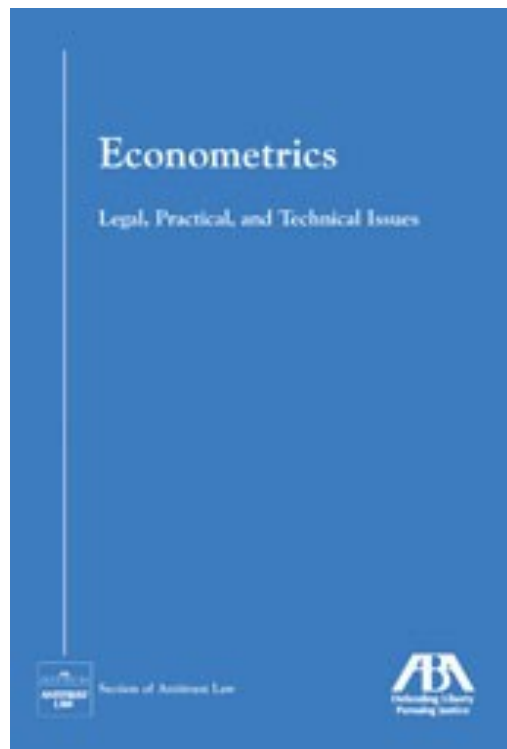


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CHAPTER IX

AUCTION MODELS

A. Introduction

When applying for a mortgage, selecting a bottle of Bordeaux, or giving roses for a special occasion, one indirectly participates in an auction. Prices of treasury bills, wine futures, and wholesale flowers are all set at auction. Like traditional market mechanisms, auctions allocate goods to buyers who are willing to pay the most for them. However, unlike traditional markets, in which slight price adjustments are usually met by commensurately small changes in sales, the winner-take-all nature of auctions can amplify the consequences of mergers and cartels. Given their economic ubiquity and sensitivity to firm strategy, the close scrutiny of auction markets by antitrust regulators is understandable.

In auction markets, antitrust legal disputes often raise questions like “is this merger anticompetitive” or “by how much did this conspiracy raise prices?” To produce evidence to answer these questions, two states of the world – one before and one after a merger, or with and without the conspiracy – must be compared. In some cases, “natural experiments,” like the collapse of a price-fixing conspiracy allow observations of both states of the world. Then, straightforward estimation using “reduced-form” econometric models allows a comparison of prices across the competitive and collusive regimes while controlling for costs and other confounding factors.

If nature hasn’t been kind enough to provide a good natural experiment, merger and conspiracy effects can be simulated with theoretical models of competition calibrated to observable data. Such “structural models” are well developed for traditional, price-setting markets. For example, in the WorldCom-Sprint merger case (see Chapter X), both the Department of Justice and interested third parties developed demand estimates for residential long distance phone service illustrating that Sprint and MCI were close substitutes. The demand

estimates were used as inputs to a structural model of competition demonstrating that the proposed merger would substantially raise prices.¹ Subsequently, the Justice Department challenged the merger and WorldCom abandoned its acquisition plans.

WorldCom and Sprint also bid against each other in auctions to supply telephone services to businesses. To estimate the merger's effect on these customers, an analogous structural model of competitive bidding could be utilized. Just as traditional firms select prices to maximize profit in light of consumer demand, auction participants choose bids to maximize profit given their costs of providing the service and value of winning the contract. The goal of structural estimation is to reverse this process and uncover the latent distribution of costs from observed bids, similar to attempting to uncover characteristics of demand from observed prices in traditional markets.

The purpose of this paper is to review the relatively young empirical literature on auctions that is especially relevant to issues that arise in antitrust cases.² In what follows, a primer on auction formats and a differentiation between varying information environments is presented. Next, reduced-form estimation of conspiracy effects is examined and then structural estimation in the context of merger analysis is considered. A discussion of the role of economic analysis of auctions in the courtroom concludes the paper.

B. Primer on Auctions

1. Introduction

Since firm behavior varies depending on the type of auction, one must understand how observed price and bidding data reflect bidders' underlying values or costs. Different auction formats generate varying amounts and type of data, potentially restricting the type of econometric

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1. See Jerry A. Hausman, Declaration of Jerry Hausman (Feb. 16, 2000) (submitted to the Federal Communications Commission).
 2. For reviews of earlier empirical literature not specifically focused on antitrust concerns, see Robert G. Hansen, *Empirical Testing of Auction Theory*, 75 AM. ECON. REV. 862 (1985); Jean-Jacques Laffont, *Game Theory and Empirical Economics: The Case of Auction Data*, 41 EUR. ECON. REV. 1 (1997). For a review of auction design, see Paul D. Klemperer, *What Really Matters in Auction Design*, J. ECON. PERSPECT. (forthcoming).

analysis that may be undertaken. To simplify the presentation, “selling” auctions are discussed, where an item is *sold* to the *highest* bidder, and in which anticompetitive mergers among bidders *reduce* price. Procurement auctions, where an item is *purchased* from the *lowest* bidder, and in which anticompetitive mergers *increase* price, will not be explicitly discussed. However, everything that follows applies equally for procurement auctions with a simple change of sign.

2. Auction Formats

To a lay person, bidding often evokes an image of a fast-talking gavel-clutching auctioneer accepting successively higher bids until only one bidder remains. This format, the English, (or ascending bid) auction may be quite cumbersome in practice if all participants must be gathered together and sufficient time allotted to allow the iterative bid-raising process to run its course.³ While such participatory auctions are apt to generate excitement and fanfare among the public, many auctions, especially in procurement settings, are sealed-bid format where each participant submits a confidential bid to the auctioneer who determines the highest bid at the auction’s conclusion. The resulting price is either the amount of the winning bid (a first-price sealed-bid auction) or the next highest bid (a second-price sealed-bid auction).

