Spatial Econometrics for Strategic Interactions in Sequential Auctions of Government Lands

Yilan Luo [a] and Wen-Chi Liao [b,1]

[a] School of Economics and Trade, Hunan University, China

[b] Department of Real Estate, NUS Business School, National University of Singapore, Singapore

Abstract

This research considers the historical outcomes of government land sales as the results of repeated simultaneous games played by developers who have participated in the sequential land auctions. In this framework, developers' past experiences in rivalries influenced their bidding behaviors against the rivals. The paper exploits spatial econometric methods to account for such strategic interactions, and the innovation is on the design of the spatial weight matrix. We deviate from the conventional approach of specifying this matrix by assumption. Instead, we apply available data on the lands, bids, and wins in government records to estimate a spatial weight matrix that captures the developers' mixed strategies. The spatial econometric analysis gives the family of spatial autoregressive models a horse race to find the most suitable specification. The regression captures the rivalry network in games. The results show that developers are more likely to place higher bids when potential rivals follow a more aggressive strategy or possess certain characteristics such as the developer's country of origin. Moreover, the spatial econometric method can also identify the direct and indirect effects of both auction strategy and developer characteristics on the outcomes.

JEL Classification: L13 L14 D83

Keywords: Spatial econometrics, land auction, bidding, foreign developer, real estate

[1] Corresponding author: Wen-Chi Liao, Associate Professor of Real Estate, National University of Singapore Business School. Email: wliao@nus.edu.sg.

1. Introduction

The industry of real estate development in many countries is considered oligopolistic as it has limited number of developers and is dominated by a few powerful firms. (Coiacetto, 2009) The Singapore land market is a good example. During the period from 2003 to 2017, 216 developers submitted 1068 bids in 119 Singapore Government Land Sales (GLS) auctions competing for commercial and residential sites. As shown in Table A1, 55% of all sites (66 auctions) were won by 14 powerful developers either independently or jointly. Under this oligopolistic structure, developers are assumed to take others' action into account when bidding for land or making pricing decisions in the product market. (Ong et al, 2003) This paper, therefore, discusses the spatial strategic interaction within repeated land auctions via depicting the mechanism of rival spillover in Singapore Government Land Sales (GLS).

This study is motivated by both anecdotal evidence and literature.

As Singapore shapes its ambition of building a global city in the 21st century, the 2009 China-Singapore Free Trade Agreement (CSFTA), along with other FTAs were implemented to facilitate the process of internationalization. It could be observed in Figure A1 and Figure A2 that the competition in Singapore GLS became fiercer after 2009, which is the year when the first mainland China developer was introduced in the land auction. While aggressive foreign bidders acquire more market share, unit winning price of auction sites were pushed higher and higher, which raises the concern toward certain types of bidders and their influence on land prices. This concern motivates a series of empirical questions regarding rival influence in repeated land auctions: What's rationale of developers to place aggressive bids? Is it a result of fierce competition? Specifically, is it because of the aggressive foreign rivals? And, would aggressive bids lead to more aggressive bids? To answer these questions, the mechanism of strategic competition in GLS auctions need to be studied.

As GLS follows the procedure of repeated first auction, one way of determining the probability of winning in GLS with a given bid lies in studying previous bidding data. In Singapore, the government would publish all the bid prices placed by every participant at the end of each GLS auction. From these announced bids the 'bidding patterns' of potential competitors may be studied. (Friedman, 1956) In fact, researchers have shown their interest in depicting the game structure of land auctions in previous works. Multiple attempts have been made to incorporate rival influence and bidding experience into land auction studies. Ooi et al.'s 2006 study included rival number variable in their hedonic land price estimation. Agarwal et al. (2018), on the other hand, depicted a sequential game from a micro-scope. The center question of their study is that: would a recent winner attend following auction for nearby site to acquire monopoly in that neighborhood. However, the systematic network of rival influence in GLS auctions was not found in any of those works and the questions concerning the mechanism of rival spillover have not been answered. The possible reason lies in the limitation of traditional OLS hedonic models. To explore the channels and magnitude of rival spillover, SAR models, which includes a spatial-lagged structure that capture spatial autocorrelation between bids, could be a useful tool.

Spatial Autoregressive Models (SAR), as they extend conventional regression models with spatial autoregressive structure, have been applied in multiple topics to capture spatial dependence and spillovers, especially in urban economics and economic geography. The basic idea of SAR is to control for the characteristics of neighbors by incorporating spatial weight matrixes, which depict the distance between locations. Aside from its usage in describing physical distance, spatial econometrists find it appealing to explore the application of social distance matrixes.

As pointed out by Anselin (2001), instead of spillover across locations, spatial econometrics could be used to capture and incorporate the interaction between economic agents in a whole system. Specifically, spatial weight matrixes could be used to explain the interaction pattern among individuals, which could further depict emergent collective behavior and aggregate patterns like peer effects (Lin, 2010). When the distance in spatial weight matrixes is “rival distance” that describe the relationship between players, SAR could capture interaction in a “game space”. (Pinkse et al., 2010) Moreover, Yang and Lee (2017) particularly pointed out that spatial weight matrix could be used to depict the agents’ asymmetric knowledge of others under the framework of a simultaneous move game. In this case, a shorter rival distance between players represents closer competition relationship and better knowledge, which could indicate stronger rival reaction. However, few has applied spatial econometric methods empirically in game contexts.

This study, therefore, takes aim at providing an empirical application of spatial econometrics in a repeated simultaneous game structure via depicting the impact of rival interaction on land auction prices in Singapore GLS. To examine the extent to which bidding price is related to rival influence, an estimated spatial weight matrix was constructed. In this weight matrix, “rival distance” between each bid pair was mapped out. When two bids are considered “proximate” to each other, the “rival spillover” are considered stronger as well.

The center hypothesis tested in this study is that developer’s bidding strategy in current auction is significantly affected by its close rival’s bidding records in recent history and its characteristics, and the level of influence could be estimated with SAR models. If so, this would help explain for an essential part of the omitted unobservables in conventional hedonic models. Comparing the results yielded by different SAR model specifications, the direct and indirect effects of developers’ strategies were also discussed. This part of analysis would provide more detailed information on the impact of certain rival features.

