non-strategic bidding behavior reveals the loss in efficiency due to the revenue signal adding noise to the cost signal that would occur in a net auction even in the absence of any strategic interaction.

For a given auction, we compute the efficiency probability by simulation. For each simulation draw, we simulate pairs of cost and revenue signals for the incumbent and each of the $(N-1)$ participating entrants. The signals are drawn from the auction-type specific estimated cost distributions and the auction-specific revenue signal distribution, which does not vary across bidder types. We then added the two signals for each bidder to find the non-strategic hypothetical bid for each bidder. Next, we check whether the bidder with the lowest bid is also the bidder with the lowest private cost signal. If this is the case, we declare the simulated auction as efficient. If not, we declare the auction as inefficient. We average this efficiency indicator over all simulation draws for a given auction. Throughout this exercise, we use 5,000 simulation draws per auction. The reported 0.77 efficiency probability is the average of this statistic over all auctions.

In column *w/ gross markups* we calculate the probability that the firm with the lowest cost signal wins a net auction if bidders bid *as if* the revenues were not a common but a private value. We consider this an economically interesting exercise as it combines the noise from the revenue signal with the strategic bidding behavior resulting from private value asymmetries. We proceed similarly to the first column: For a given auction and a given simulation draw, we simulate pairs of cost and revenue signals for the incumbent and each of the $(N-1)$ participating entrants. The signals are drawn from the auction-type specific estimated cost distributions and the auction-specific revenue signal distribution, which does not vary across bidder types. We then add the two signals for each bidder to find the hypothetical net cost signal. We then compute the markup that a bidder would charge on this compound net cost signal if she treated the signal as a pure private value signal. We obtain this markup from the estimated bid and cost distributions from the gross auction estimation. We then assume that each bidder bids its net cost signal plus the gross auction markup. We then compare whether the bidder with the lowest predicted bid (net cost signal + gross markup) is also the bidder with the lowest private cost realization. If this is the case, we declare the simulated auction as efficient. If not, we declare the auction inefficient. We average this efficiency indicator over all simulation draws for a given auction. Throughout, we use 5,000 simulation draws per auction. The reported 0.60 efficiency probability is the average of this statistic over all auctions.

G. Entry Stage

In this appendix, we describe the details of our entry model and summarize our estimation of the entry probabilities and the entry costs.

G.1. Model

Our entry model follows the framework introduced by Levin and Smith (1994) and is only played among entrants, i.e., DB enters with probability 1 in all auctions. We assume that DB is not active in the entry game because industry experts agree that DB participates in all auctions (see Frankfurter Allgemeine Zeitung (2011)). Denote the set of potential bidders including DB by $\mathcal{N}$ and the set of actual bidders by N.[54] Denote the cost of entry to an auction by κ. We assume that firms do not observe their specific cost and revenue signals before making an entry decision.[55] Instead, they only know the distribution of cost and revenue signals based on which they compute the expected profits of entering an auction with N bidders denoted by $\pi_e(N)$. In this setup, Assumptions 1 to 5 in Levin and Smith (1994) are satisfied and a unique symmetric Nash equilibrium in mixed strategies exists. Each bidder decides to enter the auction with probability $q \in (0, 1)$ such that the expected profit from entering the auction is zero. We summarize the equilibrium of the entry game in the following lemma.

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

$$\sum_{N=2}^{\mathcal{N}} \left(\binom{\mathcal{N}-2}{N-2} q^{N-2} (1-q)^{\mathcal{N}-N} \pi_e(N) \right) = \kappa. \tag{56}$$

The left-hand side of Equation (56) 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

[54] 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.

[55] We do not consider selective entry as, for example, in Sweeting and Bhattacharya (2015) because in the German SRPS market, it seems plausible that competitors of DB do not hold private information before deciding to invest into entry. Firms make considerable investments in learning about auction-specific information. For example, they hire specialized consultants to acquire information about the cost structure and to support firms in estimating future revenues.

is taken over all potential bidder configurations that can occur if the entrant under consideration has decided to enter.[56]

G.2. Estimation Procedure

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.

We define the set of potential bidders in the entry game for a particular contract 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. Based on our arguments in Section 2 we consider the entrant firms to be symmetric and to not hold private information before entering an auction, i.e., they know the distribution of signals, and therefore $\pi_e(X, N)$, but bidders receive their actual signals for costs and revenues only after having paid the entry cost.

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[57]

$$\Pi_e(X, \mathcal{N}) = \sum_{N=2}^{\mathcal{N}} \pi_e(X, N) \Pr(N | X, \mathcal{N}, i \in N), \tag{57}$$

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'

[56] Our entry model is not central to our analysis of bidder asymmetries at the bidding stage. In particular, the estimation of the bidding stage is unaffected by the structure of the entry model because it uses the bidding stage as an input but not vice versa. We believe that the entry model presented here fits our application reasonably well. Developing a richer entry model is possible but goes beyond the scope of this paper.

[57] Recall that $\mathcal{N}$ includes DB, so that there are only $\mathcal{N} - 1$ potential entrant firms.

entry behavior is binomial and given by

$$\Pr(N|X, \mathcal{N}, i \in N) = \binom{\mathcal{N}-2}{N-2} q^{N-2}(1-q)^{(\mathcal{N}-N)}. \tag{58}$$

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

$$q(X, \mathcal{N}) = \frac{\exp(\beta_X X + \beta_N \mathcal{N})}{1 + \exp(\beta_X X + \beta_N \mathcal{N})}. \tag{59}$$

We estimate the parameters (β_X, β_N) by maximum likelihood using the observed bidder entry in the combined (gross and net) sample. As auction covariates X, we include 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 network served. In addition, we include a dummy for net auctions to capture that entry costs can be systematically different across auction formats.

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

$$\kappa(X, \mathcal{N}) = \Pi_e(X, \mathcal{N}). \tag{60}$$

G.3. Estimation Results

Table 9: Estimation results: Entry costs

	Gross auctions	Net auctions
Median (in million EUR)	4.0082	5.9232
SD (in million EUR)	6.7929	3.4392

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.

Table 9 summarizes the results from our entry cost estimation. The bid preparation costs of entrants are high for both auction modes. The median entry cost is considerably smaller for gross auctions than net auctions (EUR 4.0 million versus EUR 5.9 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.