Given the choice of setting the price equal to the best or second-best bid, why would an auctioneer ever use the second-price auction? The answer is that in a second-price auction, participants bid more aggressively. Increasing one’s bid raises the probability of winning but not, as in the case of a first-price auction, the expected cost, as that is determined by someone else’s bid. Thus, participants have the incentive to bid their actual valuations.⁴ If the winning bid is equal to the bidder’s value and the actual price paid is equal to the second-highest bid, the

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3. An alternate and rarely used participatory auction is the Dutch auction, so termed due to its prevalence in allocating cut flowers in the Netherlands. The price is set initially above any reasonable bidder’s willingness to pay, and is slowly decreased until a participant “buzzes in,” paying the price at which the auction is stopped. This format allows the auctioneer to control auction speed by changing the rate at which the price decreases.
 4. See William Vickrey, Counterspeculation, Auctions, and Sealed Tenders, 16 J. FINANCE 8 (1961).

winning bidder is assured a profit. Any bid below or above that value can only decrease the expected profit. In a first-price auction, by contrast, one is unwilling to bid as aggressively since winning with a bid equal to one's value leaves them with zero profit. Instead, each participant "shades" his bid by bidding below his actual value, effectively reducing the probability of winning in exchange for a better price and higher profit if the bidder does win. Determining which format delivers a better price for the auctioneer depends on whether the second-highest bid among relatively aggressive bids is higher than the uppermost bid among less aggressive bids. Which format results in greater revenue for the seller is not trivial to determine. However, when bidders are more or less the same, the formats return equal prices, on average.⁵

Despite this "revenue equivalence," the various auction formats have significantly different implications for the relationship between bids and underlying values. A sealed-bid second-price auction, while rarely seen in practice,⁶ is ideal for the econometrician since bids are equal to values.

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5. See John G. Riley & William F. Samuelson, *Optimal Auctions*, 71 AM. ECON. REV. 381 (1981); Paul Milgrom & Robert Weber, *A Theory of Auctions and Competitive Bidding*, 50 ECONOMETRICA 1089 (1982). This equivalence of revenues suggests a powerful methodology for simulations among symmetric bidders. Even when the market format is the analytically cumbersome first-price auction, we can simulate a second-price auction since average prices will be the same for the two formats. See, e.g., Jean-Jacques Laffont, Herve Ossard & Quang Vuong, *Econometrics of First-Price Auctions*, 63 ECONOMETRICA 953 (1995); Tong Li & Quang Vuong, *Using All Bids in Parametric Estimation of First-Price Auctions*, 55 ECON. LETTERS 321 (1997). Laboratory experiments have called into question whether different auction formats do induce equivalent revenue in practice. See, e.g., Vicki M. Coppinger, Vernon L. Smith & Jon A. Titus, *Incentives and Behavior in English, Dutch and Sealed-Bid Auctions*, 18 ECON. INQ. 1 (1980). Also see John Kagel, *Auctions: A Survey of Experimental Research*, in John Kagel & Alvin Roth, eds., *HANDBOOK OF EXPERIMENTAL ECONOMICS*, Princeton: Princeton University Press, 501 (1995). The failure of revenue equivalence is likely due to bidders' risk tolerance. See Gary J. Miller & Charles R. Plott, *Revenue-Generating Properties of Sealed-Bid Auctions: An Experimental Analysis of One-Price And Discriminative Processes*, in V.L. Smith, ed., *RESEARCH IN EXPERIMENTAL ECONOMICS 3*, Greenwich, CT: JAI Press, 159 (1985).
 6. See generally Michael H. Rothkopf & Ronald M. Harstad, *Two Models of Bid-Taker Cheating in Vickrey Auctions*, 68 J. BUS. 257 (1995). The second-price format has been used in financial markets, including select

In an English auction however, observed bids can be viewed only as a lower bound on each bidder's value because bidders will bid up to their values only when necessary to win the auction. A quick "bidding war" among several participants may preclude others from registering their maximum bids.⁷ Further, because the auction concludes when the second-highest valued bidder drops out, identification of the winner's actual value is impossible.

In a sealed-bid first-price auction, participants' bids incorporate a profit margin, and thus do not directly reflect their values. For example, if one's value is likely to be substantially higher than those of other participants, they can bid significantly lower than another's value and still have a high probability of winning. Thus, the bidding data reflect both the values of bidders and the beliefs of bidders about the behavior and values of rivals. Isolating these two effects usually requires restrictive assumptions on the joint value distribution and the beliefs of bidders.⁸

Beyond the limitations inherent in the auction format on the meaning that can be inferred from the data, the data themselves may impose additional restrictions on econometric analysis. Available data may

treasury auctions on an experimental basis. See Office of Market Finance, U.S. Treasury, Washington, D.C. *Uniform-Price Auctions: Update of the Treasury Experience* (21 March 2002) available at <http://www.ustreas.gov/domfin/upas2.pdf>. For internet auctions, like those on eBay, the use of proxy bidding (you tell the computer your maximum bid, and it automatically bids for you) makes them resemble second-price auctions.

7. Even if the auction is not "freeform," (for example, a "button auction" in which participants hold a button to indicate that they are still active participants) and exit is irreversible, a multiplicity of equilibria make interpretation challenging. See Sushil Bikhchandani, Philip A. Haile & John G. Riley, *Symmetric Separating Equilibria in English Auctions*, 38 GAMES ECON. BEHAV. 19 (2002). However, we can place bounds on the distribution of valuations from free-flow English auction mechanisms. See Philip A. Haile & Elie T. Tamer, *Inference with an Incomplete Model of English Auctions* (2000) (mimeograph, on file with The University of Wisconsin-Madison).
8. See Patrick Bajari, *The First Price Sealed Bid Auction with Asymmetric Bidders: Theory and Applications* (1997) (Ph.D. Dissertation, University of Minnesota).

range from only winning bids to the entire array of bids from all participants. Techniques discussed below will also depend on whether the econometrician observes the number and identity of bidders, and whether these identities can be matched to actual bids.