One common criticism of applying spatial econometrics in social relationship study is that the exogenous assumption could easily be broken when social interaction is depicted by arbitrary spatial weights. When spatial weight matrixes are used to describe non-physical relationship, the weights are constructed using “economic distance” instead of geographic distance. When the actions of social agents are predetermined by their characteristics, the arbitrarily defined spatial weights are correlated with the residual, and thus generate endogeneity. In the GLS case, each developer’s participation decision is determined by their interest and preference on the auction land parcel and their projection of the competition environment. Thus, the competition relationship matrix is not adequate for spatial analysis.

Addressing this concern, I apply the estimated weight matrix in spatial regression, which was constructed by combining bidding relationship matrix with the predicted probability of each developer’s participation from first stage regression. With the estimated spatial weight matrix, different specifications of SAR were carried out in the second stage to measure the spillover from past rival bidding prices, as well as the one from rival’s strategy and background information. I also applied Generalized Method of Moments (GMM) estimator proposed by Qu and Lee (2015) to eliminate endogeneity.

A preview of the results from this study follows. The SAR results confirm that close rivals’ history bidding prices do have a significant impact on the strategy of bidders in current auction. When a developer senses a higher possibility for them to encounter a close rival that used to place aggressive bids, they are more likely to bid aggressively as well, and this pattern remain robust across different SAR specifications. Moreover, when the spatial lag term of rival behavior was included in SAR, the reaction pattern of developers’ certain strategy is revealed in the local indirect effects: changes in one bid’s particular explanatory variable lead to changes in not only the price of the bid itself, but also the prices in other “neighborhood” bids. In this study, developers’ bidding behavior is proved to be closely related to their potential rivals’ preferences and features.

Two rival characteristics are found to have significant influence on bidders’ decision-making process: joint venture (JV) and bidder nationality. The direct effect of a developer to form a JV with other developers is that they are more likely to place higher bids, which is a result of the pooling of resources. Focusing on the rival’s action, the coefficient of spatial lagged joint venture dummy is significantly negative. This indicates that, when all other potential competitors are more likely to adopt a JV strategy, GLS player will not match up with them in bidding price. Another interpretation of the negative effect lies in the possibility that some strong players would choose to avoid competing with JVs due to the opportunity cost. This unwillingness of participation would lead to an exaggeration of the price gap between the JVs and other bidders as well. However, developers are not reluctant to compete with foreign bidders even though foreign players have a record of bidding higher in previous auctions. Instead, local developers will be stimulated to bid higher.

Additionally, this study applies two more versions of weight matrixes with arbitrary competition relationship: different influential time windows (from three months to fifteen years) and differentiated developer influence to carry out robustness checks. Comparing the outcomes, we found that the result remains robust in both checks. Looking into the results from applying different influential time frame, we found that bidding records dates back in the history might not have such a strong spillover effect on current bid prices comparing to the ones from recent history and the three-year influential period appears to be an efficient time-window for rival effect estimation. What’s more, when the spillover effect from infrequent players were removed from the spatial structure, the estimation results is nearly unaffected. This implies that firms might only take the behavior of key players into consideration when shaping their own strategy, which points to the need to differentiate players’ market influence in future analysis. All these findings from heterogeneity analysis could provide valuable reference for future land auction studies.

Overall, the collective results from this study confirmed the existence of spatial strategic interaction in a repeated simultaneous land auction game context. Applying Singapore GLS data in SAR models, the rival influence network in this oligopolistic property development market was empirically captured and measured. This study not only provides a better understanding of the land auction price formation dynamics, but also a deeper insight in spatial spillover mechanism between rivals in repeated simultaneous games.

This significance of this chapter is four-fold. Firstly, this study could contribute to land auction studies as could improve our understanding of land price formation and rival effects in land auctions. Secondly, it could contribute to empirical game literature as we discuss the competitive bidding strategy in repeated first price auction. Thirdly, this study expands the scope of applied spatial econometrics. Lastly, the empirical findings also have implication for the industry of real estate development.

The rest of this paper proceeds as follows. Section 2 explains the game structure of GLS and tests for spatial autocorrelation in Singapore GLS. Section 3 introduces SAR methodologies, including the process of model selection, spatial weight matrix computation and the estimation method. Section 4 discusses the data. Section 5 presents the main results and the ones yielded with binary weight matrix for comparison. Results of robustness checks are presented in Section 6. Section 7 elaborates on the chapters' implication on the competitive environment in Singapore land market. Section 8 concludes.

2. Spatial Autocorrelation in Singapore GLS Game

In Singapore, state land is released for development through the Government Land Sales (GLS) Programme. GLS is managed by three land sales agents: Housing Development Board (HDB), Urban Redevelopment Authority (URA) and JTC Corporation (JTC). The auction of commercial, hotel, private residential and industrial developments, hospital land are handled by URA. In comparison to other land auction systems, the environment of Singapore GLS provides us a good opportunity to test the rival spillover in repeated simultaneous games as it adopted the first-price sealed-bid format. The procedure of GLS is shown in Figure 1.

At the beginning of each round of land sales, there is a preview period. During this period, government would release information about the land parcel, and interested bidders are invited to purchase a Developer's Packet containing their planning and design guidelines for the site. Developer could decide whether to participate or not based on both site information and the overall competitive condition.

During the bidding period, developers that chose to participate would form their bidding prices based on both site information and their knowledge of potential rivals accumulated in previous auctions without knowing who their actual rivals are and the strategy they adopt.

