Bidding Behaviour in Singapore Government Land Sales

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Introduction

- State land intended for residential development is sold by the Singapore Government every 6 months through a first-price sealed-bid auction
- Successful bidders are given the right to build and sell condominium units; condominium sales may begin before a project is completed
- Due to land scarcity, land parcels that are near to each other may be sold sequentially

Figure 1: Motivating Example: Nearby GLS Sites in Lentor Area, 2021 to 2024

Research Questions

- How do bidders behave in auctions that are spatially correlated? How might strategic bidding in occur in GLS auctions?
- What is the effect of strategic bidding in GLS on condominium prices? Should the planner redesign the auction to limit strategic behaviour?

Agarwal et al. (2018):

> *"...the incumbent winner of a previous auction is more likely to participate in subsequent nearby land sales as compared to the second-highest bidder of the same auction ... We argue that the incumbent deliberately bids up the subsequent land prices to gain pricing advantages to their own parcels."*

Key Features of GLS Auctions

- Every January and July, the government announces land it wants to sell; each site is sold via a first-price sealed-bid auction held within the 6-month window
- After an auction is called, interested parties have about 60 days to submit a bid; anyone can participate
- When the auction closes, the government announces all bids received and names of the bidders
- A few days later, the land is awarded to the highest bidder if the bid is above the reserve price (this is never revealed)
- All GLS land is leasehold; residential sites have 99 years of tenure

Data

A. Auctions
- Sample of 283 GLS auctions after 2001 (+ 129 auctions before 2001)
- Gross Floor Area (GFA) allowed, mixed use with commercial, location, bidders, bids, date of auction

B. Bidders
- Jan 2001 to Jun 2024: 138 unique bidders (83 have never won)
- Identify parent-subsidiary links based on common registered business address, stock exchange filings, shareholder financial reports etc...

C. Condominiums
- New condominium sales from 2018 to 2024 (93 projects matched to GLS)
- Location, prices, floor area, floor level, transaction date
- Complete dataset on all condominium transactions is available to purchase

D. Distances
- Between pairs of auction sites (land parcels)

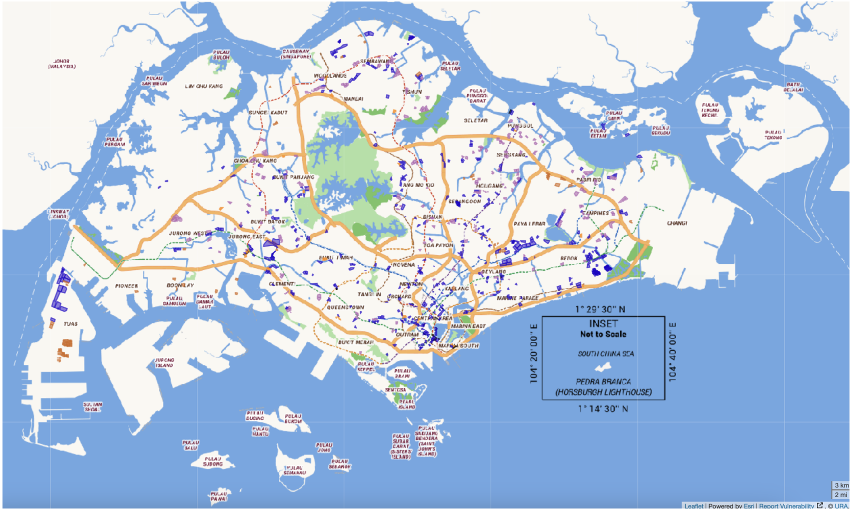
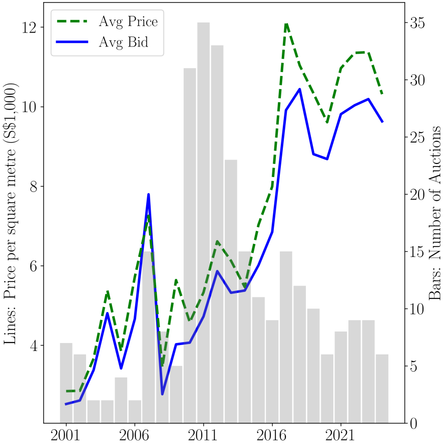
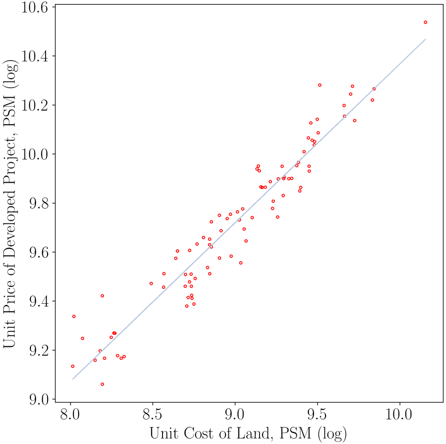