3. *Values: Common and Private*

How a bidder determines his value for an object plays a critical role in auction analysis. To illustrate the main idea, consider two auctions for art: in one, residents of a small town bid on paintings by local artists; in the other, representatives of art galleries bid on works by renowned masters. If, in the local auction, residents submit bids based on how much they would value the art hanging in their living rooms, the auction is *private value* – bidders' valuations arise from personal preferences.⁹ Dispersion of bids is caused by idiosyncratic differences in bidders' tastes. Wholesale art auctions, on the other hand, are attended by gallery representatives whose personal tastes are not relevant – representatives purchase art with the goal of reselling it to the general public in the future. In *common value* auctions, the object for sale typically has an objective, though unknown value (e.g., the future resale price). Dispersion of bids is caused by differential estimates of the object's true worth by the different bidders.¹⁰

While a seemingly semantic distinction, the antitrust implications are quite different for private and common value auctions. Mergers and collusion in private value auctions follow an intuition similar to that of traditional markets – both are always anticompetitive in the absence of offsetting efficiency gains. The primary issues are whether the anticompetitive effect is “substantial,” in the language of the Sherman Act, and whether offsetting efficiency gains ameliorate this effect. From a bidder's perspective, the value other bidders place on a given work of

9. See generally Vickrey, *supra* note 4.

10. See generally Robert Wilson, Competitive Bidding with Asymmetric Information, 13 *MANAGE. SCI.* 816 (1967); Michael H. Rothkopf, A Model of Rational Competitive Bidding, 15 *MANAGE. SCI.* 774 (1969); Robert Wilson, Competitive Bidding with Disparate Information, 15 *MANAGE. SCI.* 446 (1969). Common value auctions are actually a much broader class than we explore here, generally incorporating most environments in which bidders possess information relevant for value formation of rivals.

art informs only his chance of winning (being the highest bidder) but does not change what he is willing to pay.

Common value auctions are quite different. Humility dictates that art dealers give some credit to the competitor's ability to estimate future resale value. Thus, if no other bidder is willing to pay large sums for a given painting, it probably indicates that future resale is limited. Even if gallery representatives are good at estimating future resale values, the winning bidder is likely to be the one who has most overestimated the future resale value of the work, a phenomenon known as the "winner's curse."¹¹ To avoid the winner's curse (and to avoid overpaying for the artwork), each dealer adopts a *winner's curse correction*, reducing the bid to account for the fact that winning an auction suggests an overly optimistic estimate of the object's value.

The effects of mergers and collusion in common value auctions are not completely understood. Certainly, joint bidding reduces the number of active bidders, which has an anticompetitive effect; however, a merger also increases the amount of information available to the merging bidders. Two art dealers, having access to each gallery's appraisers, are likely to arrive at a better estimate of a painting's resale value if they pool their information. This can lead to a more confident estimate, a smaller winner's curse correction, and a higher bid. Thus, joint bidding may reduce competition but also increase the aggressiveness of bidding. Disentangling these effects is not trivial and is the subject of current research.¹² Unlike private value auctions in which the *extent* of the

11. *See generally* Richard H. Thaler, *Anomalies: The Winner's Curse*, 2 J. ECON. PERSPECT. 191 (1988).

12. *See generally* Vlad Mares, *Asymmetric Mergers in Common-Value Auctions* (2000) (mimeograph, on file with The Department of Economics, Rutgers University). In some familiar frameworks, the effects of mergers and collusion in common value auctions mimic those in traditional private value settings. *See* Vlad Mares, *Market Concentration and Prices in Common-Value Auctions* (2000) (mimeograph, on file with The Department of Economics, Rutgers University). For empirical and experimental investigations, see, e.g., Kenneth Hendricks & Robert H. Porter, *An Empirical Study of An Auction with Asymmetric Information*, 78 AM. ECON. REV. 865 (1988); Kenneth Hendricks & Robert H. Porter, *Joint Bidding in Federal OCS Auctions*, 82 AM. ECON. REV. 506 (1992); Mikhael Shor & Vlad Mares,

anticompetitive effects is the crucial determination of court action in mergers and collusion, common value auctions call into question even *whether* an anticompetitive effect exists.

Consequently, it is critical for the formulation of legal strategy to determine whether an auction is in the common or private value framework. How does one differentiate them based on past bidding data? One approach exploits the fact that the winner's curse intensifies with more bidders.¹³ In our wholesale art auction, if one gallery representative beats out another, the winner can infer that their estimate of future resale value is higher than their competitor's. However, it is likely that their estimate is the correct one and their competitor is wrong. Instead, if 100 other bidders participate, their winning implies that their estimate is higher than all 100 teams of art appraisers. Justifying why they are right and the others are wrong is substantially more difficult. With more bidders, it becomes more likely that the winner has overbid. Bidders account for the winner's curse by bidding less aggressively and a greater adjustment is required with more bidders. Conversely, the values among townsfolk in the local artist auction do not change with the number of bidders. This is because knowing that others value the work more or less has no affect on their private value. To differentiate between common and private value auctions, the researcher may determine whether bids decrease with increasing numbers of participants, which is indicative of a common value auction.¹⁴

Information Sharing in Common Value Auctions: An Experimental Investigation (2002) (mimeograph, on file with Vanderbilt University).