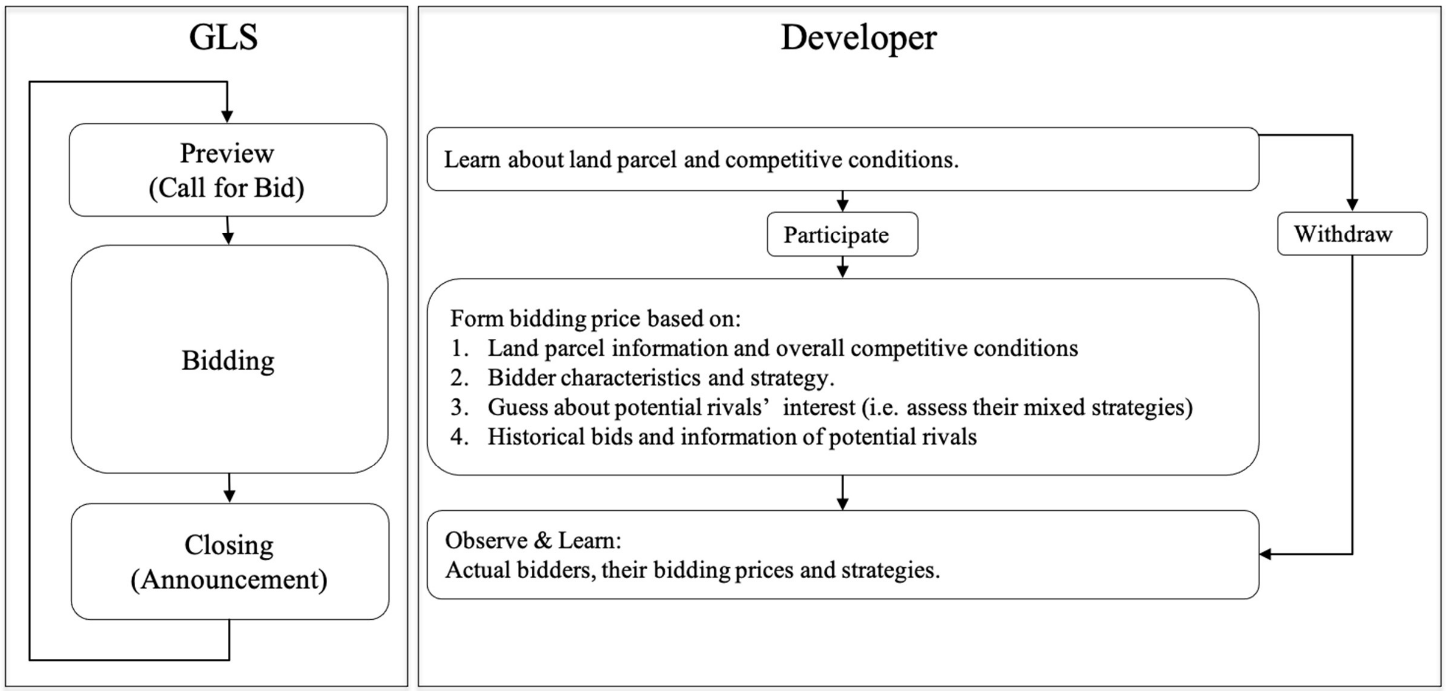

Figure 1 GLS Procedure

Developers will form their strategy rationally based on four critical factors: 1) land parcel information, 2) their own characteristics, 3) their conjectures about potential rivals' interest and 4) previous actions of other players as well as their characteristics. From individual players' perspective, all their potential rivals are playing mixed strategies, which could be expressed as a probability of participation.

Lastly, when the auction close, actual bidding prices of all bidders would be published by government and the highest bidder wins. Developers could then gather that information for future reference.

Thus, one round of GLS auction is finished and the government agency would then follow up the project development and monitor the market behavior of successful bidder. As state lands are released sequentially over time, the GLS procedure was repeated over time as well. This procedure is considered in line with the formation of sequential equilibrium, a refinement of Nash equilibrium. (Kreps & Wilson, 1982) This entire T-stages game is a dynamic game of complete and imperfect information.

Table 1 presents the estimation of Moran's I, a statistic widely used to test for spatial dependence between "locations" in "space". In this test, the n*n binary weight matrix of rival competition relationship was used, in which spatial weight take the value 1 if the bidders of the bid pair used to compete with each other in previous auctions. If not, the spatial weight is 0.

Table 1 Moran's I

Variables	Description	I
Ln(BidPrice)	Ln(Bid Price)	0.083***
Ln(GFA)	Ln(Gross Floor Area)	0.050***
Ln(PlotRatio)	Ln(Plot Ratio)	0.019***
Competition	Number of Competitors	-0.042***
Ln(Distance to CBD)	Ln(Distance to CBD)	0.059***
Ln(Distance to MRT)	Ln(Distance to MRT)	0.025***
JV	Joint Venture Dummy	0.000
Foreign	Foreign Developer Dummy	-0.016***
Bid-to-win	Conservative Developer Dummy	-0.040***
Recent Winning Experience	Recent Winning Experience in 1 Year Dummy	-0.004

*2-tail test

It could be concluded from the results that spatial autocorrelation does exist in GLS auction games and it appears in bidding prices, features of land parcel and developers' characteristics, which indicates a possibility of estimation bias if rival interaction is omitted in auction price regressions.

Comparing the test outcomes of each variable, I found that Moran's I is significantly positive for bidding prices, GFA, plot ratio and distance to urban core, which indicates that higher prices do tend to "agglomerate" with each other in the GLS competition space. It is also shown that foreign players are less likely to compete with each other. Those players who have recent winning experiences (within a year) are less likely to appear in a same auction either.

These findings suggest that the impact of rivals' certain features should also be included in spatial analysis. To further explore the spatial spillover effect of those variables, more detailed information from different SAR specifications will be needed.

