EMPIRICAL ANALYSIS OF COMPETITION IN PROCUREMENT AUCTIONS
Foreword

Janne Tukiainen’s doctoral dissertation concentrates on an analysis of public procurement auctions from empirical perspective. He applies advanced econometric techniques to empirical data from the bus transit auctions and the school yard removal auctions organized in Helsinki to address various interesting questions related to how the design of auctions affects competition and potential collusion among bidders. This is an important piece of applied research in light of the empirical significance of public procurement auctions.

The first essay focuses on the bus transit market in the City of Helsinki and studies the effects of procurement on competition. In particular, it explores the implications for competition of the merger of the City owned private company and Helsinki City’s transport department and asks whether the City should spend resources to induce more competition in this market. The second essay follows up on the first one in analyzing the data from the bus transit auctions in Helsinki. It characterizes the determinants of entry in the City of Helsinki bus transit market and contributes to the literature on endogenous entry in auctions by studying whether bidders for whom private value aspects are relatively more important make different entry choices into individual auctions than those bidders for whom common value aspects are more important. In the third essay Tukiainen continues to analyze public procurement auctions, but here the data and approach differ substantially from the first two essays. He proposes a new test to detect collusion among bidders under circumstances where such collusion can increase the procurement costs and thereby hurting welfare. The empirical application in this essay is important because it is the first empirical study of how to detect collusion implemented in the form of a territorial allocation scheme.

This study is part of the research agenda carried out by the Research Unit of Economic Structure and Growth (RUESG). The aim of RUESG is to conduct theoretical and empirical research with respect to important issues in industrial economics, real option theory, game theory, organization theory, theory of financial systems as well as problems in labour markets, natural resources, taxation and time series econometrics.

RUESG was established at the beginning of 1995 and has been one of the National Centres of Excellence in research selected by the Academy of Finland. It has been financed jointly by the Academy of Finland, the University of Helsinki, the Yrjö Jahnsson Foundation, Bank of Finland and the Nokia Group. This support is gratefully acknowledged.

Helsinki, 27 October, 2008

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Chapter 1

Introduction

1.1 Background

The study of auctions has attracted much attention in economics for several reasons. First, the analysis of auctions can help us understand important questions in other fields of economics, especially price formation, because theoretic auction models provide analytical solutions to these mechanisms. Second, the empirical analysis of auctions enables us to test economic theory, especially game theoretic models, since auction theory gives predictions on how bidders behave in equilibrium. Third, auctions are used widely in practice to conduct transactions where information asymmetries make conventional selling mechanisms unfeasible. Many goods, services, property and financial assets are sold through auctions. Public procurement auctions alone constitute a large part of the gross domestic product in many countries. Although exact numbers are hard to calculate, OECD estimates this share to be typically about 15% in the OECD countries (OECD 2005).

Because such a vast amount of public services and goods are contracted through auctions, it is very important to design these procurement auctions in an optimal way. Typically, we are interested in two different objectives. The first objective is efficiency. Efficiency means that the contract is awarded to the bidder that values it the most, which in the procurement setting means the bidder that has the lowest cost of providing a service with a given quality or achieving a given quality improvement. The second objective is to maximize the public revenue. Maximizing public revenue means minimizing the costs of procurement. Also this goal is important from the welfare point of view because public revenue is a substitute for taxation and taxes induce
welfare losses through incentive effects and collection costs. In this thesis, I analyze field data from procurement auctions and show how empirical analysis can be used to help design the auctions to maximize public revenue. In particular, I concentrate on how competition, which is defined to mean the number of bidders throughout this thesis, should be taken into account in the design of auctions.

This thesis is a collection of three essays that analyze procurement auction field data from different perspectives. In the first essay, the main policy question is whether the auctioneer should spend resources to induce more competition. In the second essay, I ask how the auctioneer can increase its revenue by changing contract characteristics like contract sizes and lengths. In the third essay, I develop and apply a test to detect collusion in auctions. The organization of this introductory Chapter is as follows. Section 1 gives an overview to the relevant literature on auction theory and the empirical analysis of auctions. Section 2 then summarizes the three essays, presents their results and discusses their contributions to the literature. Section 3 is devoted to drawing conclusions on the entire thesis. The three essays then follow in Chapters 2, 3 and 4.

1.1.1 Auction theory

There are many choices that public authorities have to consider when providing a service, for example public transport or health care. The service can be produced publicly or it can be bought from the private sector. If the authorities decide to buy the service, the next question is what is the best way to buy it. The authorities can then use an auction mechanism or they can negotiate the prices with the private sector. Bulow and Klemperer (1996) show that under some reasonable assumptions an auction with one extra bidder is always preferable to a negotiation. They suggest that the value of a negotiation skill is small relative to the value of additional competition. On the other hand, Bajari et al. (2004) argue that auctions perform poorly in comparison to negotiations when projects are complex and contractual design is incomplete. Incompleteness means that some details of the contract have to be negotiated after the auction. If the authorities decide to use an auction mechanism, there are many more decisions to make. In this Section, I concentrate on analyzing different possibilities in how to organize an auction, starting with the choice of the rules used in auctions.

The four most common auction rules are an ascending, a descending, a first-price sealed-bid and a second-price sealed-bid auction. The ascending auction, also known as the English auction, is the most commonly used auction mechanism. It is used for
example in art auctions and in internet auctions. The auctioneer publicly announces a very low starting price and then gradually increases the price until only one bidder is willing to pay it. The descending auction, also known as a Dutch auction because tulips in Netherlands are sold using it, works in the opposite way. Now the auctioneer sets up a very high starting price and decreases it until one bidder is willing to pay that price. These two auctions are also called open auctions, because the bidding behavior of all the bidders is observed by all the other bidders. Thus bidders can update their beliefs on the value of the object during the auction. Yet the first-price sealed bid auction induces the same behavior as the Dutch auction in a large class of models. In the first-price sealed bid auction, all the bidders submit one bid in a sealed envelope and the highest bid wins the object and that bidder pays his own bid. Because procurement auctions typically use this rule, it is the most important auction mechanism from an empirical point of view. The second-price sealed-bid auction, where the bidder who submitted the highest bid pays the bid of the second highest bidder, is not used much in practise, but it has gained much theoretical interest, starting with the seminal paper on auction theory by Vickrey (1961). It is interesting because it induces bidders to truthfully announce their own valuations, because the dominant strategy is to bid one’s own valuation. Some other auction rules, like an all-pay auction (e.g. Anderson et. al. 1998) and a third-price sealed-bid auction (e.g. Kagel and Levin 1993) have also gained some attention in the literature.

In some markets, the choice of the auction rule is not important. Myerson (1981) and Riley and Samuelson (1981) showed that with independent, private and symmetrically distributed valuations, absent risk-aversion and budget constraints any auction that allocates the object to the bidder who values it the most and delivers zero surplus to the bidder with the lowest valuations, delivers the same expected revenue for the auctioneer. All the standard auction rules meet these conditions. Bulow and Klemperer (1996) are able to derive the revenue equivalence under less strict conditions. They show that as long as the signals are drawn independently and the bidders are risk-neutral, any standard auction delivers the same expected revenue. However with affiliated values\(^1\), this equivalence results no longer holds. Milgrom and Weber (1982) show that then the revenue from the English auction exceeds those from the other standard auction formats.

Both of the auctions analyzed in this thesis use the first-price sealed-bid format.

\(^1\)A simple way to explain affiliated values or signals is to say that they are positively correlated. It is however a stronger relationship. A more accurate description can be found in Milgrom and Weber (1982) or Krishna (2002).
They are both procurement or low-price auctions, which means that the lowest bid wins. Bids consist of the price that a bidder wants from the auctioneer in return to providing the service described in the auctioned contract. The value of the object for sale in procurement context means the costs of providing the contracted service. There are many other modifications that can be used in the auction design. For example, the auctioneer can set a public or a secret reservation price and it is often optimal to do so (e.g. Myerson 1981), it can allow bidding for packages (Cramton et al. 2007) when multiple objects are sold and it can use some scoring rule (Asker and Cantillon 2008) when quality dimension is important besides the price. It is also possible to set an entry fee (e.g. Levin and Smith 1994) and use bid preference programs to support some bidders (Krasnokutskaya and Seim 2005).

Besides the many possible differences in the rules of the auctions, also the nature of bidders is different in different markets. Most of the theoretical work has analyzed symmetric bidders. A typical way to model auctions is that bidders draw their valuations or a signal of their valuation from some distribution. When bidders are assumed to be symmetric, they make this draw from the same distribution. Bidder asymmetry typically means (e.g. Maskin and Riley 2000) that the valuations are drawn from different distributions. In some cases it is natural to assume that the bidders are symmetric conditional on them having the same characteristics.

The main theoretical concept from the perspective of this thesis is the so called information paradigm. We talk of a private values information paradigm when the bidders know their valuations. They are not interested in the other bidders’ valuations when estimating the value of the object for sale. Only their private information is relevant to them. In a common value information paradigm, the information about the value of the object is dispersed among the bidders. This information dispersion means that if one bidder learned the other bidders’ estimate of the value of the object, they would update their own estimate. In the private value case, such updating would not happen. A typical example of a market with private values is an art auction. How I value the beauty of some painting is not affected by how someone else values it. Assuming that it is not possible to resell it, then this private appreciation constitutes the entire value of the object for sale. If reselling would be possible, an art auction turns into a common value auction. I would be interested in learning what the other bidders think the auctioned piece of art is worth in the resale market. A classic example of markets with common values is the mineral rights auction. When selling oil field drilling rights, bidders try to estimate how much oil is there to be drilled. Learning other bidders’ signals would give them better information about the true value of the
object. If the production technology were the same for all the bidders, it would be a pure common value auction. Then, the true value of the object is exactly the same for all the bidders. In an independent environment, the bidders draw their valuations independently from some distribution. We talk of affiliation when either the private values (affiliated private values environment) or the signals (affiliated common values environment) are positively correlated between the bidders.

Whether the information environment is that of common or private value, has implications for the optimal design of auctions. It is especially important when assessing the effects of competition on the auctioneer’s revenue. Milgrom and Weber (1982) show that due to the so called winner’s curse the effects of competition may change with the information paradigm. The winner’s curse arises in a situation where bidders bid in a common values environment only according to their own value estimates. With unbiased estimates and symmetric bidders, the bidder who underestimates his values the most wins the auctions and may receive a negative payoff. The expected amount of underestimation increases with the number of bidders. Rational bidders take this into account and thus may even bid less aggressively as competition increases. Strategic behavior implies that bidding is more aggressive as the number of bidders increases. With private values, only this strategic component is in play, whereas in a common value setting both of these factors matter and so the effect of competition is uncertain. Therefore, with common values it might not be in the auctioneer’s best interest to try to attract more bidders whereas with private values it always is.

Goeree and Offerman (2003) have studied auctions where there are both private and common components in the bidders’ valuations. In their model, the bidders draw both a signal on the common valuation component, like the resale value of a painting and their private valuation component, how much they like the painting. The value of the object for sale is a weighted sum of both the private and the common component. They show that then both the efficiency and revenue increase when more bidders enter the auction, and when the auctioneer can reduce the uncertainty about the common value component.

Most of the literature on auctions assumes that entry is exogenous. This means that bidders know how many other bidders will submit a bid before they submit their own bids. In many cases, this can be an unrealistic assumption. Endogenous entry has gained much attention in the literature recently. Although not the first to endogenize entry, Levin and Smith (1994) presented the most famous auction model with endogenous entry thus far. They characterize a symmetric mixed strategy equilibrium that leads to a stochastic number of entrants. A fixed and known number of identical
potential bidders have to incur an entry cost to be able to submit a bid. In equilibrium, each bidder enters with the same probability. Levin and Smith (1994) predict that the optimal reserve price is zero and the entry fee should be positive in the common value framework but zero in the private value framework. This result means that it is in the auctioneer’s interest to discourage the entry of common value bidders to some extent. Later, some authors have generalized this model further and provided more and in some case contradictory results, for example Menezes and Monteiro (2000) and Chakraborty and Kosmopolou (2001) change the setting so that bidders learn their valuations before paying the entry cost, Ye (2004) allows bidders to update their beliefs after the entry and Gal et al. (2007) allow the entry costs to differ across bidders.

Even an optimally designed auction may result in a very low revenue for the auctioneer if the bidders collude. Many cartels have been under legal prosecution and probably many more operate undetected in auctions. Collusion is one of the main reasons why theorists think that the first-price sealed bid auctions are so popular in public procurement. Robinson (1985) shows that cartels are stable when open auctions are used but not in sealed bid auctions. Milgrom (1987) argues that repeated second-price auctions are more susceptible to collusion than repeated first-price auctions. The last essay in this thesis develops an empirical method for detecting collusion. Hendricks and Porter (1989) study the detection of cartels from a theoretical point of view.

Excellent surveys on the voluminous theoretical literature on auctions are provided by Krishna (2002) and Klemperer (2004). Milgrom (2004) gives an interesting discussion on how to put all these theoretical results in practical use when designing auctions. Although the main contributions of this thesis are empirical, I contribute to the theoretical auction literature by empirical findings in the following ways. In the first essay, I show that it is possible to have markets where some bidders are more influenced by the common value components than some of their rivals. In Goeree and Offerman (2003) model, this would mean that there is bidder asymmetry concerning the weighting of the private and the common component. This possibility has been overlooked so far in the theoretical literature. Therefore the empirical results of the first essay motivate new lines of theoretical research. In the second essay, I study how the information paradigm affects the entry decisions. It is a question that is very difficult to model and thus has been overlooked in the theoretical literature show far. Therefore the empirical results of the second essay increase our knowledge of this particular question that is also of interest to theoretical research.
1.1.2 Empirical analysis of auctions

Although not as extensively studied as the theoretical models on auctions, the econometrics of auctions have gained significant and ever increasing attention in economics in the last two decades or so. The most important characterization of the methods used in the empirical analysis of auctions focuses on whether they use the structural econometric approach or the reduced form approach. In the structural approach the theoretical model is mapped seamlessly to the econometric model. In the reduced form approach, this is not true and the econometric model makes assumptions that are not necessarily exactly in line with the theoretical results. On the other hand, sometimes the theoretical models are too complex for the parameters of interest to be identifiable when used as econometric models. Typically, a reduced form approach utilizes regression techniques. These provide descriptive results on what is going on in the field data on auctions when the structural analysis is not feasible. In the first essay of this thesis, I use the structural approach. In the other two essays, I use reduced form methods because suitable theoretical models for the purposes of the research questions do not exist or the possibility to use structural analysis is limited by the properties of the data set.

Another important decision the econometrician has to make is whether to use parametric or nonparametric methods. With nonparametric methods, the analysis is flexible and the results are not driven by preliminary assumptions. However, due to limitations in the data or the complexity of the theoretical model, one often has to make parametric assumptions to simplify the estimation. Typically parametric assumptions are made about the distribution from which the bidders draw their valuations. That allows closed form solutions to the equilibrium bid functions and therefore the use of maximum likelihood methods. In the first essay of this thesis, I use nonparametric methods. In the other two essays, I have to make some standard parametric assumptions about the distributions of the error terms in the reduced form econometric models.

Earlier empirical literature is surveyed by Laffont (1997) and Hendricks and Paarsch (1995). Early studies utilized mostly reduced form econometric methods. Perrigne and Vuong (1999) survey earlier methods of structural analysis of first-price auctions. Kagel (1995) surveys experimental work on auctions. The structural empirical analysis of auctions has developed rapidly in recent years. This literature is surveyed by Hendricks and Porter (2007) who discuss both structural and reduced form approaches, Paarsch and Hong (2006) who restrict their analysis to the structural approach and cases when bidders have independent private values and emphasize parametric methods and Athey...

Paarsch (1992) conducted the first the structural analysis of auctions. Already his study was motivated by trying to distinguish whether the bidders operate under the private or the common value paradigm. Donald and Paarsch (1993, 1996) and Laffont et al. (1995) continued to develop the parametric structural methods assuming private values. Parametric structural models with common values are analyzed by Hong and Shum (2002) and Bajari and Hortacsu (2003). Elaykime et al. (1994) started the work on nonparametric structural methods and Guerre et al. (2000) made the most often cited contribution. They were able to develop an elegant nonparametric identification strategy for the independent private values environment. Li et al. (2002) extended their approach to affiliated values and Campo et al. (2003) made the extension to the asymmetric affiliated private values case. The common objective of both the parametric and the nonparametric structural approaches is to estimate the distribution of the bidders’ valuations or signals. In the parametric approach, we estimate the parameter values for some chosen flexible distribution and in the nonparametric approach we typically use kernel smoothing techniques to estimate these distributions.

Besides Paarsch (1992), also Sareen (1999), Gilley and Karels (1981), Hendricks et al. (2003) and Haile et al. (2003) have developed methods to be able to determine whether the values are private or common. Hong and Shum (2002) find empirical evidence of the negative competition effect that can arise in the common value environment thus showing that in many real world common value auctions the auctioneer would wish to limit entry. On the other hand, in many auctions more entry is beneficial. Tests for common values should be conducted to identify the markets where it is possible that more competition is harmful. Then empirical analysis similar to Hong and Shum (2003) should be conducted to determine whether the entry should actually be limited. Besides the important impacts on the optimal auction design, the assumption on the information paradigm has severe implications for the empirical analysis of a given market. These tests are therefore also useful in determining which methods should be applied with a given data. In this thesis, I use the method developed by Haile et al. (2003) to test for common values. They mention three arguments why the nonparametric nature of their tests avoids the problems with the previous suggestions. The first problem is confounding testing for the information paradigm with testing for the parametric assumptions. The second argument is avoiding having to base the test solely on bids, like Gilley and Karels (1981), which have been later shown not infer any real information about the information paradigm. The third is not having to test for a particular form of private and common values. Pinkse and Tan (2005) suggest
another possible alternative to testing using winning bids, but they do not develop the test explicitly.

**Empirical analysis of entry**

The last two essays in this thesis are both based on analyzing entry decisions. Empirical models of endogenous entry in auctions have been considered by Athey et al. (2004), Bajari and Hortacsu (2003), Bajari et al. (2007a), Krasnokutskaya and Seim (2006), Li (2005) and Li and Zheng (2006). Athey et al. (2004) form a structural model of bidding coupled with a reduced form model of entry that allows for heterogenous bidders and unobserved auction heterogeneity under the independent private values paradigm. They compare open and sealed bid U.S. Forest Service auctions. Bajari and Hortacsu (2003) use a parametric structural model to study winner’s curse and the effects of a reserve price on seller revenue when entry is endogenous in eBay coin auctions. They consider a pure common value setting with the Poisson arrival of bidders. Bajari et al. (2007a) propose an identification method for discrete games of complete information with an application to auctions. They estimate the probabilities for each of the possible equilibria, including mixed equilibria. First they estimate an auction model similar to Athey et al. (2004) and then use simulations to calculate all the equilibria. Krasnokutskaya and Seim (2005) analyze the effects of bid preference programs on participation in highway procurement. They estimate jointly a model of participation and bidding in a similar manner as Athey et al. (2004). Li (2005) considers the structural estimation of first-price auctions with entry and binding reservation prices when bidders are symmetric. He suggests a method of simulated moments estimator that can be used to test whether the reservation prices are binding, and to test the mixed-strategy of entry. Li and Zheng (2006) form a fully structural auction model with endogenous entry, an uncertain number of actual bidders, unobserved heterogeneity and mixed strategy entry equilibrium under the independent private values paradigm with symmetric bidders. They form counterfactuals on the effects of the number of bidders on procurement costs in highway mowing auctions.

Due to the nature of my research questions, I use reduced form methods typical in the more traditional literature on entry games. The most famous works in this field of research are by Bresnahan and Reiss (1990 and 1991) and Berry (1992). Berry and Tamer (2007) provide a survey on models of oligopoly entry. Also Berry and Reiss (2007) survey the empirical analysis of these entry games. In their survey on
structural methods used in the entire field of industrial organization, Wolak and Reiss (2007) discuss also these models. In these discrete choice models the researcher needs to make two important assumptions that determine their estimation strategies. First, whether entry is modelled as a static or dynamic game. That is to say whether all the decisions are made simultaneously or whether past decisions are allowed to affect the future decisions. Second, whether the shocks that affect the entry decisions of bidders are private information to the potential entrants or whether they are observed by every potential bidder. This determines whether the game is that of incomplete or complete information. Typically, auctions are thought of as static games of incomplete information but there are exceptions. For example, Jofre-Bonet and Pesendorfer (2003) model an auction as a dynamic game and Bajari et al. (2007b) as a game of complete information.

Methods of detecting collusion

Typically, cartel behavior decreases the public revenue in a significant way and is therefore detrimental to welfare, even though the bidders in the cartel get these public losses as profits. Therefore policies that hinder the work of cartels are beneficial. One such policy is to be able to detect the collusive behavior. This poses a threat that may prevent the cartel from forming in the first place and helps prosecute those guilty of collusive behavior. In their analysis on the detection of cartels, Hendricks and Porter (1989) argue that the detection of cartels is necessary case specific. Methods that are suitable for the detection of some collusive behavior do not necessary work for other collusive schemes or other markets. In the third essay, I use observed entry decisions to detect collusion in auctions. This method is suitable for the detection of a territorial allocation scheme when independent markets can be identified and the entry decisions are simultaneous. The previous literature on the detection of collusion in auctions has focused on more sophisticated collusive schemes where the bidders submit phony bids to avoid detection. In his survey on detecting cartels, Harrington (2005) states that "it has been shown that cartel formation is more likely with fewer firms, more homogenous products and more stable demand". Therefore, when the market is suspect to collusion, inducing more entry could be beneficial even in such a common value auction where the competition effect would decrease the revenue if the firms did not collude. On the other hand, when the competition effect is negative, it could be in the interest of the auctioneer to even allow collusion. However, in most cases cartels decrease the public
revenue. In an auction setting, first-price sealed-bid auctions seem to be more resistant to collusion than other standard auctions, but far from immune. There are at least two ways to fight against cartels. First, to plan the auction in a way that collusion is hard to agree upon or sustain. Second, to use policies to detect and prosecute the guilty bidders.

There has been some work on empirically detecting collusion in auctions. Porter and Zona (1993) examine bidding in auctions for state highway construction contracts in order to determine whether bid rigging occurred. They find that the bids of non-cartel firms, as well as their rank distribution, was related to cost measures whereas the rank distribution of higher cartel bids was not. They present two different analyzes. The first is based on the level of bids and other on the rank of bids. They test differences between the behavior of the cartel and non-cartel firms. They use rank distributions because they cannot control for the contract characteristics. Porter and Zona (1999) examine the institutional details of a school milk procurement process. They compare the bidding behavior of a group of firms with a control group and find them different. They argue that behavior is consistent with collusion. The approach is similar to Porter and Zona (1993) though in this case the reduced form model of firms’ bid levels is estimated together with a model for whether a bid was submitted. They test whether the bids of the suspected cartel firms are determined differently from the bids of the control group of the non-defendant firms. They also study whether the submission decision was correlated between the cartel firms. The idea of the papers by Porter and Zona is to use reduced form models to test whether the bidder behavior is consistent with competition.

Bajari and Ye (2003) introduce a general auction model with asymmetric bidders and independent private values. They state the conditions that are both necessary and sufficient for a distribution of bids to be generated by a model with competitive bidding. They also discuss how to elicit a prior distribution over firm’s structural cost parameters from industry experts and use this to compare collusive and competitive models. They apply their methodology to a data set of seal coat contracts. They use reduced form bid functions to test for conditional independence and exchangeability. The conditional independence means that conditional on the set of covariates observable to the firms, their bids are independently distributed. Exchangeability means that firm characteristics should enter the bid function in a symmetric way. The test of conditional independence is equivalent to testing that the OLS residuals of firm i’s bid function are uncorrelated with the residuals of firm j’s bid function. The test of exchangeability is equivalent to testing whether the OLS slope coefficients of the
bid function are the same for the firms. After Bajari and Ye (2003) have identified the suspect firms they use structural models to decide between the alternative models of industry equilibrium. Their estimation strategy depends on observing engineer estimates of the cost of the contract.

Some authors compare competitive and collusive models to determine which better fits the data. Among earlier of these studies are (Porter 1983) and (Ellison 1994) The general strategy is to specify structural competitive and collusive models of firms’ bids and to estimate them using cost shifters. Baldwin, Marshall and Richard (1997) and Banerji and Meenakshi (2004) use this approach for oral ascending auctions. Bajari and Ye (2003) use it for the first-price sealed-bid procurement auctions. Athey, Levin and Seira (2004) find evidence of mild degree of cooperative behavior in U.S. Forest Service sealed bid timber auctions when they compare open and sealed bid auctions. They also quantify the effects of collusion and find them significant.

1.2 Summaries of the essays

In this Section, I present the summaries of the three essays that form this thesis. First, I provide a short description of each essay. Then, I discuss each in greater detail. I highlight the contributions these essays make to the scientific literature and discuss the practical policy conclusions derived from their results. I also present the empirical methods that I use.

In the first essay, I study the effects of competition in the City of Helsinki bus transit market by conducting two tests for common values developed by Haile et al. (2003). I also extend their test by allowing bidder asymmetry. The information environment seems to be that of common values. The bus companies that have garages close to the contracted routes are influenced more by the common value elements than those whose garages are further away. Therefore, attracting more bidders does not necessarily lower procurement costs, and thus the City should not necessarily implement costly policies to induce more competition. In the second essay, I utilize the results of the first essay and compare the determinants of entry between a bidder to whom common value components seem to be more important and a bidder to whom private value components seem to be more important. I find that these bidders do not react any differently to changes in the amount of expected competition. I also find that the City should shorten the contract lengths in the bus auctions because that would decrease the importance of common value components and cheaply increase entry which now would
have a more beneficial impact on the public revenue. In the third essay, I propose a new statistical method for detecting collusion and compare it with an existing one. I apply both methods to procurement auctions that contract snow removal in schools of Helsinki. I find that two of the bidders seem to participate in a contract allocation scheme.

