Lectures on Auction Empirics, Collusion and Bidding Rings:

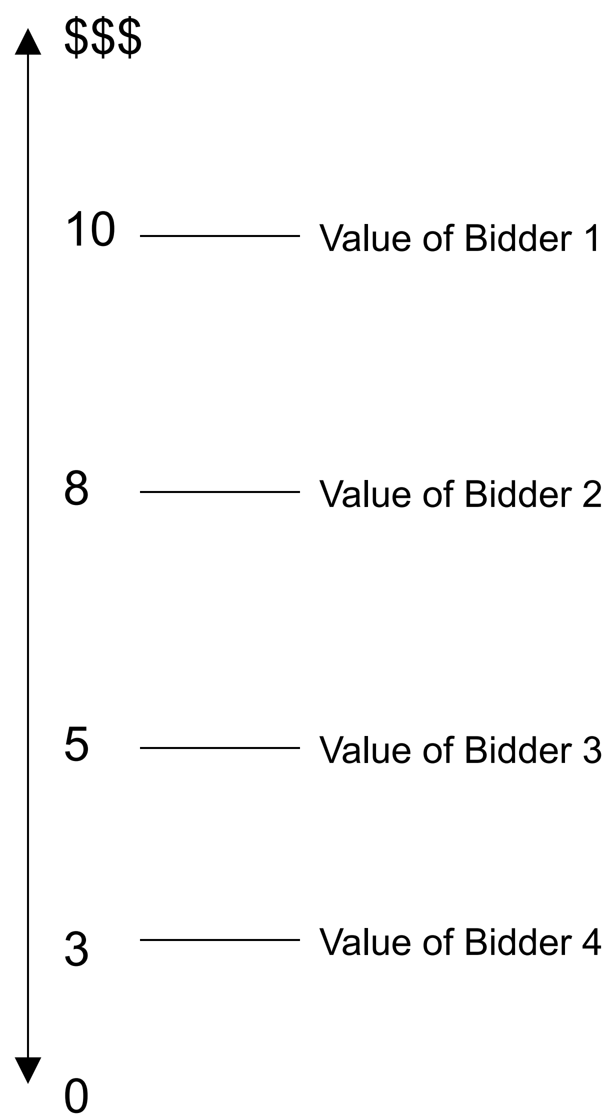
A Study of the Internal Organization of a Bidding Cartel

Asker, *American Economic Review* 2010

The reasons for looking at this are:

a) Application of everything so far
b) Illustrates the ways to deal with auction heterogeneity
c) Transition to talking about collusion and bidding rings

Introduction: Collusion in an English Auction



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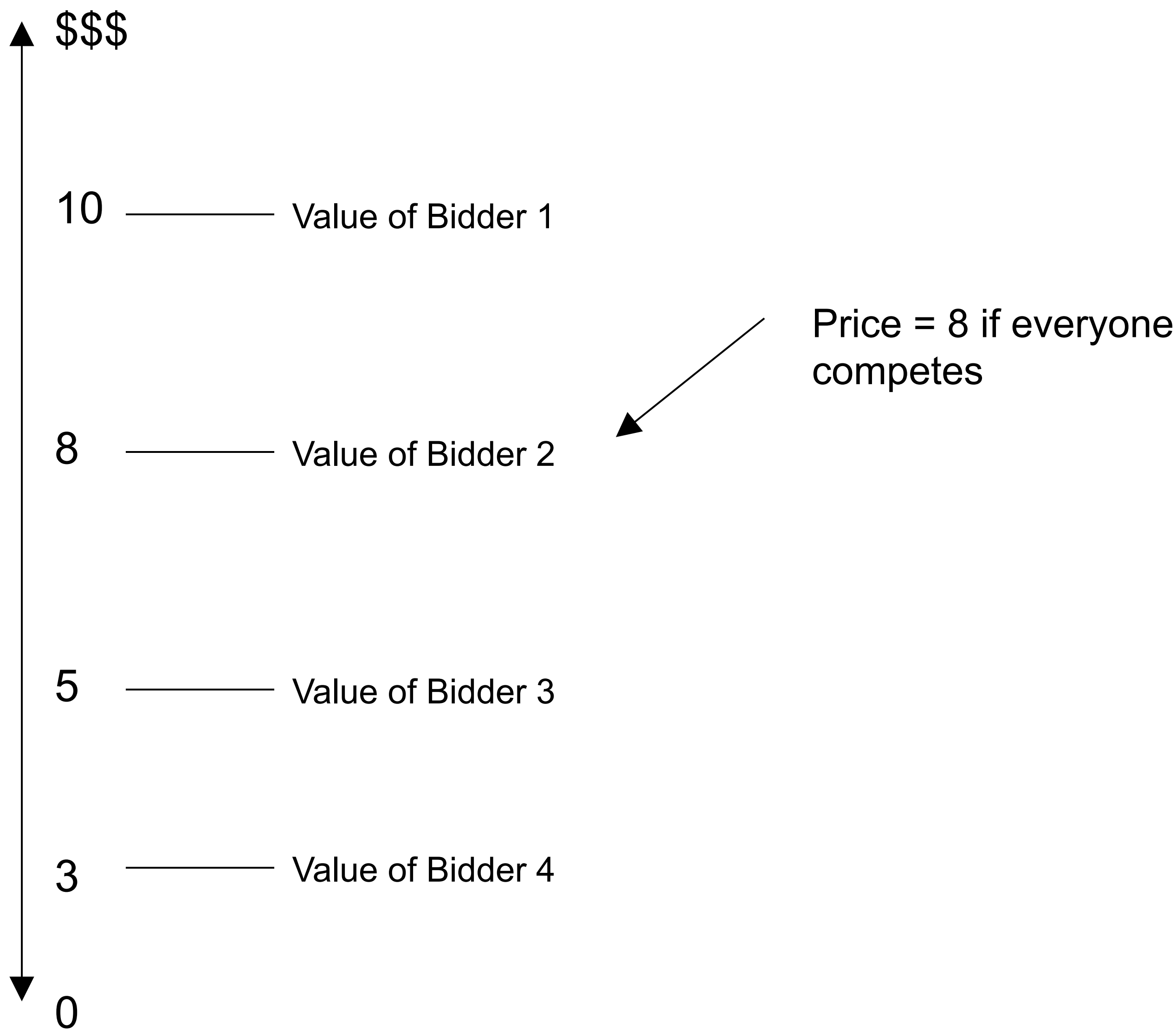

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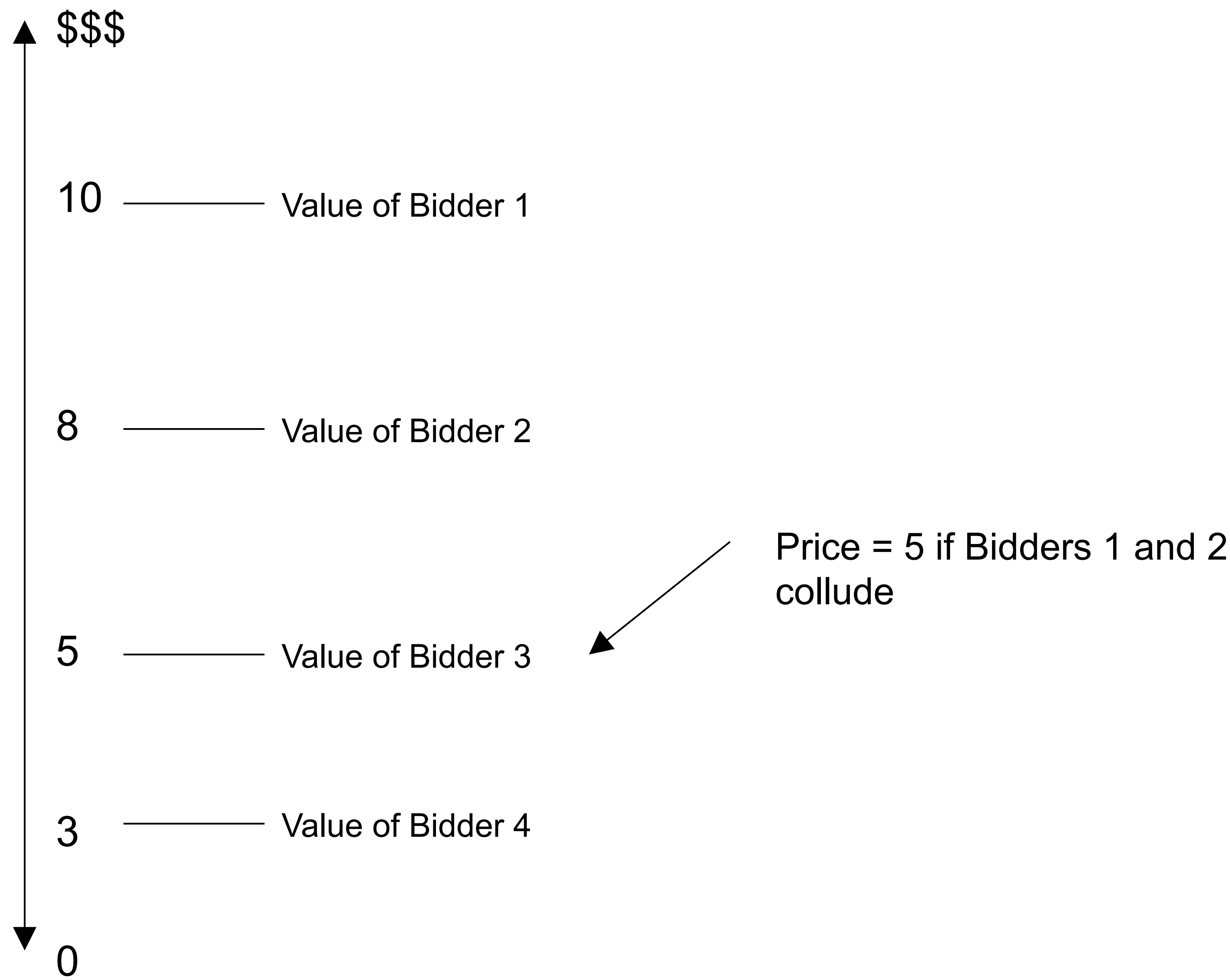

