# ASSESSING SOCIAL COSTS OF INEFFICIENT PROCUREMENT DESIGN

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**Abstract**

This paper considers the social costs implied by inefficient allocation of contracts in a first-price, sealed-bid procurement auction with asymmetric bidders. We adopt a constrained (piecewise linear) strategy equilibrium concept and estimate the structural parameters of the bidders' distribution of costs. We estimate social costs defined as the predicted cost difference between the winning firm and the most efficient bidding firm. We also compare the expected procurement costs under two different auction formats. The data is collected from procurement auctions of road painting in Sweden during 1993–1999. The results indicate that the social costs of inefficient contract allocation is about 2% of total potential production cost and that an efficient second-price auction would lower the expected procurement cost by 2.5%. (JEL: D44, H57, C15)

## 1. Introduction

Government agencies frequently use first-price, sealed-bid auctions as a tool for allocating contracts of goods and services. The monetary value of these procurement auctions may constitute a substantial fraction of the country's GDP. Hence, issues relating to such market mechanisms are of great importance for policy makers as well as other market participants. Consequently, a rapidly growing body of economic literature is devoted to the first-price, sealed-bid auction and issues such as optimal auction design, cartel formation, endogenous entry, and so forth (see e.g., Klemperer (1999) and Sareen (2002) for recent surveys on theoretical and empirical work on auctions). This paper is mainly concerned with the inefficient allocation of contracts that might take place in first-price, sealed-bid auctions with asymmetric bidders.

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The celebrated revenue equivalence theorem states that standard auction formats all yield the same expected revenue to the auctioneer (Vickrey 1961). The main assumptions required to reach this result include that the bidders behave noncooperatively and that they are risk neutral, and ex ante symmetric. For alternative sets of assumptions, the revenue ranking for the standard auction formats (English, Dutch, Vickrey, and first-price sealed-bid) has been established by various authors (see e.g., Milgrom and Weber 1982a, 1982b; Hansen 1984; Maskin and Riley 2000a). However, for a social planner, there are also other criteria of interest in the design of procurement mechanisms. For example, one may want to assure an efficient allocation of contracts.

In public procurement of construction contracts, as considered in this paper, the bidding firms usually differ in size, location, and backlogs at the time of the bidding. These differences may indicate that the firms face different opportunity costs of completing the contract. If these variations across firms are observable by the market participants, then the bidders are ex ante asymmetric in the sense that they draw their costs from disparate distributions; equivalently, the joint distribution of costs is asymmetric. This asymmetry implies that the first-price, sealed-bid auction fails to guarantee that the contract is allocated to the most efficient firm. In particular, one can show that a firm with a stochastically dominated distribution of costs bids less aggressively (further from its private cost) than other firms with stochastically dominating cost distributions (e.g., Pesendorfer 2000). Hence, the situation may arise that the lowest bidder is not the firm with the lowest costs. Consequently, the allocation of contracts is not Pareto efficient, and the efficiency loss is related to the differences in costs between the winning and the low-cost firms. The allocation of contracts is such that the procurement cost is minimized (within the auction format) whereas the production cost may be suboptimal. The social cost is defined as the difference between the production cost implied by the contract allocation and the minimum production cost among the bidders. Toward this end we ignore second-order effects in terms of costs of funds—that is, the deadweight loss caused by taxation to finance the project.

In order to quantify the social costs generated by these asymmetries, we need to compare private costs across the bidding firms. Usually the private costs of the bidding firms are not observed by the researcher. Hence, we need to infer the costs based on the observed bids. A common assumption is that the observed bids are generated by some equilibrium strategy profile in a Bayesian–Nash game. (For existence and uniqueness of such an equilibrium in asymmetric first price auctions, see e.g., Maskin and Riley 2000b and McAdams 2003.)

There are a few methods proposed in the literature on how to estimate private costs in asymmetric first-price, sealed-bid auctions. The direct approaches specify (up to a vector of unknown parameters) the joint distribution of private costs. This distribution defines the equilibrium strategies and the observed distribution of bids. Maximum likelihood, (simulated) method of moments, or quantile estimators can then be applied to estimate the unknown vector of parameters (see e.g., Paarsch 1992; Laffont and Vuong 1996; Bajari 2000; Hong and Shum 2000, 2002).[1] An intrinsic problem with this approach is that the researcher must derive the equilibrium strategy profile in order to map the distribution of unobserved costs to the distribution of observed bids.[2] This strategy profile is defined as the solution to a system of differential equations that rarely has a closed form. Numerical methods for solving the system of differential equations are required, and such methods are generically slow and unstable in these cases. Bajari (2001) and Marshall et al. (1994) discuss some numerical algorithms for solving the equilibrium bid functions.

Guerre, Perrigne, and Vuong (2000) initialized a second branch of indirect methods wherein they note that the unobserved cost is a function of the observed bid, the joint distribution of bids, and the number of bidders via the first-order condition of the equilibrium bids. By estimating the distribution of bids nonparametrically, one can create a "pseudo cost" and estimate the distribution of costs without having to find the equilibrium strategies. However, since the method is nonparametric it requires a large amount of data and/or a small number of covariates. An important feature of this method is that it facilitates testing of the theory in that the implied equilibrium bid functions should be monotonic in costs. An application to asymmetric first-price auctions is presented in Campo, Perrigne, and Vuong (2003).

A related yet parametric indirect approach is proposed by Jofre-Bonet and Pesendorfer (2003), who parameterize the distribution of bids and again use the first-order condition to solve for unobserved costs. Their model is used to account for the dynamic structure of recurrent procurement auctions of paving contracts in California. In this case, the researcher must be careful when choosing the parametric family of the joint bid distribution, since the implied equilibrium strategies should be monotonic.

The Bayesian–Nash equilibrium strategy profile can be very difficult to derive, and this fact has motivated some researchers to look at approximations of these unconstrained strategies. Armantier, Florens, and Richard (2003, AFR) propose such a method, where the bidders are assumed to be constrained in the strategy space to some predefined parametric strategies. The authors prove that, if there is an accumulation point in the strategy space as the constrained strategies become infinitely "flexible," then this point is also a Bayesian–Nash equilibrium in the unconstrained game. This approach requires parametric specification of the joint distribution of costs, but it avoids the the problematic issue of finding the

1. References on nonstructural studies in asymmetric first-price auctions can be found in e.g., Pesendorfer (2000).

2. In some special cases the researcher can rely on the revenue equivalence theorem to circumvent this problem; see e.g., Laffont, Ossard, and Vuong (1995).

unconstrained Bayesian–Nash equilibrium. Instead, the researcher is required to solve a system of nonlinear equations. The existence of such a constrained strategic equilibrium must be asserted in each case. Besides the application presented here, another empirical exercise using the constrained strategic equilibrium can be found for example in Armantier and Sbaï (2003), which considers asymmetric treasury auctions.

In this paper, we adopt the constrained strategic equilibrium approach to analyze bidding behavior in auctions for road marking contracts in Sweden from 1993 to 1999. We assume that the behavior is well described within the independent private values paradigm. We eschew nonparametric methods partly because we do not have enough data, and partly because we want to simulate over the estimated distribution of private costs in a later exercise. Finally, we argue that our data does not fit the dynamic game presented by Jofre-Bonet and Pesendorfer (2003) since there is no "continuous" procurement of contracts in Sweden. In contrast, all contracts are procured within a short period of time in the spring and the work undertaken is generally concentrated within a few months during the summer. This implies that the bidding firms cannot observe their backlog until most contracts are already allocated.[3]

Section 2 describes the constrained strategic equilibrium in the asymmetric first-price sealed-bid auction game and then presents some comparisons with the unconstrained Bayesian–Nash equilibrium. Section 3 presents the market and the data. Section 4 presents the econometric specifications, and the results are presented in Section 5. Section 6 concludes.

## 2. Constrained Strategic Equilibrium

This section presents the constrained strategic equilibrium (CSE) adapted to the case of asymmetric first-price, sealed-bid auctions within the independent private values paradigm. For a generic and comprehensive exposition with approximation theorems and an existence proof, see Armantier, Florens, and Richard (2003). In what follows, we consider a single auction for the sake of notational simplicity. In the empirical application, the derived strategies will differ across firms and auctions.