3. SAR Methodologies

3.1 Model Specifications

There are seven SAR model specifications in total that could incorporate spatial lag of dependent variable, independent variables and error term together or respectively. All seven SAR specifications, together with the baseline OLS regression, were used in this study. Regression models are listed below:

OLS: $$lnBidPrice_{iart} = \alpha + \boldsymbol{X_{rt}}\beta_r + \boldsymbol{Z_{iart}}\beta_a + \tau_t + \eta_d + \gamma_z + \tau_t * \eta_d + \varepsilon \quad (1)$$

SLM: $$lnBidPrice_{iart} = \alpha + \rho \boldsymbol{W} lnBidPrice_{jbst'} + \boldsymbol{X_{rt}}\beta_r + \boldsymbol{Z_{iart}}\beta_a + \tau_t + \eta_d + \gamma_z + \tau_t * \eta_d + \varepsilon \quad (2)$$

SAC: $$lnBidPrice_{iart} = \alpha + \rho \boldsymbol{W} lnBidPrice_{jbst'} + \boldsymbol{X_{rt}}\beta_r + \boldsymbol{Z_{iart}}\beta_a + \tau_t + \eta_d + \gamma_z + \tau_t * \eta_d + \varepsilon$$

$$\mu = \lambda \boldsymbol{W} \mu + \varepsilon \quad (3)$$

SDM: $$lnBidPrice_{iart} = \alpha + \rho \boldsymbol{W} lnBidPrice_{jbst'} + \boldsymbol{X_{rt}}\beta_r + \boldsymbol{Z_{iart}}\beta_a + \theta \boldsymbol{W} \boldsymbol{Y_{jbst'}} + \tau_t + \eta_d + \gamma_z + \tau_t * \eta_d + \varepsilon \quad (4)$$

GNSM: $$lnBidPrice_{iart} = \alpha + \rho \boldsymbol{W} lnBidPrice_{jbst'} + \boldsymbol{X_{rt}}\beta_r + \boldsymbol{Z_{iart}}\beta_a + \theta \boldsymbol{W} \boldsymbol{Z_{jbst'}} + \tau_t + \eta_d + \gamma_z + \tau_t * \eta_d + \varepsilon$$

$$\mu = \lambda \boldsymbol{W} \mu + \varepsilon \quad (5)$$

SEM: $$lnBidPrice_{iart} = \alpha + \boldsymbol{X_{rt}}\beta_r + \boldsymbol{Z_{iart}}\beta_a + \tau_t + \eta_d + \gamma_z + \tau_t * \eta_d + \varepsilon$$

$$\mu = \lambda \boldsymbol{W} \mu + \varepsilon \quad (6)$$

SDE: $$lnBidPrice_{iart} = \alpha + \boldsymbol{X_{rt}}\beta_r + \boldsymbol{Z_{iart}}\beta_a + \theta \boldsymbol{W} \boldsymbol{Z_{jbst'}} + \tau_t + \eta_d + \gamma_z + \tau_t * \eta_d + \varepsilon$$

$$\mu = \lambda \boldsymbol{W} \mu + \varepsilon \quad (7)$$

SLX: $$lnBidPrice_{iart} = \alpha + \boldsymbol{X_{rt}}\beta_r + \boldsymbol{Z_{iart}}\beta_a + \theta \boldsymbol{W} \boldsymbol{Z_{jbst'}} + \tau_t + \eta_d + \gamma_z + \tau_t * \eta_d + \varepsilon$$

(8)

For bid i in current auction r at time t, the bidding price, $lnBidPrice_{iart}$, is determined by two groups of explanatory variables. The first group provides information of bid i itself: (1) $\boldsymbol{Z_{iart}}$: feature of bidder a and the strategy it adopted in i; (2) $\boldsymbol{X_{rt}}$: characteristics of auction r in which bid i was placed. $\boldsymbol{X_{rt}}$ includes hedonic factors of auction land parcel and information concerning the competition situation. The second group of variables provide the information of rival bid j: (1) $lnBidPrice_{jbst'}$ is the spatial lag of dependent variable; (2) Vector $\boldsymbol{Z_{jbst'}}$ shows the information of bidder b and the strategy it used in bid j at time t'. t' is prior to t as developers could only learn from their experiences in the past.

Different from the OLS model, spatial weight matrix $\widehat{\boldsymbol{W}}$ were incorporated in SAR models to capture spatial dependence in rival network. $\widehat{\boldsymbol{W}}$ is a $n * n$ matrix of $\widehat{w_{ij}}$, which incorporated all predicted "rival distance" between bid i and bid j. Combining $\widehat{\boldsymbol{W}}$ with the spatial lag of dependent variable, independent variables and error term together or respectively, integrated spatial spillover of all rival bids' information on $lnBidPrice_{iart}$ could be estimated. Year, planning area and zoning fix effects are represented by τ_t, η_d and γ_z. ε and μ are error terms.

The mapping of SAR to observable information in GLS game is shown in Figure 2.

In auction a, bid i's price placed by developer r at time t is based on: 1) Land parcel information, which are hedonic factors, $\boldsymbol{X_{rt}}$; 2) Bidder characteristics and strategy $\boldsymbol{Z_{iart}}$; 3) Their guess about potential rivals' mixed strategy, estimated spatial weight matrix $\widehat{\boldsymbol{W}}$; 4) History bid prices, spatial lagged dependent variable, $\widehat{\boldsymbol{W}}lnBidPrice_{jbst'}$, and 5) information of potential rivals, that is spatial-lagged independent variables $\widehat{\boldsymbol{W}}\boldsymbol{Z_{jbst'}}$. Spatial-lagged error $\widehat{\boldsymbol{W}}\mu$ captures the unobservable autocorrelation unknown to developers.

3.2 Computation of Spatial Weight Matrix

To relax the assumption of independent observations required in conventional methods, the spatial dependence structure need to be specified. An estimated spatial weight matrix W ̂need to be constructed. W ̂should take the form of n*n, which depicted the relationship between the n observation units that make up the size n data sample. (Qu and Wang, 2015)

In the spatial analysis of repeated simultaneous land auction games, spatial weight matrix need to be implemented to capture the "proximity" between bid pairs and thus map out the complete rival influence network between each observation (bid) and its neighborhood bids.