13. Other approaches use ex-post information on object values. See, e.g., Susan Athey & Jonathan Levin, *Information and Competition in U.S. Forest Service Timber Auctions*, 109 J. POLIT. ECON. 375 (2001); Kenneth Hendricks, JORIS PINKSE & ROBERT H. PORTER, EMPIRICAL IMPLICATIONS OF EQUILIBRIUM BIDDING IN FIRST-PRICE, SYMMETRIC, COMMON VALUE AUCTIONS (Nat'l Bureau of Econ. Research, Working Paper No. 8294, 2001).
14. Nonparametric tests are proposed by Philip A. Haile, Han Hong & Matthew Shum, *Nonparametric Tests for Common Values at First-Price Auctions* (2000) (mimeograph, on file with The University of Wisconsin-Madison and Princeton University). For English auctions, see Haile & Tamer, *supra* note 7. In first-price auctions, bids are sensitive to the number of bidders even in private value settings. Further, these approaches do not uniquely identify common value auctions as other models can exhibit similar features. See Joris Pinkse & Guofu Tan, *Fewer Bidders can Increase Price in First-Price Auctions with Affiliated Private*

4. Summary

A taxonomy of auction formats involves two dimensions – the type of mechanism (e.g., first-price, second-price, English) and the source of values (e.g., private, common). Realistically, auctions are likely to exhibit characteristics of more than one mechanism. For example, during the 1980 Olympics, Soviet organizers held a sealed-bid auction for television broadcast rights. Unhappy with the aggressiveness of the bids, the auctioneer played one bid against another, effectively mixing the first-price and English auction formats. In addition, it is not uncommon for the characteristics and specifications to be a topic of negotiation between the bidders and the procurer. Subjectivity is inevitable in classifying auctions. What may appear to be a first-price sealed-bid auction may in fact be closer to an English or second-price auction.

Similarly, most auctions share features of both value paradigms. Even if one is purchasing art for personal enjoyment, future resale may enter their appraisal of its value.¹⁵ While it may be possible to differentiate among *specific* forms of private and common value auctions from the data, intuition may be a better guide in determining whether the private or common value framework is more appropriate. An empirical answer to “of all possible auction types, which is this one most likely to

Values (2000) (mimeograph, on file with The University of British Columbia). Also see Harry J. Paarsch, *Deciding Between the Common and Private Value Paradigms in Empirical-Models of Auctions*, 51 J. ECONOM. 191 (1992); Patrick Bajari & Ali Hortacsu, *Winner's Curse, Reserve Prices and Endogenous Entry: Empirical Insights from eBay Auctions* (2002) (mimeograph, on file with Stanford University).

15. For a discussion of how resale transforms private value auctions, see Philip A. Haile, *Auctions with Resale Markets: An Application to US Forest Service Timber Sales*, 91 AM. ECON. REV. 399 (2001). A general class of valuations termed *affiliated* contains common and private values as special cases. Robert Wilson, *A Bidding Model of Perfect Competition*, 44 REV. ECON. STUD. 511 (1977); Milgrom & Weber, *supra* note 5. For estimation of affiliated values auctions, see Tong Li, Isabelle Perrigne & Quang Vuong, *Structural Estimation of the Affiliated Private Value Model*, 33 RAND J. ECON. 171 (2002).

be?” does not usually exist.¹⁶ As in the art auction example where the issue was personal enjoyment versus future resale, a better question is “do the bids of others inform my value for the object?”

For two reasons, the concentration of the remainder of this chapter will be on private value auctions. First, common value auctions are very difficult to analyze, as the econometrician must distinguish between the values bidders place on the object being auctioned and the bidders’ beliefs about the values of rivals. Second, the anticompetitive effects of mergers and collusion in private value settings are measurable and the result of a mature theoretical literature, while for common value auctions the very existence of anticompetitive effects is not assured. In the next two sections, methods for analyzing collusion and mergers in private value settings will be discussed.

C. Conspiracies: Detection, Proof, and Damages

1. Introduction

Bid-rigging, especially against the government, is a much more prevalent source of antitrust litigation than other market conspiracies. A majority of criminal cases filed by the U.S. Department of Justice during the Reagan administration involved bid-rigging by auction participants.¹⁷ In this section, the use of reduced-form models to detect, prove, and estimate the damages from bid-rigging conspiracies will be examined.¹⁸

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16. See Jean-Jacques Laffont & Quang Vuong, *Structural Analysis of Auction Data*, 86 AM. ECON. REV. 414 (1996); Susan Athey & Philip A. Haile, *Identification of Standard Auction Models*, *ECONOMETRICA* (forthcoming).
17. See John McMillan, *Dango: Japan's Price-Fixing Conspiracies*, 3 *ECONOMICS AND POLITICS* 201 (1991). For broader evidence of the prevalence of bid-rigging, including internationally, see Japanese Fair Trade Commission, Annual Report on Competition Policy in Japan, 1999 (21 March 2001), available at <http://www.jftc.go.jp/e-page/report/annual/CLP99HP.pdf>; Harry Chandler & Robert Jackson, Insight Conferences, Toronto, Ontario, Roundtable on Competition Act Amendments, Beyond Merriment and Diversion: The Treatment of Conspiracies under Canada's Competition Act (2000), available at <http://strategis.ic.gc.ca/SSG/ct01767e.html> (last modified March 21, 2001).
18. This chapter focuses exclusively on collusion among bidders. For conspiracies involving the auctioneer, see Rothkopf & Harstad, *supra*

2. *Conspiracy Effects*

A simple illustration of conspiracy effects occurred in Philadelphia during a trial involving the sale of frozen seafood to the Defense Personnel Support Center (DPSC).¹⁹ Conspirators collaborated to agree on the designated winner of each upcoming auction. Remaining ring members submitted “complementary” bids above the prearranged winning price. In late 1988, following reports of an investigation into the conspiracy, prices dropped sharply. To estimate damages for the sentencing phase of the trial, a reduced-form model provided comparisons between the collusive and post-investigation competitive periods (Figure 1).

note 6; Roberto Burguet & Martin Perry, *Bribery and Favoritism by Auctioneers in Sealed Bid Auctions* (2002) (mimeograph, on file with the Institute for Economic Analysis, Spain).

19. *See generally* Luke M. Froeb, Robert A. Koyak & Gregory J. Werden, *What Is the Effect of Bid-Rigging on Prices?*, 42 *ECON. LETTERS* 419 (1993). “The case did not go to trial, so the publicly available information is very limited. The best description of the events is contained in the governments’ trial brief in *United States v. Anthony P. Parco*, 970 F.2d 901 (1992) which concerned the “sentencing of one of the defendants” at 420, note 3.