### 1.2.1 Testing for Common Costs in the City of Helsinki Bus Transit Auctions

In this essay, I study two policy questions concerning the bus transit market in the City of Helsinki. Both questions are viewed from the perspective of the effects of competition. The first is whether the merger of the City owned private company Suomen Turistiauto Oy and the Helsinki City Transport’s (HKL) bus transport department, HKL-bussiliikenne, in 1st May 2005 was good policy. The second is whether, as planned, the City should spend resources to induce more competition in this market. One possibility that has been considered by the procurement officials is to build new City owned garages and rent these to new entrants.

To answer these questions, I perform two tests developed by Haile et al. (2003) for common values. The setting is a first-price sealed-bid procurement auction. The main contribution of this essay is the empirical application and its policy implications. Novelty is achieved by extending the testing framework by allowing the bidders to be asymmetric. This I achieve by dividing the bidders into two groups: the bidders with garages far from the contracted routes and the bidders with garages near the contracted routes. I conduct the estimations and the testing separately for these groups and jointly for both the groups in the symmetric case. Another aspect of interest is showing the need for robustness checks for some arbitrary choices in the Haile et al. (2003) testing procedures. This means that the results of the test may change with some choices that the researcher has to make when conducting these tests. However, in the asymmetric specification the results are robust. To my knowledge, this is the second study that applies the Haile et al. (2003) methodology.

In practise, these tests are conducted in the following way. First, I have to make some preliminary treatments to match the data to meet the assumptions of the estimation and the testing procedures. I have to address the complications brought by

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2The first study is by Shneyerov (2006).
the quality dimension of the bids, the fact that bidders are allowed to submit combination bids and that the contracts differ in their characteristics. After this, I assume that I have a cross section data of independently drawn bids from many homogenous auctions. These are requirements of the Li et al. (2002) and Campo et al. (2003) estimation methods that are used next. Before the actual testing, I have to estimate the so called pseudo-costs. They are estimates of bidders’ ex ante expected costs conditional on them winning the auction. It is simpler just to think about these as the relevant costs that the bidders use to calculate their bids. These costs are not observed by the econometrician nor the other bidders. They have to be estimated from the bid data for all the bidders because the bids by themselves do not allow testing for common values. Auction theory (Milgrom and Weber 1982) provides the equilibrium behavior condition that is used to get a relation between the observed bids and the unobserved costs. Guerre et al. (2000) were the first to derive this identification result later extended by Li et al. (2002) and Campo et al. (2003). These pseudo-cost estimates are then used in the actual testing. The pseudo-costs are known to be independent of the number of bidders in the private value paradigm and decreasing in the number of bidders in the common value paradigm. Therefore two tests are conducted to compare the distributions of these estimated pseudo-costs. For example, the distribution of the costs in the auctions with three bidders is compared with the distribution of the costs in the auctions with four bidders. The first test simply compares the means of these cost distributions. In the second test, the location of the distributions is compared vertically by a Kolmogorov-Smirnov type test, whereas in the means test the comparison is done horizontally.

I find that there seem to be important common value elements in this market. Moreover, it seems that the bus companies with garages close to the contracted routes operate in the common value environment. For the bus companies with garages far from these routes, the information environment is not known. However, it is known that the common value elements are more important to operators with garages near the routes. Common values can arise from common future uncertainty and private values from individual efficiency differences. The result that common values are more important for the near bidders is best explained by the fact that being located near the route reduces the incentives to be efficient in organizing the empty transfer traffic. Therefore this private value component is less important for the near bidders. Moreover, the garages that are typically located near the routes are also closer to the city center, where

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3In the essay, I use word “cost” instead of “value” because of the procurement setting.
4The means have to be trimmed.
the costs of land are higher. Land rents or the opportunity costs of land are subject to future uncertainty. The common value elements that influence all the bidders are common uncertainty about winning future contracts and common uncertainty about getting enough drivers to fulfill the contract obligations in the future.

I answer two policy questions in light of these results. First, a decrease in competition caused by the merger of two city-owned bus companies may have no effects or even an reducing effect on procurement costs. Thus, from the perspective of competition, this merger decision is not open to criticism. Second, the City should not build public garages and rent them to new entrants to induce more competition. As it is not certain that the new competition brings any benefits, the City should not spend any resources to induce it. If the City chooses to pursue the proposed garage policy and must choose between two locations for which overall operating costs are equal, they should choose the garage which is more often located further away. Then at least the new entrants should react to the increased competition as planned.

1.2.2 The Determinants of Entry in an Auction with both Private and Common Value Bidders

This essay has two objectives. First, I study the determinants of entry in the City of Helsinki bus transit market. Knowing which contract and bidder characteristics affect the bid submission decisions helps the procurement agency plan the contracts to minimize procurement costs. My paper thus has a policy objective. Second, I contribute to the literature on endogenous entry in auctions by studying whether bidders for whom the private value aspects are relatively more important make different entry choices than those bidders for whom the common value aspects are more important. I use data from the City of Helsinki bus transit auctions to construct a set up that enables me to study how the information paradigm affects the entry choices.

As discussed above, it is known that the information paradigm makes a difference on how the amount of competition that the bidders expect to face affects the levels of submitted bids. It is yet to be asked in the literature whether the information

\[5\] With exogenous entry, the number of actual entrants is known exactly. In the endogenous entry model of Levin and Smith (1994), all the bidders have a commonly known entry probability. Therefore they know the expected number of actual bidders. In both the cases, the discussion (see Section 1) on how the information paradigm makes a difference in what is the effect of the amount of competition (whether an expectation or a fixed number) on bid levels is identical.
paradigm makes a difference in bidders’ entry decisions. If bidders face some entry costs, they might not want to submit a bid to every auction. For strategic reasons, all the bidders would prefer bidding in less competed contracts to bidding in more competed contracts. However, the additional effect of having common values on the entry decisions is unclear and difficult to model. In this essay, I study empirically whether common and private value bidders react differently to changes in the amount of expected competition when they make their entry decisions.

I am able to address this question because in the first essay, I find that bidders that have garages close to the contracted bus routes are more influenced by the common value elements than bidders with garages further away. I compare the participation behavior of one bidder, whose garages are always located further away from the routes under contracts than its rival’s. I test whether these bidders react to the amount of competition they expect to face differently. The possible difference could then be attributed to the different information paradigm in this set up. To test for both the effect of the information paradigm and the effect of contract and bidder characteristics on entry, I use a recent method by Bajari et al. (2007a) that allows for an empirical analysis of a static entry game. In a static entry game, the bidders make their decisions on whether to submit a bid or not simultaneously. This is a realistic assumption in these auctions. Modeling games means that one has to account for strategic interactions between the bidders. In statistical modeling, this means allowing the bidders to take into account their own beliefs about whether their competitors will submit a bid or not when making their own submission decision. In practice, Bajari et al. (2007a) propose two stage regression method where in the first stage the expected participation probabilities for each bidder are estimated given that there is variance in the contract and given bidder’s characteristics in the data. In the second stage, these probabilities are included in the regressions where the entry decisions for each bidder are modeled again.

Although there were some differences from one model specification to another regarding which variables turned out significant, the results can be summarized in three main observations. First, there are no strategic interactions, the expected participation of other bidders does not affect the entry decisions. One explanation for this is that actually the entry is not endogenous but exogenous in this market. Therefore, the results of this essay where I allow the possibility of endogenous entry do not contradict the analysis of the first essay, where I assume that the entry in these markets is exogenous. Second, the bidder’s own distance from the garage to the route is an important cost shifter. Third, bidders seem to dislike lengthy contracts. Goeree and Offerman (2003)
study a model with symmetric bidders where the objects for sale possess both private and common values. They show that then both the efficiency and revenue increase when more bidders enter the auction and when the auctioneer can reduce the uncertainty about the common value component. We know that common values typically arise from common future uncertainty. Reducing contract lengths would therefore reduce the uncertainty about the common elements. Because reducing contract lengths also should increase the number of actual bidders, which is more beneficial with the simultaneous reduction in the importance of the common value components, there would be two reasons for the City to reduce the contract lengths.

1.2.3 Participation Screen for Collusion in Auctions

The central difficulty in detecting collusion is that similar market outcomes can be a result of either a collusive or competitive behavior. For example, if two fisherman sell their product in a marketplace and set exactly the same prices, it might be a result of collusive agreement. However, it can as well be due to having to compete in prices with identical products in the same market. Without any other information, a researcher has no way of detecting possible collusion. Similarly, what at first glance looks like a territorial allocation, in a setting where bidders and contracts have different locations, can be a result of either an explicit agreement or due to cost advantages that the bidders have in different areas. Due to transaction costs for example, firms could decide to bid only on those contracts that are near the location of their operations. With different locations, territorial allocation emerges as a competitive result. We get more suspicious if the territories overlap, but firms still systematically avoid bidding for the same contracts. Unfortunately, this can be again a result of competitive behavior if the contracts are heterogenous. Some firms may have costs advantages in some types of contracts. Therefore with heterogenous contracts and bidders, participation patterns of any kind may emerge in the competitive setting. However, if we control for bidder and contract heterogeneity, then the identity of other participants should not affect the participation decision of any bidder in the competitive setting. This makes testing for collusion possible. In this particular market, spending the effort to conduct these tests seems reasonable since two bidders avoid each other in an overlapping geographical area.

In this essay, I have several objectives. First, I propose a new test to detect collusion. Bidder collusion can increase the procurement costs significantly in many cases and is
thus detrimental to welfare. I will show with Monte Carlo analysis that the test I propose is robust to unobserved heterogeneity, in particular to unobserved bidder and contract characteristics, unlike the existing method that is developed for the same purpose. I will also discuss how the old and the new test complement each other. I apply both these tests to school yard snow removal auctions in the City of Helsinki. Second, this empirical application is important in itself because it is the first empirical study of a territorial allocation scheme. Third, this essay has a practical economic policy implication. Since it points out two of the participating bidders suspect of collusion, this analysis should validate closer legal study to support the prosecution of these companies.

The new statistical method and the existing one can be used to test for collusion both in a phony bidding and in a territorial allocation setting. In an auction setting, the territorial allocation scheme means that colluding bidders simply agree to which auctions they each are going to bid to and do not bid to auctions allocated to the other cartel members. Both of these tests can be applied to any institutional setting where independent and mutually exclusive markets can be defined. However, due to their simultaneous nature, auctions are particularly well suited for the static estimation methods that are applied here. Moreover, in auctions it is easy to argue the independence of the markets under scrutiny. These tests are based on the participation decision of the bidders instead of the bid levels. The previous literature on detecting collusion in auctions has studied only phony bidding scenarios. Territorial allocation is a cruder form of collusion but one that is nevertheless observed in reality. It would be simple for the bidders to avoid being detected as having a territorial allocation scheme by starting to submit phony bids, but that should also show in this test and in many other existing tests, unless bidders would use sophisticated methods to calculate the level of phony bids thus that they would avoid detection. This would be costly to the bidders and thus reduce the incentives to collude.

I test whether the actual participation decision of one bidder affects the participation decisions of the other bidders. In the competitive setting, the identity of competitors should not affect the participation decision, given that the auctioned contracts are identical and the bidders are symmetric. For strategic reasons, the bidders would like to avoid each other, but if they are symmetric, bidder C has no reason to avoid bidder A more than bidder B. Porter and Zona (1999) propose a pairwise discrete choice analysis to detect collusion. Their test is based on the correlation of the residuals of single equation participation choice models. They explain the participation decision of each bidder separately with the bidder and contract characteristics. If there is correla-
tion in the unexplained part, i.e. the residual, of equations for any pair of bidders, this can be attributed to them colluding, given that there is no unobserved heterogeneity. Negative correlation between two bidders’ residuals implies territorial allocation and positive correlation phony bidding. Porter and Zona (1999) use it to detect phony bidding. My test is based on solving a system of simultaneous equations of participation choice. I use estimation techniques proposed by Tamer (2003). The Porter and Zona (1999) test is not robust to unobserved heterogeneity since any missing variable that affects the entry decision of one or both firms, and is observed by both the analyzed bidders, will affect the residuals and thus corrupt the test. I argue that when estimating these equations simultaneously, the test can be based on the statistical significance of competitors’ entry decisions and the error term structure of this statistical model controls for the unobservable heterogeneity.

1.3 Conclusions

In this thesis, I use recent statistical methods to answer relevant policy questions concerning how to design procurement auctions. Moreover, I develop further one existing statistical method and propose a new method that are both useful in analyzing and planning public procurement. I analyze competition policies from different perspectives with field data from two procurement auctions. I study two different questions that are both important from the perspective of both the competition authorities and the procurement authorities. The first question is whether in public procurement, the authorities should actively limit or try to induce more competition. The second question is how we can make markets that are suspect to collusion truly competitive.

The answer to the first question depends on the particular market. In some markets, attracting more bidders increases and in others decreases the public revenue. My main advice is that the authorities should conduct statistical analysis in the lines of this study before implementing any costly policies in order to affect the number of bidders. In the particular market that is analyzed in this thesis, my advice is that the City of Helsinki should not implement costly policies like building new garages to induce more competition in the bus transit auctions, but should rather implement a cheap policy of reducing contract lengths for two reasons. First, this reduces the importance of common components which should by itself increase the public revenue and moreover, it makes the policies of attracting more bidders more profitable. Second, it increases the number of actual bidders which, with the reduced importance of the common value
components, is more likely to increase the public revenue. Also the merger of the Helsinki City Transport bus transport department HKL and City-owned Private bus operator Suomen Turistiauto Oy seemed to be a good policy because it reduced the number of bidders for whom common value components are more important. As the answer to the second question, I propose a new method of detecting collusion, that should be useful in many real world cases to screen for firms that are likely to have colluded. The existence of such methods reduces the incentives to collude.

1.4 References


Sareen S (1999). Posterior Odds Comparison of a Symmetric Low-Price, Sealed-Bid


Chapter 2

Testing for Common Costs in the City of Helsinki Bus Transit Auctions1

2.1 Introduction

In an auction setting, a central issue, for both analyzing bidding strategies and designing markets is whether the bidders operate in a private or common cost environment. This is especially important when assessing the effects of competition, i.e. the number of bidders, on procurement costs and contracted service quality. Private costs have different policy implications than do common costs, since with private costs more competition always lowers expected procurement costs whereas with common costs the effect of competition is unknown. The seminal paper on structural estimation of auctions by Paarsch (1992) was motivated by this distinction. Haile et al. (2003) (denoted HHS) developed nonparametric tests for common costs in first-price auctions that overcome the limitations of the previous attempts (see HHS). I utilise the HHS tests to analyze the City of Helsinki bus transit markets.

In particular, I analyze two specific policy questions. First, I evaluate whether the merger on 1st January 2005 of the City owned private company Suomen Turistiauto Oy and the Helsinki City Transport’s (HKL) bus transport unit was a good thing. Second, I analyze whether, as planned, the City should spend resources to induce more

1A version of this Chapter will appear in the International Journal of Industrial Organization.
competition in this market. One possibility that has been considered is to build new city-owned garages and to rent these to new entrants.

The main contribution of this paper is the empirical application and its policy implications. A particularly novel feature of this study is the extension of the HHS testing framework by allowing the bidders to be asymmetric. Another novel feature is that I use a simple pooling procedure to be able to conduct the tests with only a small amount of data. A further aspect of interest is the discussion on robustness checks for some arbitrary choices in the HHS testing procedures. To my knowledge, this is the second study that applies the HHS methodology. In the other (Shneyerov 2006), only the means\textsuperscript{2} test is used.

I describe the bus transit market in Helsinki and the auction rules in Section 2. In Section 3, I explain the preliminary treatments needed to make the data suitable for the testing methodology and provide more insight on the market. In Section 4, I first present the intuition behind the tests and then show how the tests are conducted in practice. Then in Section 5, I discuss some considerations for applying these tests to my data. I present the results and discuss their robustness in Section 6. Section 7 concludes.

### 2.2 The Helsinki bus transit market

The City of Helsinki arranges tenders for its intra-city bus traffic. The first tender was arranged in 1997. The intra-city market served 100 million passengers and was valued at 177 million euros in 2000 (YTV Transport Department 2001). The data used in this study consists only of these intra-city tenders, and include 64 auctions. I do not use the data from the entire metropolitan area because of differences in market, auction rules and bidder behavior. The planning unit of Helsinki City Transport (HKL) decides routing, timetables, vehicle requirements and fleet schedules. The amount of bus kilometers in a contract can change by a maximum of ten percent per year. The City of Helsinki Supplies Department invites the tenders. The tenders are open to all licensed contractors. Also a financial analysis on the contractors’ ability to fulfill the tender specifications is conducted. The bus transport unit of HKL participates as one of the bidders.

\textsuperscript{2}Actually medians in that application.
In bids, the operators state the unit costs of the service (cost per kilometer, per hour and per vehicle day). The tendering authority uses these costs to calculate the total cost of service provision given the announced amount of traffic. This total cost is the actual monetary bid. The City receives all ticket revenues. Similar, so-called gross cost contracts, are used in many cities, as for example in London. The contract period varies from three to six years and is most often five years. The invitation to tender simultaneously covers many contracts. A single contract can cover one or more routes. The intra-city market consists of 86 routes. The set of contracts that correspond to an invitation is called a tranche, following Cantillon and Pesendorfer (2006a). Combination bidding within a tranche is allowed. The principle of awarding tenders is the best economic value, calculated by a scoring rule based on monetary bids and vehicle quality. The data are described in table 1. The data contain all the bus transit tenders held by the City of Helsinki in 1997 - 2005. The data were collected by the author from the City of Helsinki Supplies Department (Saarelainen 2004). There are 13 tranches, 64 contracts and 261 bids, of which 14 were combination bids. The number of bidders varies from two to eight.

Table 1. Bus transit tenders included in the data set.

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<th>Tranche</th>
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<th># S bids</th>
<th># C bids</th>
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<td>2/VI (05)</td>
<td>1</td>
<td>0.1</td>
<td>5</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>Total</td>
<td>64</td>
<td>54</td>
<td>247</td>
<td>14</td>
<td>2-8</td>
</tr>
</tbody>
</table>

A "tranche" refers to the set of contracts that correspond to a single invitation to tender. The year the auction was held is in parentheses. 2/III means the third tranche of the second round of the tendering of the entire traffic. "# auctions" refers to the number of auctions in a given tranche. Size gives the total size of all the contracts in a given tranche in millions of bus kilometers in a year. "# S bids" means the total number of single bids in a given tranche. "# C bids" means the total number of combination bids in a given tranche. "min - max" refers to the spread of the number of bidders per auction in a given tranche.
2.3 Matching data with methodology

The data include information on bids, scores, contract characteristics and bidder characteristics. There are several problems with the application of the HHS tests to these data. The nonparametric estimation method assumes that bidders bid in independent and homogeneous one-dimensional auctions. In contrast, the data are generated from a combinatorial auction with multiattribute bids and heterogeneous contracts. Below I discuss how to address these problems. The testing procedure is explained briefly in Section 4.1. It is possible to read it before this Section.

2.3.1 Multiattribute bids

The bids consist of a monetary part and of a quality part. The lowest monetary bid gets 86 points. Points for other bids are calculated with the formula: points for bid $i = \frac{\text{monetary value of lowest bid}}{\text{monetary value of bid } i} \times 86$. Then a maximum of 14 points is awarded for quality. The principle of giving points for different vehicle characteristics and other quality measures is clearly stated in the tender invitation. In the last three tranches of the data, the scoring rule changed so that the monetary bid was awarded a maximum of 87 points and vehicle quality 13 points. Bids are transformed into one dimension in the following way: First the price of one point is calculated by dividing the winning bid by 86 (or 87), or equivalently by dividing a bid by that bidder’s price points. Then the quality points that each bidder has received are multiplied by this price per point. That number is then subtracted from the monetary bid. This method is based on the economic intuition that an optimally behaving winning bidder submits a bid such that the known cost of getting a quality point equals the expected cost of getting a monetary point.3 Cantillon and Pesendorfer (2006a) treat quality scores in their study as noise and thus use only the monetary bid information in their estimations. The fact that scores rarely change the order of bids in my data would support this approach. The subtraction that I propose does not cause any problems in case the quality scores are just noise, because then it is just a random downward scaling. The effect of this reduction vanishes when the HHS homogenization

---

3This should hold for marginal points. If there are (dis)economies of scale in the production of quality, this will not necessarily hold for intra-marginal points. Berechman (1993, p. 121-123) argues that the bus industry in general operates under constant economies of scale with respect to fleet size.
method below is applied. Moreover, if the scores are not random, this approach makes a correction that at least is in the right direction.

2.3.2 Combination bids

Bidders can submit bids for the packages of contracts within a single tranche. The estimations that I use do not allow for combination bids. Cantillon and Pesendorfer (2006a) provide a method for the identification of a combinatorial auction. Unfortunately, this method cannot be used here for two reasons. First, they assume the private costs paradigm. Second, the presence of combination bids is necessary for their identification method, and these are rare in my data. In my data there are 14 combination bids, of which two were winning bids, for a total of five contracts. Coincidentally, 14 contracts of 64 were included in these bids. Usually bidders included the same contracts in their combinations. After the whole network had been procured once, bidders stopped submitting bids for packages even though the rules still allowed it. Thus combination bids do not play a large role in these auctions. There are three possible explanations for not submitting combination bids. First, there can be additional costs in calculating and submitting a combination bid. Second, there may be negative cost synergies between contracts. Third, costs of different contracts may be correlated. If either of the first two explanations is plausible, the auctions can be treated as independent, and one could simply omit the auctions with combinations. The third explanation is based on McAfee et al. (1989), who mention that it is always optimal for oligopolies to use bundling if the reservation values of products are independent. Identification with this correlation should be possible but should also be taken into account in the estimation. This is left for further research. Here I simply omit all auctions that were included in any of the combination bids. This leaves 50 auctions. I assume that the bidders treated these 50 auctions as independent.

2.3.3 Contract heterogeneity

There are many important auction-specific characteristics in the data. They shift the distribution of bidders’ costs and therefore have to be controlled for. HHS suggest two different ways to incorporate these observables. The first is to condition the kernel smoothing for the estimation of pseudo-costs on these observables. Because of the
curse of dimensionality, this requires much larger data than what is available. The second alternative is to regress all observed bids on the covariates and a set of dummy variables for each number of bidders. *The sum of each residual and the corresponding intercept estimate provides an estimate of each homogenized bid.* These estimates are then treated as bids in a sample of auctions of homogeneous contracts. I regress the bids on contract size in route hours, the share of required articulated/bogie buses, the share of rush hour traffic, the length of the contract in years, and dummies for the number of bidders.

Table 2 shows that there is very large variation in sizes of bids and sizes of the contracts. The highest bid is about 86 times the lowest bid. The same is true for contract size. The other contract characteristics also vary widely. The need for controlling for heterogeneity is thus obvious. The results of the bid regression are presented in Table 3. Contract characteristics explain 97% of the variation in the bids. Besides the dominant contract size, also peak hour share and the share of articulated/bogie buses matter. The regression diagnostics (not shown) do not give rise to serious concerns. The dummies for four and eight bidder auctions are negative and almost significant. However, the dummies for number of bidders are not jointly significant (F-statistic 1.15 and p-value 0.33). Amount of competition does not seem to affect the bids either way.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quality adjusted bids (mil. 2001 €)</td>
<td>1.75</td>
<td>1.16</td>
<td>0.06</td>
<td>5.19</td>
</tr>
<tr>
<td>Route hours per year (thousands)</td>
<td>42.5</td>
<td>27.8</td>
<td>1.3</td>
<td>111.2</td>
</tr>
<tr>
<td>Share of peak hour traffic</td>
<td>0.39</td>
<td>0.23</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Share of articulated/bogie buses</td>
<td>0.23</td>
<td>0.36</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Contract length (years)</td>
<td>4.78</td>
<td>0.69</td>
<td>3</td>
<td>6</td>
</tr>
</tbody>
</table>

I also use dummies for the number of bidders in the regression. There are 6 two bidder auctions, 19 three bidder auctions, 11 four bidder auctions, 11 five bidder auctions, 2 six bidder auctions and 1 eight bidder auction in the data set.
Table 3: OLS results for explaining bids by contract characteristics. Bids are in units of 1000 euros.

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Estimate</th>
<th>Std. Error</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>190</td>
<td>146</td>
<td>0.19</td>
</tr>
<tr>
<td>Route hours</td>
<td>0.04</td>
<td>0.00073</td>
<td>&lt;2e-16</td>
</tr>
<tr>
<td>Peak hour share</td>
<td>196</td>
<td>84.9</td>
<td>0.022</td>
</tr>
<tr>
<td>Artic./Bogie buses share</td>
<td>179</td>
<td>51</td>
<td>0.00057</td>
</tr>
<tr>
<td>Contract length</td>
<td>-47.2</td>
<td>29.6</td>
<td>0.11</td>
</tr>
<tr>
<td>n=2</td>
<td>-42.4</td>
<td>69</td>
<td>0.54</td>
</tr>
<tr>
<td>n=3</td>
<td>-88.2</td>
<td>45.5</td>
<td>0.054</td>
</tr>
<tr>
<td>n=4</td>
<td>-53.6</td>
<td>42.3</td>
<td>0.21</td>
</tr>
<tr>
<td>n=5</td>
<td>-88.6</td>
<td>71.9</td>
<td>0.21</td>
</tr>
<tr>
<td>n=6</td>
<td>-166</td>
<td>99.4</td>
<td>0.096</td>
</tr>
<tr>
<td>n=7</td>
<td>Reference group</td>
<td></td>
<td></td>
</tr>
<tr>
<td>n=8</td>
<td>-166</td>
<td>99.4</td>
<td>0.096</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.965</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F-statistic</td>
<td>576 (9 and 178 df)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In Table 4, I present descriptive statistics for the homogenized bids. These are presented separately for each bidder along with the number of bids submitted and contracts won. The municipal bus company HKL participated in all auctions. The five most active bidders submitted 93 percent of bids and won all but one contract. Bidders that submitted a large share of winning bids generally have a lower mean of homogenized bids.

Table 4. Descriptive statistics on homogenized bids for each participating firm.