The set of bidders, denoted by $\mathcal{N}$, consists of $n$ firms (indexed by $i = 1, \ldots, n$), competing for a government contract in a first-price, sealed-bid auction. The auction format implies that the firms submit bids simultaneously and that the low bidder wins the contract. Prior to the auction, the bidders are informed about the contract characteristics and receive a private cost $t_i \in \mathcal{T} \subset \mathbb{R}$ independently

3. The firms do know how many bids they have submitted at any given time, so there is an issue of expected backlog. Modeling the behavior in this dynamic game is beyond the scope of this paper.

drawn from a distribution $F_i(t)$ with support on $[\underline{t}, \bar{t}]$. The bidders do not observe the cost draws of the competitors, but they can observe the distributions from which the costs are drawn.

Let $\mathcal{S}$ denote the set of feasible strategies in the unconstrained auction game. For each bidder, the set of feasible constrained strategies is denoted by $\mathcal{S}^{(K)} \in \mathcal{S}$, which is a compact and convex set of functions indexed by a $K$-dimensional vector. The strategy of firm $i$, $s_i^{(K)} \in \mathcal{S}^{(K)}$, maps private costs to bids $s_i^{(K)}(t) = b \in \mathcal{B} \subset \mathbb{R}$. In this application, we define $\mathcal{S}^{(K)}$ as the set of piecewise linear splines with $K$ segments and predefined kinks. In order to reduce the dimensionality of the strategies, we impose the restriction that bid equals cost at the upper support, that is, $s_i^{(K)}(\bar{t}) = \bar{t}$.[4] This implies that there are $K$ "free" parameters for each firm that uniquely define firm $i$'s constrained strategy such that $s_i^{(K)}(t) = s^{(K)}(t; \mathbf{d}_i)$, where $\mathbf{d}_i = (d_{i1}, \ldots, d_{iK})' \in \mathcal{D} \subset \mathbb{R}^K$ (henceforth, we shall drop the superscript $K$, which indicates constrained $K$-dimensional strategies). In the application we have chosen to define the strategies in terms of slopes of the segments. That is, firm $i$'s strategy is formulated as

$$s(t; \mathbf{d}_i) = \bar{t} + \sum_{k=1}^{K} d_{ik} \mathbf{1}(\tau_k - t)(t - \tau_k) \quad \forall t \in [\underline{t}, \bar{t}] \tag{1}$$

where $\mathbf{1}(x)$ is a step function equal to 1 if $x \geq 0$ and 0 otherwise and $\tau_k$ denotes the $k$th kink and $\tau_K = \bar{t}$.[5] A suitable set of kinks $\tau = (\tau_1, \tau_2, \tau_3)$ is determined by the distribution of types. Toward this end we first use ocular inspection of the unconstrained Bayesian–Nash equilibrium (BNE) strategies to find the regions where the second derivative of the strategies with respect to types is high (in absolute values) and then position the kinks in those regions.

Firm $i$'s profit conditional on the vector of firms' private costs $\mathbf{t} = (t_1, \ldots, t_n)$, and the strategy profile $\mathbf{s} = \mathbf{s}(\mathbf{t}; \mathbf{d}) = (s(t_1; \mathbf{d}_1), \ldots, s(t_n; \mathbf{d}_n)) = (s_1, \ldots, s_n) \in \times_{i=1}^{n} \mathcal{S}$ is

$$\widetilde{U}_i(\mathbf{t}, \mathbf{s}) = (s(t_i; \mathbf{d}_i) - t_i)\mathbf{1}(y_i - s(t_i; \mathbf{d}_i))$$

where $y_i = \min_{j \neq i}\{s_j(t_j; \mathbf{d}_j)\} \in \mathcal{B}$ denotes the low bid of $i$'s opponents. Let $G_i(y)$ denote the distribution of $y_i$ with support $[\underline{y}_i, \bar{y}_i]$ and let $\widetilde{\mathbf{U}} = (\widetilde{U}_1(\mathbf{t}, \mathbf{s}), \ldots, \widetilde{U}_n(\mathbf{t}, \mathbf{s}))$. We assume that the structure of the game of incomplete information $\Gamma = (\mathcal{N}, \mathcal{T}, F, \mathcal{S}, \widetilde{\mathbf{U}})$ is common knowledge.

4. This condition stems from a boundary condition in the unconstrained Bayesian–Nash equilibrium; see Maskin and Riley (2000b) and Lebrun (1999).

5. This parameterization implies that the slope coefficient of the $j$th segment is $\sum_{k=j}^{K} d_{ik}$. We have tried other parameterizations such as low-order polynomials, but the piecewise linear splines turn out to be more stable and flexible.

Firm $i$'s unconditional profit associated with the strategy profile $\mathbf{s}$ is thus

$$\begin{aligned} U_i(s_i, \mathbf{s}_{-i}) &= \int_{\underline{t}}^{\overline{t}} \cdots \int_{\underline{t}}^{\overline{t}} \widetilde{U}_i(\mathbf{t}, \mathbf{s})\, dF(\mathbf{t}) \\ &= \int_{\underline{t}}^{\overline{t}} \int_{\underline{y}}^{\overline{y}} (s(t; \mathbf{d}_i) - t)\mathbf{1}(y - s(t; \mathbf{d}_i)) dG_i(y)\, dF_i(t) \end{aligned}$$

where $F(\mathbf{t})$ denotes the joint distribution of bidders' private costs and $\mathbf{s}_{-i} = \mathbf{s}\backslash s_i$. A constrained strategic equilibrium (CSE) defined in the strategy space is a strategy profile satisfying the mutually best-response condition such that

$$U_i(s_i^*, \mathbf{s}_{-i}) \geq U_i(s_i, \mathbf{s}_{-i}) \quad \forall s_i^*, s_i \in \mathcal{S},\ i = 1, \ldots, n$$

where the CSE profile is denoted by $\mathbf{s}^* = (s_1^*, \ldots, s_n^*)$.[6] We will follow AFR in assuming that there exists such an equilibrium in the constrained strategic concept.

Because the strategies are indexed by the vectors $\mathbf{d} = (\mathbf{d}_1, \ldots, \mathbf{d}_n)$, the CSE profile $\mathbf{s}^*$ can equivalently be defined in terms of the parameter vectors $\mathbf{d} = (\mathbf{d}_1, \ldots, \mathbf{d}_n)$ as the solution to the following maximization and fixed point problem: $\forall i = 1, \ldots, n$,

$$\begin{aligned} \mathbf{d}_i^* &= \arg\max_{\mathbf{d}_i \in \mathcal{D}} U_i(s(t_i, \mathbf{d}_i), \mathbf{s}_{-i}(\mathbf{t}_{-i}, \mathbf{d}_{-i})) \\ &= \arg\max_{\mathbf{d}_i \in \mathcal{D}} \int_{\underline{t}}^{\overline{t}} \int_{\underline{y}_i}^{\overline{y}_i} (s(t, \mathbf{d}_i) - t)\mathbf{1}(y_i - s(t, \mathbf{d}_i))\, dG_i^{(K)}(y; \mathbf{d}_{-i})\, dF_i(t) \end{aligned}$$

where we have highlighted that the distribution of opponents' low bids, $G_i^{(K)}(y; \mathbf{d}_{-i})$, is a function of the opponents' strategy parameters collected in $\mathbf{d}_{-i}$.

In solving the maximization problem we apply Monte Carlo integration techniques.[7] Conditional on the vectors of strategy parameters in $\mathbf{d}$, it is trivial to transform random cost draws from $F(\mathbf{t})$ to bids and draws from $G_i^{(K)}(y)$. However, the objective function is not continuous in $\mathbf{d}_i$ because a small change in the strategy vector $\mathbf{d}_i$ could change the value of the step function, which would complicate the numerical optimization. We therefore apply a smooth approximation of the step function using the logistic distribution kernel such that

$$\mathbf{1}(x) \approx K_h(x) = \frac{e^{x/h}}{1 + e^{x/h}}.$$

6. The reason for using ex ante payoffs is that the equilibrium strategy is defined in the strategy space rather than the action space. For unconstrained games these definitions are equivalent, but this is not necessarily true for constrained strategic games. See AFR for a discussion on the relation between equilibrium concepts in the strategy and action spaces.