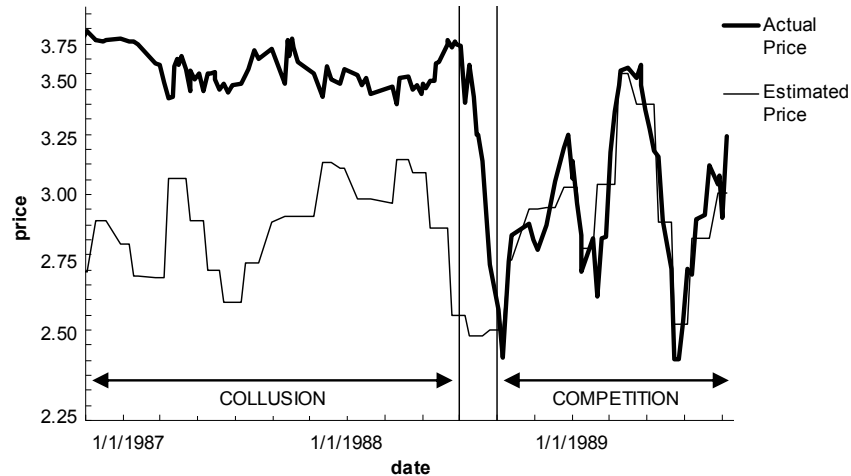


Figure 1. Actual and estimated prices for frozen perch at auction. The thick line represents observed prices. The thin line marks estimated prices calibrated to “competition” prices and backcast into the collusive period.

In Figure 1, the average price paid by the DPSC for frozen perch filets from 1987 through September, 1989, is plotted using a bold-faced line. The period before and after prices fell are marked as the “collusion” and “competition” periods, respectively. Using data on fresh perch as a cost variable, observed prices were regressed on costs for the competitive period to determine the relationship between costs and prevailing prices. These estimates then allow a “backcast” into the collusive period to determine what prices would have prevailed absent the conspiracy. The thin line marks the predicted price from the regression. Note that during the competitive regime, prices are quite volatile, while during the collusive regime, price is relatively unresponsive to large seasonal swings in costs, represented by the variation in estimated prices. During the collusive period, actual prices are on average 23 percent higher than the prices predicted by the estimation. Consequently, damages were computed as 23 percent of the total volume of commerce.

The above analysis is simplified by observing both a competitive and collusive regime.²⁰ Other natural experiments may allow for a contrast

20. For other forecasting approaches, see Jeffrey H. Howard & David L. Kaserman, Proof of Damages in Construction Industry Bid-Rigging Cases, 34 ANTITRUST BULL. 359 (1989); John P. Nelson, Comparative

between the behavior of reputed colluders and bidders outside of the conspiracy. For example, Porter and Zona examined bidding for New York highway construction contracts in the 1980s. Among suspected cartel members, it was found that only the winner, who bid competitively against non-cartel members, made a bid that was closely related to costs. Non-winning bids were only weakly related to costs, suggesting that cartel members submitted “phony bids” to fool the auctioneer into thinking that bidding was competitive.²¹ In a later paper, Porter and Zona examine bidding behavior for school milk contracts. Again, they find significant differences in bids and in participation between suspected conspirators and a “control” group of competitors.²²

Reduced-form models can also be used to differentiate between various forms of collusion. Among dairies bidding for school milk contracts, two different types of collusive agreements were suspected in different states. In Texas, bidding rings allegedly colluded by allocating jobs among conspirators, while in Florida, side payments were made to losing cartel members. The Texas scheme of allocating contracts requires that each cartel member be allowed to win a similar amount of auctions, or else there would be insufficient incentive to remain in the conspiracy. In Florida, the bidding ring allowed the dairy with the lowest costs to win each auction, thus assuring greater overall profit to the conspirators, later divided through side payments. Florida market shares were found to be more variable than those in Texas, consistent with the differences between two collusive mechanisms.²³

All of these reduced-form techniques aim to identify patterns of behavior inconsistent with competitive bidding. Uncharacteristic patterns of auction participation, bids unreflective of underlying costs,

Antitrust Damages in Bid-rigging Cases: Some Findings from a Used Car Auction, 38 ANTITRUST BULL. 369 (1993).

21. Robert H. Porter & J. Douglas Zona, *Detection of Bid Rigging in Procurement Auctions*, 101 J. POLIT. ECON. 518 (1993). The authors do not solve for “optimal” bids, but posit a very simple bidding rule. Such techniques often offer qualitatively similar evidence as more robust models but require substantially less time for the analysis.
22. Robert H. Porter & J. Douglas Zona, *Ohio School Milk Markets: An Analysis of Bidding*, 30 RAND J. ECON. 263 (1999).
23. Martin Pesendorfer, *A Study of Collusion in First-Price Auctions*, 67 REV. ECON. STUD. 381 (2000).

and rotation of auction winners all suggest potential collusion. Reduced-form regression techniques help identify these patterns by accounting for costs and other factors that otherwise could account for the hypothesized differences. Despite their success in identifying collusion in a particular setting, the broader usefulness of these approaches is limited. Many seemingly collusive behaviors can also be explained by competitive conduct. Bid rotation may reflect capacity constraints – the most recent winners of an auction have the least ability to adopt new projects;²⁴ failure to participate in an auction can be the result of a strategic cost-benefit analysis when bidding involves costs;²⁵ and low prices may be the result of market fluctuations.²⁶

3. *Detection and Proof*

Estimating the *effects* of a conspiracy with a good natural experiment and good cost data is relatively straightforward. However, *detecting* and *proving* collusion is much more difficult because bid-rigging conspiracies can take many forms.²⁷ Ring members may submit phony bids (complementary bidding), refrain from bidding altogether (bid suppression), take turns winning (bid rotation), or use side payments and subcontracting to reward losing cartel members for not bidding