<table>
<thead>
<tr>
<th>Firm</th>
<th>HKL</th>
<th>CX</th>
<th>STA</th>
<th>CR</th>
<th>PKL</th>
<th>OLA</th>
<th>LLR</th>
<th>AAS</th>
<th>LSL</th>
<th>ESL</th>
<th>AAD</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td># bids</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td># w bids</td>
<td>50</td>
<td>46</td>
<td>26</td>
<td>37</td>
<td>16</td>
<td>4</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>188</td>
</tr>
<tr>
<td>mean</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>sd</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>min</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>max</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

This table shows the number of bids and winning bids and standard descriptive statistics for each bidder. HKL = Helsingin Kaupungin Bussiliikenne. CX = Connex Oy. STA = Suomen Touristiauto. CR = Concordia Oy. PKL = Pohjolan Kaupunkiliikenne. OLA = Oy Liikenne Ab. LLR = Linjaliikenne Randell. AAS = Askainen Auto. LSL = LS-Liikennelinjat Oy. ESL = Etelä-Suomen Linjaliikenne. AAD = Auto Andersson Oy.

Observed characteristics explain most of the variation in bids. Therefore it plausible to assume that unobserved heterogeneity does not bias the results of the tests. Krasnokutskaya (2004) shows that if the data generating process follows independent
private costs with unobserved heterogeneity, then using the estimation procedures presented below leads to erroneous cost distributions. Wrongly estimated distributions have too low means and too high variances. Higher variances may lead to a situation where the null is not rejected even when it should be. My application turns out to be robust to this possible problem because the null is rejected.

2.4 Conducting the test

This section runs through the estimation and the testing procedures. Those familiar with the estimation methods proposed by Li et al. (2002) (denoted LPV) and Campo et al. (2003) (denoted CPV) and the HHS testing method can skip this section. The only novel feature here is result 2. It is the main methodological insight of this paper and makes testing in the asymmetric case meaningful.

2.4.1 Intuition behind the test

A central issue in auctions for assessing the effects of competition on procurement costs is whether the bidders operate in a private or a common cost environment. Common costs refer to a situation where information on the costs of fulfilling the contract is dispersed among the bidders. The bidders then update their beliefs about costs if they learn their competitors’ signals. Private costs refer to a situation where the bidders care only about their own signals. This distinction is called the information paradigm. Milgrom and Weber (1982) show that due to the winner’s curse the effects of competition may change with the information paradigm. The winner’s curse arises in a situation where bidders bid in a common costs environment according only to their own cost estimates. With unbiased estimates and symmetric bidders, the bidder who underestimates his costs the most wins the auctions and may receive a negative payoff. The expected amount of underestimation increases with the number of bidders. Rational bidders take this into account and thus may even bid less aggressively as competition increases. Hong and Shum (2002) find empirical evidence for this effect. Strategic behavior implies that bidders bid more aggressively as the number of bidders increases. With private costs, only this strategic component is in play, whereas in a common cost setting both of these factors matter and so the effect of competition is uncertain.
Most econometric studies simply assume the information paradigm. To simplify, in situations where bidders’ input-output efficiency is dominant and the only uncertainty is about other competitors’ efficiencies, one should assume private costs, whereas in situations where there is uncertainty about common elements such as technological development, one should assume common costs. In their study of London bus transit auctions Cantillon and Pesendorfer (2006b) argue convincingly for private costs. Here, the auction winners are compensated for changes in most input prices according to the Statistics Finland bus transit cost index. This reduces common uncertainty and therefore the theoretical (and technical) null hypothesis here is that of private costs.

Usually, a researcher observes all the bids submitted in auctions. This is unfortunately not enough to directly infer which information paradigm obtains for the bidders. With common costs, the winner’s curse and strategic behavior have opposite effects on bids when the amount of competition changes. Pinkse and Tan (2005) show that in an affiliated private values first price auction the affiliation effect causes the same response to increased competition as the winner’s curse. Therefore, to be able to test for the information paradigm we need to estimate the bidders’ conditional expectations of costs that correspond to the bids we observe. In that way, the strategic behavior is controlled for. The paradigm can then be inferred because these costs react to competition differently depending on the paradigm.

The HHS tests are conducted in the following manner. First the bidders’ expected costs conditional on winning the auction are estimated for all the bidders. This is done using structural nonparametric methods developed by LPV for the symmetric case and by CPV for the asymmetric case. The idea is to find a relation between the observed homogenized bids and the unobserved costs. In the common costs setting, these costs are increasing in the number of bidders when bidders are symmetric. With private costs, these costs are invariant in the number of bidders, symmetric or asymmetric. Then two tests for stochastic dominance between cost distributions for different numbers of bidders are conducted. The first test compares quantile trimmed means and utilizes bootstrapping procedures. The second is a modified Kolmogorov-Smirnov test based on subsampling. I will present the basic idea of the tests and the essential equations for estimation below. For further details one should refer to LPV, CPV and HHS. The working paper version of this study (Tukiainen 2007) also contains more details.


2.4.2 Pseudo-cost estimation

LPV and CPV use a special case of the affiliated values (AV) model introduced by Wilson (1977) and generalized by Milgrom and Weber (1982). Roughly, affiliation means that a higher value of one bidder’s cost estimate implies a greater probability of high values of other bidders’ cost estimates. Thus bidders adjust their behaviour if they learn the other bidders’ signals. The estimated restricted model is called the affiliated private values (APV) model. As discussed in LPV, the APV model constitutes the most general framework identified from observed bids and, since any AV model is observationally equivalent to some APV model (as shown by Laffont and Vuong (1996)), there is no loss of generality in explaining bids by restricting the set of models to APV models.

The symmetric case

Consider an auction where \( n \) symmetric risk-neutral bidders compete for a single procurement contract. In the AV model the cost of fulfilling a contract for bidder \( i \) is \( C_i = c_i(S, v_i) \) where \( v_i \) denotes the private signal and \( S \) is a common component. In the APV model \( c_i(S, v_i) = v_i \). Private costs \( v_i \) are affiliated. Competitive behavior is identified with symmetric Bayesian Nash equilibrium strategies \( s_i(v_i) \) which are increasing and differentiable. Bidder \( i \) chooses bid \( b_i \) to maximize expected profits conditional on his own information \( v_i \):

\[
\max_{b_i} (b_i - v_i) \Pr(y_i \geq s^{-1}(b_i)|v_i),
\]

where \( y_i = \min_{j \neq i} v_j \). It can be shown that the first order condition for equilibrium is sufficient for estimation. Guerre et al. (2000) provide the identification result used in LPV. The strict monotonicity of \( s() \) allows a relation between the observed bid distributions and the latent costs distributions. As shown in LPV, the first order condition derived from (1) can then be written as

\[
v_i = b_i - \frac{\Pr(B_i \geq b_i=b)}{\Pr(B_i=b_i=b)}.
\]

This can be estimated using standard nonparametric techniques. Knowing point estimates of \( v_i \) is sufficient for HHS testing. Now let \( h_G \) and \( h_g \) denote bandwidths and \( K() \) a kernel function. \( b_{it} \) represents the bid made by bidder \( i \) in auction \( t \), and \( B_{it} \)
represents the lowest bid among i’s opponents in auction t. The pseudo-costs \( \hat{v}_{it} \) are estimated with the following equation:

\[
(3) \quad \hat{v}_{it} \equiv b_{it} - \frac{\hat{G}(b, b)}{\hat{g}(b, b)}, \text{ where }
\]

\[
\hat{G}(b, b) = \frac{1}{T \times h_G \times n} \sum_{t=1}^{T} \sum_{i=1}^{n} K(\frac{b - b_i}{h_G}) \mathbb{1}\{B_{it} > b\} \quad \text{and}
\]

\[
\hat{g}(b, b) = \frac{1}{T \times h_G \times n} \sum_{t=1}^{T} \sum_{i=1}^{n} K(\frac{b - b_i}{h_g}) K(\frac{b - B_{it}}{h_g}).
\]

The sum from \( t = 1 \) to \( T \) runs through all auctions with a given \( n \geq 2 \). The estimation is conducted separately for each \( n \). In the symmetric case, I drop the lone 8 bidder auction and use 49 auctions. The vector \( T_n^* = [6, 19, 11, 11, 2] \) describes the total number of auctions for each \( n = 2, 3, 4, 5, 6 \).

**Asymmetric case**

In bus transit auctions, bidder asymmetry arises mainly from the different garage locations. The closer the route to the garage, the less transfer kilometers the buses need to drive. A transfer is the driving of an empty bus from garage to route at the start of a shift and driving the bus back at the end of a shift. Asymmetry may also arise for other reasons such as different collective labor agreements or capacity constraints. More free capacity increases incentives to bid more aggressively. Cantillon and Petsendorfer (2006a) argue that capacity effects may not be important for London bus route auctions, because firms have time to adjust their capacity between the auctions and the start of contract traffic. Similar time lags obtain in Helsinki. I assume that the only relevant source of asymmetry is the distance between garage and route.

If bidders are asymmetric and their types are not observed, one cannot distinguish between changes in cost distributions resulting from different numbers of bidders and changes resulting from different sets of bidders. HHS suggest taking one bidder at a time and constructing a sequence of the sets of opponents faced by each bidder. This would require a much larger data set than what is available. I allow for limited asymmetry by dividing the bidders into two groups based on the distance of their garage to the routes under contract and treating them as symmetric within groups. The data does not allow for more groups than two. The distances were calculated using an internet service (http://kartat.eniro.fi/) that gives road distances between street addresses in Helsinki. I used the average distance from the nearest garage of a given firm to both end points of the route, weighted by the amount of traffic for contracts consisting of many routes. A median distance (11,5 kilometers) was used as
a cut off point for the grouping. Table 5 presents the distance descriptives for each bus company. Note that all the bids by HKL and AAS belong to the group with short distance and all the bids by OLA and the four companies with no garage in the area belong to the group with long distances.

Group G0 consists of the bidders with garages near the routes and group G1 consists of the bidders with garages far from the contracted route. The bidders are assumed to be symmetric within each group. G0 consists of \( n_0 \) bidders and G1 of \( n_1 \) bidders, with \( n_0 + n_1 = n \geq 2 \). If either \( n_0 \) or \( n_1 \) is zero, the estimation reduces to the symmetric case. The estimation equations become simpler if bidder \( i \) is the only bidder in either of the groups. The analysis must be performed separately for each given pair \((n_0, n_1)\) because a bidder’s strategy depends on both the number and types of his opponents.

Let \( v_{1i} \) denote the costs of the bidders belonging to G1 and \( v_{0j} \) the costs of the bidders in G0. Bidders draw their costs from an \( n \)-dimensional cumulative distribution \( F() \). Marginal distributions may vary across subgroups. I present the estimation strategy here only for group G1, as it is analogous for group G0. Let \( y_{1i} = \min_{j: j \neq i, j \in G1} v_{1j} \) and \( y_{0i} = \min_{j \in G0} v_{0j} \). Then the problem for any bidder \( i \) of type 1 can be written as

\[
(4) \quad \max_{b_{1i}} (b_{1i} - v_{1i}) \Pr(y_{1i}^* \geq s^{-1}_1(b_{1i})) \text{ and } y_{0i} \geq s^{-1}_0(b_{1i}) \vert v_{1i}).
\]

Again the first order condition for equilibrium is sufficient for estimation. Given that \( b_{1i} = s_1(v_{1i}) \) and using the strict monotonicity of \( s() \) to get a relation between the observed bid distributions and the latent costs distributions, the first order condition (see CPV) can be written as

\[
(5) \quad v_{1i} = b_{1i} - \frac{\Pr(B_{1i}^* \geq b \text{ and } B_{0i} \geq b, b_{1i} = b)}{\Pr(B_{1i}^* \geq b \text{ and } B_{0i} \geq b, b_{1i} = b) + \Pr(B_{1i}^* \geq b \text{ and } B_{0i} = b, b_{1i} = b)},
\]

where \( B_{1i}^* \) and \( B_{0i} \) denote the lowest bids of bidder \( i \)’s opponents of a given type. The numerator can be estimated nonparametrically by \( G_i(b_1, b_1, b_1) \). The denominator is estimated as the sum of \( D_{11}(b_1, b_1, b_1) \) and \( D_{12}(b_1, b_1, b_1) \). The sum from \( t \) to \( T \) goes through the given pair \((n_0, n_1)\) of the two bidder types. \( b_{1it} \) denotes the bid made by bidder \( i \) of type 1 in auction \( t \), \( B_{1it}^* \) and \( B_{0it} \) denote the lowest bids of bidder \( i \)’s opponents in auction \( t \). Formally, \( B_{1it}^* = \min_{j: j \neq i, j \in G1} b_{1jt} \) and \( B_{0it} = \min_{j \in G0} b_{0jt} \).

Pseudo-costs can then be estimated by

\[
(6) \quad \hat{v}_{1it} = b_{1it} - \frac{G_i(b_1, b_1, b_1)}{D_{11}(b_1, b_1, b_1) + D_{12}(b_1, b_1, b_1)}, \quad \text{where}
\]

\[
G_i(b_1, b_1, b_1) = \frac{1}{T \times h_{g1} \times n_1} \sum_{t=1}^{T} \sum_{i=1}^{n_1} 1 \{B_{1it}^* \geq b_1\} 1 \{B_{0it} \geq b_1\} K(\frac{b_1 - b_{1it}}{h_{g1}}),
\]

\[
D_{11}(b_1, b_1, b_1) = \frac{1}{T \times h_{g1} \times n_1} \sum_{t=1}^{T} \sum_{i=1}^{n_1} K(\frac{b_1 - B_{1it}^*}{h_{g1}}) 1 \{B_{0it} \geq b_1\} K(\frac{b_1 - b_{0it}}{h_{g1}})
\]
\[ D_{12}(b_1, b_1, b_1) = \frac{1}{T \times h_g \times n_1} \sum_{t=1}^{T} \sum_{i=1}^{n_1} 1 \{ B_{1it} \geq b_1 \} K(\frac{b_1 - B_{0it}}{h_g}) K(\frac{b_1 - b_{1i}}{h_g}). \]

In choosing the kernel and bandwidth, I follow in both cases LPV modified by assumption 5 of HHS. A triweight kernel \( K(u) = \frac{35}{32} (1 - u^2)^{3} \{ |u| \leq 1 \} \) is used. For bandwidths, Silverman’s rule of thumb (Silverman 1986) is used. Bandwidths are of the form \( h = h_g = c_g (nT)^{-1/(1+2n)} \), where \( c_g = c_G = 2.978 \times 1.06 \times (\text{empirical std. deviation of bids}) \). The factor 2.978 follows from the use of triweight kernel instead of the Gaussian kernel. For the asymmetric case, I use only 10 auctions with \((n_0 = 2, n_1 = 3)\), 6 auctions with \((n_0 = 2, n_1 = 2)\), 5 auctions with \((n_0 = 1, n_1 = 2)\), and 8 auctions with \((n_0 = 2, n_1 = 1)\).

Table 5. Descriptive statistics on distances from garages to routes and estimated pseudo-costs for each participating firm.

<table>
<thead>
<tr>
<th>Firm</th>
<th>HKL</th>
<th>CX</th>
<th>STA</th>
<th>CR</th>
<th>PKL</th>
<th>OLA</th>
<th>LLR</th>
<th>AAS</th>
<th>LSL</th>
<th>ESL</th>
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<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<td></td>
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</tr>
<tr>
<td># mv*</td>
<td></td>
<td></td>
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<td>Pseudo-costs assuming asymmetry</td>
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<td>NA</td>
<td>NA</td>
<td>216</td>
<td>301</td>
<td>645</td>
</tr>
</tbody>
</table>

This table shows the number of bids and winning bids and standard descriptive statistics for each bidder. *Five missing values for the symmetric case are due to zeros in the denominator \( \tilde{\theta}^{*}_{B_{1},n}(b, b) \). The statistical program gives zero for some values of this kernel density estimator, because there are very few observations spread over a large area. Some of the missing values for the asymmetric case are also caused by this. Most of them however arise from the fact that I estimate the asymmetric case for only 34 auctions whereas the symmetric case is estimated for 50 auctions.

Table 5 gives the descriptive statistics for distance and pseudo-costs separately for each bidder, along with the amount of bids submitted and contracts won. Bidders that
submitted a large share of winning bids generally have a lower mean of pseudo-costs. Note that due to the nature of the homogenization process, the comparison of the homogenized bids in Table 4 and the estimated pseudo-cost in Table 5 does not allow us to draw any conclusions on the operating margins of the firms.

2.4.3 Testing

The tests in HHS are based on comparing the distributions of bidders’ expected costs $C_i$, conditional on winning the auction, for different numbers of bidders. For bidder $i$, this cost is $v_n(X_i, Y_i) = E[C_i | X_i, Y_i]$, where $X_i$ is a private signal of bidder $i$ and $Y_i$ is the lowest signal of the $(n-1)$ other bidders. Using the estimated $\hat{v}_n$, we can now conduct the test. HHS base their tests on a formal definition of private and common costs.

**Definition 1.** Bidders have private costs if and only if $E[C_i | X_1, \ldots, X_n] = E[C_i | X_i]$ and bidders have common costs if and only if $E[C_i | X_1, \ldots, X_n]$ strictly increases in $X_j$ for $j \neq i$.

HHS prove (refined in Athey and Haile (2005, p.94)) that with private costs $v_n(x, x)$ is invariant with respect to $n$ for all $x$, but with common costs and symmetric bidders strictly decreasing in $n$ for all $x$.

**Result 1.** Under the private cost hypothesis

$F_{v,n}(v) = F_{v,n+1}(v) = \ldots = F_{v,n}(v)$ for all $v$.

Under the common cost hypothesis and with symmetric bidders

$F_{v,n}(v) > F_{v,n+1}(v) > \ldots > F_{v,n}(v)$ for all $v$.

Result 1 (Corollary 1 in HHS) forms the test in the symmetric case. My contribution to this test is result 2, which forms the test in the asymmetric case. Assuming two types of bidders we obtain

**Result 2.** Under the private cost hypothesis and with asymmetric bidders

$F_{v,n_0,n_1}(v) = F_{v,n_0+1,n_1}(v) = F_{v,n_0+1,n_1+1}(v) = \ldots = F_{v,n_0,n_1}(v)$ for all $v$.

Under the common cost hypothesis and with asymmetric bidders

$F_{v,n_0,n_1}(v) > F_{v,n_0+1,n_1}(v) > F_{v,n_0+1,n_1+1}(v) = \ldots = F_{v,n_0,n_1}(v)$ for all $v$. or

$F_{v,n_0,n_1}(v) > F_{v,n_0+1,n_1}(v) > F_{v,n_0+1,n_1+1}(v) > \ldots > F_{v,n_0,n_1}(v)$ for all $v$. 

Thus if we observe equal distributions the information paradigm is unknown, but if we observe unequal distributions the environment must be common. This is not the entire partition of the relation set, but in practise the reverse relation should not be observed. Two sided tests should be conducted if a counterintuitive direction is observed. In the asymmetric case, more competition means at least the same amount of one type of bidder and more of the other type.

HHS explain the difficulties involved in tests that use estimated pseudo-costs $\hat{v}_{it}$. HHS suggest the use of two tests that look for stochastic dominance between different empirical distributions of the estimated pseudo-costs $\hat{F}_{v,n}(y) = \frac{1}{T_n \times n} \sum_{t=1}^{T} \sum_{i=1}^{n} 1\{\hat{v}_{it} < y, n_t = n\}$. The idea of their first test is to compare the distributions horizontally using quantile trimmed means. They use block bootstrapping to calculate variances. As Athey and Haile (2005) summarize it, the test is an adaptation of a standard multivariate one-sided likelihood-ratio test by Bartholomew (1959). Their second and preferred test is a generalization of the Kolmogorov-Smirnov test. The idea is to compare the distributions vertically using the sum of maximum distances as the test statistic. They normalize their test statistic to enable use of subsampling to estimate critical values. These tests are presented below for the symmetric case. For the asymmetric case, I calculate the means and distances separately for auctions with given type combinations, not just for a given number of bidders.

Tests based on means

HHS propose the use of a sample analog of the quantile trimmed mean, $\hat{\mu}_{n,\tau}$, as the basis for the test. Let $\hat{b}_{\tau,n}$ denote the $\tau$th quantile of observed bids. Then

$$\hat{\mu}_{n,\tau} = \frac{1}{T_n \times n} \sum_{t=1}^{T} \sum_{i=1}^{n} \hat{v}_{it} 1\{\hat{b}_{\tau,n} \leq \hat{b}_{it} \leq \hat{b}_{1-\tau,n}, n_t = n\}.$$  

These means are then used to formulate the following test hypothesis:

(8) $H_0$(PC with symmetry, PC or CC with asymmetry): $\mu_{n,\tau} = ... = \mu_{n,\tau}$

$H_1$(CC): $\mu_{n,\tau} < ... < \mu_{\tilde{n},\tau}$.

To test this hypothesis, one needs the variances of $(\hat{\mu}_{n,\tau}, ..., \hat{\mu}_{n,\tau})'$. Denote them by $(\frac{1}{a_{n}}, ..., \frac{1}{a_{n}})'$ and let $\Sigma$ denote the diagonal covariance matrix. HHS propose to estimate
these by a block bootstrap procedure where one auction is one block. HHS define the test statistic as

\[ \chi^2 = \sum_{n=a_n}^{n} a_n (\mu_{n,\tau}^* - \bar{\mu})^2, \]

where

\[ \bar{\mu} = \frac{\sum_{n=a_n}^{n} a_n \mu_{n,\tau}}{\sum_{n=a_n}^{n} a_n} \]

and \( \mu_{n,\tau}^* \) denotes the solution to

\[ \min_{\mu_{n-1}, \ldots, \mu_n} \sum_{n=a_n}^{n} a_n (\hat{\mu}_{n,\tau} - \mu_n)^2 \] s.t. \( \mu_n \leq \ldots \leq \mu_n \).

HHS point out that the solution to (11) can be found using the "pool adjacent violators" algorithm (Ayer et al. 1955), with the weights \( a_n \). The p-values are then calculated using equation (12), which states that, under the null, \( \chi^2 \) is asymptotically distributed as a mixture of Chi-squared random variables. HHS suggest obtaining the weights \( w(k; \Sigma) \) by simulation from the MVN(0, \( \Sigma \)) distribution, where the estimated weights for chi-squared-bar are defined by the distribution of the number of activated constraints in (11).

Under the null PC hypothesis

\[ Pr(\chi^2 \geq c) = \sum_{k=2}^{n+1} Pr(\chi^2_{k-1} \geq c) w(k; \Sigma) \]

for all \( c > 0 \), where \( \chi^2_{k-1} \) denotes a standard Chi-square distribution with \( j \) degrees of freedom, and each mixing weight \( w(k; \Sigma) \) is the probability that the solution to (11) has exactly \( k \) distinct values when the vector \( \{\mu_{n,\tau}, \ldots, \mu_{n,\tau}\} \) has a multivariate \( N(0, \Sigma) \) distribution.

**A Kolmogorov-Smirnov type test**

The second testing approach in HHS uses a smoothed sum of supremum distances between successive empirical distributions of pseudo-costs. Hence it is also called a sup-norm test.

\[ \tilde{\delta}_T = \sum_{n=a_n}^{n} \sup_{v \in [v, \hat{v}]} \left\{ \frac{1}{nT_n} \sum_{t=1}^{T_n} \sum_{n=1}^{n} 1\{n_t = n\} \Lambda(\hat{\mu}_{it} - v) \right. - \left. \frac{1}{(n+1)T_{n+1}} \sum_{t=1}^{T_{n+1}} \sum_{n=1}^{n+1} 1\{n_{t+1} = n+1\} \Lambda(\hat{\mu}_{it} - v) \right\}, \]

where \( \Lambda(\hat{\mu}_{it} - v) = \frac{\exp((v - \hat{\mu}_{it})/h')}{1 + \exp((v - \hat{\mu}_{it})/h')} \) and \( h' = 0.01 \).
HHS suggest normalizing this distribution. I use Silverman’s rule of thumb for bandwidths \( h \). HHS show that this test statistic can be approximated with subsampling. They also suggest the use of a recentering approach by Chernozhukov and Fernandez-Val (2005), where in each subsample the test statistic is recentered by the original full sample test statistic. Then the p-value is computed as

\[
\frac{1}{S} \sum_{s=1}^{S} 1 \left\{ L^s > \sqrt{T} \sum_{n=n}^{n-1} \sqrt{h_T(n)} \sup_x \left[ \hat{F}_n(x) - \hat{F}_{n+1}(x) \right] \right\},
\]

where \( L^s \) is the following modified test statistic

\[
L^s = \sqrt{R} \left\{ \frac{\sum_{n=n}^{n-1} \sqrt{h_R(n)} \sup_x \left[ \hat{F}_s^n(x) - \hat{F}_{s+1}^n(x) \right]}{\sum_{n=n}^{n-1} \sqrt{h_R(n)} \sup_x \left[ \hat{F}_n(x) - \hat{F}_{n+1}(x) \right]} \right\}.
\]

\( s = (1, \ldots, S) \) refers to a particular subsample. \( \hat{F}_n(x), \hat{F}_{n+1}(x), \hat{F}_n(x) \) and \( \hat{F}_{n+1}(x) \) note the smoothed functions presented in equation (13). \( T \) is the full sample size and \( R \) is the subsample size.

### 2.5 Problems and remedies

Below I discuss four different problems related to the applicability of the data for the testing methodology. The first problem is that the data set is small. The second is that bidders’ participation decisions are possibly endogenous. The third possible problem is bidder collusion, and the fourth is the applicability of the structural estimation method for this particular data.

I introduce pooling to the test procedure for two reasons. First, for some combinations of bidder types there are too few auctions for the purpose of subsampling. When the observations are pooled by treating the auctions with small numbers of bidders as belonging to one group and the auctions with large numbers of bidders as belonging to the other group, a larger part of the data set can be used. Typically, the results are also more robust to the choice of subsample size with larger samples. The second reason is that this pooling alleviates the problem of possible endogenous participation.

HHS tests assume that the number of bidders is exogenous and known to all bidders ex ante. HHS mention two ways in which endogenous participation may pose problems. First, if auctions with large numbers of bidders tend to be those where the contract is known by bidders to be particularly easy to operate, tests based on an assumption
that variation in participation is exogenous can produce misleading results. This would make observing the common costs paradigm more difficult. In this application, the tests suggest common costs, therefore the results are robust to this problem. Second, nonparametric identification of the pseudo-costs depends on \( n \) being independent of any unobservables. HHS describe a structure under which both problems can be overcome using instrumental variables. Lacking a proper instrument, I assume that participation is exogenous.