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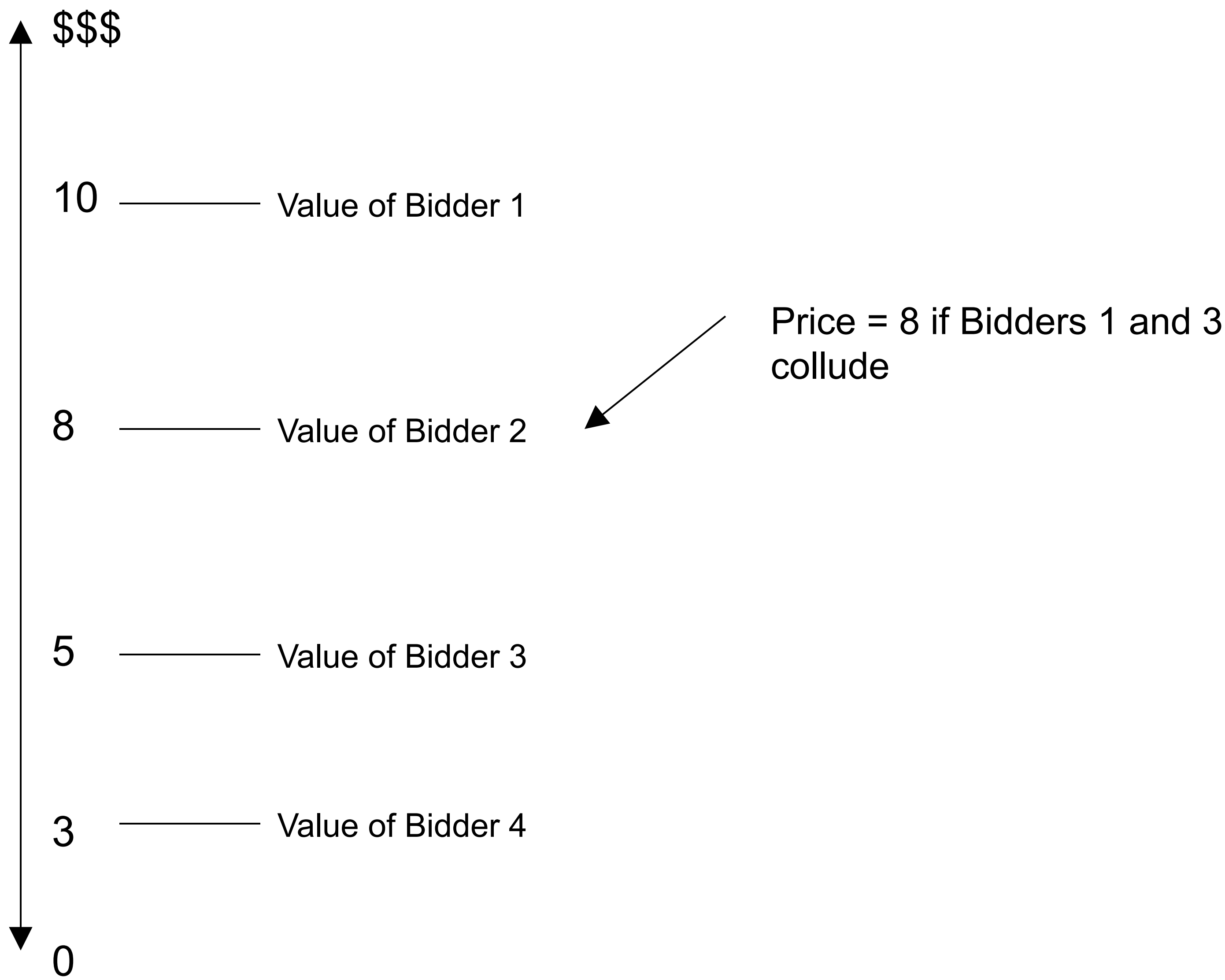

Introduction

- Research Question:
  - “How do bidding rings work in practice ?”
  - “How might rings affect market outcomes ?”

•To do this I analyze the activity of ring of 11 stamp dealers who colluded in North American stamp auctions for around 20 years

- Why is this interesting?
  - Regulatory reasons: Price Fixing and Bid Rigging are Illegal
  - There is very little evidence on how cartels organize themselves
  - We know very little about the magnitude of the impact of cartel design on revenues and efficiency

Conclusions:

- Bidding rings can introduce inefficiency into the auction, even in English (ascending price) auctions, but the effect is small.

- Weak bidders are a significant practical problem for bidding rings (a.k.a. asymmetry)

- Equilibrium analysis makes a big difference to conclusions about damages

- Rings can damage other bidders, in addition to the seller

    - Because of this, participation may be an unmeasured channel through which rings may hurt sellers and diminish market efficiency: if so then this is likely to be the most important way a ring generates damages and distorts the market

    - Other bidders seem to have the same economic basis for being able to claim damages as sellers

Ring Organization

Ring Exists:

- 11 Stamp Dealers
- Subset of all Bidders
- Each ring member decides whether interested in the object for sale

Knockout Auction:

- First Price Sealed Bid
- Decides : who gets the stamps if the ring wins
- At what price they stop
- The side payments

Target Auction:

- English – Open Outcry Ascending Bid
- Winner Pays Own Bid
- Cartel bids up to the winning knockout bid.

Ring Organization: The Knockout (Data)

Consider the following data:

Data ID	Bidder	House	Date	Lot #	Sidepayments	Rank	Knockout Bid	Target Price
989	K	hrh	5-Dec-1996	954	-250	1	3400	1350
990	C	hrh	5-Dec-1996	954	237.5	2	1850	1350
991	J	hrh	5-Dec-1996	954	12.5	3	1400	1350
992	I	hrh	5-Dec-1996	954	0	4	1200	1350
993	D	hrh	5-Dec-1996	954	0	5	725	1350

The catalog description is:

ITALY AND AREA

954 ★○🄱 **19th and 20th Century, coll. of many hundred diff., plus hundreds of dupl., in 2 Minkus albums and loose pages in carton, l.h. to unused and used, mostly Italy with a wide range of issues incl. many compl. sets, some modern n.h., blks and corner blks, Airs, back-of-book, Aegean Is., San Marino, etc., mixed condition to very fine. Est. Cash Value $750-1,000** ....

Bidding data collected and generously provided by Antitrust Division of NY State AG's Department.

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992	I	hrh	5-Dec-1996	954	0	4	1200	1350
993	D	hrh	5-Dec-1996	954	0	5	725	1350

Computing side payments:

D & I get nothing: 1350 > 1200 >725

J does get a sidepayment:

Take the difference between bid and target price:

1400 – 1350 = 50

½ of this goes to the winner (K)

½ gets split between C & J

Hence, J's sidepayment is $12.5

Structural Analysis: Model

Approach:
- IPV style model
- 2 types of bidder: strong and weak
- Focus on 2 bidder knockouts (tractable + identified + lots of data)

Bid = argmax: (Value of object - Expected payment in target if win) x (Prob of winning)

- (Expected payment to loser if win) x (Prob of winning and having to make a payment)

+ (Expected payment from winner if lose) x (Prob of losing knockout) x (Prob of beating the price in target)

Structural Analysis: Model

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First Order Condition is:

$$v_{ik} = b_{ik} - \frac{1}{2}\left[\frac{F_r(b_{ik})(1 - G_{-i}(b_{ik}))}{f_r(b_{ik})G_{-i}(b_{ik}) + F_r(b_{ik})g_{-i}(b_{ik})}\right]$$

This provides a mapping from bids to values, such that v(b) is a function: for each b there is a unique v

History of Similar Ring Designs

- This ring design belongs to a broad class of ring designs with the feature that side-payments are increasing in the amount bid in the knockout

- **Long History:**
  - Mainly observe in markets for collectables
    - Documented in Art, Coins, Antiques, Rare Books, Stamps
    - 2 Variants:
      - “nested knockout”
      - “sequential knockouts”
    - First documented instance in 1830
    - Notable mention Ruxley Lodge Estate Sale in 1919
      - 81 ring members !

Applicable Theory: Why use a ring like this?

• If everyone in the ring is ex ante homogenous then easy to design a knockout that is efficient and truthful:

- just run a first price auction for the right to bid in the target.
- distribute all revenues equally

• This is not efficient or type revealing if bidders are ex ante heterogeneous.

• In the face of this:

- Either exclude the weak types; or
- Be inclusive and try to pay people what they contribute and accept a little inefficiency

• Mailath and Zemsky (1991) and Graham, Marshall and Richard (1990)

Data

• Complete record of ring's activity from July 1996 – June 1997

• Also depositions from the taxi driver and one of the ring members

• 1967 target auctions.