7. See e.g., Judd (1998) for an introduction to Monte Carlo integration techniques.

Let $(t_i^r, y_i^r)$ denote respectively independent random draws from $F_i(t)$ and $G_i^{(K)}(y)$ where $y_i^r = \min_{j \neq i}\{s(t_j^r, \mathbf{d}_j)\}$, and consider $R$ such draws. The maximization problem can then be approximated by

$$\mathbf{d}_i^* \approx \arg\max_{\mathbf{d}_i \in \mathcal{D}} \frac{1}{R} \sum_{r=1}^{R} (s(t_i^r, \mathbf{d}_i) - t_i^r) K_h(y_i^r - s(t_i^r, \mathbf{d}_i)) \qquad \forall i = 1, \ldots, n.$$

Since the constrained strategies are simple functions of the parameters in $\mathbf{d}_i$, we can easily derive the $nK$ first-order conditions for this maximization problem as

$$\begin{aligned} \frac{\partial U_i(s(\cdot, \mathbf{d}_i^*), \mathbf{s}_{-i}(\cdot, \mathbf{d}_{-i}))}{\partial d_{ik}} = \frac{1}{R} \sum_{r=1}^{R} \frac{\partial s(t_i^r, \mathbf{d}_i)}{\partial d_{ik}} \Big\{ & K_h(y_i^r - s(t_i^r, \mathbf{d}_i)) \\ & + (s(t_i^r, \mathbf{d}_i) - t_i^r) k_h(y_i^r - s(t_i^r, \mathbf{d}_i)) \Big\} = 0 \\ \forall k = 1, \ldots, K \qquad \forall i = 1, \ldots, n & \end{aligned} \tag{2}$$

where we have assumed that the optimum occurs at the interior of $\mathcal{D}$ and $k_h(x) = dK_h(x)/dx$. For our choices of parametric forms of $s(t, \mathbf{d}_i)$ and $K_h(x)$, all derivatives on the right-hand side have simple closed forms. Hence, finding the CSE amounts the problem of finding the solution to the $nK$-system of nonlinear equations in (2).

Of central importance for this method is careful selection of $\mathcal{D}$ and of starting values for the iterative process of finding the roots in (2). If we are successful in these selections, the algorithm converges quickly and is surprisingly stable in our experience. In the empirical application we have restricted $\mathcal{D}$ to the set of parameters $\{(d_{i1}, \ldots, d_{ik})\}$ such that the strategy defined in equation (1) $(a)$ is monotonically increasing in $t$ and $(b)$ implies nonnegative profits; that is, $s(t, \mathbf{d}_i) \geq t$ for all $t \in [\underline{t}, \bar{t}]$.

In Figures 1 and 2 we illustrate the CSE for a set of asymmetric firms and its relation to the unconstrained BNE. We use a set of three asymmetric bidders, whose the distribution of types is assumed to be truncated normal $N(\mu_i, \sigma^2)$, where $\mu = (13, 14.5, 16)$, $\sigma = 3$, and $t_i \in [5, 25]$. The CSE is approximated using $R = 10{,}000$ Halton draws.[8] The kink points are defined as $(\tau_1, \tau_2, \tau_3) = (\bar{\mu} - 1.25\sigma, \bar{\mu} + 0.5\sigma, \bar{t})$. The unconstrained BNE is numerically calculated by a "forward shooting" algorithm (Runge–Kutta) combined with a

8. Halton draws are so-called equidistributed sequences on the interval [0, 1]. These are frequently used in state-of-the-art simulation-based methods in the discrete choice literature (see Train 2003). They can be interpreted as a pseudo-random sequence with better coverage than standard pseudo-random sequences produced e.g., by linear congruential algorithms. Monte Carlo studies have indicated that using Halton draws reduces the simulation variance considerably.

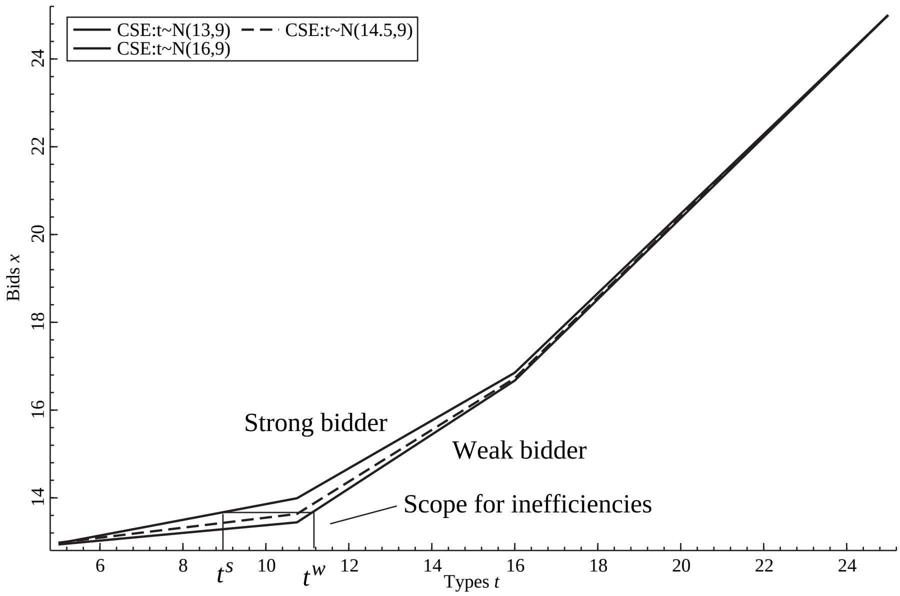


FIGURE 1. Constrained strategy equilibrium (CSE) with three asymmetric bidders and three piecewise linear splines.

search algorithm for the lower support of bids, as discussed in Bajari (2001, pp. 194–195). The solutions presented in the figure are poor in the upper region of the cost distributions owing to numerical issues. The horizontal axis shows the costs (types) and the vertical axis shows the equilibrium bid. As can be seen in the figures, the CSE solution has the same general appearance as the unconstrained solution and is reasonably close in levels in the most important regions. Of course, this relies on the positioning of the kinks, and it would be preferable if these could be determined endogenously in the optimization step. Although this is possible, it renders the optimization more problematic; hence we have chosen to use ocular inspection of the unconstrained solution to find reasonable positions of the kinks as functions of the distributions of types.

In the empirical application we also want to verify to what extent the CSE approximates the unconstrained equilibrium.[9] There are a number of criteria that could be applied. As discussed in detail in AFR, we could look at a sequence of CSEs, $\{\mathbf{s}^{(K),*}\}$ as $K \to \infty$ and focus on how the sequence of payoffs or equilibrium bids converges. If the payoffs and/or equilibrium bids changes slowly as $K$ increases then we might conjecture that the approximation is close to the accumulation point (i.e., the Bayesian–Nash equilibrium). However, we will focus on a

9. Comparisons between analytical and CSE solutions is performed e.g., by Armantier and Richard (2000).

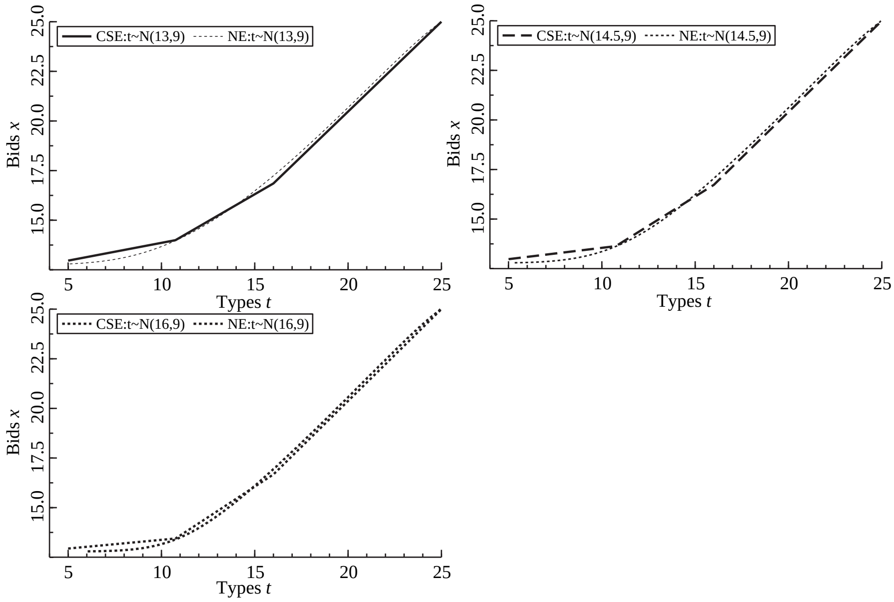


FIGURE 2. CSE and BNE with three asymmetric bidders.

computationally more convenient criteria with a straightforward game-theoretic interpretation, also proposed in AFR.