Exogenous bidder variation is most likely caused by observed bidder asymmetries in this market. A disadvantage in the location of the garage might make some bidders’ costs too high for them to be willing to spend the effort needed to submit a bid. The number of actual bidders and the number of potential bidders can differ due to the costs of calculating and submitting bids, a binding reserve price, or unobserved contract heterogeneity. Explicit reserve prices are not used in these auctions, but the tender invitation admits the possibility of a secret reserve price. A secret reserve price is probably not binding, because the city-owned company participates in all the auctions. Those bids act as a de facto reserve price from the perspective of the buyer. In theory the number of potential bidders is very large, as the tender is open to any firm meeting certain standards. However, to be able to participate competitively, a firm needs to own or rent a garage in the area. Thus it is fairly easy to detect possible new entrants. Moreover, the number of participating players is quite small, and the same players have been in the market for a long time. Thus it is reasonable to assume that most of the variation in numbers of bidders is caused by exogenous factors that are observed by the bidders. There is still a risk that some bidders have expected a different level of competition than that which obtains, which could bias the estimation results.

Pooling alleviates the possible problem of endogenous participation in the testing stage, but unfortunately it cannot help in the estimation stage. The chance of being put into the wrong group is reduced when pooling is used because the groups are larger. There is another property in the data that alleviates this problem. There are ten identical contract pairs in the data. The only thing that is heterogeneous within the pairs is that they were auctioned some years apart from each other. Of these ten pairs, five contained different numbers of bidders. Thus the contract properties cannot explain all participation choices. Some exogenous variation is created by mergers and acquisitions and entry and exit. There are some of these in the data.

Collusion would make testing impossible unless all the bidders and the researcher knew the colluders and the type of collusion. It would change the equilibrium and make defining more competition difficult. In this case collusion is unlikely, as it would
yield very low rents. The most important bidder is a public company. Therefore it has less incentive to collude, and its bids would limit the profits from colluding. The other fact that supports competitive bidding is the bidders’ very low accounting profits in this market (Valkama and Finkkilä 2003).

Another important consideration is that the pseudo-cost estimation is based on assuming Bayesian Nash equilibrium behavior. As HHS admit, this is not an innocuous assumption, although they claim that FPSB auctions seem particularly well suited to this approach. Experimental results by Bajari and Hortacsu (2005) encourage the use of these structural econometric tools. In my data, the players are experienced companies bidding for large contracts. Thus the assumption of rational behavior is plausible. Kagel and Levin (1986) find in their experiments that bidders learn equilibrium behavior only through experience. In my data, the standardized variances of bids were much larger in the first tranche than in later ones. This could be due to learning. Because of the small size of the data set, I do not remove the first tranche from the data.

2.6 Empirical results

I present the results of two different testing specifications in this section. There are more specifications in the working paper version of this study (Tukiainen 2007), but they do not change the policy conclusions. The first is the standard approach presented in HHS where there are symmetric bidders. The second is the asymmetric case with pooling. Due to the small number of observations with a given number of bidders, the actual data used in the analysis differs from one specification to another. The results for both specifications are shown in Table 6 and discussed below.

Table 6. The p-values from the means test and Kolmogorov-Smirnov type test for both symmetric and asymmetric specifications.

<table>
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<th>Symmetric</th>
<th>Asymmetric near</th>
<th>Asymmetric far</th>
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<td>Means q:5%</td>
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<td>0.032</td>
<td>0.86</td>
</tr>
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<td>Means q:10%</td>
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<td>0.75</td>
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<tr>
<td>Means q:20%</td>
<td>0.043</td>
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<tr>
<td>KS test</td>
<td>0.006</td>
<td>0.002</td>
<td>0.53</td>
</tr>
</tbody>
</table>

The results for the means test are presented for three different quantile choices: q:5%, q:10% and q:20%. The p-value result for the KS test for the symmetric case is obtained using subsample sizes 9 for three bidder auctions and 6 for four and five bidder auctions. For the
asymmetric case, the results are obtained using subsample size 9 for the pool with less bidders and 5 for the pool with more bidders. The number of subsamples taken was 500 in all cases.

2.6.1 Testing specification 1: Symmetry

To be able to use the Kolmogorov-Smirnov type test I conduct the standard testing procedure only with auctions to which three, four or five bidders have participated. The vector $T_n = [19, 11, 11]$ describes the total number of auctions for each $n = 3, 4, 5$. There is some evidence against the null in Figure 1. For most of the values of $v$, $F_{v,n=3}(v) < F_{v,n=4}(v)$, implying that the null cannot be rejected. But $F_{v,n=5}(v)$ takes the smallest values of the three distributions through most of the range of $v$, implying rejection.

Figure 1. Empirical cumulative distributions of pseudo-costs for three, four and five bidders.

Figure 1. draws $F_{v,n}(y) = \frac{1}{n \times n} \sum_{t=1}^{T} \sum_{i=1}^{n} 1\{v_{it} < y, n_t = n\}$ separately for each $n = 3, 4, 5$. 
It is very important to note from Table 6 that there are qualitative changes in the inference that depend on the choice of the amount trimmed. Thus the means test is not robust to the choice of quantile. The sup-norm test clearly rejects the null. Even though the means test is somewhat ambiguous, it suggests the presence of important common cost components across bidders. This implies the following policy conclusions. The merger of the two city-owned bus companies might have no effects - or even a decreasing effect - on the procurement costs, due to reduced competition. In any case it has a smaller increasing effect on the expected winning bid than with private costs. Thus, from the perspective of competition and on the basis of my results, this merger is not open to criticism. The other policy activity currently under consideration, i.e. the building of city-owned garages and renting them to new entrants to induce more competition, should not necessarily be undertaken. It is not certain that new competition brings any savings. Therefore the City might be better off not spending any resources on this.

2.6.2 Testing specification 2: Pooling and asymmetry

In the asymmetric case, I compare 10 auctions with two near bidders and three far bidders (i.e. $n_0 = 2, n_1 = 3$) to the pool consisting of 6 auctions with $(n_0 = 2, n_1 = 2)$, 5 auctions with $(n_0 = 1, n_1 = 2)$ and 8 auctions with $(n_0 = 2, n_1 = 1)$. This guarantees that there is no ambiguity in comparing the distributions, because the group with a large number of bidders has at least an equal number of bidders of one type and more of the other type than all the auctions in the group with the smaller number of bidders. Tests are conducted separately for the different distance groups. I omitted one auction with one near bidder and two far bidders from the data because it had one unusually small outlier value for the pseudo-cost. Table 7 presents the pooling rule I used.

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The auctions are pooled into four groups. Pool one, for example, consists of bidders with
long (over 11.5 km) distance ("d") from garage to a given route in auctions with the number of short-distance bidders "s" two and number of long-distance bidders "l" three. "n" denotes the total number of bidders. "T" denotes the number of auctions of a given type and "# bids" the number of bids going to a given pool from a given auction. "Tpool" denotes the number of auctions in a given pool.

Figure 2 shows the distributions for the short distance group. It clearly indicates common costs because the distribution for the pool with a small number of bidders gets larger or about equal values throughout the entire range of observed values. This is confirmed by the test results in Table 6. Both tests reject the null hypothesis of private costs. Both tests work well from the robustness point of view for both of the distance groups. Figure 3 presents the distributions for the two pools for the bidders with garages located far from the routes. It shows that there is no observable difference in them. The results in table 6 show that neither of the tests rejects the null of identical distributions.

Asymmetric results show that the bus companies operating from garages far from the routes could operate in either a private or common cost environment, and bus companies with garages near the routes operate in a common cost environment. We also know that even if far operators had common costs, the common cost elements are more important to the near bidders. Thus more competition reduces the bids of far operators more or increases them less on average than the bids of near operators. All the conclusions made for the symmetric case remain valid when asymmetry is taken into account. Moreover it is now possible to draw some additional conclusions on the two policy questions.

First, the two merged companies were more often near than far bidders. Thus the merger reduced the number of bidders to whom the common cost elements were more important. This actually makes the policy of inducing more competition more plausible because now the role of common elements in the market is diminished. Second, if the City chooses to pursue the proposed garage policy, and they have to choose between two locations from which the overall operating costs are equal, they should choose the garage which is more often located further away from the routes. Then at least the new entrants would react to the increased competition. For the behavior of the incumbents, the location does not matter, because assuming similar overall operating costs, incumbents do not perceive the new bidders or locations asymmetric in this respect.
Figure 2. Empirical cumulative distributions of pseudo-costs for bidders belonging to short-distance group G0. 10 auctions with \((n_0 = 2, n_1 = 3)\) are compared to a pool that consists of 6 auctions with \((n_0 = 2, n_1 = 2)\), 5 auctions with \((n_0 = 1, n_1 = 2)\) and 8 auctions with \((n_0 = 2, n_1 = 1)\).

The distribution for pool 1 is \(\hat{F}_{v,(n_0,n_1)=(2,3),d\leq11.5}(y)\) and for pool 2

\[
\frac{1}{3} [\hat{F}_{v,(n_0,n_1)=(2,2),d\leq11.5}(y) + \hat{F}_{v,(n_0,n_1)=(2,1),d\leq11.5}(y) + \hat{F}_{v,(n_0,n_1)=(1,2),d\leq11.5}(y)].
\]

\[
\hat{F}_{v,(n_0,n_1)=(s,l),d\leq11.5}(y) = \frac{1}{T_{(n_0,n_1)=(s,l)} \times n_1} \sum_{t=1}^{T_{(n_0,n_1)=(s,l)}} \sum_{i=1}^{n_1} 1\{v_{1it} < y, (n_0, n_1) = (s, l)\}.
\]
Figure 3. Empirical cumulative distributions of pseudo-costs for bidders belonging to long-distance group G1. 10 auctions with \((n_0 = 2, n_1 = 3)\) are compared with a pool that consists of 6 auctions with \((n_0 = 2, n_1 = 2)\), 5 auctions with \((n_0 = 1, n_1 = 2)\) and 8 auctions with \((n_0 = 2, n_1 = 1)\).

The distribution for pool 3 is \(\hat{F}_{v, (n_0, n_1) = (2, 3), d > 11.5}(y)\) and for pool 4

\[
\frac{1}{3}[\hat{F}_{v, (n_0, n_1) = (2, 2), d > 11.5}(y) + \hat{F}_{v, (n_0, n_1) = (2, 1), d > 11.5}(y) + \hat{F}_{v, (n_0, n_1) = (1, 2), d > 11.5}(y)].
\]

\[
\hat{F}_{v, (n_0, n_1) = (s, l), d > 11.5}(y) = \frac{1}{T_{(n_0, n_1) = (s, l)} \times n_0} \sum_{t=1}^{T_{(n_0, n_1) = (s, l)}} \sum_{i=1}^{n_0} 1\{v_{0it} < y, (n_0, n_1) = (s, l)\}.
\]
2.6.3 Robustness checks

The amount trimmed is the only arbitrarily chosen variable in the means test. Therefore I check robustness only with respect to it. For the symmetric case there are qualitative changes in the inference that depend on this choice. HHB assume that the choice of quantile size is not important, as it does not matter asymptotically. A data driven method of choosing the quantile should be formulated. One possibility would be to look at simulations using the same sample size and bandwidth selection rule as in estimating the pseudo-costs. Monte Carlo simulations could produce some rules of thumb for choosing the quantile. This is left for further research. For the asymmetric case, the results are robust with respect to the trimmed amount.

Three choices concerning subsampling may affect the results of the sup-norm test. These choices are subsample size, number of subsamples, and which repetition of the test to use. Most notably the choice of subsample size can change the results. In theory, the subsample size should be far from both 1 and T. Linton et al. (2005) suggest computing a plot of p-values against subsample sizes. If the p-value is insensitive to subsample size within a "reasonable" range, then inferences are likely to be robust. Regarding the number of subsamples taken, there is a trade-off between computer time and robustness of result. We can be quite sure of getting a correct result with 5000 draws but not necessarily with 50 draws. The p-value also changes from one push of the button to the next. Therefore one should also check whether the p-value is robust to test repetitions with the chosen subsample size and number of draws. Again Monte Carlo simulations could reveal important information on how to make these choices.

All the robustness checks conducted for this study took about three weeks on a 1300 MHz computer. For the symmetric testing specification, I decided to use the same subsample size for distributions of four and five bidder auctions because there is the same number (11) of each. The results of the symmetric specification were robust for a large range of subsample sizes. Only the two smallest (2 and 3 for all auctions) and two largest possible sizes (17 and 18 for three bidder auctions and 9 and 10 for four and five bidder auctions) show nonrobust p-values. I chose subsample sizes of 9 for three bidder auctions and 6 for four and five bidder auctions for reporting results and conducting other robustness checks. For the asymmetric case, the results are robust for changes in subsample sizes for both distance groups. I used 5 as the subsample size for pool 1 and pool 3 and 9 as the subsample size for pool 2 and pool 4 in Table 7.

It is also important to check the relationship between number of subsamples taken and p-value. The smaller the number of subsamples, the easier it is to get an erroneous
result by chance. All the results were robust in this respect. I took 500 draws for all
the reported results. I also repeated this test 50 times with the chosen subsample sizes
and number of subsamples taken. All the results were qualitatively robust also this
respect and varied only little. I report the maximum p-value of these repetitions.

2.7 Conclusions

I conducted two tests developed by HHS for common costs to analyze two specific policy
questions for the City of Helsinki bus transit market. In addition to the standard testing
framework with symmetric bidders, I allowed for asymmetric bidders. The results from
the symmetric testing show that there seem to be important common cost elements in
this market. Based on the asymmetric results, it seems that the bus companies with
garages close to the contracted routes operate in a common cost environment. Because
the equal distributions hypothesis was not rejected for bus companies with garages
far from these routes, the information environment is not known for them. Common
costs elements are more important to operators with garages near the routes. Due to
the small number of observations in the data and the somewhat arbitrary treatment
applied to the data to take combination bidding and the scoring rule into account, the
results of this study should be treated with caution. In the symmetric case, the means
test was not robust to the choice of quantile trimmed, but the Kolmogorov-Smirnov
type test was robust to the subsampling choices. The results for the asymmetric case
were robust. Common costs can arise from common future uncertainty and private
costs from individual efficiency differences. Next I provide explanations for this result.

The garages that are typically located near the routes are also closer to the city
center, where the costs of land are higher. Land rents or opportunity costs of land
are subject to future uncertainty. Unlike, for example, gasoline price changes, changes
in land rents are not covered by the contract terms. Operators could face significant
changes in production costs if the land rents increase. Another factor is that being
located near the route reduces the incentive to be efficient in organizing the empty
transfer traffic. This makes the private cost component less important. When garages
are far from the routes, the importance of land rents is lesser and the need to efficiently
organize the transfer traffic is greater.

Another element that could be driving common costs is outside options. Bidders
also participate in auctions for metropolitan transit. When they commit their garages
to traffic in one contract, they could reduce their chances to participate and win in
later auctions. Uncertainty about winning future contracts is common. There could also be common uncertainty about the results of future negotiations with labor unions. There could be strikes or other frictions that are not covered by contract. The industry also suffers from the undersupply of driver labor (Helsingin Sanomat 29 January 2007 and 12 February 2007). Therefore it is not certain whether the bidders get enough drivers if they win contracts.

Valkama and Finkkilä (2003) studied the economic effects of tendering of bus services in the Helsinki Metropolitan Area. They analyzed firm accounting data from 1998 to 2001 and found that tendering reduced the firms’ profits dramatically and the tendered traffic induced losses. For example, operating margin, net income, and return on capital were negative in 2001. Since 2003 the firms have managed to break even or make small profits (see e.g. (HKL 2006)). This could be evidence of common costs. It might have taken time for firms to learn to take the winner’s curse effect into account.

The symmetric result provides clear answers to the two policy questions posed in this study. First, a decrease in competition caused by the merger of the two city-owned bus companies may have no effects or even an reducing effect on procurement costs. Thus, from the perspective of competition, this merger decision is not open to criticism. The reasons for the merger remain valid. These include separating further the planner (HKL planning unit) and one bidder (HKL bus transit department), possible synergies, and avoiding the presence of two companies with the same owner in the auctions. Second, the City should not build public garages and rent them to new entrants to induce more competition. As it is not certain that new competition brings any benefits, the City should not spend any resources to induce it. Asymmetric results make it possible to draw additional conclusions. First, the two merged companies were more often near than far bidders. Thus the merger reduced the number of bidders to whom common cost elements were more important. This actually makes the policy of inducing more competition more plausible because now the role of common elements is diminished. Second, if the City chooses to pursue the proposed garage policy and must choose between two locations for which overall operating costs are equal, they should choose the garage which is more often located further away. Then at least the new entrants will react to the increased competition.
2.8 References


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Krasnokutskaya E (2004). Identification and Estimation in Highway Procurement
Chapter 3

The Determinants of Entry in an Auction with both Private and Common Value Bidders\(^1\)

3.1 Introduction

A vast majority of studies on auctions assume that bidders always know the number of actual bidders. This exogenous entry assumption is valid in cases where there is no binding reservation price and entry costs\(^2\) are very small. In those cases, we would expect every potential bidder to always submit a bid. However, in a typical procurement auction data, we observe that the amount of bids submitted changes from one auction to another. Entry could still be exogenous if there were some exogenous and commonly observed shocks that make some bidders too disadvantaged to be willing to pay the entry cost. Then all the bidders would know which bidders enter in the equilibrium. Also in some cases the actual participants are publicly announced. In many cases the assumption of exogenous entry is not plausible. Endogenous entry has been one of the main research questions in the literature on auctions in the recent years.

This paper has two objectives. First, I study the determinants of entry in the City of Helsinki bus transit market. Knowing which contract and bidder characteristics affect the bid submission decisions helps the procurement agency to plan the contracts

\(^1\)A version of this Chapter has appeared in the HECER Discussion Paper series, No 214 / April 2008.

\(^2\)Typical entry costs consist of entry fees and/or information acquisition costs.
to minimize the procurement costs. My paper thus has a policy objective. I conduct the estimations for the determinants of entry in such a way that they allow for the possible endogenous entry. Second, I contribute to the literature on endogenous entry in auctions by studying whether bidders for whom private value aspects are relatively more important make different entry choices than those bidders for whom common value aspects are more important.

In an auction setting, the second question is central. Common values refer to a situation where the information about the value of the auctioned object is dispersed among the bidders. In such an environment, bidders would update their beliefs about the value of the object if they learned their competitors’ signals on this value. Private values refer to a situation where the bidders care only about their own signals. This distinction is called the information paradigm. I use procurement auction data to construct a set up that enables me to study how the information paradigm affects the entry choices.

Due to a phenomenon known as the winner’s curse, the effects of competition may change with the information paradigm. The winner’s curse arises in situations where bidders bid in a common value environment only according to their own value estimate. With unbiased estimates and symmetric bidders, the bidder who underestimates his valuation most, wins the auctions and may receive a negative payoff. The expected amount of underestimation increases with the number of bidders. Rational bidders take this into account and thus bid less aggressively as competition increases. On the other hand, strategic behavior implies that bidders bid more aggressively when the number of bidders increases. With private values, only this strategic component is in play, whereas in the common values setting both of these factors matter and thus the overall effect of competition on bids is uncertain. It is yet to be asked whether the information paradigm makes a difference when bidders make entry decisions. If bidders face some entry costs, they might not want to submit a bid to every auction. For strategic reasons all the bidders would prefer bidding to less competed contracts over more competed contracts. However, the additional effect of having common values on the entry decisions is unclear. In cases when the entry cost is an information acquisition cost, the bidders base their entry decisions on their expected profits of entry. Since these differ for private and common value bidders, one would expect the entry decisions to differ as well. It is however difficult to say to which direction. Here I study whether common value bidders make different entry choices than private value bidders when the amount of expected competition changes.

I am able to address this question because in Tukiainen (2008), I find some evidence
that some bidders are more influenced by common value elements than others in the City of Helsinki bus transit auctions. Bidders that have garages close to the contracted bus routes seem to be more influenced by the common value elements than bidders with garages further away. So far there are no theoretical results that analyze this form of bidder asymmetry. It could complicate the theoretical analysis beyond tractability. Therefore an empirical approach to answer whether the information paradigm affects the entry choice is important. I utilize the particular form of asymmetry found in these bus transit auctions. I compare the participation behavior of one bidder, for whom the private value components are more important than to its rival in every auction, with another bidder for whom the common value components are always more important than to its rival. I test whether these bidders react to the amount of competition they expect to face differently. The possible difference could then be attributed to the different information paradigm in this set up.

According to the endogenous entry model that Levin and Smith (1994) (denoted LS) study, the auctioneer does not want to deter entry when values are private but could want to set reservation prices to deter entry when values are common. The intuition is that every new bidder in the common value auctions reduces the expected bids of all the bidders. This would suggest that in markets with both private and common valued bidders, the auctioneer would wish to attract more private value bidders and maybe restrict the participation of common value bidders. If common value bidders were more reluctant to enter heavily competed auctions than private value bidders, attracting more private value bidders would achieve both of the goals. Goeree and Offerman (2003) study a model with symmetric bidders where the objects for sale possess both private and common values. They show that then both efficiency and revenue increase when more bidders enter the auction, and also when the auctioneer can reduce the uncertainty about the common value component. Therefore it is very policy relevant to study whether there are some contract characteristics that either increase entry or reduce the importance of uncertainty about the common value component or both. We know that common values typically arise from common future uncertainty. As Tukiainen (2008) discussed, in the auctions analyzed here, the main uncertainty is about getting enough bus drivers in the future and about the development of land rents. Reducing contract lengths would therefore reduce the uncertainty about the common elements. If reducing contract lengths would also increase entry, there would be two reasons to reduce them. To test for both the effect of the information paradigm and the effect of contract and bidder characteristics on entry, I use a recent method by Bajari et al. (2007a) (denoted BHKN) that allows for an empirical analysis of static
entry game with strategic interactions.

In the next Section, I analyze the relation of my work to the existing literature more closely. In Section 3, present the Helsinki bus transit market and describe the data. In Section 4, I shortly discuss the estimation method, how it fits the data and how I set up my estimations. Section 5 presents the results and Section 6 concludes.

3.2 Related literature

Entry has been studied widely in empirical industrial organization literature (e.g. Bresnahan and Reiss 1990 and 1991, Berry 1992). Berry and Tamer (2007) provide a survey on the traditional entry literature. Empirical models of entry in auctions have been considered by Athey et al. (2004), Bajari and Hortacsu (2003), Bajari et al. (2007b), Krasnokutskaya and Seim (2005), Li (2005) and Li and Zheng (2006). Athey et al. (2004) form a structural model of bidding coupled with a reduced form model of entry that allows for heterogenous bidders and unobserved auction heterogeneity under independent private values (IPV) paradigm. They compare open and sealed bid U.S. Forest Service auctions. Bajari and Hortacsu (2003) use a parametric structural model to study winner’s curse and the effects of a reserve price on seller revenue when entry is endogenous in eBay coin auctions. They consider a pure common value setting with the Poisson arrival of bidders. Bajari et al. (2007b) propose an identification method for discrete games of complete information with an application to auctions. They estimate the probabilities for each of the possible equilibria, including mixed equilibria. First they estimate an auction model similar to Athey et al. (2004) and then use simulations to calculate all the equilibria. Krasnokutskaya and Seim (2005) analyze the effects of bid preference programs on participation in highway procurement. They estimate jointly a model of participation and bidding in a similar manner as Athey et al. (2004). Li (2005) considers the structural estimation of first-price auctions with entry and binding reservation prices when bidders are symmetric. He suggests a method of simulated moments estimator that can be used to test whether the reservation prices are binding, and to test the mixed-strategy of entry. Li and Zheng (2006) form a fully structural auction model with endogenous entry, an uncertain number of actual bidders, unobserved heterogeneity and mixed strategy entry equilibrium under IPV paradigm with symmetric bidders. They form counterfactuals on the effects of the number of bidders on procurement costs in highway mowing auctions. The common econometric goal of all these structural auction papers is to estimate the distribution of bidder’s
private values and the distribution of entry costs. I apply the method proposed by BHKN for estimating static games of incomplete information. They generalize the discrete choice models to allow for the actions of a group of agents to be interdependent. This method allows a reduced form analysis of a situation where there is no existing equilibrium behavior structure.

LS presented the theoretical auction model with endogenous entry that is the basis of most of the above empirical work. They characterize a symmetric mixed strategy equilibrium that leads to a stochastic number of entrants. A fixed and known number of identical potential bidders have to incur an entry cost to be able to submit a bid. In equilibrium each bidder enters with the same probability. Previously, McAfee and MCMillan (1987) and Engelbrecht-Wiggans (1993) studied models of entry where bidders have entry costs but both assumed pure strategies. Smith (1982 and 1984), Samuelsson (1985) and Engelbrecht-Wiggans (1987) were the first to examine endogenous entry. They were interested in the efficiency and optimality of reserve prices. Also Harstad (1990) and Hausch (1993) treated entry stochastically in a simpler setting than LS do. Chakraborty and Kosmopolou (2001) extend the LS framework so that bidders are asymmetrically informed about their valuations when making the entry decision. With asymmetry they mean that, unlike in LS they observe their signals before paying the entry cost. This reverses the LS predictions that the optimal reserve price is zero and entry fee positive (zero) in a common (private) value framework. Also Menezes and Monteiro (2000) change the LS setting so that bidders learn their valuations before paying the entry cost. Ye (2004) generalizes the LS model so that bidders can update their beliefs after entry. In an ongoing work Harstad (2005) extends the endogenous entry model further by introducing affiliation and generalizing the information flows. Cox et al. (2001) test experimentally a model of endogenous entry, exit and bidding in common value auctions. They find that observed entry is lower than predicted by the model and that winner’s curse occurs among inexperienced bidders. Gal et al. (2007) extend the LS model by allowing the entry costs to differ across bidders. The resulting game is bi-dimensional, because bidders receive signals on both the value and the entry cost. They find that partially reimbursing the entry costs of high entry cost types increases revenue.