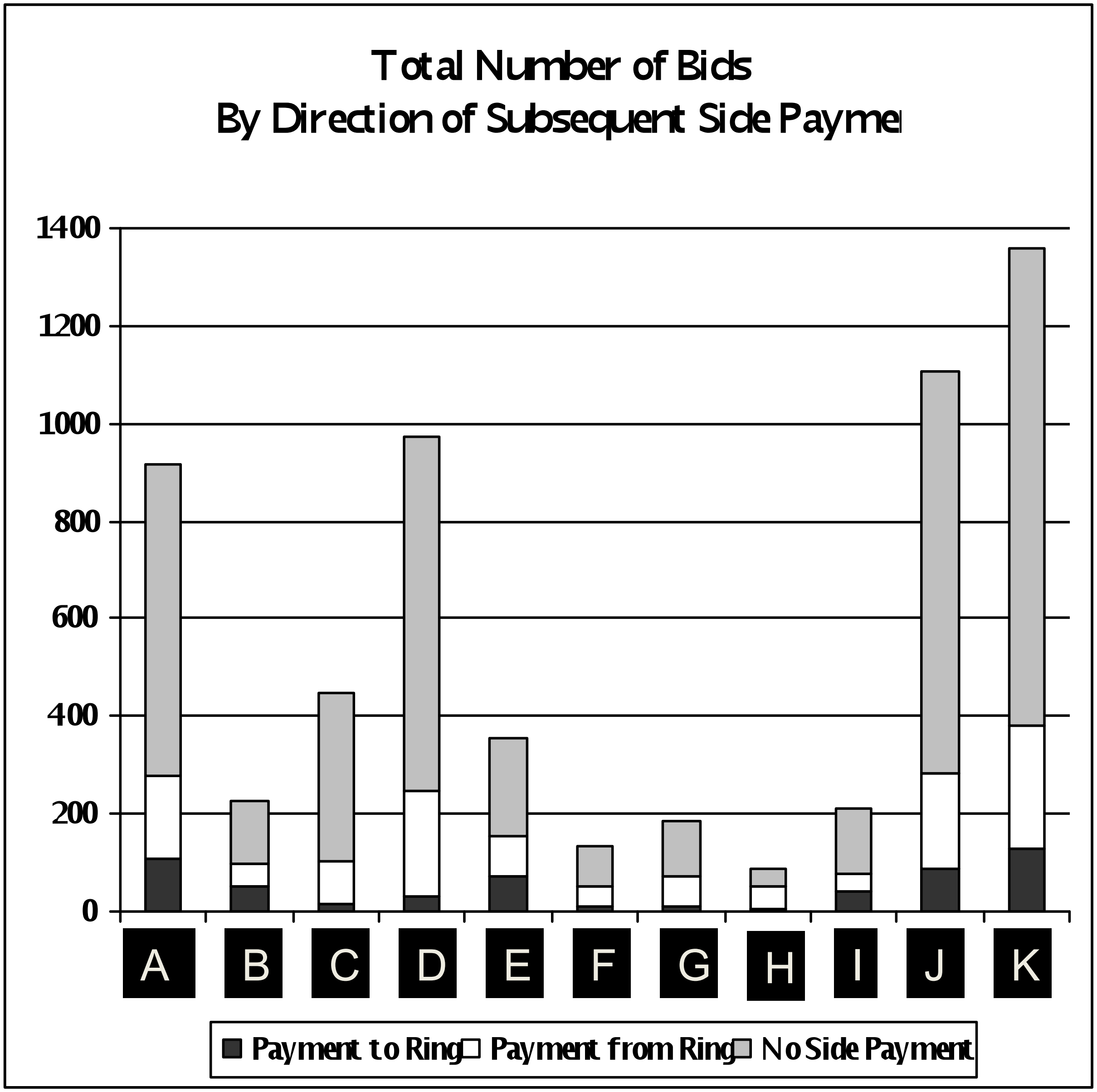
  •Data Summary:

Table 2: Bidding by number of bidders in the knockout

# of Bidders	Target Auction (W inning Bid) Mean	Target Auction (W inning Bid) Standard Dev.	Knockout Auction (Median Bid) Mean	Knockout Auction (Median Bid) Standard Dev.	% Of lots won by ring	Total Number of lots
1	733	1262	616	1134	19%	623
2	1314	2016	1066	2048	36%	367
3	2014	3246	1750	3029	48%	260
4	2217	3492	2293	4082	69%	196
5	2249	3419	2092	3322	68%	144
6	2098	2628	2163	3014	74%	91
7	2979	3425	3655	4116	86%	74
8	4790	4904	6233	7726	96%	26

Notes: Does not include the Harmer-Schau auctions. All subsequent analysis also excludes these auctions.

Bidder Heterogeneity & Participation



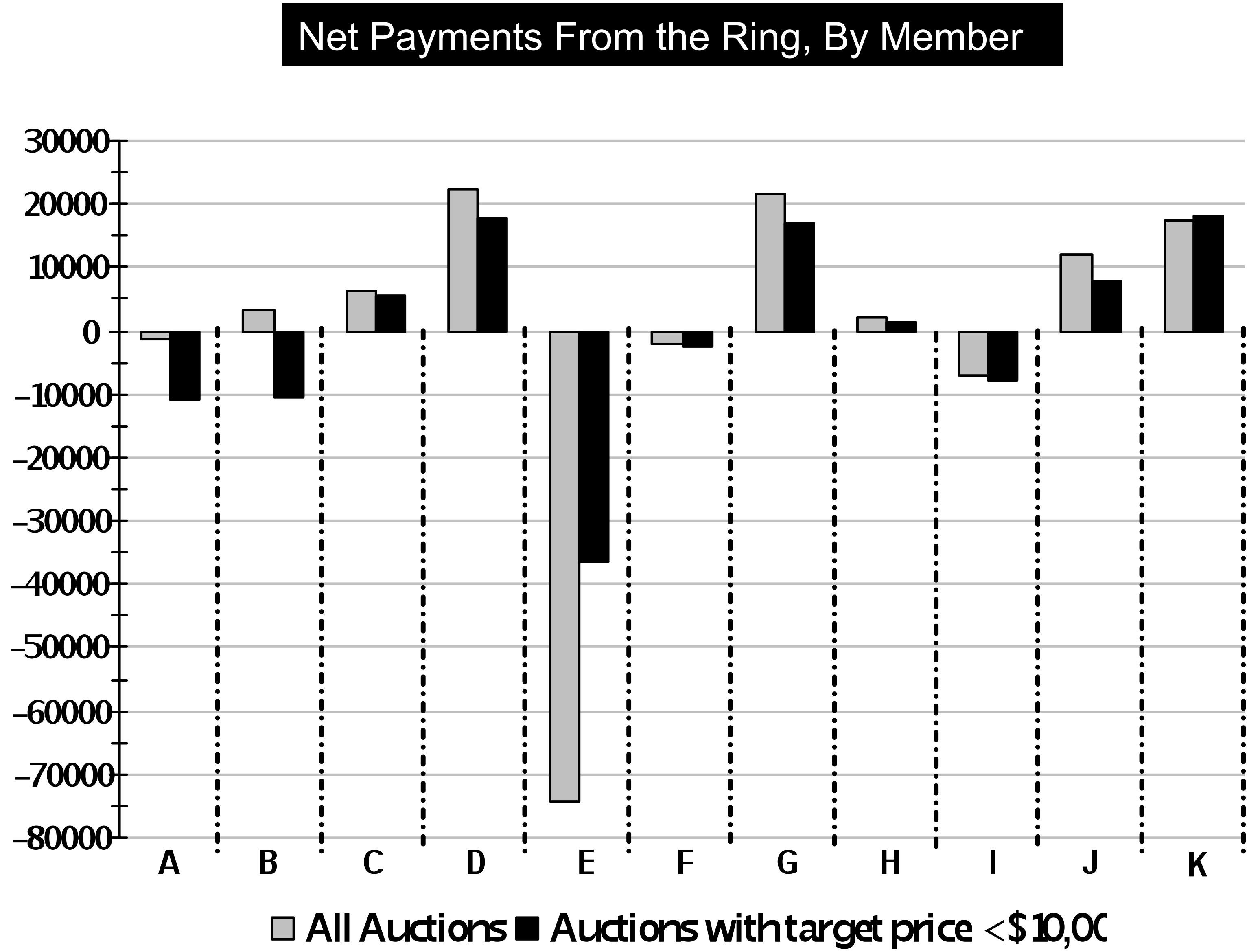
‘Weaker’ Bidders

Table 5: Knockout outcomes, by ring member

Ring Member	Auctions with at least 2 ring members interested (n≥2)			
	% High KO Bid	receive sidepayn	% pays sidepayments	# of Knockouts
A	33%	22%	12%	607
B	52%	21%	16%	175
C	20%	23%	5%	368
D	10%	20%	3%	686
E	38%	24%	21%	348
F	28%	28%	4%	116
G	10%	34%	5%	184
H	4%	34%	0%	50
I	44%	17%	20%	209
J	30%	22%	9%	686
K	28%	21%	9%	861

Introduction
Ring Organization
Applicable Theory
Data
Reduced Form Analysis
Structural Analysis
Results
Conclusion

‘Weaker’ Bidders



Reduced Form: Summary

- Ring participants are heterogeneous
- ‘Weaker’ bidders are a problem

Structural Analysis

Objectives:

A. Measure damages:
   - To the seller
   - To the other bidders who are not members of the ring

B. Measure the market inefficiency introduced by this knockout design

C. Measure the returns to the cartel from colluding

- It all amounts to estimating a version of a markup

Structural Analysis: Estimation (Basic Idea)

Observables: b_{ik} , other Bids in auction k, Bids in other auctions

Nonparametric estimation (kernels) give densities

Empirical CDF gives distributions

2 Bidders in Knockout

IPV Setting

$$v_{ik} = b_{ik} - \frac{1}{2}\left[\frac{F_r(b_{ik})(1 - G_{-i}(b_{ik}))}{f_r(b_{ik})G_{-i}(b_{ik}) + F_r(b_{ik})g_{-i}(b_{ik})}\right]$$

Compute valuation, bootstrap standard errors

Structural Analysis: Estimation (Issues)

1. Getting the distribution of the winning target price (highest non-ring valuation)

   There is a selection problem in the data which I explicitly model.