Figure 2: All Past and Present Government Land Sale Sites in Singapore

Government Land Sales and Property Prices



(a) Government Land Sales, 2001-2024



(b) Condo Price vs. Land Cost (Log-Log)

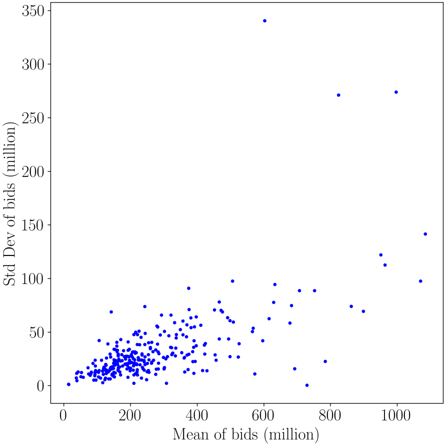
Auction Characteristics

	Period (Days)	Mixed Use	GFA (sqm)	No. of bidders	Price (million)	Price ($/sqm)
mean	59	0.13	47,819	9.8	322	7,050
std. dev.	33		20,845	4.5	225	3,941
min	26	0	3,308	1	15	1,592
25%	42	0	34,790	7	181	3,891
50%	50	0	47,964	9	256	6,043
75%	64	0	59,607	13	389	9,319
max	364	1	125,997	24	1451	25,733

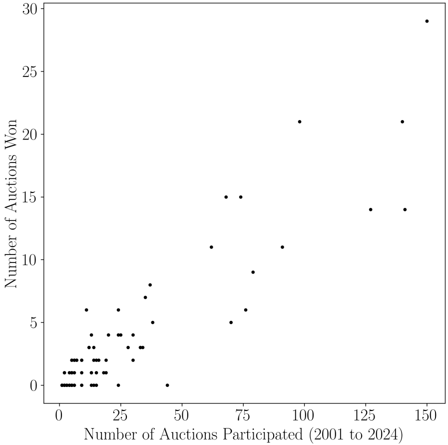
Table 1: Summary Statistics of GLS Residential Auctions, Jan 2001 to Jun 2024

Notes: Mixed Use = 1 for residential projects with commercial shops; GFA: Gross Floor Area; Price refers to amount paid by highest bidder, in constant 2019 Singapore Dollars

Auction and Bidder Heterogeneity



(a) Auctions



(b) Bidders

Bid Function

- Estimate a bid function with OLS to account for auction-level heterogeneity
- Let bid_{it} denote the nominal bid submitted by bidder i in auction t

$$\begin{aligned}\log(bid_{it}) = \beta_0 &+ \beta_1 \log(GFA_t) + \beta_2 \log(numberbids_t) + \beta_3 \log(tenderperiod_t) \\ &+ \beta_4 \mathbb{1}(HDB_t) + \beta_5 \mathbb{1}(commercial_t) \\ &+ \theta_{year} + \theta_{location} + \varepsilon_{it}\end{aligned}$$

- Take $\exp(\hat{\varepsilon}_{it})$ as the "standardised bid"