Auctions where bidders have both private and common components in their valuations have drawn some attention in the recent literature. More generally they belong to a class of auctions where the essential feature is that signals on valuations are multidimensional, because there is a signal for both the private and common component. Maskin (1992), Dasgupta and Maskin (2000) and Jehiel and Moldovanu (2001) have
studied these auctions. The main feature is that no auction format is efficient when signals are multidimensional although Pesendorfer and Swinkels (2000) are able to derive some conditions for restoring efficiency in a uniform price auction with many bidders. These auctions are inefficient because a bidder with an overly optimistic conjecture about the common component may outbid a bidder with a higher private valuation. Jackson (2005) shows that equilibrium fails to exist when valuations have both components in second price and English auctions. Goeree and Offerman (2003) are able to derive the equilibrium by aggregating the multidimensional signals into a single statistic by relying on the independence assumption. They study the effects of competition and information disclosure in this set up and find that increasing both reduce the inefficiency. Goeree and Offerman (2002) use an experimental setup to study efficiency in these auctions and find observed efficiencies close to the predicted ones. Compte and Jehiel (2002) propose a model where bidders know their private component and are differently informed about the common component. They study the welfare effect of adding one bidder to one-object sealed-bid second price and ascending auctions. They find that with symmetric bidders, an extra bidder is good for welfare whereas with asymmetric information about the common element this is not the case. Compte and Jehiel (2002) tackle bidder asymmetry in their model, but that particular asymmetry is different from what I am interested in. They assume that bidders draw their signals from different distributions. In my auction data, the bidders are asymmetric also in the sense that they put different weights on the private and common value component. In the extreme case, one bidder could be a pure common value bidder and another have independent private values. Asymmetry in this dimension has not been addressed in the literature before. The theoretical analysis of a model with both common and private values that allows for this particular form of asymmetric and endogenous entry is beyond the scope of this paper and possibly beyond the reach of existing analytical tools. I focus on an empirical analysis on how differences in the information paradigm affect the entry choices. Although I do not impose this complex information structure on the estimations explicitly, this is still the first empirical analysis of auctions that studies bidder behavior when values have both private and common component.

3.3 The market and the data

The City of Helsinki arranges tenders for its intra-city bus traffic. The first tender was arranged in 1997. The intra-city market served 100 million passengers and was
valued at 177 million euro in 2000 (YTV Transport Department 2001). The data used in this study consists only of these intra-city tenders, and include 55 auctions. I include all auctions up to 1st January 2005, the date when Suomen Turistiauto Oy (STA), a company owned by the City of Helsinki, and the Helsinki City Transport’s (HKL) bus transport unit merged. Since STA is one of the two firms that I analyze here, it is not possible to include any newer data. I cannot use the data from the entire metropolitan area\(^3\) either, because of differences in the market characteristics, auction rules, the set of participants and bidder behavior. The planning unit of HKL decides routing, timetables, vehicle requirements and fleet schedules. The amount of bus kilometers in a contract can change by a maximum of ten percent per year. The City of Helsinki Supplies Department invites the tenders. The tenders are open to all licensed contractors. Also a financial analysis on the contractors’ ability to fulfill the tender specifications is conducted. The bus transport unit of HKL participates as one of the bidders.

In bids, the operators state the unit costs of the service (cost per kilometer, per hour and per vehicle day). The tendering authority uses these costs to calculate the total cost of service provision given the announced amount of traffic. This total cost is the actual monetary bid. The City receives all ticket revenues. Similar, so-called gross cost contracts, are used in many cities, for example in London. The contract period varies from three to six years and is most often five years. The invitation to tender simultaneously covers many contracts and a single contract can cover one or more routes. The intra-city market consists of 86 routes on average, with some changes in the network from year to year. The set of contracts that correspond to an invitation is called a tranche, following Cantillon and Pesendorfer (2006). Combination bidding within a tranche is allowed. I do not make a distinction whether a given bidder included a given contract in some combination or submitted a single bid to it or both, all of these possibilities count simply as an entry to that auction. Combination bidding violates the assumption of independent auctions needed for the econometric analysis. I hope that this is an innocuous violation for two reasons. First, submitting combination bids is rare. Second, it is reasonable to assume that bidders would have submitted bids to the same contracts even if combinations were not allowed. Then auctions are independent with respect to entry choices and the combination bidding only changes the bidding strategies. The principle of awarding tenders is the best economic value,

\(^3\)The Helsinki Metropolitan area consists of the Cities of Espoo (237968 inhabitants 31st December 2007), Helsinki (568361 inhabitants), Kauniainen (8511 inhabitants) and Vantaa (192399 inhabitants). YTV organizes the regional and the intra-city bus traffic tenders in Espoo and Vantaa.
calculated by a scoring rule based on monetary bids and vehicle quality. I collected the data from the City of Helsinki Supplies Department (Saarelainen 2004). It is summarized in Table 1. There are 11 tranches and 55 contracts in the data. 215 single bids and 14 combination bids were submitted. The number of actual bidders varies from two to eight. The amount of auctions in a given tranche varies from one to nine. No combination bids were submitted after the entire traffic was procured once nor are they in tenders following this data collection.

Table 1. Bus transit tenders included in the data set.

<table>
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<th>Tranche</th>
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<th># comb. bids</th>
<th># bidders</th>
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<td>1/IA (98)</td>
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<td>0</td>
<td>4</td>
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<tr>
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<td>23</td>
<td>1</td>
<td>2-6</td>
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<tr>
<td>1/III (98-99)</td>
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<td>4</td>
<td>2-6</td>
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<td>0</td>
<td>3-5</td>
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<td>20</td>
<td>0</td>
<td>3-5</td>
</tr>
<tr>
<td>2/IV (03)</td>
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<td>2-8</td>
</tr>
</tbody>
</table>

A "Tranche" refers to the set of contracts that correspond to a single invitation to tender. The year the auction was held is in parentheses. "2/III" means the third tranche of the second round of the tendering of the entire traffic. "# auctions" refers to the number of auctions in a given tranche. "# single bids" means the total number of single bids in a given tranche. "# comb. bids" means the total number of combination bids in a given tranche. "# bidders" denotes to the spread (min - max) of the number of bidders per auction in a given tranche.

Table 2. presents some descriptive statistics on contract characteristics and bidding decisions for each bidder. There are 10 potential bidders of which five are fringe firms. Bidder HKL submitted bids to all the 55 auctions and won 38 % of them. CX submitted bids to 52 of the 55 auctions and won 8 auctions. The third and fourth most active firms STA and CR submitted bids on and won about the same amount of auctions. PKL submitted bids to 29 % of the auctions and won 31 % of those. The five fringe bidders did not win any of the auctions. There are some differences between the bidders on what type of contracts they on average submitted bids on. The fringe bidders never participated in contracts that required the use of articulated/bogie buses. PKL participated on average in smaller auctions that the other four large bidders and was
more reluctant to bid when articulated/bogie buses were used. HKL and STA have the garages nearest on average and three of fringe firms do not have a garage at all.

Table 2. Participation, its success and the mean of contract characteristic when actual bidder for each bidder separately.

<table>
<thead>
<tr>
<th></th>
<th>HKL</th>
<th>CX</th>
<th>STA</th>
<th>CR</th>
<th>PKL</th>
<th>AAS</th>
<th>OLA</th>
<th>LLR</th>
<th>LSL</th>
<th>ESL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bids</td>
<td>55</td>
<td>52</td>
<td>39</td>
<td>38</td>
<td>16</td>
<td>6</td>
<td>6</td>
<td>6</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>% submitted</td>
<td>100</td>
<td>95</td>
<td>71</td>
<td>69</td>
<td>29</td>
<td>13</td>
<td>11</td>
<td>11</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Wins</td>
<td>21</td>
<td>8</td>
<td>10</td>
<td>11</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>% won</td>
<td>38</td>
<td>15</td>
<td>26</td>
<td>29</td>
<td>31</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Mean distance</td>
<td>5.8</td>
<td>13.8</td>
<td>8.2</td>
<td>14.4</td>
<td>20.9</td>
<td>7.7</td>
<td>15.1</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>C mean line hrs</td>
<td>42.3</td>
<td>43.3</td>
<td>37.1</td>
<td>41</td>
<td>30.1</td>
<td>18.2</td>
<td>38.9</td>
<td>40.8</td>
<td>27.2</td>
<td>47.5</td>
</tr>
<tr>
<td>C mean rush%</td>
<td>0.4</td>
<td>0.41</td>
<td>0.41</td>
<td>0.35</td>
<td>0.32</td>
<td>0.24</td>
<td>0.33</td>
<td>0.32</td>
<td>0.43</td>
<td>0.28</td>
</tr>
<tr>
<td>C mean a/b bus d</td>
<td>0.38</td>
<td>0.37</td>
<td>0.36</td>
<td>0.42</td>
<td>0.19</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>C mean c. length</td>
<td>4.9</td>
<td>4.9</td>
<td>4.8</td>
<td>4.9</td>
<td>4.7</td>
<td>5</td>
<td>4</td>
<td>4.5</td>
<td>3.5</td>
<td>5</td>
</tr>
</tbody>
</table>

"Bids" denotes the number of bids submitted. "% submitted" is "Bids" divided by 55, the total number of auctions in the data. "Wins" denotes the number of auctions that the given bidder has won. "% won" is "Wins" divided by "Bids". "Mean distance" presents the mean distance from the garage to the route for each bidder and all auctions in the data. The last four rows present the means of contract characteristics conditional on the given bidder submitting a bid, therefore the notation "C mean". "line hrs" stands for thousands of line hours in a year, i.e the size of the contract. "rush%" is the share of rush hour traffic. "a/b bus d" is a dummy for whether the contract requires articulated/bogie buses and "c. length" denotes the contract length in years. HKL = Helsingin Kaupungin Bussiliikenne. STA = Suomen Turistiauto Oy. CX = Connex Oy. CR = Concordia Oy. PKL = Pohjolan Kaupunkiliikenne. OLA = Oy Liikenne Ab. LLR = Linjaliikenne Randell. AAS = Askaisten Auto or Auto Andersson Oy. LSL = LS-Liikennelinjat Oy. ESL = Etelä-Suomen Linjaliikenne.

In the empirical analysis, I will concentrate on the bidders STA, CR and PKL because these firms have sufficient variation in their entry decisions. STA stands for Suomen Turistiauto Oy, a City owned private company. CR stands for Concordia Bus Finland Oy, a Finnish subsidiary of Concordia Bus, one of the ten largest European public transportation groups. It is also the leading Nordic bus transportation group. PKL denotes Pohjolan Kaupunkiliikenne Oy. It is a subsidiary of Pohjolan Liikenne Oy, the largest domestic road transportation company. That in turn is a subsidiary of VR-group, the rail monopoly and transportation company owned by the Finnish state.

In these bus transit auctions, bidder asymmetry arises mainly from the different garage locations. The closer the route to the garage, the less transfer kilometers the buses need to drive. A transfer is the driving of an empty bus from garage to route
at the start of a shift and driving the bus back at the end of a shift. Asymmetry may also arise for other reasons such as different collective labor agreements or capacity constraints. More free capacity increases incentives to bid more aggressively. Cantillon and Pesendorfer (2006a) argue that capacity effects may not be important for London bus route auctions, because firms have time to adjust their capacity between the auctions and the start of contract traffic. Similar time lags obtain in Helsinki. If indeed capacity is not important, the assumption of independent auctions is more plausible. Figure 1.

presents the distances from the garage to the route(s) for the three bidders that will be the object of the empirical analysis. The distances were calculated using an internet service (http://kartat.eniro.fi/) that gives road distances between street addresses in Helsinki. I used the average distance from the nearest garage of a given firm to both end points of the route, weighted by the amount of traffic for contracts consisting of many routes. The main purpose of this figure is to show that the garages of STA are always nearer to the route(s) under contract than the garages of PKL. Therefore the common value components are always more important to STA than PKL. I compare how these two bidders will react to their expectation of Concordia’s (CR) participation.

Figure 1. Distance from the garage to the route for bidders STA, CR and PKL.

The auctions are indexed in the x-axis with 1 being the first auction and 55 the last auction.
The distance is in kilometers in the y-axis.

3.4 Estimation

BHKN propose a method for estimating static games of incomplete information. They generalize a discrete choice model to allow the actions of agents to be interdependent. BHKN state many contributions that their model makes to the literature, but the main reason for me to use it is its computational simplicity in my application. BHKN propose to estimate the discrete game in two steps. BHKN describe the procedure as follows: "In a first step, the economist estimates the probability that one, out of a finite number of possible choices, is observed conditional on the relevant covariates. In the second step, the economist estimates a single agent random utility model, including as controls the equilibrium beliefs about the behavior of others from the first step". I present here their simplest entry example (BHKN, p. 5-8).

The BHKN model goes as follows. Finite number of players $i = 1, ..n$ simultaneously choose an action $a_i = 0, 1$, where $a_i = 1$ denotes entry. State variables $x_i$ are common knowledge and observed by the econometrician. There are also state variables which are private information to the bidders. This shock for a bidder $i$ when he chooses an action $k$ is denoted by $\epsilon_{ik}$. Let $\epsilon_i$ denote the vector of the individual $\epsilon_{ik}$’s. BHKN assume that the $\epsilon_{ik}$’s are distributed i.i.d. across agents and actions. The periodic utility for the player $i$ is then

$$u_i(a, x, \epsilon_i; \theta) = \Pi_i(a_i, a_{-i}, x; \theta) + \epsilon_{ik}. \quad (1)$$

The difference of the BHKN model from standard discrete choice models is that the actions $a_{-i}$ of other players enter into $i$’s utility. When the decision rule of BHKN model is a function $a_i = \delta_i(x, \epsilon_i)$, they define $\sigma_i(a_i|x)$ as:

$$\sigma_i(a_i = k|x) = \int 1\{\delta_i(x, \epsilon_i) = k\} f(\epsilon_i) d\epsilon_i. \quad (2)$$

This is the probability that the bidder $i$ chooses the action $k$ conditional on the state variables that are public information. $1\{}$ is an indicator function and $f$ denotes the density function of $\epsilon$. BHKN define the player $i$’s expected utility $\pi_i$ from choosing the action $a_i$ when the vector of parameters is $\theta$ and the vector of bidder and contract characteristic is $x$ as
\[ \pi_i(a_i, x, \epsilon_i; \theta) = \sum_{a_{-i}} \Pi_i(a_i, a_{-i}, x; \theta) \sigma_{-i}(a_{-i}|x) + \epsilon_{ik}, \]
where 
\[ \sigma_{-i}(a_{-i}|x) = \Pi_{j \neq i}(a_j|x) \]
denotes \( i \)'s beliefs about other agent’s actions.

BHKN define the deterministic part of the expected payoff as
\[ \Pi_i(a_i, x; \theta) = \sum_{a_{-i}} \Pi_i(a_i, a_{-i}, x; \theta) \sigma_{-i}(a_{-i}|x). \]

They state that it follows immediately that the optimal action for player \( i \) satisfies the equation (5).
\[ \sigma_i(a_i = k|x) = \Pr\{\epsilon_i | \Pi_i(a_i = k, x; \theta) + \epsilon_{ik} > \Pi_i(a_i = h, x; \theta) + \epsilon_{ih}, \] where \( h \neq k \} \]

When the utility is assumed to take a linear form, equation (6) presents the payoff structure in a static entry game when the outside option is assumed to be zero. This payoffs structure is typically assumed in the static entry game literature (e.g. Bresnahan and Reiss, 1990 and 1991 and Berry, 1992).
\[ \Pi_i(a_i, a_{-i}, x; \theta) = \{ x^0_i \beta_i + \delta_i \sum_{j \neq i} 1\{a_j = 1\} \text{ if } a_i = 1 \]
\[ 0 \text{ if } a_i = 0 \]

Combining this payoff structure with equation (5), we get
\[ \sigma_i(a_i = 1|x) = \Pr\{\epsilon_i | x^0_i \beta_i + \delta_i \sum_{j \neq i} 1\{a_j = 1\} > 0\} \]
\[ = \Phi(x^0_i \beta_i + \delta_i \sum_{j \neq i} 1\{a_j = 1\}) \]
\[ = \frac{\exp(x^0_i \beta_i + \delta_i \sum_{j \neq i} \sigma_j(a_j = 1|x))}{1 + \exp(x^0_i \beta_i + \delta_i \sum_{j \neq i} \sigma_j(a_j = 1|x))}, \text{ for } i = 1, \ldots, n. \]

Now \( \Phi \) is some cumulative distribution function. The last equality holds assuming that the error terms that capture the private shocks to the profitability of submitting a bid, are distributed extreme value. Equation (7) gives the probability that the bidder \( i \) enters given the observables and the distribution of the shocks.

According to BHKN, observing a large number of entry decisions we can estimate \( \sigma_i(a_i = 1|x) \) by any one of a number of standard techniques. They state that this simply boils down to estimating the probability that a binary response \( a_i \) is equal to one conditional on a given set of covariates \( x \). BHKN argue that knowing these first stage estimates \( \sigma_i(a_i = 1|x) \) for all \( i \), we can then estimate the structural parameters of interest \( \beta_i \) and \( \delta_i \) in the second stage. They propose a linear probability model to estimate the first stage. In the second stage they propose a logit model (assuming extreme value distribution for error terms) to estimate a following pseudo-likelihood function:
\[ L(\beta, \delta) = \prod_{t=1}^{T} \prod_{i=1}^{n} \left( \frac{\exp(x_i'\beta_i + \delta_i \sum_{j \neq i} \sigma_j(a_j=1|x))}{1 + \exp(x_i'\beta_i + \delta_i \sum_{j \neq i} \sigma_j(a_j=1|x))} \right)^{1\{a_{i,t}=1\}} \]

\[ \left(1 - \frac{\exp(x_i'\beta_i + \delta_i \sum_{j \neq i} \sigma_j(a_j=1|x))}{1 + \exp(x_i'\beta_i + \delta_i \sum_{j \neq i} \sigma_j(a_j=1|x))} \right)^{1\{a_{i,t}=0\}} \]

where \( t = 1, ..., T \) denotes a given auction. BHKN argue that to be able to separately identify the effects of \( \beta_i \) and \( \delta_i \) on the entry choice, we need an exclusion restriction. We need a variable that is included in the first stage but can be excluded from the second stage. In other words, we need to assume that at least one the competitors’ characteristics affect a given bidder’s revenue only indirectly. It is plausible to assume that this holds for the distance variable in the auctions here. It is also important that the distance variable is exogenous. Since the bidders made their location decisions before the auctions started and there have not been important changes in garage locations, this is a plausible assumption.

BHKN argue that "if the error term has atomless distribution, then player i’s optimal action is unique with probability one. This is an extremely convenient property and eliminates the need to consider mixed strategies as in a standard normal form game". They show that their model has a unique equilibrium in the two firm case, given a linearity assumption. For more players, they use a homotopy method to calculate all the equilibria of the game. I assume that the equilibrium is unique in my data.

BHKN propose a nonparametric generalization of this estimation method but that would require much larger data set than I have. However, it is possible to add some flexibility to the estimation by using a semiparametric approach that BHKN also propose. They suggest a two stage least squares estimation with nonparametric first stage. For practical purposes, they show that STATA "ivreg" command with robust standard errors can be used to obtain consistent estimates. The first stage is now some nonparametric approximation like sieve or orthogonal polynomial regression and the second stage is linear regression. I use orthogonal polynomials in the first stage. These polynomial transformations of the contract characteristics are inserted as instruments for the endogenous variables, which are the participation decisions of competitors.

The BHKN method is very useful for my analysis, because it can be used with only a small amount of observations. A structural approach based on equilibrium bidding behavior would require more from the data both with respect to the amount of observations and the nature of the data generating process. Because we would need to conduct the estimation of the bidding stage as well, the combination bidding would have to be addressed more carefully. If dealt in the same way as in (Tukiainen 2008),
the data set would become even smaller than it is now. Moreover, an equilibrium bidding condition that would capture all the elements of interest does not exist.

I am interested in estimating the determinants of entry decisions for bidders STA and PKL. The specific question is whether they behave differently with respect to the expected participation of CR. Because of the small number of observations and the participation patterns evident in Table 1, I need to make some assumptions in the econometric modeling. The five fringe bidders have too few and bidders HKL and CX too many bids for reasonable discrete choice analysis. First, I assume that STA, PKL and CR do not care about the participation of the fringe bidders. This allows me to limit the number of explanatory variables. Second, I assume that STA, PKL and CR treat the distances of HKL and CX as exogenous contract characteristics. Therefore I conduct the analysis for the bidders STA, PKL and CR and then test whether the estimated coefficients of how STA and PKL react to the expected participation of CR differ from each other.

BHKN make two essential assumptions. First, the game is static. This is a plausible assumption in my auction data. Each single auction and auctions within the same tranche are simultaneous games and therefore static. However, these individual auctions are held sequentially. This could induce dynamics through changes in capacity. However, as argued in Section 3, capacity is probably not important since time lags between the auctions and the actual service production are large enough to allow capacity adjustments with low enough costs. Second, the information is assumed to be incomplete, that is the shock are private. In a complete information game, the error term of player \( i \) would depend on the actions of all the players, not just \( i \)’s. Then it would present information known by all the players, but not the econometrician. It is hard to say which assumption fits this market better. The less players there are and the longer they have been in the same market, the more plausible the complete information assumption becomes. It can also be the case that the nature of information changes as firms learn more about each other. Bajari et al. (2007b) have proposed an estimation method for such games where they also utilize structural auction econometrics. They state that parameters estimated assuming private information, when information is common, are not generally consistent, but "they will be roughly in the correct neighborhood". Therefore even if the assumption of incomplete information is not correct, we should obtain results that give roughly a correct picture on the determinants of entry in this market.
3.5 Results

I conduct two different estimations suggested by BHKN. First is the linear model using ordinary least squares in the first stage and logit in the second stage. Second is the semiparametric method that maintains the linearity assumption, but the first stage is made more flexible by orthogonal polynomial transformations. Otherwise it is a standard two stage least squares estimation. The results from the first stage of the first estimation are presented in Table 3. These also provide information on how bidder and contract characteristics influence participation decisions. All the three analyzed bidders seem to bid more on contracts that are near their garages as one would suspect. STA and PKL seem to operate under decreasing returns to scale since they bid more on larger contracts and have a negative sign on the square of the contract size variable. Time when the auction was held matters for CR and PKL. CR was more active in the early years and PKL in the later years. STA and PKL seem to favor short contracts. PKL avoids the use of articulated/bogie buses. STA avoids contracts where HKL has an advantage in the sense that they are near to HKL’s garages and CR avoids CX in a similar manner. All of these preliminary results are in line with what one would expect. The explanatory power of the models is fairly good. These results encourage to use the chosen estimation approach even with only 55 data points for each bidder.

Table 3. Results of the first stage linear probability estimations.

<table>
<thead>
<tr>
<th>Variable</th>
<th>STA</th>
<th></th>
<th>CR</th>
<th></th>
<th>PKL</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>coef.</td>
<td>s.e.</td>
<td>coef.</td>
<td>s.e.</td>
<td>coef.</td>
<td>s.e.</td>
</tr>
<tr>
<td>constant</td>
<td>-4.10</td>
<td>3.56</td>
<td>4.96</td>
<td>3.12</td>
<td>-9.84</td>
<td>3.63***</td>
</tr>
<tr>
<td>log line hrs</td>
<td>1.34</td>
<td>0.74*</td>
<td>-0.85</td>
<td>0.64</td>
<td>2.54</td>
<td>0.74***</td>
</tr>
<tr>
<td>log line hrs^2</td>
<td>-0.07</td>
<td>0.03*</td>
<td>0.04</td>
<td>0.03</td>
<td>-0.13</td>
<td>0.04***</td>
</tr>
<tr>
<td>rush%</td>
<td>-0.20</td>
<td>0.27</td>
<td>-0.30</td>
<td>0.25</td>
<td>-0.23</td>
<td>0.25</td>
</tr>
<tr>
<td>a/b bus d</td>
<td>-0.15</td>
<td>0.12</td>
<td>-0.04</td>
<td>0.10</td>
<td>-0.29</td>
<td>0.11**</td>
</tr>
<tr>
<td>c. length</td>
<td>-0.30</td>
<td>0.11***</td>
<td>-0.04</td>
<td>0.09</td>
<td>-0.18</td>
<td>0.10*</td>
</tr>
<tr>
<td>time1</td>
<td>0.15</td>
<td>0.17</td>
<td>-0.51</td>
<td>0.15***</td>
<td>-0.08</td>
<td>0.17</td>
</tr>
<tr>
<td>time3</td>
<td>0.13</td>
<td>0.12</td>
<td>0.09</td>
<td>0.10</td>
<td>0.33</td>
<td>0.12***</td>
</tr>
<tr>
<td>dist. HKL</td>
<td>0.09</td>
<td>0.04**</td>
<td>0.03</td>
<td>0.03</td>
<td>-0.0006</td>
<td>0.03</td>
</tr>
<tr>
<td>dist. CX</td>
<td>-0.02</td>
<td>0.02</td>
<td>0.06</td>
<td>0.02***</td>
<td>-0.03</td>
<td>0.02</td>
</tr>
<tr>
<td>dist. Own</td>
<td>-0.07</td>
<td>0.02****</td>
<td>-0.08</td>
<td>0.02****</td>
<td>-0.04</td>
<td>0.02**</td>
</tr>
<tr>
<td>R^2</td>
<td>0.42</td>
<td></td>
<td>0.62</td>
<td></td>
<td>0.48</td>
<td></td>
</tr>
</tbody>
</table>

"log line hrs" denotes the logarithm of line hours in a year and "log line hrs^2" its square. "rush%" stands for the share of rush hour traffic. "a/b bus d" is a dummy for the contract requiring the use of articulated/bogie buses. "c. length" denotes the contract length in years. "time1" is the time dummy for the very first tranche and "time3" is the time dummy for the last four tranches in the data, the time period after the entire traffic was tendered once.
"dist. HKL" is the distance from the nearest HKL garage to the route(s) in a given contract and "dist. CX" in the same for the bidder Connex. "dist. Own" is the distance of the bidder for whom we conduct the estimation. N=55 for each bidder. "***" means 10 % significance level, "****" means 5 % significance level, "*****" means 1 % significance level and "******" means 0.1 % significance level for two-sided tests.