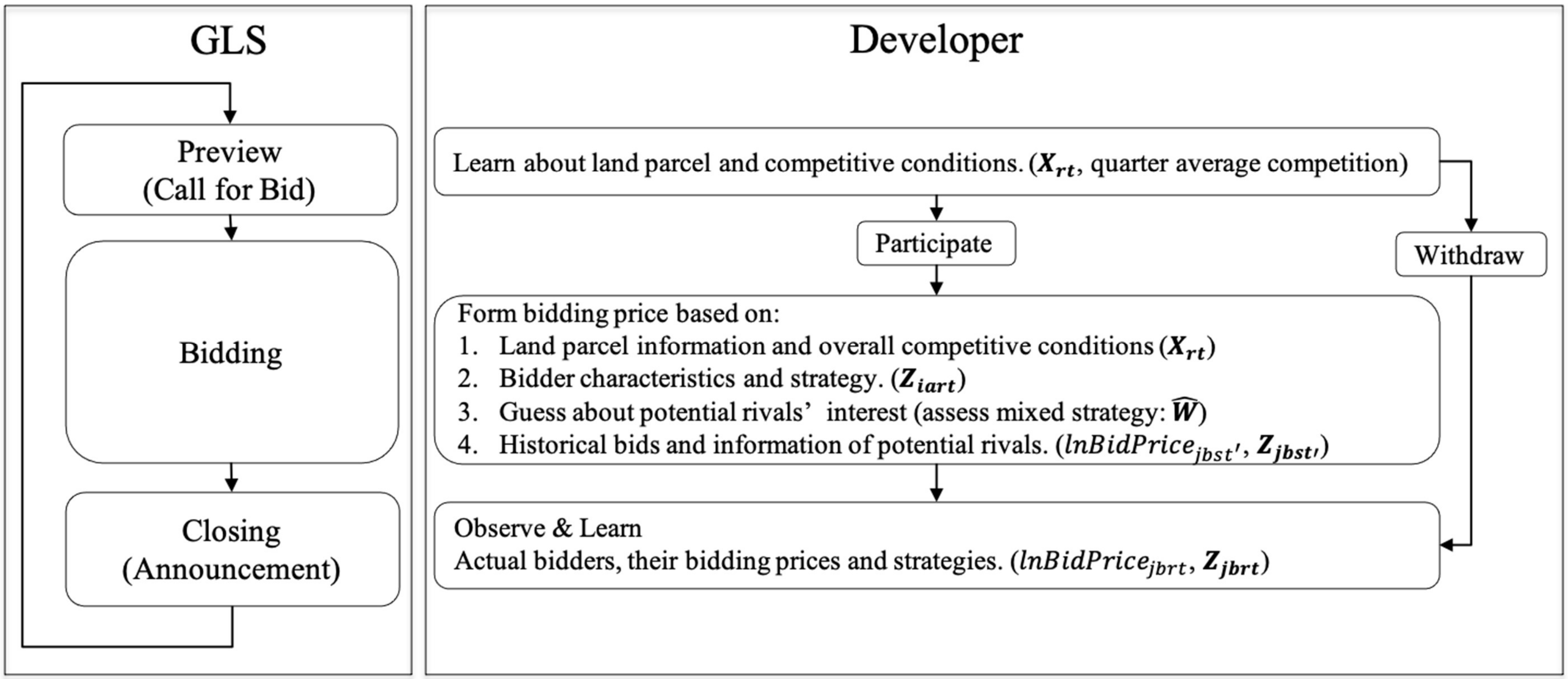

Figure 2 GLS Framework

In this study, $\widehat{\boldsymbol{W}}$ is constructed as follows:

First, I generate bivariate normal random variables that represent the past bidding relationship. $\boldsymbol{W_1}$ is a 1068×1068 matrix, in which each element w_{1ij} equals to 1 if the bidder of bid i have competed with bidder of bid j in the past. Therefore, I constructed a neighbor dummy matrix $\boldsymbol{W_1}$ in which non-zero value could only exist in the upper right triangle.

Secondly, probability of each developer's participation is estimated in first stage OLS regression using land parcel information and competition information.

$$Participate_{art} = \alpha + \boldsymbol{X_{rt}}\beta_r + \tau_t + \eta_d + \gamma_z + \varepsilon \tag{9}$$

$Participate_{ra}$ is the dummy that shows whether developer a have taken part in auction game r or not. $\boldsymbol{X_{rt}}$ is the vector of information regarding auction r at time t. $\boldsymbol{X_{rt}}$ includes both the land parcel characteristics and *QuarterCompetition*, the average competitor number of all auctions in the quarter auction r took place. This variable was used as a proxy of the popularity of this land plot. τ_t is the year fix effect (FE) while η_d is the planning area FE and γ_z is the FE that controls for zoning. ε is the error term.

The explanatory variables in the first stage OLS regression were used as instrumental variables since they are the determinants of developers' preference of auction lands. The results of first stage OLS regression is listed in Table 2.2. Results of logit regression were also provided for comparison.

Table 2 First Stage Regressions

Dependent Var: Participate	(1) OLS	(2) Logit
Log (Gross Floor Area)	-0.0109***	-0.2177***
	(0.0035)	(0.0701)
Plot Ratio	0.0067**	0.1369**
	(0.0027)	(0.0566)
Log (Distance to CBD)	-0.0023	-0.0105
	(0.0028)	(0.0567)
Log(Distance to MRT)	-0.0021	-0.0589
	(0.0031)	(0.0652)
Quarter Average Competition	0.0060***	0.1100***
	(0.0008)	(0.0164)
Constant	0.1002**	-2.2916**
	(0.0487)	(0.9812)
Observations	25,920	25,920
R2 /Pseudo R2	0.0120	0.0294
Year FE	YES	YES
Planning Area FE	YES	YES
Land Use FE	YES	YES

The estimated coefficients in Table 2.2 were used to calculate for the likelihood of developers in each auction, $\widehat{Participate}_{ra}$,. All predicted outcomes take value from 0 to 1. With these predicted probabilities, a $n * n$ matrix $\widehat{\boldsymbol{W}}_{\boldsymbol{2}}$ that depict the similarities of bidders is constructed. Each spatial weight in $\widehat{\boldsymbol{W}}_{\boldsymbol{2}}$ is the average possibility for the bidders of this bid pair to participate in correspondent auction.

Taking the Hadamard product of $\boldsymbol{W}_{\boldsymbol{1}}$ and $\widehat{\boldsymbol{W}}_{\boldsymbol{2}}$, an estimated matrix that controls for endogeneity was formed. After the row-normalizing process, an adequate spatial matrix $\widehat{\boldsymbol{W}}$ for SAR regression is generated.

3.3 Estimation Method

We applied Generalized Method of Moments (GMM) estimator proposed by Qu and Lee (2015) to eliminate the endogeneity issue arises with the application of "social distance".