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24. See Kevin Lang & Robert W. Rosenthal, *The Contractors' Game*, 22 RAND J. ECON. 329 (1991); Mireia Jofre-Bonet & Martin Pesendorfer, *Bidding Behavior in a Repeated Procurement Auction: A Summary*, 44 EUR. ECON. REV. 1006 (2000); MIREIA JOFRE-BONET & MARTIN PESENDORFER, ESTIMATION OF A DYNAMIC AUCTION GAME, (Nat'l Bureau of Econ. Research, Working Paper No. 8626, 2001).
 25. Relying on observed bid data without accounting for endogenous participation can severely bias the results. See Robert G. Hansen, *Sealed-Bid versus Open Auctions: The Evidence*, 24 ECON. INQ. 125 (1986).
 26. See Laura H. Baldwin, Robert C. Marshall & Jean-Francois Richard, *Bidder Collusion at Forest Service Timber Sales*, 105 J. POLIT. ECON. 657 (1997).
 27. For examples of incentive-compatible collusion mechanisms, see R. Preston McAfee & John McMillan, *Bidding Rings*, 82 AM. ECON. REV. 579 (1992). Efficient cartels need to elicit true values and allocate the object to the highest-value member. See generally Daniel A. Graham & Robert C. Marshall, *Collusive Bidder Behavior at Single-Object Second-Price and English Auctions*, 95 J. POLIT. ECON. 1217 (1987); George J. Mailath & Peter Zemsky, *Collusion in Second Price Auctions with Heterogeneous Bidders*, 3 GAMES ECON. BEHAV. 467 (1991).

aggressively. Detecting or proving conspiracies requires identifying patterns of bidding consistent with various collusive schemes.

Several recent articles attempt to codify the telltale signs of collusion into general properties that must be satisfied by competitive bidding, and when violated, indicate collusion.²⁸ Tests for two properties are proposed. The first, “conditional independence,” implies that all bids should be independent when adjusted for costs and public information. For example, if firms placed bids that depend on their own costs and on the characteristics of the product being auctioned, then the econometrician can estimate these bids from observable data. Obviously these estimates will not be exact (some margin of error will exist between the actual bids and the estimated ones), but these errors should be independent across bidders. Conversely, collusion may impose correlation of bids among ring members if, for example, the cartel sets the winning complementary “phony” bids lower than the agreed-upon winning bid. The second condition, “exchangeability,” implies that a firm’s bid should depend only on firm and product-specific characteristics and not the firm’s identity. Simply put, two identical firms bidding on identical items could easily swap bids and the econometrician would be none the wiser. Alternately, if some firms systematically behave differently from others then collusion is suspected.

The above conditions may help identify conspiracies but it is easy to construct collusive mechanisms that would escape detection. For example, imagine bidders in an auction agreeing that whoever wins a project will pay the other bidders \$100, to be divided equally among them, akin to revenue sharing in professional sports. Without any additional agreement on the formation of bids, each participant bids competitively. However, the effective cost of the project increases by \$100 for each, resulting in a proportional increase in bids. Since the addition of a constant does not alter correlation, an econometrician examining this data would see no greater violation of independence than if the bidding was truly competitive. Similarly, since the bids still reflect

28. *See generally* Patrick Bajari & Garrett Summers, *Detecting Collusion in Procurement Auctions: A Selective Survey of Recent Research* (2001) (mimeograph, on file with Stanford University). A specific method of incorporating the beliefs about costs of industry experts is proposed in Patrick Bajari & Lixin Ye, *Deciding Between Competition and Collusion* (2001) (mimeograph, on file with Stanford University).

each bidder's costs (adjusting for the \$100 addition) in a uniform fashion, exchangeability need not be violated.

The above example represents a potential shortcoming of any methodological approach to detect bid-rigging. Once a test for collusion is adopted, members can organize the collusive ring in a way that is not detectable by the specific screens imposed. Further, testing for violations of independence and exchangeability is extremely susceptible to misspecification of costs. Given that the econometrician must control for firm and product-specific attributes before the tests can be applied, the extensive data required for these tests is a lot more than what is normally generated at auction. If costs or values are known, then a simple take-it-or-leave-it offer to the lowest-cost firm can generate higher revenues for the seller than an auction. Hence, the choice of auction as an allocation mechanism often coincides with poor cost data.

Ideally, a charge of collusion would be backed up with the proverbial smoking gun. Econometric evidence alone is unlikely to meet the burden for criminal prosecutions, though it may form a substantial part of evidence in a civil trial. The most meaningful use of econometric techniques in bid-rigging cases may be during the sentencing phase, in which the existence of collusion and the identity of conspirators can be presupposed. In the investigative phase, in which collusion is only suspected but the ring members are not known, econometric tests of multiple subsets of auction participants will likely falsely identify ring members.

However, if a conspiratorial agreement can be demonstrated, econometric techniques can support the claim that an act was actually taken. For example, the Department of Justice charged that in the auctions for telephone spectrum rights, Omnipoint Corporation used the last three digits of its bids to signal both an interest for a particular license and an implicit threat to bid for a competitor's license. While seeing million dollar bids end in uneven dollar amounts conveniently reflecting area codes of major telephone markets appears quite suspicious, statistical evidence demonstrated that actual differences in prices and participation patterns were observed between these auctions and others in which no such signaling occurred.²⁹

D. Mergers: Structural Analysis

29. United States v. Omnipoint Corp., No. 98-2750, 1999 WL 135161 (D.D.C. Feb. 25, 1999).

The econometrics of collusion and mergers in auctions represents two sides of the same coin. For collusion, there is speculation of a competitive world given our observation of joint bidding behavior. In mergers, a world is foretold in which currently competitive firms instead bid jointly. While one may observe both a collusive and competitive period when analyzing a cartel, the effects of mergers prior to their consummation must be predicted.