Dependent Variable: $\log(bid_{it})$	**(1)**	**(2)**
$\log(GFA_t)$	0.978***	0.944***
	(0.016)	(0.016)
$\log(numberbids_t)$	0.030*	0.054***
	(0.016)	(0.016)
$\log(tenderperiod_t)$	-0.138***	-0.098***
	(0.025)	(0.024)
$\mathbb{1}(HDB_t)$	-0.151***	-0.134***
	(0.017)	(0.016)
$\mathbb{1}(commercial_t)$	0.240***	0.227***
	(0.022)	(0.021)
Constant	9.451***	9.566***
	(0.199)	(0.198)
Fixed effects θ		
year	Yes	Yes
location	Yes	Yes
bidder	No	Yes
Observations	2,139	2,139
R-squared	0.849	0.883

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure 5: OLS Results

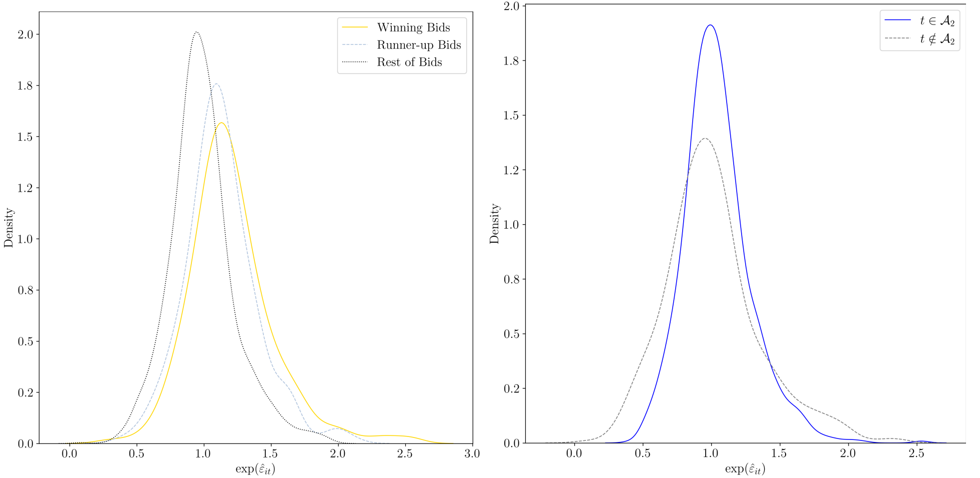


Figure 6: Distribution of Standardised Bids (OLS residuals from **(1)**)

Approach

- I use regression discontinuity to study how outcomes in early auctions A_1 affect outcomes in later auctions A_2
- Define: $Z_{it} = \varepsilon_{it} - \varepsilon^*_{-it}$, where ε^*_{-it} denotes the next highest bid in auction t
- Identification: at cutoff $Z = 0$, close runner-ups of A_1 auctions provide a control group for close winners of A_1 auctions
- Estimate a q-order local-polynomial on each side of the cutoff

To form a pair (A_1, A_2), A_1 is linked to A_2 if

1. Euclidean distance between A_1, A_2 is 2 km or less, **and**
2. A_2 is launched in ≤ 4 years from A_1's date of award

205 out of 265 (77% of projects) from 2001 to 2024 are paired; 728 pairs obtained

		$q = 1$	$q = 2$	$q = 3$	$q = 4$
(a)	Pr(*Participation in* A_2)	0.296***	0.350***	0.363***	0.375***
		[0.085]	[0.091]	[0.093]	[0.115]
	N_l	728	728	728	728
	N_r	726	726	726	726
	h	0.034	0.066	0.112	0.110
	b	0.080	0.122	0.168	0.154
(b)	Pr(*Win in* A_2)	-0.260***	-0.308***	-0.344**	-0.357**
		[0.092]	[0.116]	[0.149]	[0.167]
	N_l	248	248	248	248
	N_r	281	281	281	281
	h	0.047	0.071	0.084	0.111
	b	0.101	0.117	0.121	0.152

Robust and bias-corrected standard errors reported in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
q = order of the local-polynomial estimator on both sides of $Z = 0$.
N_l and N_r denote number of observations to the left and right of $Z = 0$.
h = main bandwidth for RD point estimator.
b = bias bandwidth for bias-correction estimator.
Estimation employs Epanechnikov kernels.
Bandwidth selection is according to Calonico et al. (2020) using *rdrobust*.