2. Observed auction level heterogeneity

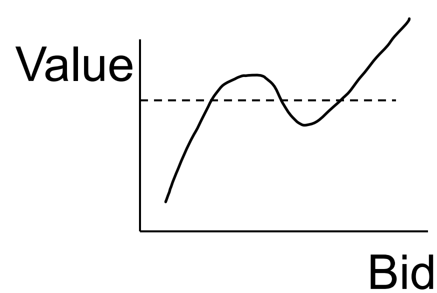
   First stage OLS regression approach

3. Unobserved auction level heterogeneity

   Adopt the deconvolution technique first adapted to first price auctions to deal with unobserved heterogeneity by Krasnokutskaya (2004).

4. Non-monotonicity of bid function

   Need to make sure smoothing parameters do not let this happen



Steps in Estimation

Step 1: Regress Bids on observed auction characteristics

Step 2: Work with residual from step 1

Step 2a: Do the deconvolution

Step 3: Work with a sample drawn from the idiosyncratic bid distribution

Step 3a: Selection correction on distribution of highest non-ring bid

Step 3b: Adapted GPV procedure

Step 4: Add the common element from the deconvolution back in

Step 5: Add the observed auction characteristics back in

Step 6: Counterfactual simulations

Structural Analysis: Issues 1: Selection

- See page 21 of the paper for the (tedious) algebra

Structural Analysis: Issues 2

- Observed auction level covariates
- Empirical model is that

$$v_{ik} = e^{x_k \beta}(u_{ik}\varepsilon_{ik})$$

- Apply Haile et al (2006), which amounts to a first stage regression of

$$\ln(b_{ik}) = x_k\beta + \ln(f[u_{ik}, \varepsilon_{ik}])$$

- And then use the coefficient estimate to pop out the private information component
- Functional form is attractive because implies greater variance in the bids for 'higher value' auctions – reflected in the data

Structural Analysis: Issues 2

- Apply Haile et al (2006), which amounts to a first stage regression of

$$\ln(b_{ik}) = x_k\beta + \ln(f[u_{ik}, \varepsilon_{ik}])$$

- Crucial Assumption:

  Lemma 2: if when $v = u$, b is an equilibrium bid,

  then if $v = \Gamma u$, Γb is an equilibrium bid.

- Applies to

$$v_{ik} = b_{ik} - \frac{1}{2}\left[\frac{F_r(b_{ik})(1 - G_{-i}(b_{ik}))}{f_r(b_{ik})G_{-i}(b_{ik}) + F_r(b_{ik})g_{-i}(b_{ik})}\right]$$

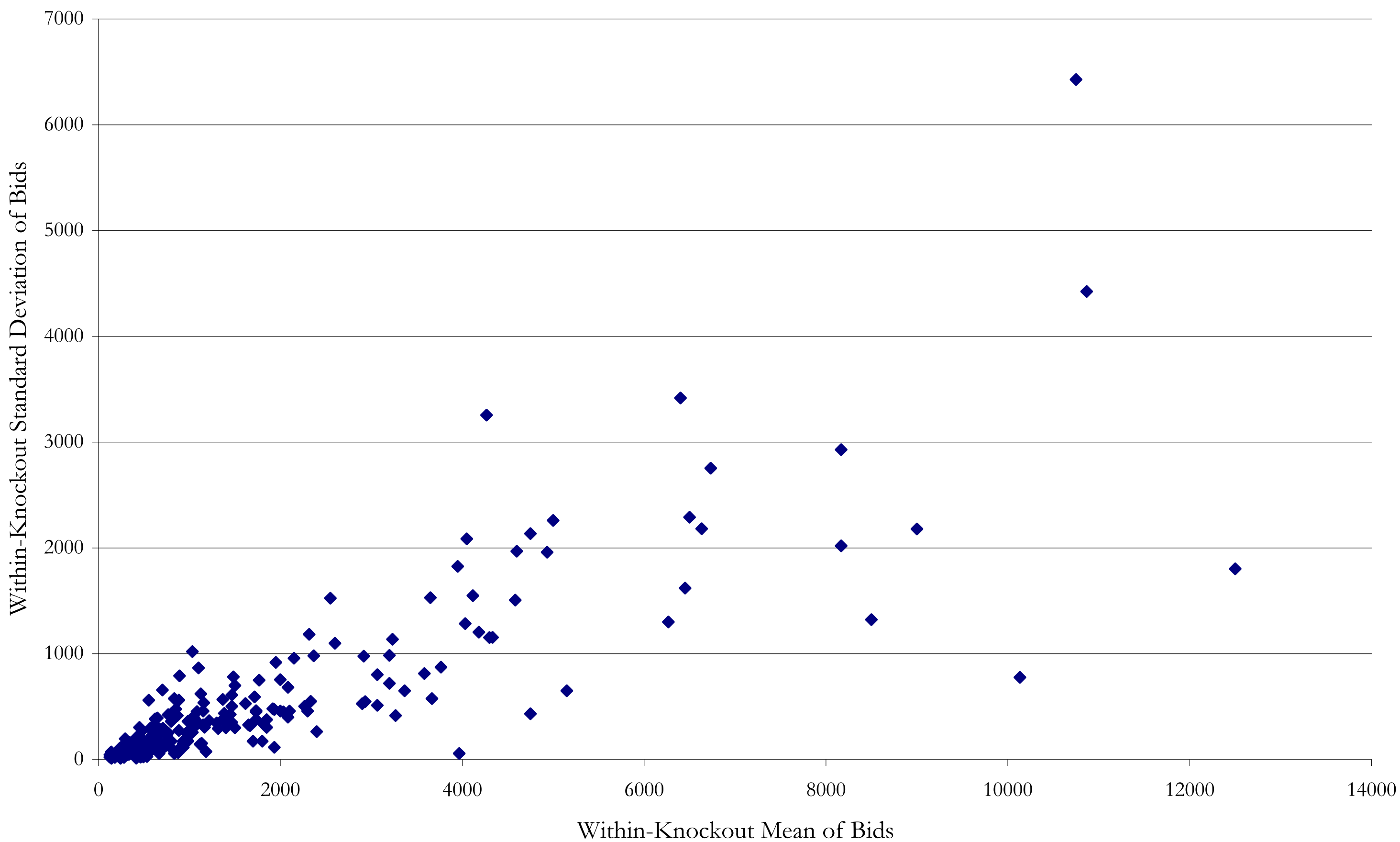
- But not to

$$v_{ik} = b_{ik} - \frac{G_{-i}g_{-i}}{2f_r G_{-i}^2 + 4F_r G_{-i} g_{-i}} \int_{-\infty}^{b_{ik}} F_r(x)dx - \ldots$$

Structural Analysis: Issues 2

- Why Lemma 2 is important:

Figure A1: Within Auction Mean vs Standard Deviation of Bids: 3 Bidder Knockouts



Structural Analysis: Issues 3

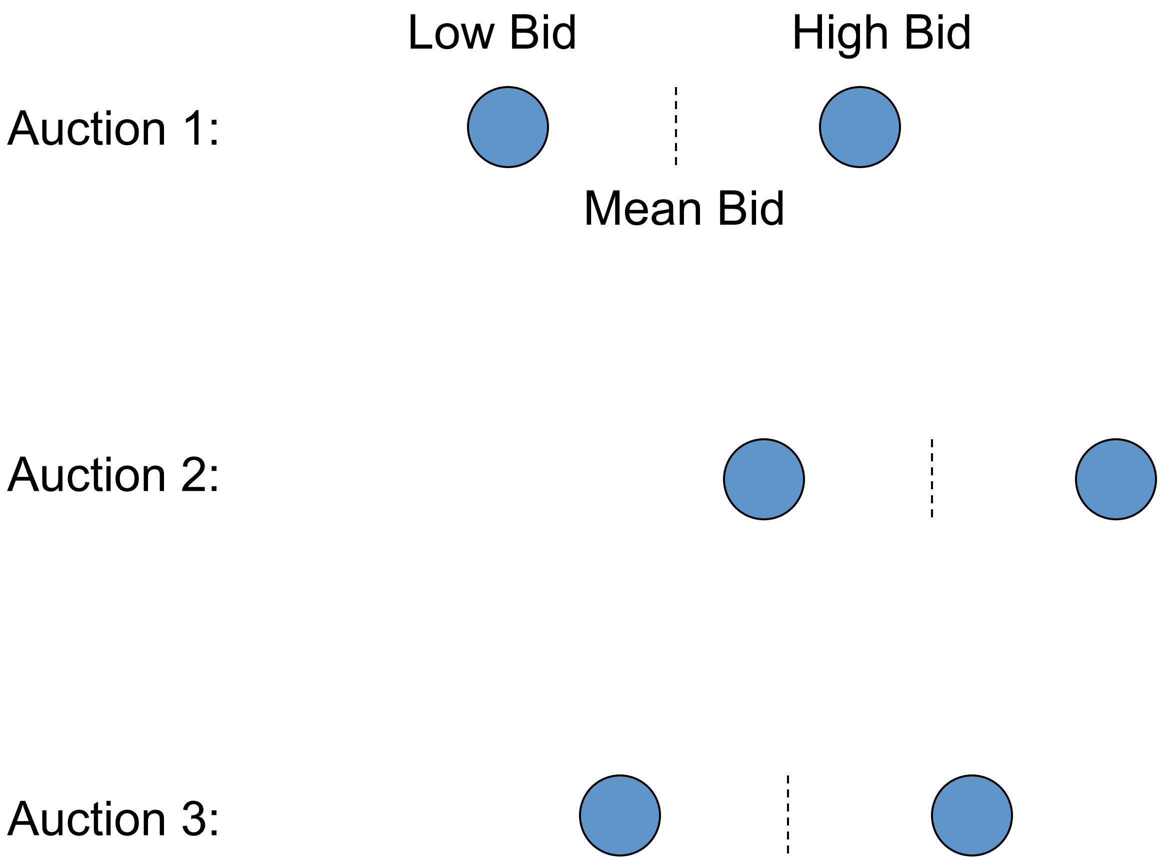
- Unobserved auction level heterogeneity
  - E.g. imperfections or rare elements only apparent from a close inspection of the stamps for sale
  - Dealers spent considerable time inspecting the stamps
- Empirical model is that

$$v_{ik} = e^{x_k \beta}(u_{ik}\varepsilon_k)$$

- Krasnokutskaya (2006) has an approach to this issue that exploits the statistical properties of characteristic functions for FPSB auctions
- This builds in a paper by Li & Vuong (1998) focusing on measurement error models
- Allows you to separate the distributions of u_{ik} and ε_k