Consider the expected gains a bidder would make by using an unilateral best response in the action space, given that the opponents still use their constrained strategies. This implies that the bidder can unilaterally deviate from his constrained strategy whereas the opponents cannot. Formally, consider the expected utility

$$U_i^{\mathrm{BR}}(\mathbf{s}_{-i}^*) = \int_{\underline{t}}^{\overline{t}} \max_{b \in \mathcal{B}} \int_{\underline{y}_i}^{\overline{y}_i} (b-t)\mathbf{1}(y-b)\, dG_i^*(y)\, dF_i(t)$$
$$\approx \frac{1}{L}\sum_{l=1}^{L} \max_{b\in\mathcal{B}} \frac{1}{R}\sum_{r=1}^{R} (b-t^l)K_h(y^r-b)$$

where $G_i^*(y)$ denotes the distribution of firm $i$'s opponents low bid in CSE. The criteria we will use is based on the relative difference between the best response expected utility and the expected utility in the CSE, namely

$$C_i = \frac{U_i^{\mathrm{BR}}(\mathbf{s}^*) - U_i(\mathbf{s}^*)}{U_i(\mathbf{s}^*)}. \tag{3}$$

A value of $C_i$ close to zero indicates that, for firm $i$, the actions implied by the constrained strategy are "close" (in the payoff sense) to constituting an equilibrium in the extensive-form game with an unilateral unrestricted strategy space. Hence, the bidder has a weak incentive for unilaterally deviating from the CSE. This is taken as an (inconclusive) indication of that CSE being close to the unconstrained BNE.

## 3. Data and Market Characteristics

Each spring, the Swedish Road Administration (SRA henceforth) contracts firms for maintenance of road markings in Sweden.[10] The firms are contracted through a first-price, sealed-bid auction. The SRA's seven regional offices—where a regional office is responsible for the procurement in its region—conduct the auctions. A region consists of three or four provinces. In each province, there are normally three types of road marking contracts subject to procurement bidding: thermoplastic, spray plastic, and hand-applied road markings. Each contract is let in a separate auction. The local office requires in general that a bidding firm submit its sealed bids for the desired contracts simultaneously for all the provinces in their region. Also, each local office decides on its own when to announce the contracts for the procurement of road markings in its region, when the sealed bids must be tendered, and when to announce the results. Therefore, the outcome of the auctions in one region may or may not be common knowledge before the firms must submit their bids in another region. During the studied period 1993–1999, twelve firms have been active in bidding. Some of them are nationwide, meaning that they can operate in every province in Sweden, whereas other firms operate in just a few provinces. The contracted firms normally fulfill their undertaking during the summer (May–September).

The local office invites firms to tender bids for contract of road markings by advertising the project and, on request, by sending out an inquiry document to potential bidding firms. Among other things, this document contains information about the demanded quantity of marking color, technical requirements of the road marking material, required thickness and width of road markings, instructions on how the bids will be evaluated, and the last possible day to tender bids. The tendered bids are denoted in price per kilo or price per meter. A bidding firm is also usually required to enclose descriptions of its organization as well as the type of material and the road marking equipment it intends to use.

To collect the data we went to the SRA's local offices and obtained extracts from minutes of the results from the auctions. We have focused upon the procurement of thermoplastic road markings, which represents about half of the SRA's

10. For 1993–1999, on average the SRA spent about 100 million SEK yearly on procurement of different types of road markings (1 SEK $\approx$ 0.105 euro).

total cost for procurement of road markings. The data set covers all procurement auctions of thermoplastic road markings in every province for the period 1993–1999. The original data set consists of 138 auctions with a total of 621 bids.[11] All bids are tendered in terms of price per unit (kilo or meter).[12] The data set also contains information about the date and province of each auction, the quantity (in tons) of road marking material demanded, the number of firms that received the inquiry document, and the identity of all bidders. We converted all bid data into real terms (1999 price level) using a branch price index.[13]

The data that we collected refers exclusively to contract characteristics, such as size measured in tons, $\mathrm{TON}_{it}$, contract site, and so forth. However, in the analysis it is important to capture any difference across firms that may explain some of the variation in the bids. At this stage we focus on two different dimensions. Since road markings require heavy equipment (trucks, boilers, etc.), a firm's distance to the contract site may influence its costs. Furthermore, the production also requires some special skills of the work force. Hence, given that a firm has limited access to these specialists, a firm's costs may be characterized by increasing marginal costs. We construct two variables that measure these dimensions.

From their office minutes we extract the location of the bidding firms' headquarters (and production plants in the relevant cases). We assume that a firm must transport its equipment from this location to the contract site. Since we do not have access to the true distance, we construct a pseudo-distance as the Euclidean distance between the headquarters (production plant) and the geographical center of the province in which the contract is to be undertaken. The distance is scaled such that it approximately reflects the distance in kilometers. If a firm has more than one production plant, we automatically define the distance as the distance between the closest plant and the contract province.

The second variable measures a firm's "reserved" utilization rate at any given time. This variable is constructed in two steps. First, we calculate the total contract size, measured in tons, that each firm has won in any single year. Firm $i$'s capacity,

11. In a couple of auctions we lack some of the rejected bids.

12. A contract for thermoplastic road marking implies painting both thick and thin lines. For a given quantity of road marking material, the thicker the line, or the broader the line, the lower the contractor's cost per kilo. In the inquiry document the local office very roughly specifies over what types of road marking lines the demanded quantity material is to be distributed. As a general rule, the bidding firms do not submit their bids in terms of a total sum for carrying out the contract but rather in terms of price per kilo or price per meter for each type of road marking line. Once all the bids are submitted, the SRA computes each firm's bid as a weighted average of its prices for the various types of lines. The weight put on each price is given in the inquiry document, i.e., it is common knowledge prior to the deadline. The firm that submits the lowest weighted average bid gets the contract. For the years 1993–1995, the tendered bid has been a weighted average price per kilo, and since 1996 a firm's bid is expressed as a weighted average price per meter. Using the relationship between price per meter and the quantity of road marking material needed to produce one meter's worth of road marking of a given type of line, we have converted all bids into price per kilo.

13. The branch index is "Entreprenadindex E84 2162 Vägmarkeringar", which includes wage rates, material costs, etc. for this type of construction project.

$\mathrm{CAP}_i$, is then defined as the maximum total contract size that firm $i$ has won in any year. Next, a firm's utilization rate at the letting of contract $t$, $\mathrm{UTIL}_{it}$, is defined as the ratio between the sum of the sizes of the previously won (and announced) contracts in auctions within the same year but prior to the letting of auction $t$ and the firm's capacity. We measure the "potential" utilization rate, $\mathrm{PUTIL}_{it}$, as the ratio between the sum of won and unannounced contracts (in tons) at the letting date of contract $t$ and the firm's capacity.[14] It should be noted that the SRA is not the single buyer of these services, since also municipalities procure road markings. Therefore, a firm's utilization rate may be hidden because we observe only part of the market for any firm. Moreover, some of the firms are involved in other types of construction projects that may affect the firm's utilization rate. However, at this stage we abstract from these features. We also construct an indicator variable $\mathrm{INCUM}_{it}$ that equals 1 if firm $i$ was the incumbent bidder on contract $t$, and we construct variables that control for some of the competitors' costs. For each firm we construct the variables $\mathrm{CMIND}_{it}$ and $\mathrm{CMINU}_{it}$ which are defined as the minimum distance and utilization rate of the bidding competitors.[15]

We shall give some descriptive statistics of the sample used in the empirical analysis. From the original data set, consisting of 621 bids, we have excluded auctions relating to the Gotland region (28 bids).[16] Furthermore, in order to identify firm-specific effects, we need to exclude those few firms that are observed only in a small number of auctions. If we lack information on some bidders in an auction, this implies that we cannot infer the cost distribution for that firm. This consequently invalidates the use of any observations relating to that specific auction. Finally, we exclude any auction consisting of fewer than three bidders.