As stated by Qu and Lee (2015), the GMM estimator is based on proper linear and quadratic moment conditions, it can be asymptotically as efficient as the Quadratic Maximum Likelihood Estimation (QMLE) estimator under normality. As GMM estimator is estimated based on moment conditions obtained from relevant components in the first order condition, it is considered more efficient and it doesn't have to give each moment equal weight. What's more, it is also considered to have the merit of computational simplicity and robustness. The GMM estimator is now incorporated in the spatial econometric package. (StataCorp. 2017)

4. Data

This section discusses the Singapore GLS data.

In this study, the data of URA residential land sales from 2003 to 2017 were used. In this dataset, information of both land parcel (lease years, development type, site area, planning area, GFA) and auction (award date, tenderers and their bidding prices) are provided for each auction. The total auction number in the sample is 119, including 1068 bids submitted by 216 developers individually or jointly from 2003 to 2017.

The spatial distribution of sample auction land parcels is shown in Figure 2.3. The map shows the location of residential land parcels along with two auction characteristics: award year and competition number. The color of points represents the award year, the deeper the color, the later the site sold. The size of each point, on the other hand, shows the number of participants for that auction. It could be observed that most of the recent auction land parcels locate in the central region, and those sites are more popular among bidders.

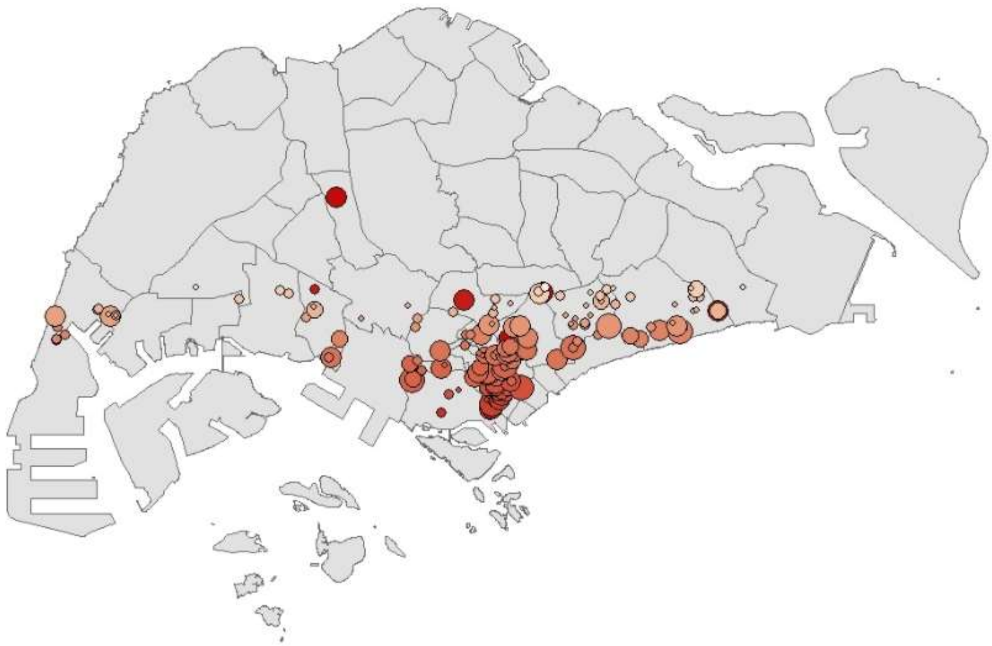

Figure 3 Award Year and Competition Number of GLS Sites

The dependent variable of interest in the following spatial analysis is the logarithmic form of bid prices, $ln(Bid\ Price)$. The independent variables are similar to previous hedonic land price studies, including auction related variables (number of competitors, auction time), auction land specifics (GFA, plot ratio, land use, planning area, distance to nearest MRT station and distance to CBD) and bidder characteristics (JV, nationality, bid-to-win strategy and recent winning experiences within 1 year).

I include the player nationality dummy, *Foreign Bidder*, here since many local developers accused the incoming foreign developers of driving up overall bidding price level and corner out local companies by bidding aggressively.[2] *Recent Winning Experience* is a dummy that takes the value 1 if the participant won an auction in the past year, which indicates both the current land stock of the recent winners and the financial restriction they might face. *Bid-to-Win* is a dummy variable that distinguish bidders' strategy. While some developers do not mind participating in more auctions, some are more determined to win particular sites and they "bid

[2] Sing Tien Foo & Chia Liu Ee, 11 AUG, 2019, "Commentary: Did aggressive land bidding by Chinese developers push up Singapore property prices?", CNA https://www.channelnewsasia.com/news/commentary/land-bidding-chinese-developers-singapore-property-rising-cost-11764932

to win". I here define Bid-to-Win players as the ones have an overall winning probability higher than 20%. *JV* is an indicator of joint venture strategy.

5 Results

5.1 Descriptive Data

Descriptive data is shown in Table 3 and Table 4.

Table 2.3 Summary Statistics (By Auction Site)

VARIABLES	(1) N	(2) mean	(3) Std.dev	(4) min	(5) max
Winning price (in thousand)	119	3.470e+08	3.600e+08	11368800	2.569e+09
Gross floor area (sqm)	119	40988.2	25434.071	3000	157738
Area	119	16.266	8.019	2.741	45.623
Plot ratio	119	3.338	2.233	.258	13.002
Lease years	119	97.966	8.462	15	99
Competition number	119	8.958	4.454	2	24
Distance to CBD (km)	119	5.319	6.054	.238	24.74
Distance to nearest MRT station (km)	119	.539	.511	.017	2.589

Table 2.4 Summary Statistics (By Auction Bid)

VARIABLES	(1) N	(2) mean	(3) Std.dev	(4) min	(5) max
Bidding Price (in million)	1068	268.002	263.35	5.7	2568.687
JV	1068	.271	.444	0	1
Foreign Bidder	1068	.224	.417	0	1
Bid-to-Win	1068	.156	.363	0	1
Recent Winning Experience	1068	.919	.272	0	1

Looking at rival characteristics in Table 2.4, it is shown in Column (2) that 27.1% of all bids are placed by JVs. Foreign bids constitute 22.4% percent of all bids. 15.6% of all bids is placed by bid-to-win players. More than 90% of bids were placed by developers that have winning experience in the recent year.