Structural Analysis: Issues 3

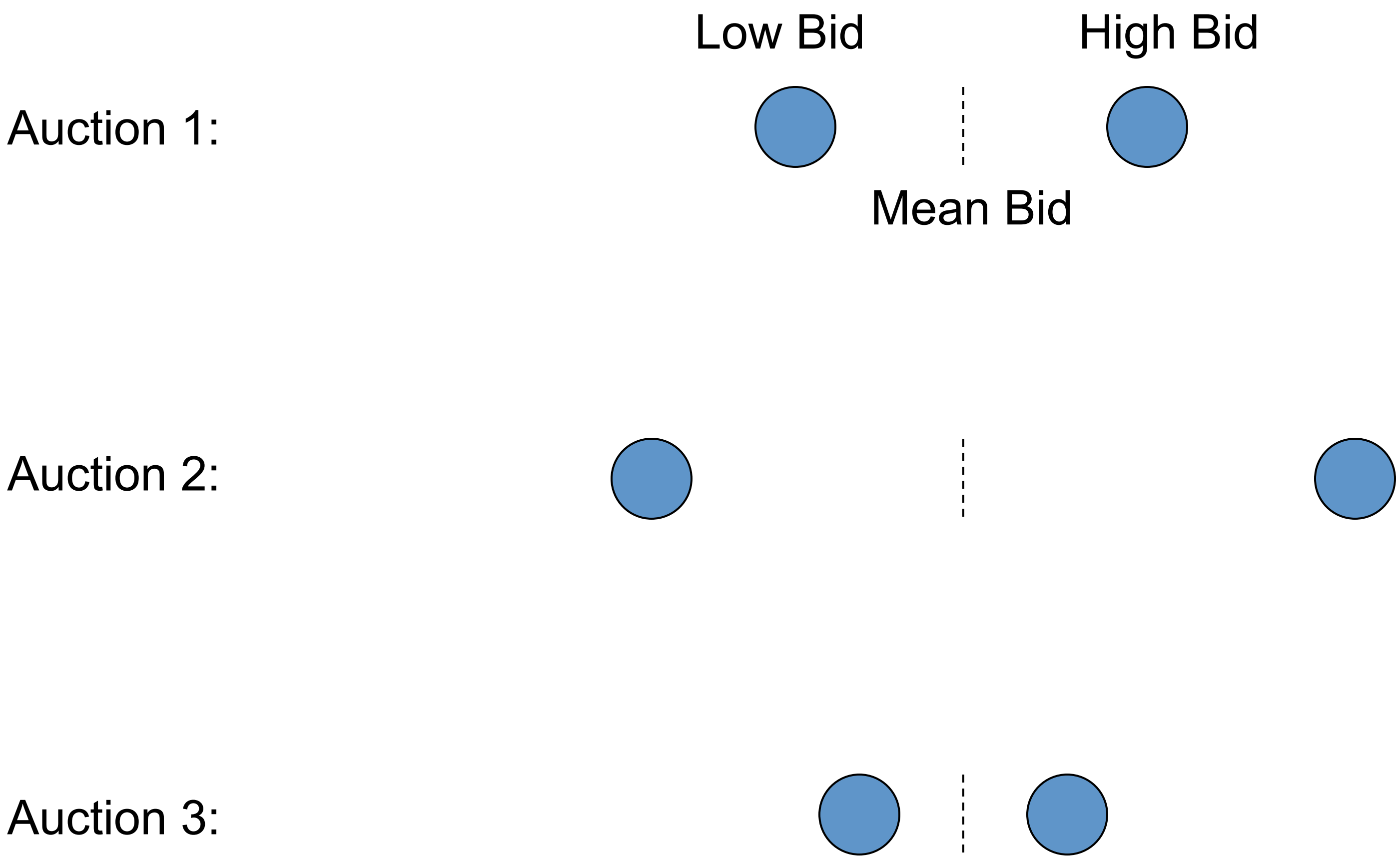
- Idea:



If there was no variation in the within auction variation then could use the across auction variation in biding to estimate the auction level effect

Structural Analysis: Issues 3

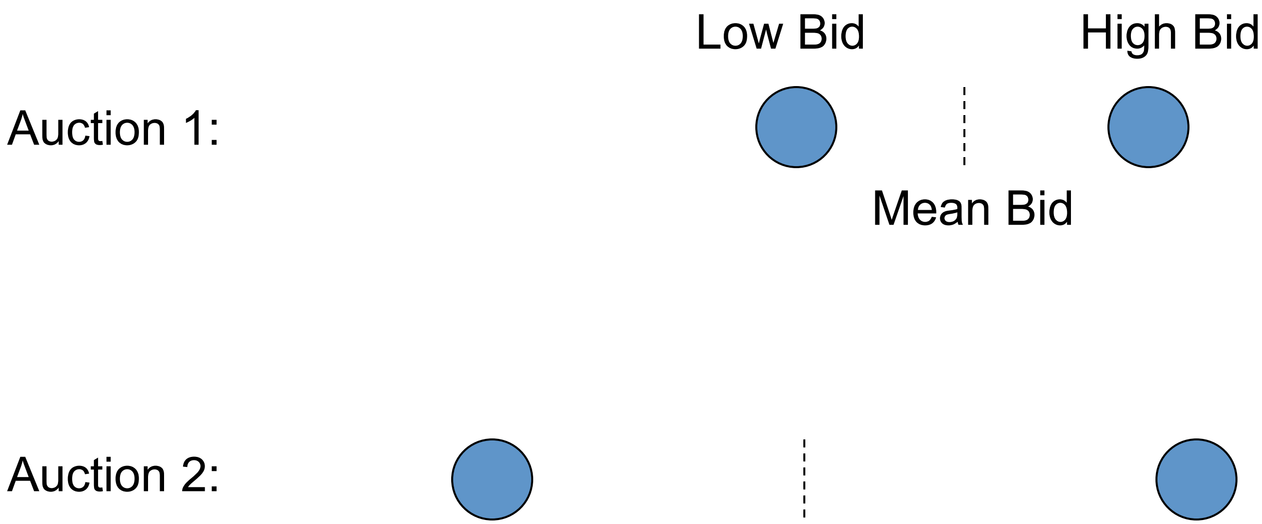
- Idea:



If there was no variation in the cross-auction variation then could use the within auction variation to estimate the variation in bids relevant to private information

Structural Analysis: Issues 3

- Life gets interesting when have both things going on



- Use an estimator based on the inverse Fourier transformation to de-convolute the common and private components of the variation in bids

Structural Analysis: Issues 3

- Life gets interesting when have both things going on
- For each auction:
  - $b_1 = \ln[f(v_1)] + \varepsilon$, $b_2 = \ln[f(v_2)] + \varepsilon$

The empirical characteristic function is estimated nonparametrically using

$$\widehat{\psi}(z_1, z_2) = \frac{1}{n} \sum_{k=1}^{K} \exp\left(iz_1 b_{1k} + iz_2 b_{2k}\right)$$

The characteristic functions of the marginal distributions are estimated using

$$\widehat{\phi}_{\ln(\varepsilon)}(t) = \int_0^t \frac{\partial \widehat{\psi}(0, z_2)/\partial z_1}{\widehat{\psi}(0, z_2)} dz_2$$

$$\widehat{\phi}_{\ln f(v_2)}(t) = \frac{\widehat{\psi}(0, z_2)}{\widehat{\phi}_{\varepsilon}(t)} \quad \text{and} \quad \widehat{\phi}_{\ln f(v_1)}(t) = \frac{\widehat{\psi}(z_1, 0)}{\widehat{\phi}_{\varepsilon}(t)}$$

This allows densities to be recovered by taking an inverse Fourier transformation

$$\widehat{g}_Y(x) = \frac{1}{2\pi} \int_{-T_n}^{T_n} d(t) \exp(-itx)\, \widehat{\phi}_Y(t)\, dt \qquad \text{where } Y \in \{\ln(\varepsilon), \ln f(v_1), \ln f(v_2)\} \tag{5}$$

where $d(t)$ is a damping function (see Diggle and Hall (1993)). Assumptions that are required for this procedure are

Structural Analysis: Issues 3

- Necessary assumptions with economic content:
  - $b_1 = \text{Inf}(v_1) + \varepsilon$, $b_2 = \text{Inf}(v_2) + \varepsilon$ is the functional form
  - $\text{Inf}(v_1)$, $\text{Inf}(v_2)$ and ε are mutually independent
  - Lemma 2: if when $v = u$, b is an equilibrium bid,
    then if $v = \Gamma u$, Γb is an equilibrium bid.