There are 90 auctions in the remaining sample. Table 1 presents some statistics on the allocated contracts and the bidding firms. In panel A, the firm-specific variables refer to the contracted firm. The sample statistics indicate that the winning firm is geographically closer and has a lower utilization rate than a bidding firm on average which indicates that there may be some asymmetries relating to these firm-specific variables. Panel C shows 9, 16, 37, and 28 contracts with 3, 4, 5, and 6 bidders, respectively. The average percentage difference between the lowest and the second lowest bid is 3.2%; this measure varies between 0% and 20% with a standard deviation of 3.1%, indicating that there is substantial private information regarding costs.

14. A firm has "won a contract at time $t$" if the winner (the firm) of the contract has been publicly announced. A firm's "open contracts" are those on which the firm has submitted bids yet no winner has been announced. In many cases, several contracts have the same letting date. In such cases we have included those bids submitted to the other contracts in the open contracts.

15. Note that we use the bidding, not the potential, competitors' observable costs.

16. Gotland is an island some distance east of Sweden. There is a single bidder active on Gotland that almost exclusively wins all contracts.

TABLE 1. Descriptive statistics on contracts and winning bids (90 contracts).

| | Mean | Std | Min | Max |
|---|---|---|---|---|
| A. Contract attributes and winning firms (90 contracts) | | | | |
| No. of bids | 4.93 | 0.94 | 3.00 | 6.00 |
| Bid per kg (SEK) | 14.71 | 0.71 | 11.85 | 16.33 |
| Ton | 169.70 | 109.26 | 35.00 | 575.00 |
| Distance ($\approx$ km) | 92.73 | 62.60 | 20.12 | 403.76 |
| Reserved util. rate | 0.09 | 0.16 | 0.00 | 0.65 |
| Potential util. rate | 0.96 | 0.92 | 0.00 | 5.69 |
| Incumbent firm | 0.50 | 0.50 | 0.00 | 1.00 |
| B. Firm characteristics (444 bids) | | | | |
| Bid per kg (SEK) | 15.36 | 1.03 | 11.85 | 21.23 |
| Distance ($\approx$ km) | 147.99 | 108.50 | 18.99 | 696.97 |
| Reserved util. rate | 0.14 | 0.22 | 0.00 | 1.00 |
| Potential util. rate | 1.20 | 1.13 | 0.00 | 5.95 |
| Incumbent firm | 0.16 | 0.36 | 0.00 | 1.00 |
| Diff., low–second bid (in %) | 3.2 | 3.1 | 0 | 20 |
| C. No. of bidders | 3 | 4 | 5 | 6 |
| No. of contracts | 9 | 16 | 37 | 28 |

Note: 1 SEK $\approx$ 0.1 euro.

## 4. Econometric Specifications

In order to assess the importance and source of asymmetries, we initially estimate a simple reduced form for bid levels using contract attributes and firm characteristics as regressors. In the reduced form, we are not constrained to contracts for which we can observe the characteristics of all bidding firms. Hence, the sample used for this analysis is larger than the sample used for the structural analysis. The sample consists of 578 observed bids. The reduced bid-level model is defined as

$$\ln b_{ic} = \mathbf{z}'_{ic}\theta + \hat{\lambda}_{ic}\gamma + \epsilon_{ic} \tag{4}$$

where $\mathbf{z}_{ic}$ includes contract $c$'s attributes (including region dummies), firm $i$'s characteristics (including firm dummies), and the number of bidders, and $\hat{\lambda}_{ic}$ denotes the estimated Mill's inverse ratio based on $\hat{\delta}$ from equation (5) to control for selection bias. The $\theta$ and $\gamma$ parameters are estimated using OLS with robust standard errors.

Because the error term in the bid level equation could be correlated with the decision to submit a bid, we need to account for sample selection bias in that equation. The selection equation is defined as

$$q^*_{ic} = \mathbf{w}'_{ic}\delta + \nu_{ic} \quad \forall i, c \tag{5}$$

where $\mathbf{w}_{ic}$ is a vector of contract attributes and firm characteristics (including region and firm dummies) and $\nu_{ic} \sim N(0, 1)$. The firm is assumed to submit a bid if, and only if, $q^*_{ic} > 0$. The set of independent variables includes variables that affect the firms' probabilities of winning and the profits conditional on winning. The parameter vector $\delta$ is estimated using maximum likelihood on the sample of all observed firms in the data set. Hence, we assume that all firms are potential bidders for all contracts.

As indicated by the unconstrained Bayesian–Nash equilibrium, $\mathbf{z}_{ic}$ and $\mathbf{w}_{ic}$ should include contract attributes as well as firm characteristics of all firms. However, in order to reduce the number of independent variables, we only include firm $i$'s characteristics and a small subset of the opponent firms' characteristics believed to have important influence on profits and probability of winning—namely, the minimum of the bidding competitors' distances and reserved utilization rates.

In some regressions we include reserved and potential utilization rates as well as an indicator for incumbent firm in the vector of firm characteristics. One should note that these variables could be considered endogenous since they are determined by previous bidding behavior. However, as mentioned initially, the timing of the procurements implies that the winners in one region are usually not announced before the bids are to be submitted in other regions. This suggests that the utilization rate is unknown, and therefore irrelevant, for bidding behavior in most auctions. However, the potential utilization rate measures the quantity on which the firm has submitted bids on up to the date of the auction. One can argue that the potential utilization rate affects bidding behavior via capacity constraints. The incumbency variable may also be endogenous if, for example, the firms believe that winning the province contract for one specific year reduces the costs for contracts in succeeding years in the same region. We argue that this is not necessarily the case here because each contract involves several small work sites scattered over the province. That is, local knowledge in one year does not necessarily spill over in cost advantages in subsequent contracts. In contrast, we believe that the incumbency variable captures measurement errors in the distance variable—for example, if the firms have depots in the regions that are unreported in the procurement minutes.

The element of interest in the structural analysis is the distribution of types, $F_i(t)$, which is the distribution of costs in this application. This distribution is assumed to be truncated normal with constant variance across firms and contracts.[17] Hence, the structural parameters to be estimated are the coefficients in the conditional (linear) mean $\beta$ and the variance $\sigma^2$ such that

$$F_{ic}(t) = F(t; \mathbf{v}_{ic}, \beta, \sigma^2) = \frac{\Phi\left(\frac{t-\mathbf{v}'_{ic}\beta}{\sigma}\right)}{\Phi\left(\frac{25-\mathbf{v}'_{ic}\beta}{\sigma}\right) - \Phi\left(\frac{5-\mathbf{v}'_{ic}\beta}{\sigma}\right)} \quad \text{for } t \in [5, 25] \qquad (6)$$

17. An obvious alternative would be to allow for firm- and/or contract-dependent variances. However, since the dependent variable is measured in terms of cost per unit (kilo) and since the contracts are fairly homogeneous in the production process, we assume that the variances of private costs per unit are identical across all observations.

where $\mathbf{v}_{ic}$ is a vector of contract attributes and firm characteristics and where $\Phi(\cdot)$ denotes the standard normal distribution function. As will be clear, the truncation occurs very far out in the tails, so the truncation probability in the denominator is very close to unity. Hence, for the sake of simplicity we will actually use OLS to estimate the parameters in equation (6).

If the cost draws, $t_{ic}$, were observable then the estimation would be completely standard, using (say) maximum likelihood methods on the sample likelihood function associated with equation (6). Unfortunately the costs are not observed and this straightforward estimator is not feasible. One alternative would be to derive the associated likelihood function of the observed bids, which is a function of the parameters in $F_{ic}(\cdot)$ and the CSE parameters in $\mathbf{d}_c$. This likelihood is a nontrivial transformation of the joint distribution of types and likely is most very difficult to find.