The results from the second stage of the first estimations are presented in Table 4. Including the strategic component in the estimations changes the results of this logit analysis compared with those of the OLS first stage. In the first model specification, the contract characteristics are not important for STA. It only cares for the distance from its own garages to the routes and about the participation probability of PKL. This "prop. s. PKL" variable affects STA in the opposite direction than one would expect under normal competition. One explanation is collusion with a phony bidding scheme. This is however unlikely since then also the "prop. s. STA" variable should have positive effect on PKL’s participation. This is however negative. A more plausible explanation is that the model suffers from multicollinearity. Now the participation likelihood of PKL captures the effects of contract characteristics for STA. To check this, I estimate the model STA2 where "prop. s. PKL" is dropped. The results of the second model specification give credibility to the multicollinearity suspicion, because STA again cares for the same variables as in the linear first stage. The only exception being the use of articulated/bogie buses that it seems to avoid now. The main variable of interest, how STA reacts to the expected participation of CR, "prop. s. CR" is robust to the different model specifications. PKL gets very similar results to the first stage in both specifications and these results are the same in both specifications. The only difference is that its own distance and the contract length are no longer significant when the strategic elements are taken into account, but they still have the expected sign. For neither PKL nor STA, the expected participation of CR seems to matter. Based on this estimation, common value bidders do not behave any differently than private value bidders when making the entry decisions. Since neither is significantly different from zero, no explicit test is needed to test their difference. One possible explanation for this result is that entry is exogenous in this market, bidders know who are going to submit a bid before the auction.

It is important to note that I report only the standard errors that are obtained directly from the logit estimation in a standard way. The standard errors should have been calculated by bootstrapping that includes both the steps. Unfortunately, for some of the samples the logit model did not converge. Therefore I report only the standard
errors from the logit. These are probably too small and therefore the results of this estimation should be taken only as descriptive. It still shows the need for two different model specifications.

Table 4. Results of the second stage logit estimations.

<table>
<thead>
<tr>
<th>Variable</th>
<th>STA1 coef.</th>
<th>s.e.</th>
<th>STA2 coef.</th>
<th>s.e.</th>
<th>PKL1 coef.</th>
<th>s.e.</th>
<th>PKL2 coef.</th>
<th>s.e.</th>
</tr>
</thead>
<tbody>
<tr>
<td>constant</td>
<td>-51.2</td>
<td>41.9</td>
<td>-876</td>
<td>463*</td>
<td>-644</td>
<td>263**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>log line hrs</td>
<td>-19.7</td>
<td>18.5</td>
<td>17.8</td>
<td>10.3*</td>
<td>184</td>
<td>94.6*</td>
<td>134</td>
<td>54.1**</td>
</tr>
<tr>
<td>log line hrs^2</td>
<td>1.02</td>
<td>0.96</td>
<td>-0.91</td>
<td>0.54*</td>
<td>-8.96</td>
<td>4.54**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>rush%</td>
<td>2.64</td>
<td>4.63</td>
<td>-12</td>
<td>3.42</td>
<td>-9.74</td>
<td>7.77</td>
<td>-4.82</td>
<td>5.90</td>
</tr>
<tr>
<td>a/b bus d</td>
<td>-0.10</td>
<td>2.18</td>
<td>2.18</td>
<td>1.76**</td>
<td>-6.45</td>
<td>4.54**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>c. length</td>
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<td>2.52</td>
<td>-566</td>
<td>2.31**</td>
<td>-6.72</td>
<td>4.12</td>
<td>-3.22</td>
<td>2.26</td>
</tr>
<tr>
<td>time1</td>
<td>6.59</td>
<td>7.73</td>
<td>7.23</td>
<td>4.45</td>
<td>-1.16</td>
<td>3.92</td>
<td>-1.40</td>
<td>3.11</td>
</tr>
<tr>
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<td>2.08</td>
<td>2.48</td>
<td>1.58</td>
<td>10.4</td>
<td>4.84**</td>
<td>8.11</td>
<td>4.33*</td>
</tr>
<tr>
<td>dist. HKL</td>
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<td>0.62</td>
<td>0.85</td>
<td>0.56</td>
<td>1.26</td>
<td>1.16</td>
<td>0.69</td>
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</tr>
<tr>
<td>dist. CX</td>
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<td>0.24</td>
<td>0.05</td>
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<td>0.43</td>
<td>-0.44</td>
<td>0.42</td>
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<tr>
<td>dist. Own</td>
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<td>1.24</td>
<td>0.47***</td>
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<td>0.71</td>
<td>-0.75</td>
<td>0.49</td>
</tr>
<tr>
<td>prop. s. CR</td>
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<td>0.91</td>
<td>2.55</td>
<td>-0.99</td>
<td>4.33</td>
<td>-0.57</td>
<td>4.02</td>
</tr>
<tr>
<td>prop. s. PKL</td>
<td>12.7</td>
<td>6.30**</td>
<td>- -</td>
<td>-</td>
<td>- -</td>
<td>-</td>
<td>- -</td>
<td>-</td>
</tr>
<tr>
<td>prop. s. STA</td>
<td>- -</td>
<td>-</td>
<td>- -</td>
<td>-</td>
<td>- -</td>
<td>-</td>
<td>- -</td>
<td>-</td>
</tr>
</tbody>
</table>

Variables are explained in the caption of Table 2. In addition "prop. s. CR", "prop. s. PKL" and "prop. s. STA" denote the propensity scores or choice probabilities, i.e. the fitted values, of these three bidders calculated from the first stage estimations. The variable "prop. s. CR" is in bold because that is the main variable of interest. N=55 for both bidders. *** means 10% significance level, **** means 5% significance level, ***** means 1% significance level and ****** means 0.1% significance level for two-sided tests.

The results of the semiparametric estimation are presented in Table 5. The main result of these estimations is the same as in the parametric estimation. For neither PKL nor STA, the expected participation of CR seems to matter. The common value bidders do not seem to behave any differently than private value bidders when making the entry decisions. For PKL, the effect of contract characteristics are very similar to the first estimation. The only difference is in the model PKL2. It also seems to care about the distance of CX and in a surprising direction. PKL bids more to those contracts that are near to CX. STA seems only to care about its own distance. In the model STA2, it also wants to avoid long contract periods. The policy conclusions are derived based on these results.
Table 5. Results of the semiparametric two stage least squares estimations.

<table>
<thead>
<tr>
<th>Variable</th>
<th>STA1 coef.</th>
<th>s.e.</th>
<th>STA2 coef.</th>
<th>s.e.</th>
<th>PKL1 coef.</th>
<th>s.e.</th>
<th>PKL2 coef.</th>
<th>s.e.</th>
</tr>
</thead>
<tbody>
<tr>
<td>constant</td>
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<td>6.48</td>
<td>-4.20</td>
<td>4.00</td>
<td>-11.3</td>
<td>3.05</td>
<td>-11.0</td>
<td>2.92</td>
</tr>
<tr>
<td>log line hrs</td>
<td>0.13</td>
<td>1.45</td>
<td>1.34</td>
<td>0.85</td>
<td>2.79</td>
<td>0.61</td>
<td>2.71</td>
<td>0.58</td>
</tr>
<tr>
<td>log line hrs^2</td>
<td>-0.00</td>
<td>0.08</td>
<td>-0.07</td>
<td>0.04</td>
<td>-0.14</td>
<td>0.03</td>
<td>-0.14</td>
<td>0.03</td>
</tr>
<tr>
<td>rush%</td>
<td>0.08</td>
<td>0.37</td>
<td>0.05</td>
<td>0.42</td>
<td>0.16</td>
<td>0.34</td>
<td>0.08</td>
<td>0.82</td>
</tr>
<tr>
<td>a/b bus d</td>
<td>-0.06</td>
<td>0.18</td>
<td>-0.16</td>
<td>0.14</td>
<td>-0.30</td>
<td>0.14</td>
<td>-0.29</td>
<td>0.11</td>
</tr>
<tr>
<td>c. length</td>
<td>-0.16</td>
<td>0.12</td>
<td>-0.23</td>
<td>0.12</td>
<td>-0.10</td>
<td>0.13</td>
<td>-0.11</td>
<td>0.27</td>
</tr>
<tr>
<td>time1</td>
<td>0.31</td>
<td>0.21</td>
<td>0.30</td>
<td>0.19</td>
<td>0.16</td>
<td>0.25</td>
<td>0.09</td>
<td>0.20</td>
</tr>
<tr>
<td>time3</td>
<td>-0.04</td>
<td>0.15</td>
<td>0.07</td>
<td>0.14</td>
<td>0.23</td>
<td>0.13</td>
<td>0.25</td>
<td>0.13</td>
</tr>
<tr>
<td>dist. HKL</td>
<td>0.07</td>
<td>0.06</td>
<td>0.05</td>
<td>0.05</td>
<td>-0.05</td>
<td>0.05</td>
<td>-0.04</td>
<td>0.35</td>
</tr>
<tr>
<td>dist. CX</td>
<td>-0.02</td>
<td>0.04</td>
<td>-0.03</td>
<td>0.03</td>
<td>-0.05</td>
<td>0.03</td>
<td>-0.04</td>
<td>0.02</td>
</tr>
<tr>
<td>dist. Own</td>
<td>-0.06</td>
<td>0.01</td>
<td>-0.06</td>
<td>0.02</td>
<td>-0.03</td>
<td>0.03</td>
<td>-0.03</td>
<td>0.02</td>
</tr>
<tr>
<td>entry CR</td>
<td><strong>0.24</strong></td>
<td><strong>0.36</strong></td>
<td><strong>0.32</strong></td>
<td><strong>0.26</strong></td>
<td><strong>0.50</strong></td>
<td><strong>0.30</strong></td>
<td><strong>0.38</strong></td>
<td><strong>0.27</strong></td>
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<tr>
<td>entry PKL</td>
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<td>0.38</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>entry STA</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.06</td>
<td>0.33</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>R^2</td>
<td>0.44</td>
<td>0.43</td>
<td>0.49</td>
<td>0.52</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Variables are explained in the caption of Table 2. In addition "entry CR", "entry PKL" and "entry STA" denote the endogenous variables, i.e. the participation dummy, of these three bidders. The results are obtained with STATA "ivreg" command with robust standard errors. As instrumental variables, I used two orthogonal polynomial transformations of the contract characteristics. These were calculated with R "poly" command. The variable "entry CR" is in bold because that is the main variable of interest. N=55 for both bidders. "*" means 10 % significance level, "**" means 5 % significance level, "***" means 1 % significance level and "****" means 0.1 % significance level for two-sided tests.

### 3.6 Conclusions

I have constructed a set up from a data set on the City of Helsinki bus transit auctions to test whether common value and private value bidders make different entry decisions. More specifically, I have tested whether one bidder that is always more influenced by common value components reacts to the amount of expected competition differently than another bidder who always puts more weight on the private value components. Tukiainen (2008) argues that bidders that have garages close to the contracted bus routes are more influenced by the common value elements than bidders with garages further away. I find that the near bidder and the far bidder do not react to changes in the expected amount of competition any differently. Moreover, the analysis supports a conclusion that the entry is exogenous rather than endogenous in this market.
The analysis was conducted using estimations developed by BHKN. Besides measuring the effects of strategic interactions, the analysis provided information on how the different contract and bidder characteristics affect the entry choices of the bidders. I estimated two different two stage models. Three main results arise from the more flexible estimations: First, there are no strategic interactions, the expected participation of other bidders does not affect the entry decisions. Second, the bidder’s own distance from the garage to the route matters for the common value bidder STA but not for the private value bidder PKL. Third, the contract length matters for STA but not for PKL. In addition, there was evidence of decreasing economies of scale with respect to the size of the contracts for PKL. PKL also avoided contracts where special buses were required. In addition to these results, the parametric estimations show that there is reason to suspect that actually both the bidders operate under decreasing economies of scale with respect to the size of the contracts and that both the bidders avoid contracts where special buses were required. Moreover, according to the first stage of the parametric approach, also PKL seems to care for its own distance and avoids long contracts.

The main policy result is based on the finding that all of the analyzed firms seemed to dislike long contracts. Whether this was statistically significant for all the bidders depends on the estimated model. Longer contract period increases the common future uncertainty and therefore the common value component becomes more important. If the contract period is shortened, it decreases the importance of common costs. According to Goeree and Offerman (2003) already this should increase the auctioneer’s revenue. In addition, a decreased contract period should increase entry in this market. With less uncertainty about the common components, the possible increased entry should be more profitable for the auctioneer than with longer contract periods. Thus two separate effects arise from shortening the contract length that would both increase the auctioneer’s revenue. Even if the entry is not increased with shorter contracts, we know that at least entry should not decrease and thus the information effect should work unhindered. Therefore the City of Helsinki should experiment by shortening the average contract length from five to for example four years.

3.7 References


Chapter 4

Participation Screen for Collusion in Auctions\(^1\)

4.1 Introduction

I propose one new statistical method and use one existing method to test for collusion in a territorial allocation setting. Both of these tests can be applied to any institutional setting where independent and mutually exclusive markets can be defined. However, I discuss them in the light of my application, which is a procurement auction. Due to their simultaneous nature, auctions are particularly well suited for the static estimation methods that are applied here. Moreover, in auctions it is easy to argue the independence of the markets under scrutiny. These tests are based on the participation decision of the bidders instead of the bid levels. Collusion is defined here as an explicit arrangement among a group of bidders that limits competition between the participants. Collusion can take many forms in auctions. Typical methods include different contract allocation mechanisms, like territorial allocation or job rotation, and submitting phony bids. The previous literature on detecting collusion in auctions has studied only phony bidding scenarios.

I test whether the participation of one bidder affects the participation decision of other bidders. In the competitive setting the identity of competitors should not affect the participation decision, given that the auctioned contracts are identical and the bidders are symmetric. For strategic reasons bidders would like to avoid each

\(^1\)A version of this Chapter has appeared in the HECER Discussion Paper series, No 213 / April 2008.
other, but if they are symmetric, bidder C has no reason to avoid bidder A more than bidder B. Porter and Zona (1999) (denoted PZ) propose a test based on the correlation of the residuals of single equation participation choice models. Negative correlation between two bidders’ residuals implies territorial allocation and positive correlation phony bidding. PZ use it to detect phony bidding. I propose a test that is robust to unobserved heterogeneity, unlike the PZ test. This is based on solving the simultaneous equations model of participation. I use estimation techniques proposed by Tamer (2003).

The central difficulty in detecting collusion is that similar market outcomes can be a result of either collusive or competitive behavior. Territorial allocation can be a result of either an explicit agreement or due to cost advantages that firms have in different areas. Due to transaction costs for example, firms could decide to bid only on those markets that are near the location of their operations. With different locations, territorial allocation emerges as a competitive result. We get suspicious if the territories overlap, but firms still systematically avoid bidding for the same contracts. Unfortunately, this can be again a result of competitive behavior if the contracts are heterogenous. Some firms may have costs advantages in some types of contracts. Therefore with heterogenous contracts and asymmetric bidders, participation patterns of any kind may emerge in the competitive setting. However, if we control for bidder and contract heterogeneity, then the identity of other participants should not affect the participation decision of any bidder in the competitive setting. This makes testing for collusion possible. I apply the methods to school yard snow removal auctions in the City of Helsinki held in the autumns of the years 2003-2005. In Figure 1. I present the spatial participation pattern in these auctions in the year 2003. It marks on the city map the schools that each bidder has participated in and the location of bidders’ and city’s garages. The map shows that two bidders (A and K) seem to avoid each other. Moreover they systematically avoid each other in an overlapping geographic area, the city center. This suggests collusive behavior in this market. This I put to test.

I make two contributions to the literature on collusion in auctions. First, I propose a new test to detect collusion. I will show with Monte Carlo analysis that it is robust to missing variables unlike the existing method. I will also show that the old and the new test complement each other. Second, the empirical application is important in itself because it is the first empirical study of a territorial allocation scheme. The minor contribution of this paper is the policy implications of the empirical application.

This study is related to two different fields of empirical industrial organization. The first is the literature on the detection of collusion. The second is the entry literature,
as it is possible to think of this problem as an entry game with a single auction as an analog of a single market. Harrington (2005) provides a recent survey on detecting cartels. Also Levenstein and Suslov (2006) have a recent survey on cartel studies but they do not address auctions nor the detection of cartels. Berry and Tamer (2007) provide a survey on empirical analysis of entry models. The existing studies on the detection of collusion in auctions (Bajari and Ye (2003), Baldwin, Marshall and Richard (1997), Banerji and Meenakshi (2004), Porter (1983), Porter and Zona (1993,1999)) have only applications to phony bidding scenarios.

In Section 2, I present the market of the application and analyze its characteristics with respect to collusion. In Section 3, I present both the PZ test and my own test. I conduct Monte Carlo analysis to examine the finite sample properties of these tests in Section 4. Then I present the data and descriptive statistics in Section 5 and the results in Section 6. Finally, Section 7 concludes.

4.2 School yard snow removal market

One of the two main objectives of this paper is to detect possible collusion in the school yard snow removal markets in the City of Helsinki. This particular market is interesting because it allows the analysis of territorial allocation. This is the first empirical application that tries to detect that form of collusion. This is surprising because territorial allocation is fairly typical form of collusion. For example of all the reported Finnish cartels from a period 1959 - 1990, when cartels were legal, 7.2 % of the cartels were of this form. On the other hand, the cases where bidders use the territorial allocation scheme with overlapping territories may be limited. In this Section, I explain the rules of the auction in question and give a general description of the market. Harrington (2005) states that "it has been shown that cartel formation is more likely with fewer firms, more homogenous products and more stable demand". In this Section, I also show that these are all true for the market under scrutiny.

In Figure 1, I present the spatial participation pattern. It marks on the city map the schools that each bidder has submitted bids on in year the 2003. Also the location of the bidders' and city’s garages is marked on the map (bold and larger letters). Most firms seem to participate more actively near their garages than further away. The map shows the bidders A and K seem to avoid each other. Moreover they systematically avoid each other in an overlapping geographic area, as we can see at the lower left corner. Of the other bidders, bidder R submits bids to all but two contracts and
three small bidders, T, S and P, only a few bids. This map raises suspicions about collusive territorial allocation. Maps for years 2004 and 2005 are in Appendix 1. It is interesting to note that in the year 2005 the participation pattern no longer implies collusive behavior.

Figure 1. Bidder participation in school yard snow removal auctions in Helsinki 2003.

Small capital letters present the location of schools and which bidders (A,K,P,R,S,T) have bid to a given school. "-" means that there were no bids. The approximate location of bidders’ and city’s (C) garages are marked with larger and bold capital letters.

Starting from the autumn 2003, the City of Helsinki has auctioned the snow removal services for school yards. All the contracts are auctioned simultaneously. The bidders
submit single sealed bids for four different type of services for each school. First service type consists of snow ploughing and sanding. Second service is the transportation of snow from the school to the snow dump. Third service is the transportation of sand from the school to the snow dump and the fourth is washing the yard. The last two services are needed only once every spring. Different services can be allocated to different firms within the same school. The lowest bid wins the given contract and the winner is paid their unit bid times the respective size of the contract. After the auction, all the bids are public knowledge. Thus all bidders detect deviators from collusive agreements easily. The bids are in unit costs. In the first service for example, winner’s bid is in euro per square meter. That times the school yard size in square meters is the payment per ploughing. Snow has to be ploughed every time there is 5 cm of snow on the ground. Typically, bidders submitted bids to all of the services, but there are exceptions. For example one firm participated only in the snow transportation service and they bid for all the schools. I consider only the bidding to the first service type because it is the most important in monetary terms. For the purpose of this study, the chosen service type does not matter. The amount of schools contracted differs from year to year. In the year 2003, there were 153 schools, in 2004 37 schools and in 2005 65 schools. This number varied according to how much of the services the City wanted to provide itself. I restrict the discussion in this Section mainly to the year 2003 because that is the year that I suspect that the collusion took place.

It states in the invitation to tender that "the buyer reserves the rights to transfer some of the contracts to be serviced by the city itself". This means that city announces that it has set a secret reserve price for the contract. The secret reserve price means that the city does not accept bids that are too high. In this case too high means a bid higher than the costs that the City would incur by providing the service itself. It seems that this secret reserve price is binding for many firms in most auctions. In 2003, a total of six bidders participated in the snow ploughing and sanding services. Of 153 contracts there were 2 with zero bidders, 85 with one bidder, 60 with two bidders, 5 with three bidders and 1 with four bidders. If the secret reserve price was not binding, we would expect all the potential bidders that are not capacity constrained to submit a bid in all the auctions. Also entry costs could limit the participation. However, there is little reason to suspect that bid preparation includes large costs to the firms in these markets because the bidding process is very simple and they have previous experience from providing the service under contract. An industry expert explained that it would take him about two minutes to calculate a bid in this sort of market because costs are very well known. The actual number of submitted bids can still change due to capacity
constraints and different number of potential bidders in different areas of the city. PZ observe a similar distribution of actual bidders on their data set of school milk bidding. They suggest that small number of actual bidders indicates that "there may not be significant firm-specific information in the markets. If bidders knew their costs as well as the costs of the other potential suppliers, then under a set of standard assumptions either one or two bids would be observed. The low cost supplier would submit a bid just below the cost of the next-lowest-cost supplier, and the next-lowest supplier would be indifferent between bidding at its own cost and not bidding." In contrast to the markets analyzed in PZ, there is more uncertainty about the costs of other bidders evident in this market. The bidders use somewhat different equipment, they have different main activities and possibly efficiency differences. It is also implausible that the asymmetries among bidders would be so large that it is common knowledge which will be the cost ordering of the bidders in all the auctions. I think that the explanation of a binding secret reserve price possibly jointly with territorial allocation is more plausible. Also capacity constrains could limit the bidding of especially the small bidders.

Snow removal is typically a secondary activity for the firms. The main activities of three larger participants are construction, paving, delivery services and landscaping. Three smaller firms do real estate maintenance as their main activity. The common feature for all these firms is that they use the snow removal equipment for these main activities outside the winter period. Flambard and Perrigne (2006) argue in their study of snow removal contracts in Montreal, that because snow removal is a secondary activity to supplement income, capacity constraints do not seem to be a major issue in their auctions. For the Helsinki auctions, this is probably true for the larger companies. On the other hand, the smaller companies are typically one man firms with very limited amount of equipment. Three smaller firms only submit from three to six bids to schools located near their office. Another reason to suspect that the large firms are not constrained by capacity is the fact that they have subcontracting deals with each other. Thus they have access to additional capacity beyond their own. These firms also participate in other snow removal auctions that the City holds. The secondary nature of the activity also acts as an entry barrier. No seller can enter just the snow removal activity alone. The required equipment is too expensive in relation to the industry’s part-year nature for it to be profitable. On the other hand there are numerous construction firms in the area that already have the necessary equipment.

Flambard and Perrigne (2006) investigate the potential asymmetry among bidders. They find empirical evidence of asymmetry resulting from firm location, because in the urbanized part of the city the storage costs are prohibitive. Their assessments of
most of the market conditions hold also for the snow removal contracts here. The only difference being that in they study streets and I study schools. They argue that because of the equipment size and weather conditions, firms located far from the snow removal location will have to rent storage space for their equipment. This additional cost can induce some asymmetry among firms. They further argue that this asymmetry may prevent the least efficient firms from participating to the auction as their bids will not be competitive.

Markets can be described by the nature of demand, the nature of the production process and the nature of competitive interaction among bidders. Demand for snow removal services is very inelastic, because the weather is not affected by the price. Neither do the conditions stated in the invitation to the tender about when the service should be provided depend on prices. This property makes collusion more profitable because the increase in prices due to collusion does not reduce demand. The product is homogenous. There can be very little quality differences in snow removal. It is either removed or not. On the other hand, the existence of the secret reserve price makes the demand elastic. If cartel bids too high, the contract may not be awarded to anyone. Thus reservation prices reduce the incentives to collude. The production processes can be different due to differences in snow removal equipment.

Besides the fairly inelastic demand, there are other characteristics in this market that may facilitate collusion. First, firms compete only on prices, which simplifies the cartel operations. Thus the cartel needs only to coordinate the participation or the level of bids. Second is that publicly announcing all the bids and the bidder identities make it easier for the cartel to detect deviation. Markets are easily defined, allowing the assignment of territories. The set of participating firms is small and there are entry barriers making it possible to submit higher carter bids. Subcontracting is typical in this market. This provides an easy way to distribute the cartel rents and also facilitates direct communication and a pretext for the meetings of the cartel. The representative of the buyer (City service center PALMIA) thinks it is plausible that some of the firms could be colluding. However, there is no legal outside evidence. On the other hand, the simultaneous nature of these auctions makes it more difficult to sustain collusion. Bidders can punish from deviation only in the next year auction. However if the bidders meet in the other markets that they are active on, for example construction, they can possibly punish there. Also subcontracting deals allow a way to punish deviators.

As can be seen from the participation maps (Figures 1-3) the behavior of bidder A changes over time. In the year 2005 it bids to seven same schools as bidder K whereas in the year 2003 they never bid to the same school. K generally bids to the same
schools in 2005 as in 2003. Therefore, with respect to equipment and location, it would probably have been possible for A to compete with K also in the year 2003, because I am not aware of any technology or location changes for A. This is further evidence for collusive behavior in 2003.

Job rotation is a similar phenomenon to territorial allocation. In a sequential auction setting job rotation can exist either as a result of collusion or as a result of an efficient outcome of a competitive bidding process when capacity constraints or decreasing returns to scale matter (Hendricks and Porter 1989). This makes the detection of collusion more difficult in sequential setting. In contrast to sequential auctions where the winners of previous auctions are observed, in simultaneous auctions the bidders do not observe how much capacity is already committed when making the decisions of participating in a given auction. Thus there is no backlog. In a simultaneous setting, capacity constraints or decreasing returns to scale affect only the total number of auctions that seller participates in. If there is enough uncertainty about other bidders’ costs, competitive bidding should not result in the case where certain bidders systematically avoid each other. Assuming that bidders don’t know to which homogenous auctions the competitors are going to bid, we can think that firms randomly submit bids to contracts up to their capacity. Then it is highly unlikely that some firms manage to systematically avoid each other when there are many contracts. Also in sequential auctions, the bidders may signal their preferences to other bidders more easily than in simultaneous auctions. Territorial allocation can be a result of competitive behavior when there are large observable cost differences among bidders. Still if these differences are controlled for we should not observe that identity in itself matters in a competitive setting.