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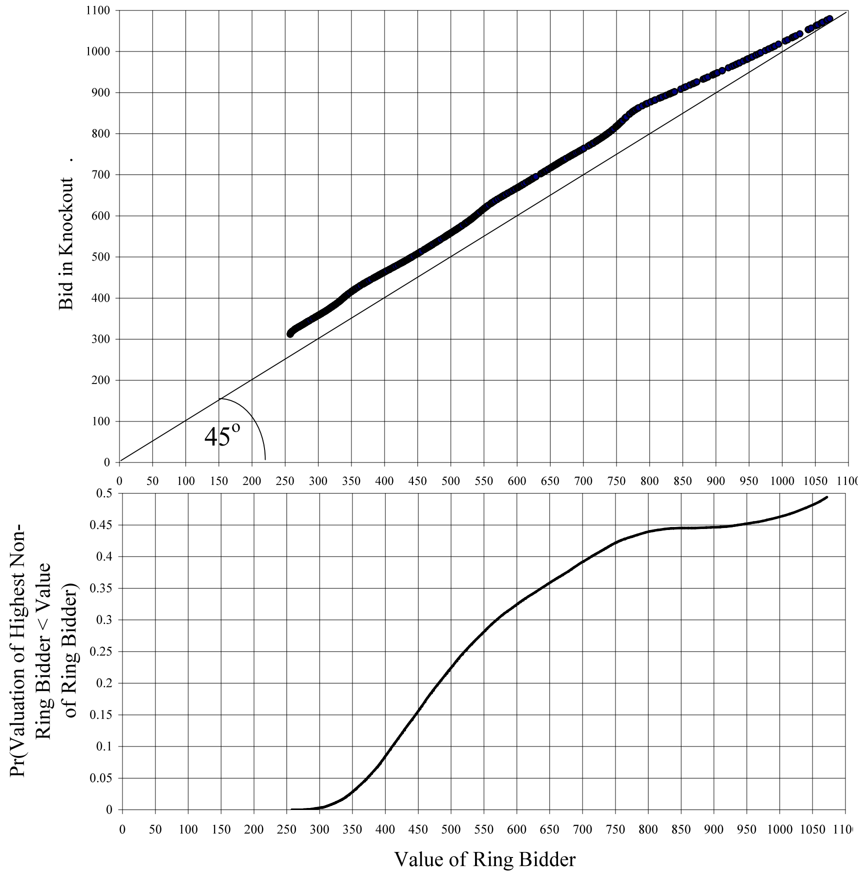
Structural Analysis: Results

- 2 Bidders, IPV, known number of bidders, unknown identities
- Bidding function in Knockout, Strong Bidder



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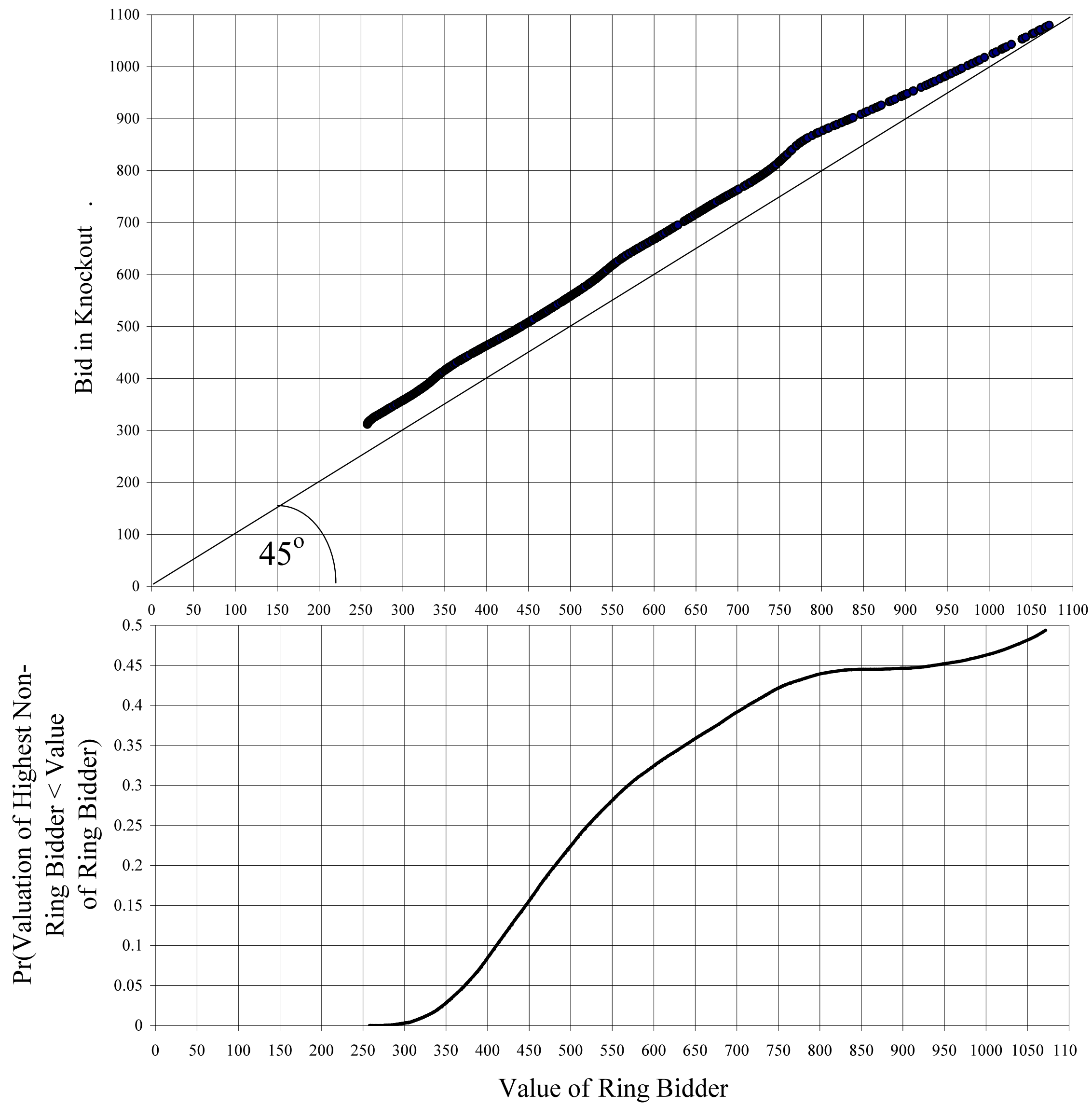

Assessing Damages

• An estimated model allows us to run the counterfactual experiment: What would have happened if the cartel did not exist?

•Note that the estimated model allows standard errors to be computed and thus we can engage in statistical inference (i.e. hypothesis testing etc).

• What we learn:

    • Sellers suffer to the tune of $30 each time the ring wins

    • But when the ring loses they get somewhere between $0 and $20 more

    • Competing bidders get hurt by about $10 when the ring wins and $0 to $20 when the ring loses

    • The ring made about $25 each time they won

    • Economic efficiency was not affected in any meaningful way, unless participation was detered by the ring.

Results: Damages to Seller

- 2 Bidders, IPV, known number of bidders, unknown identities
- Defn: Naïve Damages = max(0, 2nd Highest Knockout Bid – Target Price)

Table 7: Damages to the seller

Model:		With unobserved auction hetrogeneity			No unobserved auction hetrogeneity		
	Assumption	Point estimate	90% Confidence interval: Lower bound	90% Confidence interval: Upper bound	Point estimate	90% Confidence interval: Lower bound	90% Confidence interval: Upper bound
Mean naïve damages ($)		74.21	49.10	152.74	149.53	93.40	197.74
Mean damages ($)	U. B.	36.99	23.47	81.88	105.74	51.99	141.75
	L. B.	26.50	16.09	73.87	99.15	44.38	136.20
Mean damage ratio	U. B.	0.96	0.91	0.98	0.88	0.84	0.93
	L. B.	0.97	0.93	0.98	0.89	0.85	0.95
Proportion of auctions with Pr>Pc	U. B.	0.00	0.00	0.00	0.00	0.00	0.00
	L. B.	0.19	0.04	0.21	0.097	0.040	0.17
Mean damage ratio (Pr>Pc)	L. B.	1.07	1.02	1.13	1.10	1.04	1.25
Proportion of auctions with Pr<Pc	U. B.	0.27	0.17	0.39	0.34	0.23	0.43
	L. B.	0.27	0.17	0.39	0.34	0.23	0.43
Mean damage ratio (Pr<Pc)	U. B.	0.83	0.74	0.88	0.64	0.57	0.74
	L. B.	0.83	0.74	0.88	0.64	0.57	0.74
Proportion of auctions with Pr=Pc	U. B.	0.73	0.61	0.83	0.66	0.57	0.77
	L. B.	0.54	0.46	0.73	0.57	0.46	0.68
Proportion of target auctions won		0.34	0.08	0.49	0.37	0.18	0.45
Simulated auctions		100000	100000.00	100000.00	100000		

Notes: Damage ratio is the ratio of the price received with the ring to the price received with competitive bidding. All means are over target auctions that the ring won (unless further conditioned as noted). L. B. = Lower Bound, U. B. = Upper Bound. Pr refers to the price sellers receive with the ring, Pc is the price with competitive bidding. Confidence intervals are bootstrapped with 5,000 iterations.

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Results: Damages to Seller

UB:

2^{nd} Non-value = 1^{st} Non-ring value

LB:

2^{nd} Non-Ring value = min (2^{nd} Ring Value, 1^{st} Non-ring Value)

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Simulated auctions		100000	100000.00	100000.00	100000		

Notes: Damage ratio is the ratio of the price received with the ring to the price received with competitive bidding. All means are over target auctions that the ring won (unless further conditioned as noted). L. B. = Lower Bound, U. B. = Upper Bound. Pr refers to the price sellers receive with the ring, Pc is the price with competitive bidding. Confidence intervals are bootstrapped with 5,000 iterations.