Figure 7: Regression Discontinuity Results

		$q=1$	$q=2$	$q=3$	$q=4$
(c)	$-\log(1+\sum_{l=1}^{12} GFA_{A_1-l}^{won})$	-2.879*	-1.910	-3.926*	-4.234*
		[1.655]	[1.417]	[2.079]	[2.360]
	N_l	248	248	248	248
	N_r	281	281	281	281
	h	0.028	0.073	0.079	0.102
	b	0.066	0.139	0.115	0.138
(d)	$\log(unit\ bid)\ inA_2$	-0.151	-0.168	-0.180	-0.140
		[0.118]	[0.134]	[0.150]	[0.163]
	N_l	248	248	248	248
	N_r	281	281	281	281
	h	0.054	0.076	0.094	0.108
	b	0.091	0.120	0.143	0.154

Robust and bias-corrected standard errors reported in brackets.

*** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$

$q =$ order of the local-polynomial estimator on both sides of $Z = 0$.

N_l and N_r denote number of observations to the left and right of $Z = 0$.

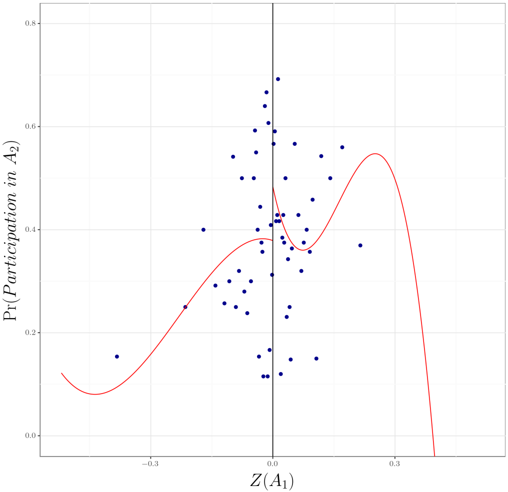
$h =$ main bandwidth for RD point estimator.

$b =$ bias bandwidth for bias-correction estimator.

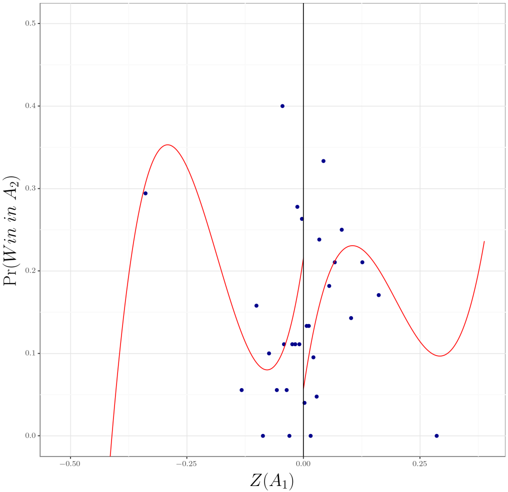
Estimation employs Epanechnikov kernels.

Bandwidth selection is according to Calonico et al. (2020) using *rdrobust*.

Figure 8: Regression Discontinuity Results (Continued)