5.2 Main Results

Table 5 provides SAR results that examines the spatial spillover effect between bid pairs. In this section, I only include the spatial interaction if the time gap between the two bids is shorter than 3 years. Otherwise, the rival bids' influence is considered faded and have zero spatial spillover on current bidding prices.

Table 5 Main Results

Dependent Var: ln(Bid Price)	(1) OLS	(2) SAC	(3) SLM	(4) SEM	(5) GNSM	(6) SDM	(7) SDE	(8) SLX
ln(Gross Floor Area)	0.1362***	0.1395***	0.1364***	0.1323***	0.1357***	0.1411***	0.1385***	0.1407***
	(0.0235)	(0.0331)	(0.0329)	(0.0330)	(0.0327)	(0.0323)	(0.0325)	(0.0323)
Plot Ratio	0.2184***	0.2001***	0.2182***	0.2198***	0.2223***	0.2232***	0.2231***	0.2221***
	(0.0313)	(0.0348)	(0.0373)	(0.0371)	(0.0348)	(0.0361)	(0.0361)	(0.0364)
Competition Number	-0.0191***	-0.0180***	-0.0192***	-0.0184***	-0.0170***	-0.0181***	-0.0180***	-0.0186***
	(0.0039)	(0.0066)	(0.0066)	(0.0066)	(0.0064)	(0.0063)	(0.0063)	(0.0063)
ln(Distance to CBD)	3.0026***	2.9480***	2.9966***	3.0164***	3.0125***	2.8264***	2.7858***	2.7927***
	(0.2946)	(0.4542)	(0.4555)	(0.4598)	(0.4579)	(0.4278)	(0.4361)	(0.4333)
ln(Distance to CBD) squared	-0.1790***	-0.1769***	-0.1786***	-0.1797***	-0.1801***	-0.1681***	-0.1656***	-0.1661***
	(0.0182)	(0.0295)	(0.0293)	(0.0296)	(0.0294)	(0.0274)	(0.0280)	(0.0278)
ln(Distance to MRT)	-0.1116***	-0.0911*	-0.1095**	-0.1124**	-0.0973**	-0.1022**	-0.1034**	-0.1032**
	(0.0399)	(0.0482)	(0.0480)	(0.0477)	(0.0467)	(0.0464)	(0.0465)	(0.0465)
JV	0.1249***	0.1263***	0.1218***	0.1256***	0.1017***	0.1063***	0.1033***	0.1050***
	(0.0204)	(0.0248)	(0.0247)	(0.0248)	(0.0239)	(0.0238)	(0.0239)	(0.0238)
Foreign Bidder	0.0550***	0.0536***	0.0529***	0.0537***	0.0482***	0.0477***	0.0485***	0.0489***
	(0.0148)	(0.0129)	(0.0130)	(0.0129)	(0.0135)	(0.0135)	(0.0135)	(0.0135)
Bid-to-Win	0.0241	0.0214	0.0215	0.0238	0.0189	0.0192	0.0227	0.0229
	(0.0166)	(0.0157)	(0.0159)	(0.0157)	(0.0166)	(0.0167)	(0.0162)	(0.0162)
Recent Winning Experience	-0.1900***	-0.1912***	-0.1899***	-0.1908***	-0.1900***	-0.1896***	-0.1926***	-0.1929***
	(0.0220)	(0.0194)	(0.0191)	(0.0193)	(0.0191)	(0.0190)	(0.0190)	(0.0188)
ρ.ln(Bid Price)		**0.0035****	**0.0039*****		**0.0098**	**0.0112***		
		(0.0015)	**(0.0015)**		**(0.0065)**	**(0.0066)**		
λ.error		0.0179		0.1384*	0.1087		0.1535	
		(0.0941)		(0.0834)	(0.1141)		(0.1146)	
θ.JV					-0.4224***	-0.4229***	-0.4435***	-0.4244***
					(0.0918)	(0.0925)	(0.0926)	(0.0937)
θ.(Foreign Bidder)					0.2209**	0.2068**	0.2418**	0.2295**
					(0.1006)	(0.1009)	(0.0993)	(0.0998)
θ.(Bid-to-Win)					-0.0836	-0.0969	0.0079	0.0052
					(0.1060)	(0.1078)	(0.0700)	(0.0707)
θ.(Recent Winning Experience)					-0.0064	-0.0238	0.1812***	0.1831***
					(0.1181)	(0.1209)	(0.0453)	(0.0458)
Constant	8.3401***	8.4821***	8.3394***	8.3104***	8.3658***	8.9215***	9.1113***	9.0549***

	(1.0928)	(1.7499)	(1.7711)	(1.7879)	(1.7287)	(1.6534)	(1.6803)	(1.6693)
Observations	1,068	1,068	1,068	1,068	1,068	1,068	1,068	1,068
R2/Pseudo R2	0.9571	0.9574	0.9575	0.9570	0.9585	0.9586	0.9585	0.9585
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Planning Area FE	YES	YES	YES	YES	YES	YES	YES	YES
Land Use FE	YES	YES	YES	YES	YES	YES	YES	YES
Year*Planning Area FE	YES	YES	YES	YES	YES	YES	YES	YES

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

Comparing the baseline OLS results in Column (1) with SAR results in Column (2) to (8), it could be observed that the overall direction and quantity of hedonic coefficients is consistent, especially the ones in which spatial-lagged explanatories are omitted.

Column (2), (3), (5) and (6) in Table 5 gives the estimation results of four SAR specifications that include spatial lagged terms dependent variable. Comparing with the OLS results in Column (1), it could be observed that there exists a positive relationship between bidding prices and rival bids. However, the coefficient of rival price spillover, ρˆ, is less than 0.01, which indicates a very small positive correlation between rivals' bidding prices. The relationship is significant in SAC and SLM and became less significant in GNSM and SDM estimations, in which the indirect effect of rivals were controlled.

The results presented in Column (5)-(8) from Table 5 show the coefficients of rival features. It could be seen that, two rival characteristics have significant impact on bid prices. Pseudo R2 in these models are improved as well. These findings indicate the need to incorporate spatial-lagged explanatories in SAR structure.