A more computationally convenient estimator, proposed by Florens, Protopopescu, and Richard (1997) and Armantier and Richard (2000), is defined as the solution to the following fixed point problem. Consider a candidate vector of structural parameters $(\beta^{(l)}, \sigma^{(l)})$ indexed by $l$. Given this vector and the vector of contract attributes and firm characteristics, we can solve for the CSE parameters $\mathbf{d}_c^{(l)}$ using the techniques presented in Section 2.[18] Thus, we can then apply the inverse strategy profile to the observed bids and generate types that correspond to observed bids as

$$t_{ic}^{(l)} = s^{-1}(\mathbf{x}_{ic}; \mathbf{d}_{ic}^{(l)}).$$

Taking these types as observed, we can trivially apply the unfeasible estimator and produce new (updated) estimates on the structural parameters $(\beta^{(l+1)}, \sigma^{(l+1)})$. We can then repeat the procedure to find a updated set of types, and so on. Assuming that the sequence $\{\beta^{(l)}, \sigma^{(l)}\}$ converges as $l \to \infty$, it follows that the estimator (and the solution to the fixed point problem) is defined as the convergence point; that is,

$$\hat{\beta} = \beta^{(l+1)} = \left( \sum_{ic} \mathbf{v}_{ic}\mathbf{v}_{ic}' \right)^{-1} \sum_{ic} \mathbf{v}_{ic} t_{ic}^{(l)}, \tag{7}$$

$$\hat{\sigma}^2 = \sigma^{2,(l+1)} = \frac{1}{C} \sum_{c=1}^{C} \frac{1}{n_c} \sum_{i=1}^{n_c} \left( t_{ic}^{(l)} - \mathbf{v}_{ic}' \beta^{(l+1)} \right)^2, \quad l \to \infty.$$

In practical applications we cannot let $l \to \infty$. Hence, we apply a "double-stop rule" by which we check for relative changes in the parameter and the type

18. The bandwidth of the logistic kernel is chosen as $h = 1.06(\text{std}) R^{-1/5}$ where std is the standard deviation of the simulated sample (Silverman 1986).

space. Specifically, we stop the iterative process when the following criteria are satisfied:

$$\max_{ic} \left| \frac{t_{ic}^{l+1} - t_{ic}^{l}}{t_{ic}^{l}} \right| < 0.0001,$$

$$\max \left| \frac{\beta^{l+1} - \beta^{l}}{\beta^{l}} \right| < 0.0001,$$

$$\max \left| \frac{\sigma^{l+1} - \sigma^{l}}{\sigma^{l}} \right| < 0.0001.$$

The set of kinks $\tau_c = (\tau_{c1}, \tau_{c2}, \tau_{c3})$ is defined as functions of the distribution of types. We want these kinks to be located close to the regions where there is "much action" in the strategies — that is, where (the absolute value of) the second derivative of the unconstrained strategies with respect to types is high. Numerous inspections for various sets of distribution of types suggested that using $(\tau_{c1}, \tau_{c2}, \tau_{c3}) = (\bar{\mu}_c - 1.25\sigma^{(l)}, \bar{\mu}_c + 0.5\sigma^{(l)}, \bar{t})$ works well in our application, where $\bar{\mu}_c = 1/n_c \sum_{i=1}^{n_c} \mathbf{v}_{ic}' \beta^{(l)}$.

To assess the quality of the CSE at the fixed-point solution defined by equation (7), we present some descriptive statics on the criteria proposed in equation (3). The expected "best response" profit (per unit) is approximated using $L = 1{,}000$ and $R = 10{,}000$ Halton draws. The expected profit (per unit) in the CSE is approximated using $R = 10{,}000$ Halton draws. We also present some illustrations on the relations between the best-response and CSE actions.

Since Monte Carlo techniques are employed to solve the CSE, we should account for the contribution from simulations in the estimator for the covariance matrix. This could be done either by using theoretical results on these contributions or by bootstrapping techniques. Unfortunately, there are no theoretical results known to us that apply to this sort of estimation, and the time to convergence is too high for allowing a reasonable amount of bootstrap samples. Consequently, we have used a large number of Halton draws ($R = 10{,}000$) when approximating the integrals in the CSE solution, and we presume that this is sufficient for the simulation contributions to be small in comparison to the sampling variance. The standard errors presented in the tables refer to the estimated OLS covariances.[19]

The expected social cost of inefficient allocation of contracts, denoted by $S$, can be defined as the expected difference between the contracted firm's contract cost and the lowest contract cost in the set of bidding firms.[20] In an efficient

19. We have replicated the analysis using 20,000 Halton producing results almost identical to the results presented below. This indicates that the number of random draws used in the analysis is sufficient to produce stable results.

20. Note that we weight the bids measured in SEK per kilo by the reported size of the contract in tons.

auction, this difference is always zero. We approximate this expectation using the average of a large number $M$ of simulated outcomes of the observed procurements. In the simulations, we use the observed distribution of contract attributes and firm characteristics. Specifically, we use the following definition:

$$S_c = \frac{1}{M}\sum_{m=1}^{M}(t_{jc}^{m} - \min_i\{t_{ic}^{m}\}_{i\in\mathcal{N}_c})\mathrm{TON}_c = T_c^{\mathrm{fp}} - T_c^{\mathrm{min}}$$

$$S = \sum_{c=1}^{C} S_c$$

where $t_{ic}^{m}$ denotes firm $i$'s cost draw in the $m$th simulation for contract $c$ and where $j$ is the index of the winning firm. The average simulated costs for winning firms of contract $c$ is denoted by $T_c^{\mathrm{fp}}$ and the average minimum cost of the bidding firms is denoted by $T_c^{\mathrm{min}}$. The set of bidding firms for contract $c$ is denoted by $\mathcal{N}_c$. The predicted social cost in the sample, denoted by $\hat{s}$, is calculated using the predicted types and observed winner:

$$\hat{s} = \sum_{c=1}^{C}(\hat{t}_{jc} - \min\{\hat{t}_{ic}\}_{i\in\mathcal{N}_c})\mathrm{TON}_c.$$

In the results we present the relative social costs, which are the social costs divided by the minimum costs—that is, $S/\sum_{c=1}^{C} T_c^{\mathrm{min}}$.

In the asymmetric case, the second-price (Vickrey) auction is an efficient mechanism. However, it is not clear whether this auction mechanism yields significantly lower procurement costs than the first-price mechanism. Hence, in the following exercise we will compare the procurement cost outcomes of the two competing mechanisms. We define the expected excessive procurement cost, denoted by $P$, as the difference between the total procurement cost in a first-price auction procedure and the potential total cost under a second-price procedure. Formally:

$$P_c = \frac{1}{M}\sum_{m=1}^{M}(x_{jc}^{m} - \min_i\{t_{ic}^{m}\}_{i\in\mathcal{N}_c\backslash c})\mathrm{TON}_c = X_c^{\mathrm{fp}} - X_c^{\mathrm{sp}}$$

$$P = \frac{1}{C}\sum_{c=1}^{C} P_c$$

where $x_{jc}^{m}$ denotes the winning bid in the first-price auction, $\min_i\{t_{ic}^{m}\}_{i\in\mathcal{N}_c\backslash c}$ denotes the second-lowest cost of bidding firms (representing the winning bid in the second-price auction), and $X_c^{\mathrm{fp}}$ and $X_c^{\mathrm{sp}}$ denote the average winning bids

TABLE 2. Estimates on submission and bid levels of active firms.