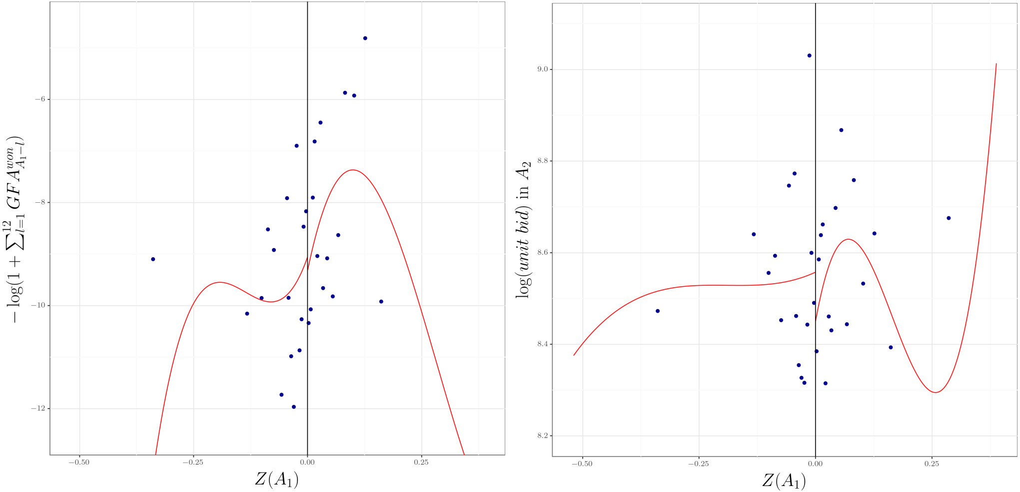


(a) Pr(*Participation in* A_2)



(b) Pr(*Win in* A_2)

Figure 9: Regression Discontinuity Plots: $q = 3$



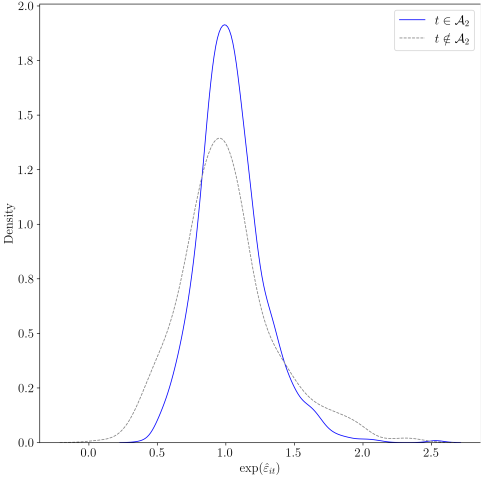
(a) $-\log(1+\sum_{l=1}^{12} GFA_{A_1-l}^{won})$ (b) $\log(unit\ bid)$ *in* A_2

Figure 10: Regression Discontinuity Plots (Continued): $q=3$

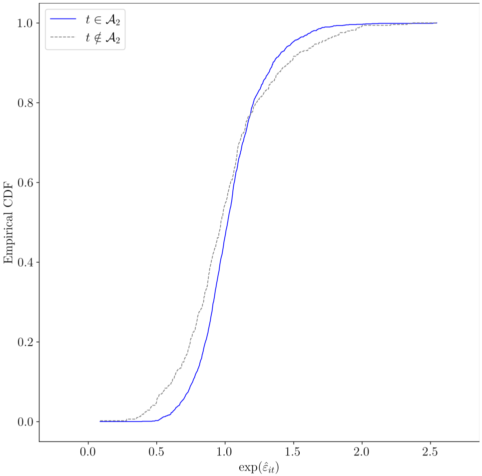
Dependent Variable: $\log(b_{it})$	**(1)**	**(2)**	**(3)**	**(4)**
$\log(GFA_t)$	0.971***	0.970***	0.938***	0.937***
	(0.016)	(0.016)	(0.016)	(0.016)
$\log(\text{Number of bids})_t$	0.031*	0.033**	0.054***	0.053***
	(0.016)	(0.016)	(0.016)	(0.016)
$\log(\text{Tender Period})_t$	-0.120***	-0.119***	-0.088***	-0.088***
	(0.025)	(0.025)	(0.024)	(0.024)
$\mathbb{1}(HDB)_t$	-0.144***	-0.144***	-0.129***	-0.129***
	(0.017)	(0.017)	(0.016)	(0.016)
$\mathbb{1}(Commercial)_t$	0.253***	0.254***	0.237***	0.236***
	(0.022)	(0.022)	(0.021)	(0.021)
$\mathbb{1}(t \in \mathcal{A}_1)$	0.027	0.027	0.018	0.018
	(0.017)	(0.017)	(0.016)	(0.016)
$\mathbb{1}(t \in \mathcal{A}_2)$	0.124***	0.120***	0.093***	0.097***
	(0.019)	(0.019)	(0.018)	(0.018)
$\mathbb{1}(t \in \mathcal{A}_2) \times (i = A_1 \text{ winner})$		0.006		-0.031*
		(0.019)		(0.019)
$\mathbb{1}(t \in \mathcal{A}_2) \times (i = A_1 \text{ runner-up})$		0.038*		-0.008
		(0.021)		(0.020)
Constant	9.438***	9.436***	9.578***	9.591***
	(0.197)	(0.197)	(0.197)	(0.197)
Fixed effects θ				
year	Yes	Yes	Yes	Yes
location	Yes	Yes	Yes	Yes
bidder	No	No	Yes	Yes
Observations	2,139	2,139	2,139	2,139
R-squared	0.853	0.853	0.884	0.884