Benefit-cost analysis of mergers requires a quantitative estimate of the resulting anticompetitive effect. Without one it is impossible to trade off the benefits of a merger against its economic costs, except in an ad hoc way.³⁰ Structural auction models can be used to estimate merger effects both in second-price or English auctions and, with greater difficulty, in first-price auctions.³¹

To model the effect of a merger, it is assumed that the private value of the merged firm is the maximum of its coalition member values. This implies that the merged firm wins all the auctions that any of its pre-merger component pieces would have won. This characterization has been used by the antitrust enforcement agencies to model the unilateral effects of “naked” (no efficiencies) mergers between hospitals, mining equipment manufacturers, defense contractors, and others.³² Following a

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30. See generally Gregory J. Werden, Luke M. Froeb & Steven Tschantz, *The Logit Model for Simulating Unilateral Competitive Effects*, [THIS VOLUME: Chapter ??](#). Once merger effects have been computed, it is possible to determine the compensating marginal cost reductions (or value increases) necessary to offset the anticompetitive price rise. Because losing bidders set the price, merger efficiencies do not affect prices paid by the merging firms. However, by making the merged firm a stronger loser, efficiencies raise prices paid by non-merging firms, potentially offsetting the anticompetitive effects of the merger. See Lance Brannman & Luke Froeb, *Mergers, Cartels, Set-Asides and Bidding Preferences in Asymmetric Second-Price Auctions*, 82 REV. ECON. STAT. 283 (2000); Steven Tschantz, Philip Crooke & Luke Froeb, *Mergers in Sealed vs. Oral Auctions*, 7 INT. J. ECON. OF BUS. 201 (2000).
31. While not the focus of the previous section, numerical methods with structural models are also used in collusion detection and damage estimation. See, e.g., Patrick Bajari, *Comparing Competition and Collusion: A Numerical Approach*, 18 ECON. THEORY 187 (2001).
32. Jonathan B. Baker, *Unilateral Competitive Effects Theories in Merger Analysis*, 11 ANTITRUST 21 (1997).

merger, competition is reduced, and the merged bidders' profits increase; however, there is no reduction in efficiency since the item is still won by the bidder with the highest value. The effect of the lower winning price is purely a transfer of profit from the auctioneer to the merged bidders. In order to discuss welfare losses of mergers, one must envision the auctioneer as a consumer.³³

Since bidders bid their true values in a second-price auction, it is relatively easy to quantify the effects of a merger. A merger pushes down the price to the third-highest bid when the merging bidders would have finished first and second. In all other auctions, the merger has no effect. Hence, to estimate the effects of the merger, the auctions in which the merging bidders submitted the two highest bids are first identified and the difference between the second and third highest bids in these auctions is then measured. By summing these merger effects across all such auctions and dividing by the total number of auctions in the data, the "expected" or average merger effect is calculated. This method of estimating the merger effect is termed "nonparametric" because no model parameters are estimated from the data.

When the joint cost or value distribution is identified,³⁴ it is possible to compute directly the expected merger effect. Unfortunately, identification requires abundant, high-quality data. In some cases, econometricians will be able to collect data on individual auctions, including the identity of bidders and the amount of the winning bid. More typically, however, econometricians will have aggregate data, such as annual quantities and revenue but other crucial information such as data on losing bids is often missing. Since the effect of a merger depends on the frequency of one-two finishes and the actual value of the three highest bids, more complete data are essential for estimating merger effects.

Without data on losing bidders, it is impossible to infer the likely effects of a merger without making additional assumptions. One common restriction employed by econometricians is a specification that bidder value distributions are characterized by independence of irrelevant

33. However, the auctioneer may be able to protect herself from the effects of mergers by raising the reserve price, the lowest bid that the auctioneer will accept. Some increases in reserve prices post-merger may actually render the merger unprofitable. See Keith Waehrer & Martin K. Perry, *The Effects of Mergers in Open Auction Markets*, RAND J. ECON. (forthcoming).

34. See generally Athey & Haile, *supra* note 16.

alternatives.³⁵ This means that if one bidder drops out of the bidding, rival winning probabilities (shares) increase in proportion to existing shares. This assumption implies that second-place finishes, crucial to predicting merger effects, are in proportion to first-place finishes. For example, if three bidders, A, B, and C, have winning probabilities of 0.5, 0.25, and 0.25, respectively, when bidder A wins, bidder B will finish second half of the time (with equal probability to bidder C). When bidder B wins, bidder A finishes second 2/3 of the time.

If second-place finishes are in proportion to first-place finishes, then merger effects are related to the shares, or frequency of auctions won, of the merging bidders.³⁶ Such an approach cannot take into account bidders who are especially “close to” or “distant from” their competitors. To accommodate correlations among bidders, a “characteristics” approach is used. Each bidder’s value is specified as a function of the characteristics of the bidder and the object or service being auctioned.³⁷ For example, if hauling costs are important, as in road paving or timber auctions,³⁸ the location of each bidder is an important characteristic of the value distribution that determines how much competition is lost by the merger. In auctions distant from the merging bidders, where a non-merging bidder is located closer to the job than the merging bidders, the merger effect will be relatively small because the probability of a one-two finish by merging bidders is small.³⁹

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35. This is analogous to the independence of irrelevant alternatives (IIA) restriction used in demand estimation which implies that if one firm raises price, it loses quantity to rivals in proportion to their shares. *See generally* Werden, Froeb & Tschantz, *supra* note 30.
 36. Luke Froeb, Steven Tschantz & Philip Crooke, Second-Price Auctions with Mixtures of Power-Related Distributions (2001) (mimeograph, on file with Vanderbilt University).
 37. Another way to relax this assumption is to admit correlation among bidder values directly, but such models are still in their infancy. *See* Luke Froeb & Steven Tschantz, *Mergers Among Bidders with Correlated Values*, in MEASURING MARKET POWER, (Daniel J. Slottje ed., forthcoming).
 38. Bajari, *First Price Sealed Bid Auction*, *supra* note 8; Brannman & Froeb, *supra* note 30.
 39. To illustrate how the IIA assumption can distort merger effects when bidders are correlated, imagine that *A* is a Detroit construction firm and *B* and *C* are identical construction firms located in Phoenix. If half of all