| Coeff. | Probit (a) | All bids (b) | Winning bids (c) | Nonwinning bids (d) |
|---|---|---|---|---|
| CONST | 4.08** | 2.72** | 2.60** | 2.73** |
| | (0.83) | (0.04) | (0.07) | (0.04) |
| LNTON | 0.16* | −0.02** | −0.01 | −0.02** |
| | (0.08) | (0.00) | (0.01) | (0.00) |
| NBIDS | | −0.01 | −0.00 | −0.01* |
| | | (0.00) | (0.01) | (0.00) |
| LNDIST | −0.64** | 0.02** | 0.02* | 0.02* |
| | (0.12) | (0.01) | (0.01) | (0.01) |
| UTILR | 0.55 | 0.01 | −0.08** | 0.01 |
| | (0.34) | (0.02) | (0.03) | (0.02) |
| PUTILR | 0.05* | −0.01** | −0.00** | −0.01 |
| | (0.02) | (0.00) | (0.00) | (0.00) |
| LNCMIND | −0.07 | 0.01 | 0.02 | 0.01 |
| | (0.14) | (0.01) | (0.01) | (0.01) |
| CMINU | 2.79** | 0.09* | 0.17** | 0.07 |
| | (0.92) | (0.04) | (0.05) | (0.05) |
| INCUM | 1.28** | −0.01* | −0.02 | 0.01 |
| | (0.34) | (0.01) | (0.01) | (0.01) |
| $\lambda$ | | 0.06** | −0.03 | 0.07** |
| | | (0.02) | (0.02) | (0.02) |

Notes: The dependent variable is $\ln(bid)$. In columns (b)–(d), White's standard errors are presented in parentheses.
* and ** denotes (respectively) significance on 10% and 1% level (double-sided). Firm and region dummies included but not reported here.

in the first- and second-price auctions, respectively. The predicted excessive procurement cost in the sample is calculated as

$$\hat{p} = \sum_{c=1}^{C} (x_{jc} - \min_i \{\hat{t}_{ic}\}_{i \in \mathcal{N}_c \setminus j}) \mathrm{TON}_c$$

i.e., the difference between the observed bid and the predicted second low cost of the bidding firms. In the results, we will report the relative excessive costs defined as $P / \sum_{c=1}^{C} X_c^{\mathrm{fp}}$.

## 5. Results from Auctions of Road Marking Contracts

In Table 2, we present the estimated parameters of reduced form as defined in eqations (4) and (5). We also present estimates on bid levels based on 124 winning and 454 nonwinning bids.

The results in Table 2 exhibit some interesting features. The probit model indicates that the probability of submitting a bid decreases with distance LNDIST and increases with the potential utilization rate PUTILR and the minimum utilization rate of competitors CMINU. The former may be an artifact of firms submitting bids on numerous contracts simultaneously due to the timing of auctions. We also notice that incumbent firms are significantly more likely to submit a bid, which could reflect that the distance variable is measured with error. The contract size LNTON is significantly positive at the 10% level, which suggests that larger contracts receive more attention from potential contractors.

There are also significant differences across firms and regions (not reported in the table), indicating that firms are potentially asymmetric. The results are in general consistent with economic intuition, except that a firm's potential utilization rate was expected to be negatively correlated with the submission decision as a result of capacity constraints. However, it follows from intuition to find that the minimum utilization rate of competitors is significantly and positively correlated with the entry decision. One potential interpretation of this is that a firm supposes that its competitors are "busy" and therefore (falsely) expects them to submit higher bids. As this would increase a firm's expectation of winning the contract, it increases the incentives for submitting a bid.

The parameters of the bid level model based on all bids (578 observations) generally exhibit the expected signs: larger contracts receive lower bids per unit (bids are in SEK per kilo), whereas distance and competitors minimum utilization rate increase the bid levels. Neither the number of bidders nor the distance of competitors enters in a significant way, although the signs are as expected. The exception is the potential utilization rate, which enters in a negatively significant way; that is, higher utilization rates imply lower bid levels, all else equal. This could be explained perhaps by a U-shaped cost function with respect to the utilization rate, where most firms are situated on the downward-sloping segment. Finally, the $\beta_\lambda$ parameter LAMBDA is significantly positive, indicating that the error terms in the submission and bid level functions are positively correlated. One (counterintuitive) interpretation of this is that a firm that is more likely to submit a bid is also more likely to submit a high bid.

Column (c) presents the results based on the winning bids (124 observations), column (d) the nonwinning bids (454 observations). Some interesting results emerge from these estimates. The utilization rate and the potential utilization rate reduce the bid level for winning firms. Furthermore, a higher utilization rate of competitors implies higher bids. Column (d) shows the corresponding estimates based on the nonwinning bids. The main differences between the results in (c) and (d) are:

1. contract size and number of bidders enters with a negative significant coefficient in nonwinning bids;
2. the utilization rate, the potential utilization rate, and the competitors' utilization rates are not significant for nonwinning bids;
3. the estimated parameter $\beta_\lambda$ is insignificant for winning bids (almost negatively significant) but significantly positive for nonwinning bids.

TABLE 3. Estimates on structural parameters.

| | Costs (a) | Bids (b) | Costs (c) | Bids (d) |
|---|---|---|---|---|
| CONST | 14.833** | 16.434** | 15.133** | 16.675** |
| | (0.819) | (0.570) | (0.859) | (0.602) |
| LNTON | −0.574** | −0.670** | −0.573** | −0.674** |
| | (0.121) | (0.084) | (0.122) | (0.085) |
| LNDIST | 0.596** | 0.439** | 0.561** | 0.408** |
| | (0.106) | (0.074) | (0.110) | (0.077) |
| UTIL | | | −0.462 | −0.206 |
| | | | (0.329) | (0.230) |
| PUTIL | | | −0.027 | −0.015 |
| | | | (0.070) | (0.049) |
| INCUM | | | −0.411* | −0.231* |
| | | | (0.164) | (0.115) |
| NCC | 0.692** | 0.520** | 0.694** | 0.510** |
| | (0.206) | (0.144) | (0.230) | (0.161) |
| JOC | 0.826** | 0.741** | 0.726** | 0.690** |
| | (0.199) | (0.139) | (0.201) | (0.140) |
| CLE | 0.185 | 0.157 | 0.102 | 0.114 |
| | (0.205) | (0.143) | (0.209) | (0.146) |
| FOG | −0.560* | 0.037 | −0.628* | −0.011 |
| | (0.257) | (0.179) | (0.257) | (0.180) |
| SAN | −0.352 | −0.295 | −0.491 | −0.389 |
| | (0.868) | (0.605) | (0.881) | (0.617) |
| PRO | 0.531* | 0.437** | 0.449* | 0.388** |
| | (0.213) | (0.148) | (0.215) | (0.150) |
| STOC | −0.322 | −0.201 | −0.257 | −0.161 |
| | (0.272) | (0.190) | (0.276) | (0.193) |
| SKAN | −0.361 | −0.199 | −0.277 | −0.161 |
| | (0.546) | (0.381) | (0.547) | (0.383) |
| SYDO | −0.447* | −0.313* | −0.340* | −0.257* |
| | (0.191) | (0.133) | (0.198) | (0.138) |
| NORR | 0.383 | 1.196** | 0.548 | 1.282** |
| | (0.406) | (0.283) | (0.415) | (0.290) |
| VAST | −0.231 | −0.026 | −0.162 | 0.015 |
| | (0.180) | (0.125) | (0.184) | (0.129) |
| MITT | −0.646** | −0.557** | −0.493* | −0.478** |
| | (0.206) | (0.144) | (0.220) | (0.154) |
| $\sigma$ | 1.190 | 0.829 | 1.181 | 0.827 |

Notes: Reference firm is EAB reference region is MALA. Standard errors in parentheses.
* and ** denote significance on 10% and 1% levels (double-sided), respectively.

Hence, there is a negative (insignificant) correlation between submission and the level of the winning bid, but a positive correlation exists between submission and nonwinning bids.

We conclude from the results in this section that the firms' bids are related to firm-specific characteristics such as distance to contract site, the potential utilization rate, incumbency, and perhaps even the utilization rate (significant for winning bids). These will therefore be included in the structural analysis as control variables for the observable shifts in the firms' cost distributions. We will also include the (log of) contract size to control for economies of scale.

In Table 3 we present the results from the estimations based on the fixed point algorithm. We have chosen to include those variables that turned out significant in the reduced-form analysis. Since the utilization and incumbency variables might be endogenous, we estimate a simplified specification wherein these variables are excluded from the model. For comparison, we also present estimates based on a simplified reduced-form bid model.[21] The data set used for the structural analysis consists of 90 auctions and 444 bids. We assume that the cost draws made for each firm in each auction are conditionally independent. The fixed point problem in the CSE algorithm is solved using $R = 10{,}000$ Halton draws.