Results: Damages to other bidders

- 2 Bidders, IPV, known number of bidders, unknown identities

Table 8: Damages to the non-ring bidders

Model:	With unobserved auction hetrogeneity		
	Point estimate	90% Confidence interval: Lower bound	Upper bound
Damages due to misallocation:			
Proportion of target auctions ring won	0.34	0.08	0.49
Proportion of target auctions ring won with damages	0.19	0.04	0.21
Mean damages (conditional on ring winning target auction, $)	10.48	1.18	15.31
Damages due to price inflation:			
Mean damages (conditional on ring not winning target auction, $)	104.20	70.34	142.76
# Simulated auctions	10000		

Notes: All estimates obtained using the lower bound assumption. Confidence intervals are bootstrapped with 5,000 iterations.

LB:

2^{nd} Non-Ring value = min(2^{nd} Ring Value, 1^{st} Non-ring Value)

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Results: Efficiency

- 2 Bidders, IPV, known number of bidders, unknown identities

Table 9: Impact on market efficiency

Model:	With unobserved auction hetrogeneity		
	Point estimate	90% Confidence interval:	
		Lower bound	Upper bound
Mean efficiency loss ($)	7.24	1.58	16.44
Mean proportional efficiency losses:			
Ring active	0.003	0.0002	0.006
No ring bidders	0.08	0.02	0.12
Only ring bidders	0.27	0.21	0.41
Proportion of target auctions won	0.35	0.09	0.46
# Simulated auctions	100000		

Notes: Means are conditional on the ring winning. The mean proportional efficiency losses a
not just those won by the ring. Confidence intervals are boostraped with 5,000 iterations.

Results: Efficiency

- 2 Bidders, IPV, known number of bidders, unknown identities

Table 9: Impact on market efficiency

Model:	With unobserved auction hetrogeneity		
	Point estimate	90% Confidence interval: Lower bound	Upper bound
Mean efficiency loss ($)	10.56	1.22	15.40
Mean proportional efficiency losses:			
Ring active	0.004	0.0002	0.006
No ring bidders	0.08	0.02	0.13
Only ring bidders	0.29	0.20	0.42
Proportion of target auctions won	0.34	0.08	0.49
# Simulated auctions	100000		

Notes: Means are conditional on the ring winning. The mean proportional efficiency losses a
not just those won by the ring. Confidence intervals are bootstrapped with 5,000 iterations.

Results: Returns to the ring

- 2 Bidders, IPV, known number of bidders, unknown identities

Table 10: Returns to the ring

Model:	With unobserved auction hetrogeneity		
	Point estimate	90% Confidence interval: Lower bound	Upper bound
Mean naïve return (equiv. damages, $)	74.21	49.10	152.74
Proportion of ring wins that harmed ring	0.19	0.04	0.21
Mean return to ring (harm, $)	-10.48	-15.39	-1.20
Mean return to ring (benefit, $)	36.91	23.49	81.88
Mean return to ring (net, $)	26.42	16.06	73.86
Mean proportional price discount	0.96	0.91	0.98
# Simulated auctions	100000		

Notes: All means are over target auctions that the ring won. Confidence intervals are boostraped

Conclusions:

- Bidding rings can introduce inefficiency into the auction, even in English (ascending price) auctions, but effect small.

- Weak bidders are a problem for bidding rings (a.k.a. asymmetry)

  - Since they diminish the effectiveness of the ring should the weak ring members be prosecuted to the same extent as other members ?

- Equilibrium analysis makes a big difference to conclusions

- Rings can damage other bidders, in addition to the seller

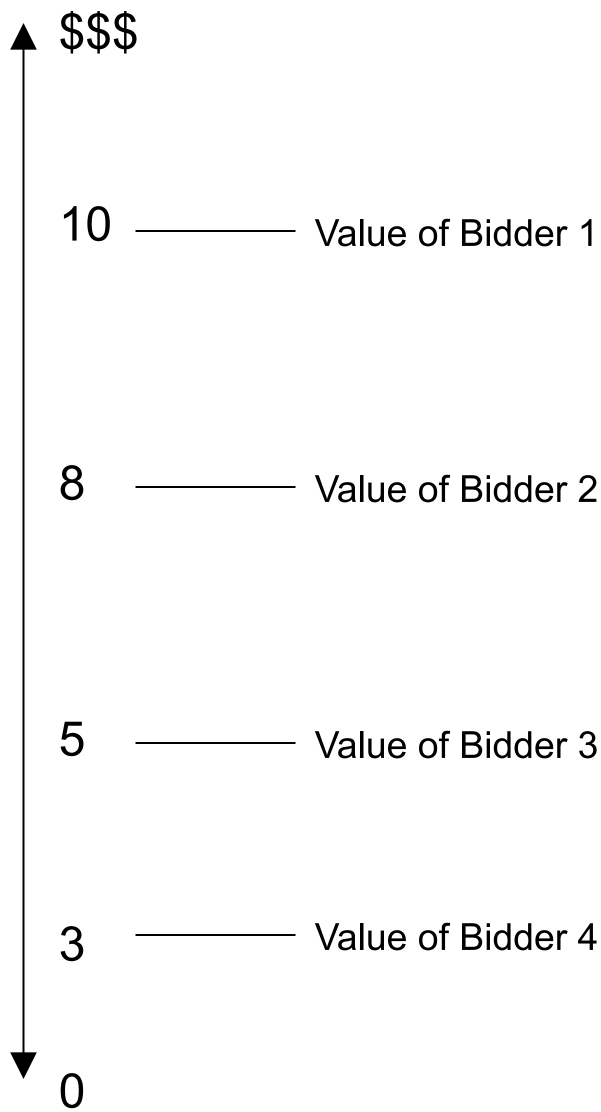
  - Because of this, participation may be an unmeasured channel through which rings may hurt sellers and diminish market efficiency

  - Other bidders seem to have the same economic basis for being able to claim damages.

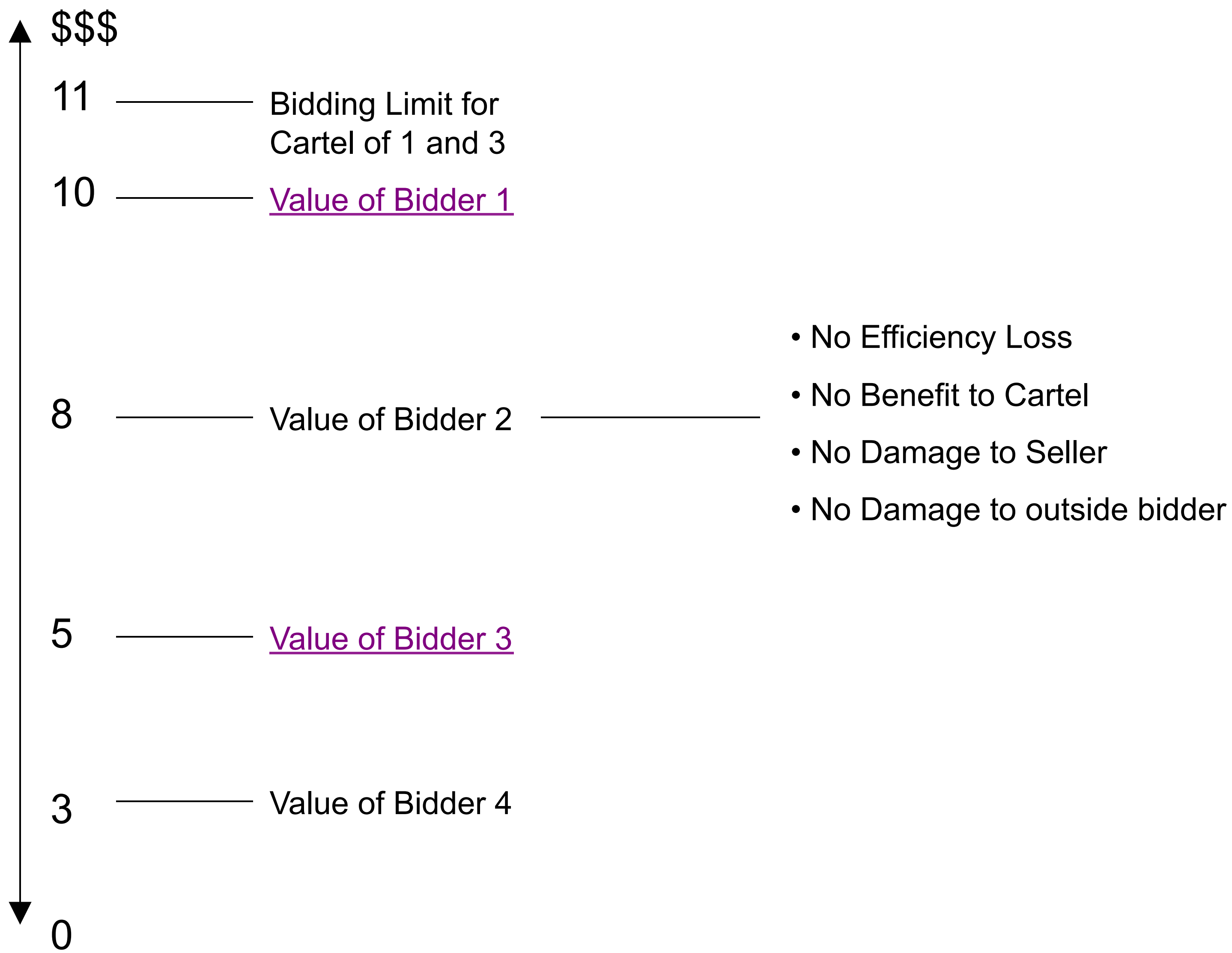
- Auction level heterogeneity is a serious applied issue in drawing inference about damages etc

Let’s conclude by reminding ourselves of the basic economics at play in this ring…