The important players are probably not capacity constrained. If they were, they would have more incentives to avoid bidding to the same contracts. In a simultaneous game it is not possible to exactly know where the others are going to bid. Therefore we should observe that bidders anyway sometime bid to the same contracts if there is no way of communicating to each other what actions firms are going to take. Explicit communication is explicit collusion. If the game is played repeatedly, bidders can perhaps infer each others’ future actions from past decisions. If incumbency for example explains a lot of participation decision, the collusion could as well be tacit. Existence of capacity constraints does not make this testing approach invalid but it can change the interpretation on the type of possible collusion. Unfortunately the information on contracts in 2002 was not available and thus the effect of incumbency cannot be checked.
4.3 Testing

In this section, I present the methods that I use to detect the possible collusion in this market. I present both the existing PZ test and propose a new test. I discuss how the new test nests the existing test and I also discuss their relative strengths and weaknesses. While I present both tests here only in a two-bidder case, they extend to a \( n \)-bidder case by conducting pairwise analysis for all the possible pairs of bidders. The PZ test could also be extended to the \( n \)-bidder case by using multivariate probit analysis.

4.3.1 The model

Assume that there are two competing firms, denoted 1 and 2, that do not know ex ante to which markets the other firms are going to bid. Assuming that the value of the outside option is zero and the payoffs are linear, a standard simultaneous single market entry game can be presented with the following payoffs:

\[
\begin{align*}
    y_2 &= 0 & y_2 &= 1 \\
    y_1 &= 0 & 0,0 & 0, x_2 \beta_2 - u_2 \\
    y_1 &= 1 & x_1 \beta_1 - u_1,0 & x_1 \beta_1 + \delta_1 - u_1, x_2 \beta_2 + \delta_2 - u_2
\end{align*}
\]

This game maps directly into a following model:

\[
\begin{align*}
    y^{\ast}_i &= x_i \beta_i + y_2 \delta_i + u_i, \\
    y_i &= 1 \text{ if } y^{\ast}_i \geq 0, \text{ otherwise } y_i = 0, \ i = 1, 2.
\end{align*}
\]

Now \( y^{\ast}_i \) denotes the latent continuous variable that determines the participation decision. In an auction setting, \( y^{\ast}_i \) is the expected profit of bidder \( i \) from submitting a bid. Bidder \( i \) submits a bid to an auction if \( y^{\ast}_i \geq 0 \). \( x \) includes all the observable variables that affect the bidder’s costs and its probability of winning the auction. These include the contract and bidder characteristics. We observe \( y_i = 1 \) if the bidder \( i \) submitted a bid and \( y_i = 0 \) if it did not. This model nests both the PZ test and the new test. Next I present both the tests. I show that given some assumptions, the \( \delta_i \)'s are a measure of collusion.
4.3.2 The PZ test

PZ propose several tests to detect collusion in auctions. They utilize both the participation decisions and the bid levels to test whether some bidders submitted phony bids. PZ use legal evidence to create a control group made up of non-defendant firms that bid on Ohio school milk contracts. They compare the behavior of this control group with the behavior of defendant firms. I present and use here one of their many tests that can be used, similar to the new test that I propose, to detect territorial allocation and can be applied outside an auction setting. They test for the statistical independence in the probability of bidding using a standard pairwise procedure. PZ state: "Under the null hypothesis of independent action based on public information and the maintained specifications of our probit submission model, knowledge of whether one particular firm bids should not help predict whether another firm has also bid. In the case of complementary bidding, if one cartel member bids, then other ring members also bid. In this case the unexplained portion of the competitive bidding equation is positively correlated across cartel firms. In the case of territorial allocation, if a particular cartel member bids, then other cartel members will tend to not bid. Then the unexplained portion of the competitive bidding equation is negatively correlated across cartel firms." They propose to use the Spearman correlation coefficients computed using pairs of weighted residuals based on the control group probit models. PZ use the control group estimates also for the cartel group to address the problem of endogeneity that arises because the participation decisions of cartel firms are affected by collusion. This biases the estimates of the effect of observables on their participation. Assuming that all the bidders are identical, the control group estimates can be used as unbiased estimates also for the treatment group. There is a trade-off between the endogeneity problem and the need to make the assumption that all the firms react identically to changes in the explanatory variables when deciding whether to use the control group or not, when such is available. In situations where bidders have different production technologies or differ in some other important respects, it could be better not use a control group at all.

To get the PZ test from the system of equations (1), define \( \epsilon_1 = y_2 \delta_1 + u_1 \) and \( \epsilon_2 = y_1 \delta_2 + u_2 \) and assume a bivariate normal distribution of these new error terms \( \epsilon_i \). The PZ test is a test of correlation between the error terms \( \epsilon_i \). This they carry out by estimating the two equations of the system (2) separately by univariate probit and then calculating a Spearman correlation between the error terms of these two probit equations.
\[ y_1^* = x_1 \beta_1 + \epsilon_1, \]
\[ y_2^* = x_2 \beta_2 + \epsilon_2, \]
\[ y_i = 1 \text{ if } y_i^* \geq 0, \text{ otherwise } y_i = 0, \quad i = 1, 2. \]

\( \begin{pmatrix} e_1 \\ e_2 \end{pmatrix} \sim IIDN \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right) \)

If the Spearman correlation is negative and statistically significant, we can conclude that we are missing some variable from the estimation that affects the bidders differently and significantly. If we have no other missing variables, this is the competitor’s decision to bid. For example, firm 1 bids on those contracts that are allocated to it in the collusion scheme and firm 2 avoids those contracts as agreed. The benefit of this test is that it does not require many observations and that it is identifiable even when the firms under scrutiny never bid to the same contracts. It is also computationally very fast, easy to implement and has better convergence properties than simultaneous equation methods. The test hypothesis in PZ case is:

No collusion, \( H_0: Corr(\epsilon_1, \epsilon_2) = 0 \),
Collusion, \( H_1: Corr(\epsilon_1, \epsilon_2) \neq 0 \).

PZ detect positive correlation and thus conclude phony bidding. Since the PZ test is a test of endogeneity in a bivariate probit model, there are numerous other ways to test for endogeneity in this model. This includes the standard trio of likelihood ratio, Lagrange multiplier and Wald tests. The first test of endogeneity in a bivariate probit model was introduced by Kiefer (1982) to the statistics literature. Monfardini and Radice (2006) survey and compare these tests with a Monte Carlo analysis in a recursive probit framework. The PZ test hypothesis can also be written as

No collusion, \( H_0: \rho = 0 \),
Collusion, \( H_1: \rho \neq 0 \).

**Identification in the PZ test**

PZ make the following two key assumptions:

**Identification assumption 1:** \( x_1 \) and \( x_2 \) capture entirely the competitive effect.

Firms would prefer being the only bidder to competing against other firms. If this is not controlled for in the estimation, it creates negative correlation in the residuals
that would make us point out innocent firms as guilty of territorial allocation or make it harder to detect phony bidding. For this reason PZ include the observed competitors’ characteristics in \( x \). They seem to implicitly assume that this captures all the strategic reasons for the bidders to avoid each other in a competitive setting. With these assumptions, \( \rho_c \) is a measure of collusion since it captures the effect of the \( \delta_i \)’s. It means that knowledge of whether one particular firm bids should not help to predict whether another firm has also bid when firms are not colluding.

Identification assumption 2: We have an iid sample \( \{(y_{1i}, y_{2i}), x_{1i}, x_{2i}\} \) such that
\[
0 < \Pr[y_1, y_2|(x_1, x_2)] < 1 \text{ for all } (y, x_1, x_2) \in Y \times R^{d_1} \times R^{d_2} \text{ where } x = (x_1, x_2) \in R^d \text{ and } Y = \{(0,0), (1,1), (0,1)(1,0)\}.
\]

This standard assumption is also required for both the tests.

Identification assumption 3: \( (\epsilon_1, \epsilon_2) \sim IIDN\left(\begin{bmatrix} 0 \\ \rho \end{bmatrix}, \begin{bmatrix} 1 & \rho_c \\ \rho_c & 1 \end{bmatrix}\right) \), where \( \epsilon_i = y_j \delta_i + u_i, i = 1, 2 \).

This does not seem like an innocuous assumption because the \( y \)’s are discrete variables and yet the error terms are assumed to follow a smooth continuous distribution.

Identification assumption 4: \( Cov(u_1, u_2) = \rho_u = 0 \).

Given this assumption, \( \rho_c = \delta_1 \delta_2 Cov(y_1, y_2) \), and then a test for the significance of \( \rho_c \) can be used as a test for collusion, since it is then essentially a test for the joint significance of the \( \delta_i \)’s in the system (1). This assumption is the main weakness of the PZ test. The test is not robust to such unobserved heterogeneity that is observed by both the firms and unobserved by the econometrician. Any missing variable that is correlated with the participation decision and affects both bidders (directly or indirectly and in the same or in a different direction) will enter the residuals and thus corrupt the test. Next, I propose a new test that is robust to such missing variables.

4.3.3 The new test

The main contribution of this paper is the following. I propose to test for collusion by estimating the simultaneous equation system (1) fully and basing the collusion test on whether the \( \delta’i’s differ significantly from zero. Tamer (2003) provides an estimation
method to this model. The main benefit of this test is that it is robust to unobserved heterogeneity. In the case of territorial allocation, both $\delta_i$'s are negative and in the case of phony bidding they are positive. The test hypothesis is now:

No collusion, $H_0$: $\delta_i = 0$ for all $i = 1, 2$
Collusion, $H_1$: $\delta_i \neq 0$ for some $i = 1, 2$.

The main difference between the new test and the PZ test is that I estimate the $\delta_i$'s separately from $\rho_u$ whereas PZ estimate their joint effect. It is also possible to assume any known distribution for the error terms $u_i$. More specifically, my test of collusion is a test of whether the $\delta_i$'s are non-zero (and of the same sign). I need not make the problematic identification assumptions 3 and 4, but I have to maintain the identification assumptions 1 and 2. The significance of the $\delta_i$'s can be calculated with separate t-tests and it should be possible also to use for example the Wald test to test for joint significance.

**Identification in the new test**

The identification rests on the following four assumptions. Assumptions 2-4 are the identification assumptions 1-3 in Tamer (2003, p. 153). The assumption 1 is needed for me to be able to interpret the model, in particular the $\delta_i$'s, as a collusive model instead of a competitive model as Tamer (2003) does.

**Identification assumption 1**: as above.

There are two reasons for the firms to avoid each other. The first is the strategic reason that is in play when the firms are competing. The second is the possible collusive agreement. When the firms are colluding, they communicate their entry decision. Thus firm $i$ knows the exact value of $y_j$. However, when the firms are competing and there are private shocks, they can only build expectations on the other firm’s participation decision. This allows for separating the competitive and collusive effects of the competitor’s participation in the estimation. Identification of this model is based on the assumption that when the firms compete, the shocks are private and therefore $\Pr(y_j = 1|x_j)\mu_i$ captures the strategic effects more accurately that using the actual participation decision. Firm $i$ forms an expectation on $\Pr(y_j = 1|x_j)\mu_i = d_j\mu_i$, where $d_j$ denotes those characteristics of bidder $j$ that are observed by bidder $i$, $i \neq j$. Then
the strategic element is controlled for by simply including the characteristics of the analyzed competitor in $x$. The characteristics of other competitors are thought of as contract characteristics and are therefore in the $x$ vector as well. Now $y_j \delta_i$ consists only of the collusive effect. Because colluding firms do not compete against each other, we have $\delta_i < 0$ (territorial allocation) or $\delta_i > 0$ (phony bidding) and $\mu_i = 0$ when the firms collude. When the firms are competing, $\delta_i = 0$ and $\mu_i < 0$. If the firms collude only in some auctions and compete in others, both the effects could be negative but are still correctly identified since the collusive effect is estimated based on the actual participation and the competitive effect on the expected participation. Instead of $d_j$, one could include more refined estimates of $\Pr(y_j = 1|x_j)$ in the equation. One could utilize for example the two stage approach proposed by Bajari et al. (2007a). Because an improvement in this dimension is not the objective of this paper, I maintain this linear identification assumption that PZ make for the sake of simplicity.

For us to be able to control for the strategic behavior in the way explained above, firms must get private shocks to the profitability of entry when competing. With incomplete information, the bidders form beliefs about other bidders’ participation decisions. Given these beliefs, they have a unique response in a two-bidder game, given their own shock. These beliefs can be controlled for by including the competitors’ characteristics in the $x$. With complete information $u_1$ and $u_2$ are common knowledge to the firms but unobserved by the econometrician. With incomplete information $u_i$ is private information and thus observed only by firm $i$. This assumption makes a difference to the econometric analysis. There is currently no method for determining which information structure the data generating process follows. Fewer bidders and more experience in the market make complete information more plausible. The incomplete information assumption that PZ need to make seems to be natural in most auction settings when firms are competing. Gibbons (1992) for example, uses auctions as an example of incomplete information games in his influential textbook on game theory. This assumption was made for example in the entry analysis conducted by Seim (2006). However, when firms are colluding it seems natural that they communicate these private shocks to each other, thus making the environment that of complete information.

**Identification assumption 2:** as above.

**Identification assumption 3***: Let $U = (u_1, u_2)$ be a random vector independent of $x$ with a known joint conditional distribution $F_u$ that is absolutely continuous with mean 0 and unknown covariance matrix $\Omega$. 
Note that since there are no restrictions on $\Omega$, this assumption implies that the correlation of the error terms is allowed. Therefore, the $y$’s are allowed to be correlated with the error terms. Only the independence of $x$ from $u$’s is needed. Moreover, Tamer (2003, page 154) discusses that even the assumptions on the independence of $x$’s from $u$’s and that the distribution $F_u$ is known can be relaxed.

When I assume that $F_u$ is bivariate normal, that is $(u_1, u_2)^T \sim \text{IIDN} \left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho_u \\ \rho_u & 1 \end{bmatrix} \right)$, model (1) nests also the PZ testing approach, because when $\delta_i = 0$, $u_i = \epsilon_i$. This shock structure allows for common shocks, i.e. missing variables that are observed by both the firms but not by the econometrician. These enter into the common component of the error term $\rho_u$. When estimating all the parameters simultaneously, $\rho_u$ captures the effects of all the missing variables that affect the entry decisions of both bidders (directly or indirectly through the other bidder and in the same or in a different direction). Therefore the $\delta_i$’s are estimated correctly even in the presence of unobserved heterogeneity. For example there could be differences in production technologies that make it more costly for bidder 1 to provide the service to certain schools, but the characteristics of these particular schools do not hinder bidder 2. For example firm 1 has larger vehicles and thus trouble getting them through the gates of certain schools. This is unobserved by the econometrician but observed by bidder 2. Then bidder 1 would usually avoid those schools and therefore bidder 2 would bid more often to those schools. This will make $\rho_u$ negative. The PZ test would be corrupted but my test would not. Variables that are observed by one bidder and unobserved by the other bidders and the econometrician enter in the private part of the error term. Both the old and the new test are robust to such missing variables. Therefore the new test is robust all such missing variables that would corrupt the PZ test.

**Identification assumption 4*: $\delta_1 \times \delta_2 > 0$.**

Note that this assumption allows both the territorial allocation case (both $\delta$’s negative) and the phony bidding case (both $\delta$’s positive).

**Identification assumption 5:** There is one unique continuous regressor in either the $x_1$ or $x_2$.

Tamer (2003) makes this identification assumption in his Theorem 1 (page 153). This means that an exclusion restriction is required. Typically the firm characteristics provide these. These assumptions joint with his comments on Theorem 1 on page 154 lead to the following conclusions: Assuming $x$’s have a full rank, the parameter vector
\((\beta_1, \beta_2, \delta_1, \delta_2)\) is identified. Moreover, if \(x\)'s have rich enough support, all the parameters in the covariance matrix \(\Omega\) should be point identified. Tamer (2003) argues that since this is a threshold crossing model, it is possible to normalize the variances in \(\Omega\) to one. Then the identification of \(\Omega\) boils down to identification of \(\rho_u\).

Because my test relaxes two of the identification assumptions needed for the PZ test, it can be thought of as a nested structure. However, the PZ test does not require an exclusion restriction. Therefore my test nests the PZ test only in some data sets. Since Tamer (2003) shows that the separate effects of the \(\beta\)'s and the \(\delta\)'s (and in some cases the \(\rho_u\)) are identified from this simultaneous equations model (1), there is no endogeneity problem in this testing approach even though by construction the \(y\)'s are correlated with the \(u\)'s whenever \(\rho_u \neq 0\).

**Estimation in the new test**

Model (1) is exactly the one discussed in Tamer (2003). He assumes that the error terms are common knowledge for the firms but unobserved by the econometrician. This assumption allows him to interpret the actual participation decision as a relevant measure of the competitive effect. He also assumes that the firms play only pure strategies. According to Tamer (2003), this game always has multiple equilibria for large enough supports of the error terms. This needs to be taken into account in the estimation. There are some recent studies on structural analysis of entry games in auctions. They have different approaches to addressing the problem of multiplicity of equilibria. For Bajari and Hortacsu (2003) multiple equilibria is not a concern as they only consider the number of bids, not the identity of the entrant. Athey et al. (2004) abstract away from the multiple equilibria problem by arguing that "as is often the case with entry models, there may be many equilibria, as a result, our results compare sets of equilibria across auction methods". Krasnokutskaya and Seim (2006) verify the uniqueness of the equilibrium entry probabilities numerically. Li and Zheng (2006) take the fully structural approach to estimate a model that allows for endogenous entry, an uncertain number of actual bidders, unobserved heterogeneity and mixed strategy entry equilibrium under the independent private values paradigm. Their model requires observations where \(n \geq 2\). Most of the auctions in my application data have only 1 bidder. Also Li (2005) allows for mixed strategies. Both of these papers assume symmetric bidders. Bajari et al. (2007b) use simulations to calculate all the equilibria.
One common econometric goal of all these structural auction papers is to estimate the
distribution of bidder’s private costs and the distribution of entry costs. They do not
provide any methods to test for collusion, which is the aim of this study. I follow the
existing literature on detecting collusion in auctions and use reduced form methods.
It is much easier to answer my questions in a reduced form. This is an unrealistic but
hopefully innocuous assumption.

Various methods to conduct this estimation have been proposed in the literature.
For example, Greene (1998) states that this kind of model can be estimated with a
bivariate probit model without having to pay any heed to the simultaneity problem.
It seems that Greene (1998) is implicitly assuming a unique equilibrium, as he states:
"in the bivariate probit model, unlike in the linear simultaneous equations model, if
the two dependent variables are jointly determined, we just put each other on the
right-hand side of the other equation and proceed as if there were no simultaneity
problem". I do not use this method in the application because according to a Monte
Carlo analysis, it always overestimated the negative effect of δ_i’s, thus making the
empirical size 100% in every model in Table A1.1. I used STATA command "biprobit"
to estimate a seemingly unrelated simultaneous probit equation. It also had severe
convergence problems. To be able to obtain any results, I had to limit the number of
iterations in the maximization for over half of the simulated sets of data for most data
generating processes in Table A1.1.

In territorial allocation setting it is natural to assume that δ_i’s are both negative.
Then, according to Tamer (2003), it is easy to see that Pr[(0, 0|x)] + Pr[(0, 1|x)] +
Pr[(1, 0|x)] + Pr[(1, 1|x)] > 1. This is an example of an incoherent model. Tamer
(2003) argues that although the system (1) is an example of an incoherent model,
with some restrictions on the parameters it becomes a coherent model2. It remains
an incomplete model but Tamer (2003) then shows that this incompleteness will not
present any problems for the identification. Typically, econometricians have imposed a
coherency condition δ_1 * δ_2 = 0. This condition changes the model into a recursive one
and thus eliminates the simultaneity. Bresnahan and Reiss (1990 and 1991, denoted
BR) and Berry (1992) transform the model into one that predicts the joint outcome
[(0,1) or (1,0)]. This provides consistent point estimates for the parameters of interest
but involves loss of information. Bjorn and Vuong (1985) and Kooreman (1994) assume

---

2A structural model is complete and coherent if for any value of regressors there exists a unique
value for the responses. Tamer (2003) uses coherency to refer to an existence of a solution to the
model and calling the model complete if the solution is unique. An analog in games is the existence
of Nash equilibria and whether it is unique.
that unique outcome is chosen with known probability in the region of incompleteness. According to Tamer (2003) this may lead to inconsistent estimates. Toivanen and Waterson (2005) eliminate the possibility of multiple equilibria by assuming that the entry game proceeds as Stackelberg competition. Seim (2006) uses simulations to show that her model has a unique equilibrium.

BR provides one estimation method that is useful in my case. Instead of using an ordered probit as BR do, I use the simultaneous equation formulation of their idea provided by Tamer (2003). Tamer (2003) also proposes a new and more efficient estimator. It is however computationally more challenging and conducting Monte Carlo analysis using it would take a lot of time. Moreover, it uses multidimensional kernel smoothing that requires more data points than I have available in the application. For these two reasons, that estimation method is not used here.

The maximum likelihood estimator presented by Tamer (2003) that uses the BR idea, is defined by a following log-likelihood

$$L_{ML}(b) = \sum_{t=1}^{T} \left[ y_{t1}y_{t2} \log(P_1(x_t, b)) + (1 - y_{t1})(1 - y_{t2}) \log(P_2(x_t, b)) \right]$$

where $P_1(x_t, b) = \Pr[(y_{t1} = 1, y_{t2} = 1)|x] = \Pr(u_{t1} \geq -x_t\beta_1 - \delta_1; u_{t2} \geq -x_t\beta_2 - \delta_2)$ and $P_2(x_t, b) = \Pr[(y_{t1} = 0, y_{t2} = 0)|x] = \Pr(u_{t1} < -x_t\beta_1; u_2 < -x_t\beta_2)$

There are $t = 1, \ldots, T$ auctions in the data. $y_{t1}$ gains value one if bidder 1 submitted a bid in auction $t$, otherwise it is zero. Assuming that $u_1$ are distributed bivariate normal, $P$’s are known functions and (3) can be maximized with standard numerical optimization methods.

The benefit of this test is that it is robust with respect to missing variables, but that comes with a cost. This test requires more observations than the PZ test. It also requires that there are some auctions in the data where both bidders have submitted a bid. The need to rely on numerical optimization methods means that it is also harder to implement, may have convergence problems and is computationally time consuming.

4.4 Monte Carlo analysis

I conduct Monte Carlo analysis to compare the finite sample properties of the new test that I propose (called BR) with the existing PZ test. This is done by comparing the
empirical power and size of these different tests. The Monte Carlo model is chosen to reflect the characteristics of the actual application. Variable $x$ can be thought of as a contract characteristic, like contract size and variables $z$’s as the bidder characteristics, like distance. Following the application, I discretize the $z$ variables. I assume that there are three different firms in the markets, of which the collusion test is conducted only for the firms 1 and 2. The BR estimation is based on the model (4) and is estimated with the equation (3). The PZ model is estimated with single equation probits omitting $y_j\delta_i$ from the model (4).

$$y_1^* = \beta_{10} + x\beta_{11} + z_1\beta_{12} + \min(z_2, z_3)\beta_{13} + y_2\delta_1 + u_1$$

$$y_2^* = \beta_{20} + x\beta_{21} + z_2\beta_{22} + \min(z_1, z_3)\beta_{23} + y_1\delta_2 + u_2$$

$$(u_1, u_2)^T \sim IIDN \left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right).$$

I use eight different specifications in the data generating process. They are summarized in Table 1. To address the multiplicity of equilibria, the data generation is conducted in a following way. First I generate $x$ from a uniform (0,1) distribution. The three $z$’s are discrete variables that gain values 0,1,2,3,4,5 or 6 each with equal probability. Then I calculate the following cell probabilities for $y$’s. Let $\beta_{10} + x\beta_{11} + z_1\beta_{12} + \min(z_2, z_3)\beta_{13} = x_1\beta_1$ and $\beta_{20} + x\beta_{21} + z_2\beta_{22} + \min(z_1, z_3)\beta_{23} = x_2\beta_2$. Then, I assign the multiple region (see Tamer (2003)) an equal change of being a bid by either bidder. This is done by reducing $[(P_{00} + P_{01} + P_{10} + P_{11}) - 1]/2$ from both $P_{01}$ and $P_{10}$. Then I use these new cell probabilities to randomly assign simultaneously values for the pair $(y_1, y_2)$.

$$y_2 = \begin{cases} 0 & y_1 = 0 \\ 1 & y_1 = 1 \end{cases}$$

$$P_{00} = BVN(-x_1\beta_1, -x_2\beta_2, \rho)$$

$$P_{01} = BVN(-x_1\beta_1 - \delta_1, x_2\beta_2, \rho)$$

$$P_{10} = BVN(x_1\beta_1, -x_2\beta_2 - \delta_2, \rho)$$

$$P_{11} = BVN(x_1\beta_1 + \delta_1, x_2\beta_2 + \delta_2, \rho)$$

<table>
<thead>
<tr>
<th>Model</th>
<th>$\beta_{10}, \beta_{20}$</th>
<th>$\beta_{11}, \beta_{21}$</th>
<th>$\beta_{12}, \beta_{22}$</th>
<th>$\beta_{13}, \beta_{23}$</th>
<th>$\delta_1, \delta_2$</th>
<th>$\rho$</th>
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<td>0.2</td>
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<tr>
<td>6.</td>
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</tr>
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</table>

Table 1. Different model specifications used in the Monte Carlo analysis.
The results are presented in Table 2. The PZ results were obtained using a STATA "simulate" routine. The results for the BR were obtained using the R statistical package, with the "optim"-command solving the maximization problem\(^3\). Although the Monte Carlo analysis for the BR method is time consuming, I was able to calculate results in 5 days when I ran the processes on four different processors simultaneously.