Standard errors in parentheses
*** p< 0.01, ** p< 0.05, * p< 0.1

Figure 11: Additional OLS Results: Larger bids are submitted in A_2 auctions

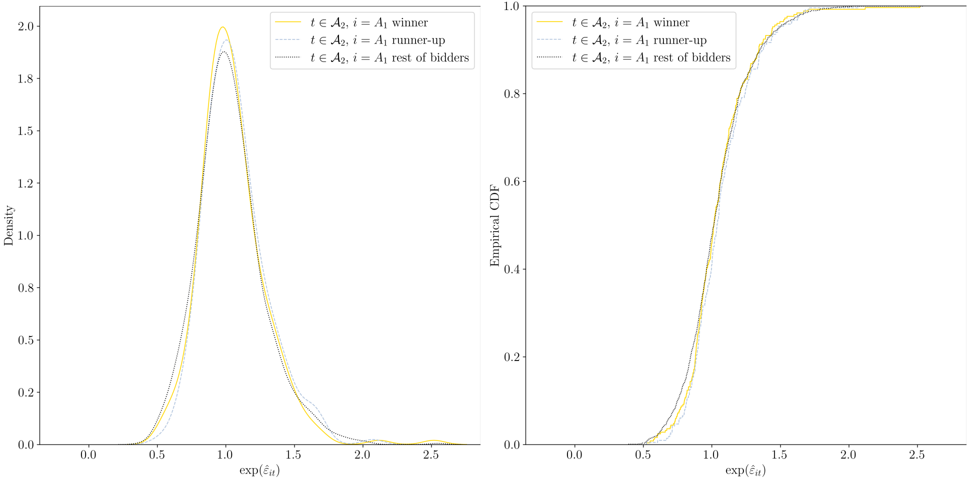


(a) Estimated pdf



(b) Estimated cdf

Figure 12: Distribution of Standardised Bids in Spatially Correlated Auctions



(a) Estimated pdf (b) Estimated cdf

Figure 13: Distribution of Standardised Bids by Different Groups of Bidders

Summary of Findings

- I study how property developers bid in GLS auctions for residential development — auctions that are correlated over space and time
- Using a RD approach, close winners are 30-38% more likely than close runner-ups to bid in a subsequent auction (launched within 2km and 4 years of the first parcel), but 26-36% *less likely to win it*
- I compare the bid distributions of spatially correlated auctions (A_2) versus auctions with no spatial correlation; the null hypothesis that bids are drawn from the same distribution is strongly rejected
- Spatially correlated auctions have second-order stochastic dominance over non spatially correlated auctions; i.e. bidding is larger on average in A_2
- Within spatially correlated auctions, I find no evidence of strategic bidding — bids by different profiles of bidders appear to be drawn from the same distribution

Agarwal, S., Li, J., Teo, E., & Cheong, A. (2018). Strategic sequential bidding for government land auction sales – evidence from singapore. *The Journal of Real Estate Finance and Economics*, *57*(4), 535-565.