In addition, the variance of the value distribution is also very important in determining the degree to which competition is “localized.” Generally, one can measure how different a firm’s value can be from auction to auction. Large variance, even when controlling for cost-side variables such as distance from a job site, implies relatively “global” competition in that any potential bidder is likely to draw a high value for the object being auctioned and therefore be a significant competitor. Conversely, low variance means that only bidders who share similar characteristics, like proximity to the job site, are notable competitors. Depending on the location of merging bidders, a higher variance may either decrease or increase the expected merger effect.

In first-price auctions, more and better data are typically available, including the amount of each losing bid. However, the relationship between observed bids and underlying values is more complex because bidders no longer have an incentive to bid their true values. Instead, they balance the benefits of a higher bid (a higher probability of winning) against its costs (lower profit if they win). Observed bids are lower than values, and the amount of shading of bids below values depends upon each bidder’s beliefs of the likely bids of other participants. While each auction participant predicts the behavior of other bidders, the participant’s competitors are undertaking a similar calculation involving predictions of their behavior. The solution to these simultaneous equations is the equilibrium bid. For any assumed value distribution, it is possible to solve for the relationship between bids and values,⁴⁰ but the

lumber auctions are held in Michigan and half in Arizona, we would expect *A* to win all of the Michigan auctions, due to high interstate shipping costs, and *B* and *C* to submit higher bids than *A* in the Arizona auctions, each winning roughly half of these auctions. The winning probabilities will match those discussed above, but frequency of second-place finishers would differ qualitatively. A merger between *A* and *B* would have little effect since the only possible price change (from *B* to *C*) would be quite small. Hence, IIA would seriously overestimate the merger effects. Conversely, if *B* and *C* merge, this would effectively eliminate competition in the Arizona auctions, causing substantial price changes.

40. See Bajari, *First Price Sealed Bid Auction*, *supra* note 8; Robert C. Marshall, Michael J. Meurer, Jean-Francois Richard & Walter Stromquist, *Numerical Analysis of Asymmetric First Price Auctions*, 7 GAMES ECON. BEHAV. 193 (1994); John Riley & Huagang Li, *Auction Choice: A Numerical Analysis* (1997) (mimeograph, on file with the University of California, Los Angeles); Serdar Dalkir, John W. Logan &

models are computationally difficult. In addition, mergers in first-price auctions affect prices in subtle and complex ways. This often leads to the selection of distributions chosen more for their computational tractability than their realism.⁴¹

Given the difficulty of working with first-price auctions, it is often useful to assume that the auction mechanism is second-price and draw inferences from this analysis. For example, for a tractable class of “power-related” distributions, mergers that move an industry towards symmetry have bigger price effects in English or second-price auctions than in first-price sealed-bid auctions.⁴² Thus, if two smaller firms plan to merge, making the industry more symmetric, the effects of the merger in a second-price auction (a simple exercise) can be computed and this estimate can be used to “bound” the effects of the merger in the first-price auction. Since the merger effects are known to be overestimated, small price increases allow one to conclude that the merger will not substantially lessen competition.

E. Conclusion

Several conclusions come out of this analysis. First, in common value auctions, mergers and conspiracies can have pro-competitive effects due to the information sharing among merging parties or conspirators. If values have a significant common component, an anticompetitive effect cannot be assumed.

Robert T. Masson, *Mergers in Symmetric and Asymmetric Noncooperative Auction Markets: The Effects on Price and Efficiency*, 18 INT. J. IND. ORGAN. 383 (2000); Tschantz, et al., *supra* note 30. For a novel alternate approach, see Emmanuel Guerre, Isabelle Perrigne & Quang Vuong, *Optimal Nonparametric Estimation of First-Price Auctions*, 68 ECONOMETRICA 525 (2000).

41. Estimation of parametric structural models presents additional challenges especially for first-price auctions. Latent bounds on the distribution of bids depend on the very underlying model parameters which one is interested in estimating. For workarounds, see Stephen G. Donald & Harry J. Paarsch, *Piecewise Pseudo-Maximum Likelihood Estimation in Empirical Models of Auctions*, 34 INT. ECON. REV. 121 (1993).

42. See Tschantz, et al., *supra* note 30.

In private value auctions, mergers and conspiracies have the usual anticompetitive effects, and both reduced-form and structural econometric techniques may be used to offer evidence of the conspiracy and to estimate its effects. Detection of conspiracies, however, is much more difficult as conspiracies may take many forms, and any adopted detection methodology may induce cartels to cooperate through a different collusive mechanism.

When available data cannot identify the underlying cost or value distributions, structural estimation requires abandoning techniques with heavy data requirements in favor of simpler, less robust approaches, thus trading off realism for computational ease. Despite the recent development of numerous sophisticated econometric models, the time constraints inherent in litigation and the limited data available in the midst of legal investigations render many of them impractical. Realistically, simple reduced-form models or well-developed structural techniques with sufficient assumptions to allow for the handling of limited data may be the most useful.

Such sacrifices imply potentially stringent assumptions with varying levels of realism. Fortunately, case law holds that in the computation of damages, an expert “is allowed some economic imagination so long as it does not become fantasy.”⁴³ In short, reasonable speculation is permissible.

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43. MCI Communications Corp. v. AT&T, 708 F.2d 1081 (7th Cir. 1983). *Also see* Story Parchment Co. v. Paterson Parchment Paper Co., 282 U.S. 555, 561-66 (1931). Estimates must be based on “reasonable inference, although the result be only approximate” at 563.