Implications: Collusion in an English Auction



Implications: Collusion in an English Auction



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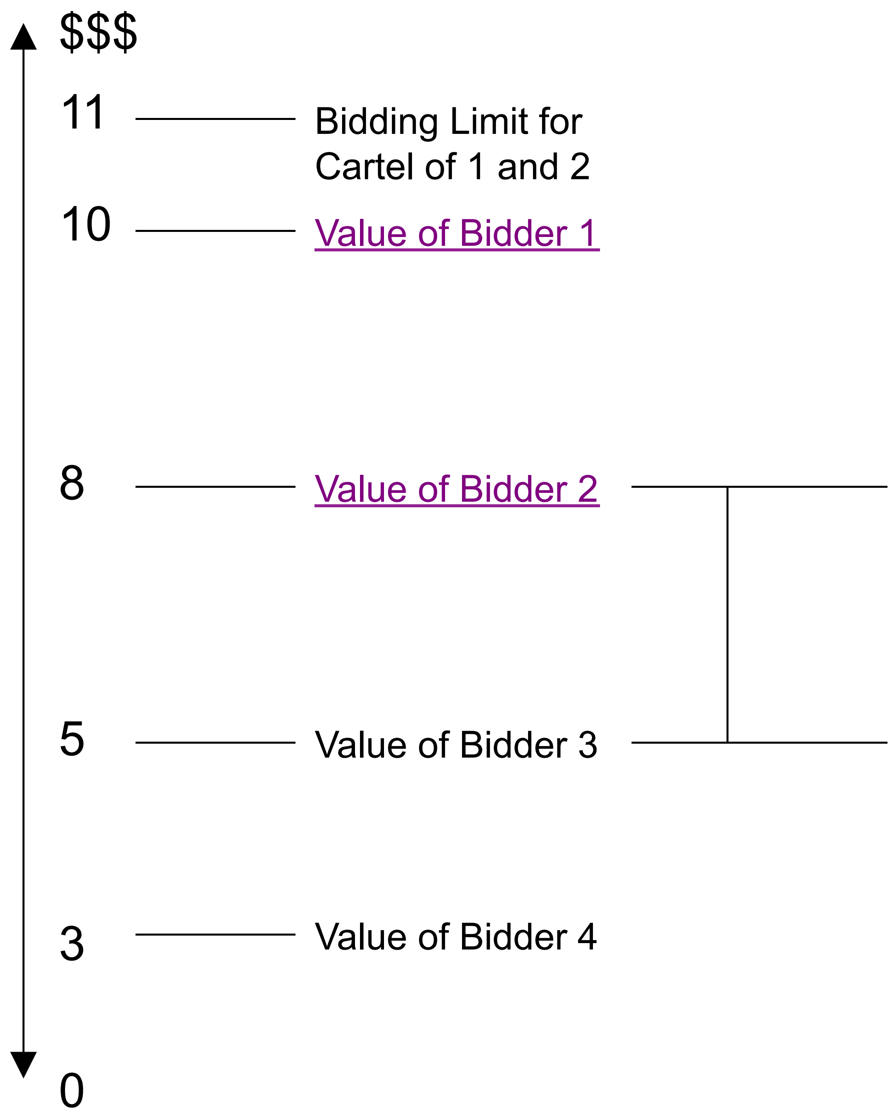

- No Efficiency Loss
- Benefit to Cartel
- Damage to Seller
- No Damage to outside bidder

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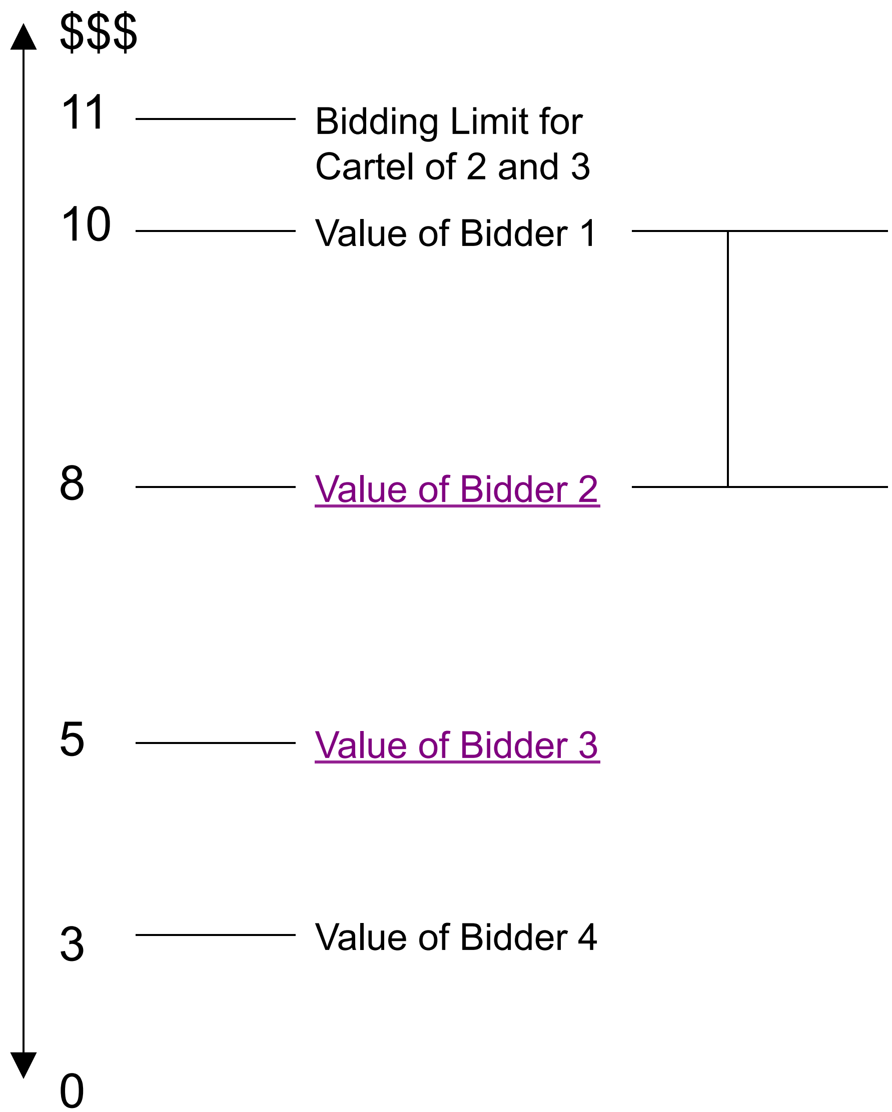

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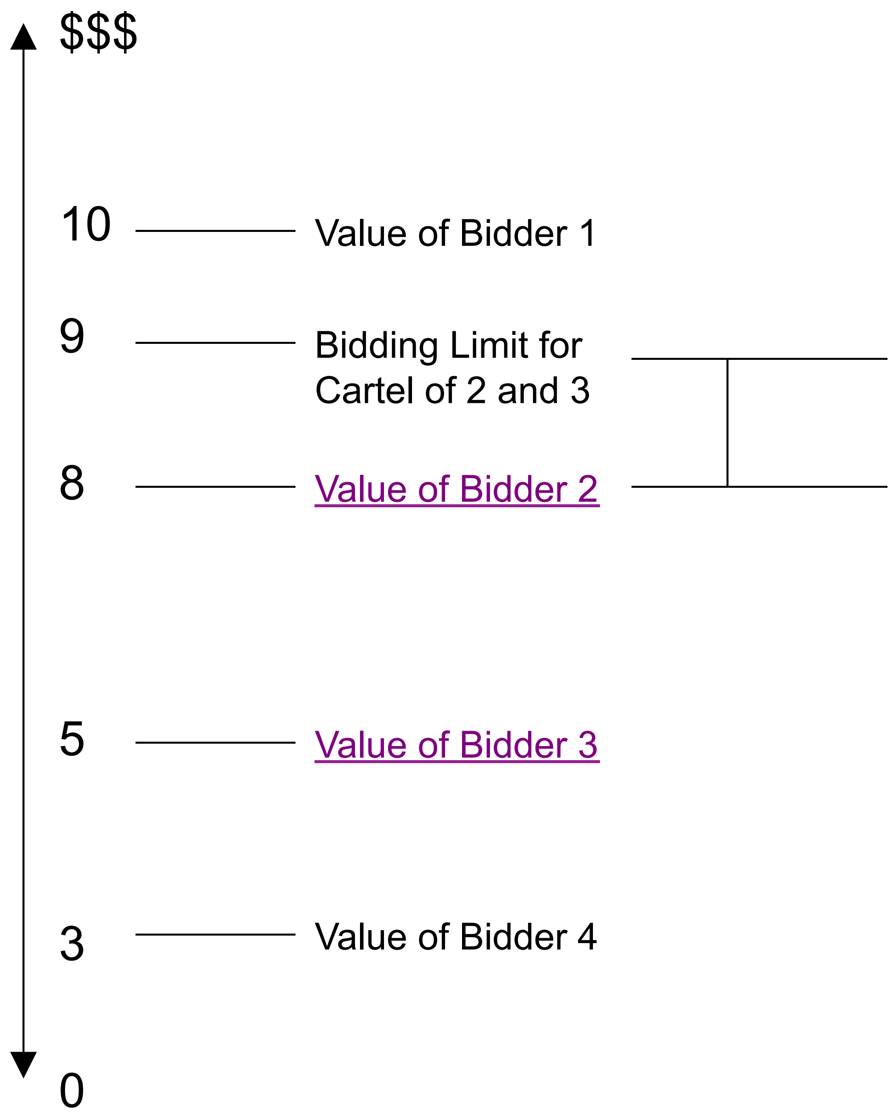
Implications: Collusion in an English Auction



- No Efficiency Loss
- No Damage or Benefit to Cartel
- Benefit to Seller
- Damage to outside bidder