In Table 3, coefficients relating to the firm-specific variables of distance and incumbency are significant, whereas the coefficients relating to the poorly measured utilization rates are insignificant. Furthermore, some of the firm- and regional-specific dummies are significant, suggesting that there is some unobserved heterogeneity across firms and regions.

Comparison across columns indicates that costs are more sensitive to than bids to variations in firm-specific variables. For example, the effect of distance is higher on costs than on bids, which seems intuitive because strategic considerations dictate that the bids cannot fully compensate for cost increases. In fact, this feature is actually by construction of the strategies. Nevertheless, the size of the differences are interesting. Finally, the estimated standard deviation of the stochastic cost draw is 1.16.

Before we draw any further conclusions based on the estimates in Table 3, we present some evidence of the quality of the CSE. As discussed in Section 2, we analyze the expected utility gains a firm would receive if it were to use an unilateral best response (BR) strategy conditional on its opponents using their constrained strategies. The criteria $C_{ic}^{(K)}$ measures the relative difference between the BR and the CSE profits. The average relative difference is about 2.1% with a standard error of 1.6 and a mode at 1. This means that the expected profit would increase by 2.1% on average if BR were used. The criteria ranges between $-0.2\%$ and 9.1% over firms and contracts.[22] The distribution of $C_{ic}^{(K)}$ is presented in Figure 3. Further, to show the similarities between the BR and CSE strategies, we illustrate in Figure 4 the equilibrium bids in the BR and CSE formats for a representative bidder. One striking feature is that the CSE is very close to the BR. We have

21. We have not controlled for selection bias in this table. Further, in contrast to the results presented in Table 2, we have not used the logarithmical bid as dependent variable.

22. One should note that all firms in an unconstrained BNE use their best response simultaneously, and this should imply that expected profits in the BNE are less than in the unilateral BR case. Also, the small negative number obviously stems from approximation error.

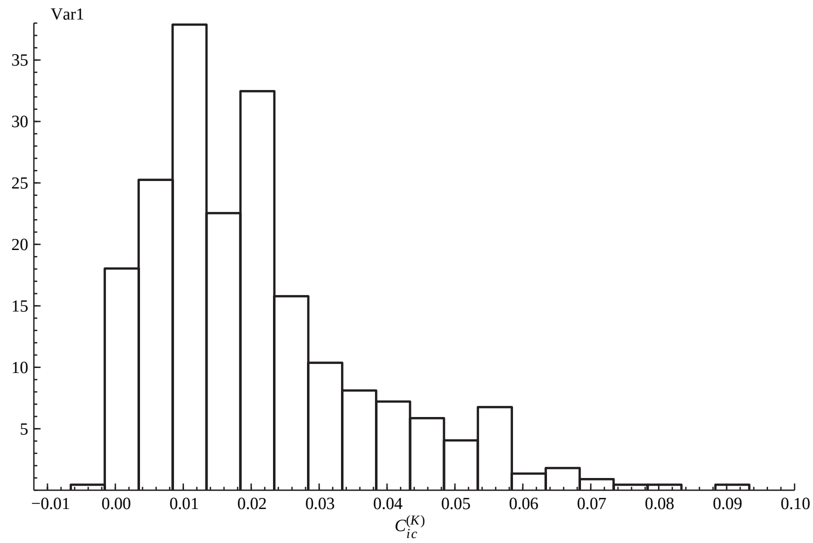


FIGURE 3. Density of $C_{ic}^{(K)}$.

superimposed the relevant density of the types, $f_i(t)$, to assess if the differences are located in important regions of types.

Based on the estimated distribution of the costs, we can assess the social costs of inefficiently allocated contracts. Some selected statistics are collected in Table 4.

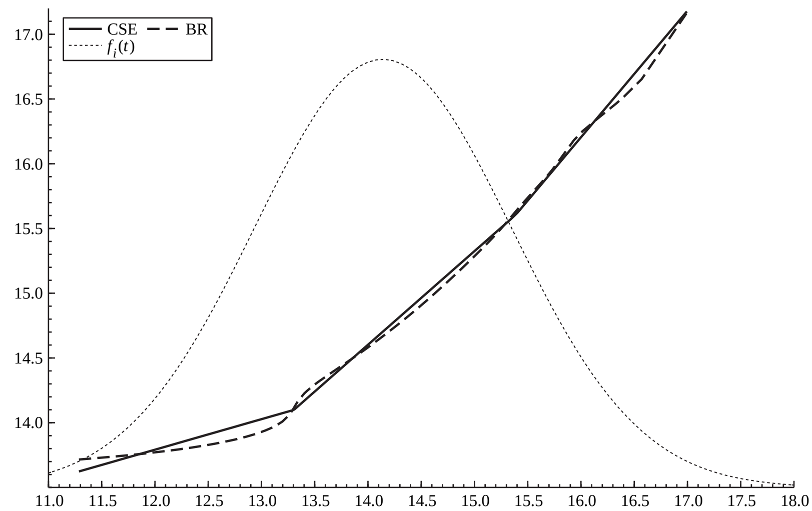


FIGURE 4. BR and CSE strategies.

TABLE 4. Selected statistics on social costs.

| | (a) | (b) |
|---|---|---|
| No. of inefficient alloc. (of 90 contracts) | 16 | 16 |
| Predicted social costs $\left(\frac{\hat{s}}{\left(\sum \hat{T}_c^{\min}\right)} \times 100\right)$ | 2.0% | 1.9% |
| Expected social costs $\left(\frac{S}{\left(\sum \hat{T}_c^{\min}\right)} \times 100\right)$ | 0.02% | 0.04% |
| Predicted excessive costs $\left(\frac{\hat{p}}{\left(\sum \hat{X}_c^{fp}\right)} \times 100\right)$ | 2.5% | 2.4% |
| Expected excessive costs $\left(\frac{P}{\left(\sum \hat{X}_c^{fp}\right)} \times 100\right)$ | 0.47% | 0.45% |

Note: Based on $M = 2{,}000$ replications of the data set.

Based on the specification where the endogenous variables are excluded, we predict 16 (out of 90) contracts being allocated to other than the low-cost firm. The additional cost resulting from this inefficiency is calculated to be about 2% of the minimum costs of completing the contract. The expected value of the social costs is simulated at about 0.02%. Furthermore, if a second-price auction mechanism were used, the predicted procurement costs for the observed sample would be reduced by approximately 2.5%.

Finally, the average markup (i.e., the percent increase in bids above costs) is about 3% for nonwinning bids and 4% for winning bids. This means that the winning firm actually pads its costs more than the average nonwinning firm.

## 6. Conclusions

This paper investigates the social costs induced by inefficient allocation of contracts in a first-price, sealed-bid auction with ex ante asymmetric bidders. We adopt a constrained strategy equilibrium approach where the players are constrained to simplified strategies so that we may estimate the structural elements of their private values. Conditional on these estimates, we investigate the importance of inefficiently allocated contracts.

The empirical analysis is based on procurements of road-marking services in Sweden during 1993–1999. We observe bids that are assumed to be generated via profit-maximizing firms with private and conditionally independent costs.

The market is spatially dispersed with relatively high transportation costs. The potential suppliers (i.e., the bidding firms) are located at various places, and consequently the costs for transportation vary across firms and contracts. These asymmetries are observable for all participants in the market. Hence, the firms are assumed ex ante asymmetric. This asymmetry implies that the first-price, sealed-bid auction design no longer guarantees that the low-cost firm receives the contract. If the low-cost firm fails to win the contract then there is a social cost due to inefficient procurement design. We find that, for the present sample, the social costs of inefficient allocations are about 2% of minimum costs; that is, the production costs induced by the first-price mechanism are about 2% higher than the minimum attainable production costs by allocating the contracts using a second-price auction.

The second-price auction is efficient even if the bidders are asymmetric. The expected procurement costs in the second-price auction differ from those in the first-price auction (see e.g., Milgrom and Weber 1982c; Hansen 1984). In simulations based on the estimated structural parameters, we find that a second-price format reduces the predicted procurement cost in the sample by about 2.5% of total procurement costs. There may thus be reason for the procurer to consider the second-price auction, since this format guarantees an efficient allocation of contracts and also offers lower procurement costs.

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