The results are overall encouraging for the use on the new test. For models with no unobserved heterogeneity (1.-4.), the PZ test has much better power. It detects guilty firms more often. For models with unobserved heterogeneity (5.-8.), which is generated with \(\rho\), PZ fails utterly as expected. Either having huge amount of type I errors (model 5.) when there is such unobserved heterogeneity that makes the firms avoid each other (negative \(\rho\)), or very low power (model 8.) when unobserved heterogeneity makes the firms bid to the same contracts (positive \(\rho\)). BR estimation does roughly as well with unobserved heterogeneity as without it. The only concern with BR is the low power results. This concern is alleviated by the fact that the BR method produces on average accurate estimates for all the parameters. Because \(\rho\) is estimated accurately on the average, BR can be used jointly with PZ as a way to evaluate whether there are missing variables. Therefore the Monte Carlo analysis shows that BR method in cases with unobserved heterogeneity works much better that PZ and in the case with no unobserved heterogeneity is complementary to PZ. Therefore the test that I propose works as expected and should be used instead of or in addition to the existing PZ method.

\(^3\)I examined the different algorithms available in "optim" command with Monte Carlo analysis. The Nelder-Mead algorithm worked the best. It also gave more accurate results on average than the "nlm"-command, that utilizes the delta method.
Table 2. Power and Size results for the Monte Carlo comparison of the tests with 5 % significance level.

<table>
<thead>
<tr>
<th>Model</th>
<th>Obs</th>
<th>PZ, power</th>
<th>PZ, size</th>
<th>BR, power</th>
<th>BR, size</th>
<th>BR, ρ</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>250</td>
<td>4.5 %</td>
<td></td>
<td>7.3 %</td>
<td>0.04 ; 6 %</td>
<td></td>
</tr>
<tr>
<td>2.</td>
<td>250</td>
<td>49.9 %</td>
<td></td>
<td>24.6 %</td>
<td>0.05 ; 7 %</td>
<td></td>
</tr>
<tr>
<td>3.</td>
<td>250</td>
<td>74.9 %</td>
<td></td>
<td>30.3 %</td>
<td>0.06 ; 6 %</td>
<td></td>
</tr>
<tr>
<td>4.</td>
<td>250</td>
<td>88.6 %</td>
<td></td>
<td>36.9 %</td>
<td>0.04 ; 6 %</td>
<td></td>
</tr>
<tr>
<td>5.</td>
<td>250</td>
<td>97.8 %</td>
<td></td>
<td>8.6 %</td>
<td>-0.46 ; 29 %</td>
<td></td>
</tr>
<tr>
<td>6.</td>
<td>250</td>
<td>98.7 %</td>
<td></td>
<td>26.9 %</td>
<td>-0.53 ; 35 %</td>
<td></td>
</tr>
<tr>
<td>7.</td>
<td>250</td>
<td>0.1 %</td>
<td></td>
<td>4.5 %</td>
<td>0.52 ; 37 %</td>
<td></td>
</tr>
<tr>
<td>8.</td>
<td>250</td>
<td>8.1 %</td>
<td></td>
<td>30.7 %</td>
<td>0.55 ; 38 %</td>
<td></td>
</tr>
</tbody>
</table>

In the last column titled "BR, ρ", the first number is the mean of the estimated ρ’s and the second number is the share of these estimates that are significantly different from zero. In both the tests the actual size is 9.75 % since the BR test is based on either of the δi’s being significant at 5 % level. The PZ test is adjusted accordingly. I do not report the ρ for the PZ test, because it is a different ρ than in the BR test and thus comparing the two is not relevant.

4.5 Data and modeling choices

There are 258 auctions in the data with 335 bids submitted. 28 auctions did not receive any bids, of which 19 where held in 2004. Nine bidders participated in these auctions. Six in 2003, three in 2004 and six in 2005. Three firms exited the market after 2003 and three new entered in 2005. The participation decisions of bidders are described in Table 3 along with the bid levels. It shows the number of bids submitted, the number of contracts won, the number of contracts won conditional on facing any competition and bid level information for each bidder. It also shows to which city areas a given bidder submitted bids and in which years the bidder submitted any bids. Only three players submitted bids every year. By looking at the map we notice that only A and K avoid each other in the same city area. Therefore I conduct the tests only for the bidders A and K. Moreover, bidder R submitted too many bids in the year it participated and bidders T,S, H and O too few bids to be of any use in analysis of discrete choice models. There is too little variation in their decisions to use the tests for them.

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>K</th>
<th>R</th>
<th>T</th>
<th>S</th>
<th>P</th>
<th>H</th>
<th>J</th>
<th>O</th>
</tr>
</thead>
<tbody>
<tr>
<td># of bids</td>
<td>42</td>
<td>98</td>
<td>151</td>
<td>3</td>
<td>3</td>
<td>16</td>
<td>1</td>
<td>19</td>
<td>2</td>
</tr>
<tr>
<td># wins</td>
<td>33</td>
<td>89</td>
<td>97</td>
<td>1</td>
<td>1</td>
<td>4</td>
<td>1</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td># of wins</td>
<td>com</td>
<td>16</td>
<td>66</td>
<td>12</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>mean bid</td>
<td>0.097</td>
<td>0.071</td>
<td>0.089</td>
<td>0.100</td>
<td>0.090</td>
<td>0.107</td>
<td>0.050</td>
<td>0.103</td>
<td>0.097</td>
</tr>
<tr>
<td>sd bid</td>
<td>0.005</td>
<td>0.020</td>
<td>0.005</td>
<td>0.017</td>
<td>0.052</td>
<td>0.021</td>
<td>NA</td>
<td>0.022</td>
<td>0.018</td>
</tr>
<tr>
<td>min bid</td>
<td>0.082</td>
<td>0.040</td>
<td>0.085</td>
<td>0.080</td>
<td>0.060</td>
<td>0.068</td>
<td>0.050</td>
<td>0.071</td>
<td>0.084</td>
</tr>
<tr>
<td>max bid</td>
<td>0.110</td>
<td>0.156</td>
<td>0.980</td>
<td>0.110</td>
<td>0.150</td>
<td>0.135</td>
<td>0.050</td>
<td>0.140</td>
<td>0.110</td>
</tr>
<tr>
<td>South(centre)</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Northwest</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>North</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>East</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Year 03</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Year 04</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Year 05</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

The data includes information on contract characteristics and bidder characteristics. Contract characteristics include the school yard size and some measures of its shape or "tightness" that is intended to capture how difficult it is to plough the yard. These are the number of walls or fences that surround the yard, the number of permanent obstacles like trees or small buildings in the yard and dummy for whether the yard includes tight spaces. The shape variables are obtained by looking at the 1:1250 - maps of the school areas. This allows detail to the point of a single tree. Contract characteristics also include the distance to the schools from the city’s garages to account for possible changes in the secret reservation price. The information on the bidders is limited. Bidders did not agree to be interviewed. They only answered a few short questions. The most important variable that we are interested in is the location of bidder garages. We could use that to calculate the distances from garages to the contracted schools. I did not receive the accurate addresses of the garages but the firms gave their location information on postal code level. I assumed that the garage is located in the middle of the given postal code area. This creates measurement errors to distance variable. Another and perhaps even more important reason to use something else than just the distance to capture the cost shifters of the firms is that according to an industry expert another important factor is where the bidders’ main activities are located at the time. Bidders prefer schools near their construction sites for example. This is not observable. Thus we need to construct proxy variable for firms’ cost shifters. I also use four area dummies in the analysis to capture the bidders’ strengths in larger
area around the school. These area dummies also capture the possible changes in the number of potential bidders.

To proxy all firm specific cost shifters, I construct a variable called "ofsix" - how many of the six nearest schools of a given school a given bidder submitted a bid in a given year. This variable captures not only the distance, but also the overall costs of the bidder in the close proximity of a given school. There is a possible endogeneity problem with this proxy. Bidder might have or might not have bid to some of the near schools due to collusion instead of cost conditions. To capture the competitive effect, I calculate the maximum "ofsix" among a given bidder’s competitors. I use this variable instead of including the "ofsix" variables of all the competitors, because then the "ofsix" variable works as the exclusion restriction.

Another source of possible endogeneity is that unlike PZ, I do not have a control group. PZ use parameter estimates gained from control group probit estimations in testing. This is because the participation of collusive firms is affected by collusion thus biasing the estimated effect of observables on their participation. Assuming symmetry the control group estimates can be used as unbiased parameter estimates also for the test group. I do not have any outside evidence nor enough bidders to form a control group. I need to assume that this possible bias in the parameters of the control variables does not bias the estimates of the test statistics. However, I do not need to assume bidder symmetry like PZ.

Figure 2 in Appendix 1 shows the scatter plots of bids in relation to school yard size for each bidder separately. Bidder A participated in smaller auctions than other bidders. The reason for this could be that they operate only in the center of the city where yards are typically smaller. It can also be because they specialize in smaller yards due to their different equipment. We note that unit bids are decreasing in yard size, implying economies of scale. These seem to be decreasing. Thus I include yard size and its square in the econometric analysis.

4.6 Results

The results of both the tests are presented in Table 4. In the PZ test, I have estimated probit models separately for the bidders A and K. I estimate the model using data for all the three years 2003-2005. It is not possible to conduct the BR test separately for the different years. The activity variable "ofsix" is significant at all standard levels for
both the bidders and has the expected positive sign. Bidder A seems to bid close to the
city garages, more in the south region of the city and more to difficult yards. This is in
line with the fact that they advertise having equipment best suited for difficult yards.
Surprisingly, the competition variable, i.e. the maximum of competitors’ activity, has
a positive and significant sign, which means that bidder A bids more to auctions where
tough competition is expected. Bidder K seems to get some returns to scale from
ty yard size. The residuals of these two probit models are negatively correlated. This
correlation is significant at 1 % level. This implies that collusion occurred at least
during some of the three years in the data. Collusion is also supported by the fact that
competitors’ characteristics are not important for bidder K and for bidder A the effect
of competition is opposite to what it should be under competition. Thus the results
of the PZ test suggest collusive behavior. This is assuming that I have not overlooked
any important explanatory variable.

The results from estimating the simultaneous equation model (1) with the BR
approach are presented also in Table 4. Unfortunately, the convergence properties of
BR likelihood maximization with my data are not very good. The results are not
robust to the starting values of the algorithm nor to different algorithms used. Often
convergence is not achieved and the parameter estimates are those that the algorithm
reached at the iteration limit. The Hessian matrix is only rarely well behaving. Despite
these problems, the computations for the results that I report below have some desired
properties. First, with the starting values chosen, the likelihood function reached a
higher value at the iteration limit than for any other set of starting values for the
preferred Nelder-Mead algorithm. Second, the Hessian matrix allowed for computing
standard errors for all the variables. The identification problems encountered in this
empirical application could be due to not having a rich enough support in the $x$’s.
Another explanation for convergence problems is that my exclusion restriction is a
discrete variable. However, the same problem did not seem to hinder the identification
in the Monte Carlo exercise. Due these problems in the numerical optimization, these
results should be treated with some caution.

The activity variable "ofsix" is significant for both the bidders and has the expected
positive sign. Competitors’ characteristics are not important. A also bids more to
schools with difficult yards. K is significantly more active in 2005. A bids more to
south area and seems to bid close to the city garages. The test statistic is negative
for both firms and is also significant for $\delta_K$. K avoid schools where A actually bids.
Therefore, bidders A and K seem to collude according to both the tests. The BR
results also show that rho is close to zero and the null hypothesis of zero rho is not
rejected (although the 95% confidence interval is practically the whole support of \( \rho \)). This is some evidence for the conclusion that the model is not missing any important variables. Thus the PZ results are more convincing. Collusion is also implied by the fact that the strategic elements do not seem to be important for the bidders, because they do not avoid bidding to contracts that their competitors are likely to bid to.

The behavior of firms A and K seems to be more consistent with a collusive than a competitive model. In terms of Harrington (2005), this is a screening result, which means that I have identified this market as suspect to collusion. This can also be thought of as the verification of the cartel because the method by construct identifies the exact model of collusion (territorial allocation). This is not however sufficient for the prosecution of the colluding firms. Screening is useful in fairly quickly analyzing the market to detect those where more attention should be put to find legal evidence.

Table 4. The estimation results

<table>
<thead>
<tr>
<th></th>
<th>PZ</th>
<th></th>
<th>BR</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bidder A</td>
<td>Bidder K</td>
<td>Bidder A</td>
<td>Bidder K</td>
</tr>
<tr>
<td>constant</td>
<td>-*</td>
<td>-*</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>city dist</td>
<td>****</td>
<td>+</td>
<td>****</td>
<td>-</td>
</tr>
<tr>
<td>yard size</td>
<td>-</td>
<td>**</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>yard size sq</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>walls</td>
<td>+**</td>
<td>+</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>obstacles</td>
<td>+</td>
<td>-</td>
<td>+**</td>
<td>-</td>
</tr>
<tr>
<td>shape</td>
<td>+**</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>t03</td>
<td>ref group</td>
<td>ref group</td>
<td>ref group</td>
<td>ref group</td>
</tr>
<tr>
<td>t04</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>t05</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>**</td>
</tr>
<tr>
<td>OfsixA</td>
<td>****</td>
<td>NA</td>
<td>+*</td>
<td>NA</td>
</tr>
<tr>
<td>Max Ofsix -A</td>
<td>+**</td>
<td>NA</td>
<td>-</td>
<td>NA</td>
</tr>
<tr>
<td>OfsixK</td>
<td>NA</td>
<td>****</td>
<td>NA</td>
<td>+****</td>
</tr>
<tr>
<td>Max Ofsix -K</td>
<td>NA</td>
<td>-</td>
<td>NA</td>
<td>-</td>
</tr>
<tr>
<td>Area S</td>
<td>+****</td>
<td>-</td>
<td>+**</td>
<td>-</td>
</tr>
<tr>
<td>Area NW</td>
<td>ref group</td>
<td>ref group</td>
<td>ref group</td>
<td>ref group</td>
</tr>
<tr>
<td>Area N</td>
<td>ref group</td>
<td>ref group</td>
<td>ref group</td>
<td>ref group</td>
</tr>
<tr>
<td>Area E</td>
<td>ref group</td>
<td>ref group</td>
<td>ref group</td>
<td>ref group</td>
</tr>
<tr>
<td>delta</td>
<td>NA</td>
<td>NA</td>
<td>-0.27</td>
<td>-0.76*</td>
</tr>
<tr>
<td>Rho</td>
<td>-0.165***</td>
<td></td>
<td>-0.098 (s.e. 0.65)</td>
<td></td>
</tr>
<tr>
<td>Log lik</td>
<td>-24.8</td>
<td>-144.2</td>
<td>-148.9</td>
<td></td>
</tr>
</tbody>
</table>

A unit of observation is school. \( n = 258 \). "city dist" is the distance from the nearest City garage. "yard size" is the yard size of the school and "yard size sq" its square. "walls" is the number of walls surrounding the yard, "obstacles" the number of obstacles in the yard and "shape" a dummy for yards including tight areas. "t03 - t05" are the year dummies and "Area X" the area dummies. "Ofsixi" is the activity of bidder i. It tells to how many of the
six nearest schools of a given school the bidder i has submitted a bid on. "Max Ofsix -i" is
the maximum of the Ofsix variable among i’s competitors. "delta" denotes the test variable
δ. "**" means 10 % significance level, "***" means 5 % significance level, "****" means 1 %
significance level and "*****" means 0.1 % significance level for two-sided tests (one-sided for
delta).

4.7 Conclusions

I have a proposed a new test to detect collusion that is based on participation decisions.
The test is conducted by estimating two simultaneous discrete choice equations with
methods proposed by Tamer (2003). This test can be applied to all environments
where independent and mutually exclusive markets can be defined. Auctions are only
one potential application environment. The test is best suited for detecting territorial
allocation schemes. It can also be used to detect phony bidding but there are also
other tests for that purpose. Monte Carlo analysis shows that this test has the desired
properties. Namely that it is robust to missing variables unlike the existing test with
otherwise similar properties by PZ. The PZ test is better in a sense that it requires less
from the data, both in terms of number and the nature of observations. The old test
also has better convergence properties and better power. The new test complements
it as it can be used to check whether the model has important missing variables that
would invalidate the existing test approach.

I apply both these tests to school yard snow removal auctions in the City of Helsinki
and find some evidence of collusion. Both the tests suggests collusion. Moreover the
analyzed firms do not behave strategically as we would expect in the competitive
setting. Two bidders seem to participate in a contract allocation scheme. According to
descriptive evidence, the collusive regime seems to last only the year 2003. However due
to possible endogeneity problems and problems in the numerical optimization, these
results should be treated with caution. Still, this analysis should validate closer legal
study to support the prosecution of these two companies.

4.8 References

Mattei.


Appendix 1. Participation patterns

Figure 2. Scatter plots of bids and school yard size for each bidder separately for snow ploughing and sanding contract (bid 1 + bid 2) in year 2003.
Figure 3. Bidder participation in school yard snow removal auctions in Helsinki 2004.

Small capital letters present the location of schools and which bidders (A, K, P) have bid to a given school. - means that there were no bids. The approximate location of bidders’ and city’s (C) garages are marked with larger and bold capital letters.
Figure 4. Bidder participation in school yard snow removal auctions in Helsinki 2005.

Small capital letters present the location of schools and which bidders (A, H, J, K, O, P) have bid to a given school. - means that there were no bids. The approximate location of bidders’ and city’s (C) garages are marked with larger and bold capital letters.
Appendix 2. The second Monte Carlo analysis

I conduct a second Monte Carlo analysis to study how the tests behave when I make four changes to the data generating process. First, I assume that there are only two firms in the market. Then it is not possible to meet the exclusion restriction in the estimation. Second, I assume that there is no competition effect ($\beta_{13}$ and $\beta_{23}$ are zero) even in the size simulations. Third, I increase the amount of observations in the data. Fourth, The $z$’s gain only four different values. Again, the variable $x$ can be thought of as a contract characteristic, like contract size and variables $z$’s as the bidder characteristics, like distance. The BR estimation is based on the model (A2.1) and is estimated with the equation (3). The PZ model is estimated with single equation probits omitting $y_j\delta_i$ from the model (A2.1).

\begin{align*}
y^*_1 &= \beta_{10} + x\beta_{11} + z_1\beta_{12} + z_2\beta_{13} + y_2\delta_1 + u_1 \\
y^*_2 &= \beta_{20} + x\beta_{21} + z_2\beta_{22} + z_1\beta_{23} + y_1\delta_2 + u_2
\end{align*} \tag{A2.1}

\begin{equation}
\begin{pmatrix}
u_1 \\
u_2
\end{pmatrix} \sim \text{IIDN} \begin{pmatrix}
0 \\
1
\end{pmatrix} \begin{pmatrix}
1 & \rho \\
\rho & 1
\end{pmatrix}.
\end{equation}

Again, I use eight different specifications in the data generating process. They are summarized in Table A2.1. The data generation is conducted in a following way. I generate $x$ from a uniform (0,1) distribution. The $z$’s are discrete variables that gain values 1,2,3 and 4 each with 25 % probability. The multiplicity of equilibria is addressed as before. I use similarly adjusted cell probabilities as before to randomly assign simultaneously values for the pair ($y_1, y_2$).

<table>
<thead>
<tr>
<th>Model</th>
<th>$\beta_{10}$</th>
<th>$\beta_{11}$</th>
<th>$\beta_{12}$</th>
<th>$\beta_{13}$</th>
<th>$\delta_1$</th>
<th>$\delta_2$</th>
<th>$\rho$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>0</td>
<td>0.3</td>
<td>-0.3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2.</td>
<td>0</td>
<td>0.3</td>
<td>-0.3</td>
<td>0</td>
<td>-0.3</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3.</td>
<td>0</td>
<td>0.3</td>
<td>-0.3</td>
<td>0</td>
<td>-0.45</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4.</td>
<td>0</td>
<td>0.3</td>
<td>-0.3</td>
<td>0</td>
<td>-0.6</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5.</td>
<td>0</td>
<td>0.3</td>
<td>-0.3</td>
<td>0</td>
<td>0</td>
<td>-0.5</td>
<td>0</td>
</tr>
<tr>
<td>6.</td>
<td>0</td>
<td>0.3</td>
<td>-0.3</td>
<td>0</td>
<td>-0.45</td>
<td>-0.5</td>
<td>0</td>
</tr>
<tr>
<td>7.</td>
<td>0</td>
<td>0.3</td>
<td>-0.3</td>
<td>0</td>
<td>0</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>8.</td>
<td>0</td>
<td>0.3</td>
<td>-0.3</td>
<td>0</td>
<td>-0.45</td>
<td>0.5</td>
<td>0.5</td>
</tr>
</tbody>
</table>

The results are presented in Table A1.2. The PZ results were obtained using STATA "simulate" routine. The results for BR were obtained using the R statistical package, with the "optim"-command solving the maximization problem. Monte Carlo analysis for the BR method was very time consuming. It would have taken about half a year
of computer time to get all the results in Table A1.2, if I had used only my 3.0 GHz single processor computer. The calculations were made feasible by dividing the tasks into multiple processors. At best I used 16 different processors.

Even with the handicap of not meeting the exclusion restriction, the results are overall very encouraging for the use on the new test. For models with no unobserved heterogeneity (1.-4.) PZ has much better power. It detects guilty firms more often. For these models, it however does worse in size, meaning it points out innocents as guilty too often. For models with unobserved heterogeneity (5.-8.), which is generated with $\rho$, PZ fails utterly as expected. Either having huge amount of type I errors (model 5.) or very low power (model 8.), depending on the sign of $\rho$. BR estimation does almost as well with unobserved heterogeneity as without it. The only concern with BR is the low power results. This concern is alleviated by the fact that the BR method produces on average accurate estimates for all the parameters. Only the estimates for $\delta$’s seem to be slightly closer to zero than they should be. Because $\rho$ is estimated accurately on average, BR can be used jointly with PZ as a way to evaluate whether there are missing variables. Therefore the Monte Carlo analysis shows that BR method in cases with unobserved heterogeneity works much better that PZ and in the case with no unobserved heterogeneity is complementary to PZ. Therefore the test that I propose works as expected and should be used instead of or in addition to the existing PZ method.

I also conducted the Monte Carlo analysis for some of these models for a large number of observations (10000 observations, with 100 repetitions) to check whether the tests are consistent in a sense that the power converges to one as the number of observations increase. Both the tests seem to be consistent.
Table A1.2. Power and Size results for the Monte Carlo comparison of the tests with 5% significance level.

<table>
<thead>
<tr>
<th>Model</th>
<th>Obs</th>
<th>PZ, power</th>
<th>PZ, size</th>
<th>BR, power</th>
<th>BR, size</th>
<th>BR, p</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>500</td>
<td>13.5%</td>
<td>8.9%</td>
<td>0.06; 6.5%</td>
<td>0.06; 6.5%</td>
<td></td>
</tr>
<tr>
<td>1.</td>
<td>1000</td>
<td>18.9%</td>
<td>9.7%</td>
<td>0.05; 7.1%</td>
<td>0.05; 7.1%</td>
<td></td>
</tr>
<tr>
<td>2.</td>
<td>500</td>
<td>69.5%</td>
<td>28.6%</td>
<td>0.07; 6.8%</td>
<td>0.07; 6.8%</td>
<td></td>
</tr>
<tr>
<td>2.</td>
<td>1000</td>
<td>90.1%</td>
<td>34.5%</td>
<td>0.04; 6.4%</td>
<td>0.04; 6.4%</td>
<td></td>
</tr>
<tr>
<td>3.</td>
<td>500</td>
<td>89.7%</td>
<td>39.8%</td>
<td>0.07; 7.2%</td>
<td>0.07; 7.2%</td>
<td></td>
</tr>
<tr>
<td>3.</td>
<td>1000</td>
<td>98.7%</td>
<td>48.0%</td>
<td>0.06; 6.8%</td>
<td>0.06; 6.8%</td>
<td></td>
</tr>
<tr>
<td>4.</td>
<td>500</td>
<td>97.0%</td>
<td>50.6%</td>
<td>0.08; 5.5%</td>
<td>0.08; 5.5%</td>
<td></td>
</tr>
<tr>
<td>4.</td>
<td>1000</td>
<td>99.7%</td>
<td>62.6%</td>
<td>0.07; 6.8%</td>
<td>0.07; 6.8%</td>
<td></td>
</tr>
<tr>
<td>5.</td>
<td>500</td>
<td>54.4%</td>
<td>11.1%</td>
<td>-0.42; 34%</td>
<td>-0.42; 34%</td>
<td></td>
</tr>
<tr>
<td>5.</td>
<td>1000</td>
<td>80.7%</td>
<td>10.8%</td>
<td>-0.45; 55%</td>
<td>-0.45; 55%</td>
<td></td>
</tr>
<tr>
<td>6.</td>
<td>500</td>
<td>100%</td>
<td>28.0%</td>
<td>-0.45; 35%</td>
<td>-0.45; 35%</td>
<td></td>
</tr>
<tr>
<td>6.</td>
<td>1000</td>
<td>100%</td>
<td>34.5%</td>
<td>-0.46; 64%</td>
<td>-0.46; 64%</td>
<td></td>
</tr>
<tr>
<td>7.</td>
<td>500</td>
<td>0.0%</td>
<td>5.2%</td>
<td>0.52; 73%</td>
<td>0.52; 73%</td>
<td></td>
</tr>
<tr>
<td>7.</td>
<td>1000</td>
<td>0.0%</td>
<td>7.1%</td>
<td>0.52; 90%</td>
<td>0.52; 90%</td>
<td></td>
</tr>
<tr>
<td>8.</td>
<td>500</td>
<td>7.0%</td>
<td>46.7%</td>
<td>0.55; 72%</td>
<td>0.55; 72%</td>
<td></td>
</tr>
<tr>
<td>8.</td>
<td>1000</td>
<td>4.0%</td>
<td>61.6%</td>
<td>0.53; 89%</td>
<td>0.53; 89%</td>
<td></td>
</tr>
</tbody>
</table>

In the last column titled "BR, p", the first number is the mean of the estimated ρ’s and the second number is the share of these estimates that are significantly different from zero. In BR test the actual size is 9.75% since the test is based on either or the δ’s being significant at 5% level.