Specifically, rivals' JV strategy is negatively correlated with developers' auction price, which is in opposite direction with the impact of developers' own JV strategy. As for nationality, while foreign developers are proved to be more aggressive overall, local bidders are stimulated to adopt a more aggressive strategy when competing with a foreign rival.

It could also be observed that rivals' recent winning experience tend to have a positive correlation with bidding prices when the spatial lagged dependent variable is not included in regression. This change implies that, the estimation of past bidding prices and certain rival features' influence could be biased if key variables are omitted in the SAR structure.

In Column (2), (4), (5) and (7), the spatial lag of error term is included in the SAR structure and the coefficients of spatial-lagged error appear to be insignificant in all specifications. Therefore, the spillover of unobservable factors is negligible.

Although the results presented in Table 5 are only intermediate results that reflect spatial autocorrelation, they could provide valuable information for model comparison and selection.

5.3 Model Comparison

As stated in Anselin (2002), the selection of SAR models should be motivated on either theoretical or practical grounds. However, the mechanism of rival spillover in repeated first price land auctions has not been specified in literature. Statistical tests, therefore, are required for model comparison.

As all seven SAR specifications were used in this study, it is necessary to apply statistical tests for model comparison and selection. Figure A3 shows my logic of SAR model selection using LM test based on Anselin' s textbook (2017). The results of LM tests are given in the Table 6.

Table 6 Model Selection Diagnostics

Test	Statistic	df	p-value
Spatial error:			
Moran's I	10.160	1	0.000
Lagrange multiplier	1297.790	1	0.000
Robust Lagrange multiplier	1292.950	1	0.000
Spatial lag:			
Lagrange multiplier	193.245	1	0.000
Robust Lagrange multiplier	188.406	1	0.000

It is shown in Table 6 that Moran's I of spatial error is significantly positive, which indicates the need to incorporate spatial-lagged error term in SAR structure. This finding is confirmed by the LM test results. Both LM-lag and LM-error diagnostics provide significant result, which indicates that spatial-lagged dependent variable and spatial-lagged error appears to be significant when they are included in the SAR structure respectively. What's more, the robust LM multipliers, which tests their significance against the other terms' existence in the SAR model, are also significant. These results, altogether, suggest that ρ and λ does not equal to 0. (Osland, 2010)

However, as the LM test results in Table 6 only compare models with spatial error and spatial-lagged dependent variables, the outcomes did not mention the SAR specifications with spatial-lagged independent variables. In fact, previous land auction studies have included variables like number of participating bidders and the price difference between the winning bids and other bids in hedonic models to capture intensity of competition environment. (Dong and Sing, 2014). In Kwiek's 2011 work, he argued that aside from cooperation, competitors' reputation of "being aggressive" has an impact on bidders' bidding strategy in a repeated auction framework as well. All these findings indicate that spatial-lagged developer characteristic explanatories, which have been proven to have a crucial influence on auction outcome, should not be omitted in the SAR structure.

To further compare all seven specifications, I include weighted rival characteristics in model structure, and the LM test results are presented in Table 7 below.

Table 7 Model Selection Diagnostics (with spatial-lagged explanatories)

Test	Statistic	df	p-value
Spatial error:			
Moran's I	9.846	1	0.000
Lagrange multiplier	1047.956	1	0.000
Robust Lagrange multiplier	1043.684	1	0.000
Spatial lag:			
Lagrange multiplier	187.464	1	0.000
Robust Lagrange multiplier	183.192	1	0.000

In this case, it could be observed that all the LM results are still significant, which means that spatial-lagged error and spatial-lagged dependent variables are still necessary components in the model when spatial-lagged explanatories are included. Therefore, GNSM is considered as an appropriate choice for estimation. Only in GNSM, the indirect spillover effects coming from both potential rival's past bids ($lnBidPrice_{jbst'}$), and their characteristics ($\boldsymbol{Z}_{\boldsymbol{jbst'}}$), as well as unobservable sources of spillover (μ) are tested at the same time. This allows us to test if any of those rival features have significant spatial correlation with developers' bidding behavior. If so, the patterns of direct and indirect effects could be discussed as well.

This conclusion is also supported by LeSage et al. (2008). They suggested that, among all SAR specifications, it is more intuitive to apply GNSM specification for rival relationship analysis. Although SEM has been used in many spatial growth studies, it is theoretically correct only if 1) there is no omitted explanatory variables at all, or 2) if there is not spatial correlation between included explanatory variables. These are very strong assumptions that could hardly be met in real life context. SDE and SLX, on the other hand, assume independence between each bid price, but include characteristics from rivals in the form of explanatory variables and error terms. SLM and SAC include a spatial lag of rivals' bid prices, but exclude these competitors' strategy. These two model specifications could hardly depict the real situation as it is highly possible that these models omitted some key channels of rival spillover. Comparing the pseudo R^2 of column (2) and (3) in Table 5 with the ones in column (4)-(8), these statements could be further confirmed.

5.4 Effect Analysis

Table 5 gives the intermediate results that reflect spatial autocorrelation, in which the coefficients of developers' own characteristics include is the sum of direct effect and bidders' reaction of rival's perception. The results of effect analysis shown in Table 8, on the other hand, could provide an accurate estimation of direct and indirect effect.

Table 8 Direct and Indirect Effect from GNSM estimation

	Direct		**Indirect**	
	dy/dx	Std.Err.	dy/dx	Std.Err.
Ln(Gross Floor Area)	0.1357***	0.0327	0.0012	0.0009
Ln(Plot Ratio)	0.2223***	0.0348	0.0020	0.0014
Competition Number	-0.0170***	0.0064	-0.0002	0.0001
Ln(Distance to CBD)	3.0125***	0.4579	0.0272	0.0189
Ln(Distance to CBD)^2	-0.1801***	0.0294	-0.0016	0.0011
Ln(Distance to MRT)	-0.0973**	0.0467	-0.0009	0.0007
JV	0.1017***	0.0239	-0.3868***	0.0847
Foreign Bidder	0.0482***	0.0135	0.2032**	0.0922
Bid-to-win	0.0189	0.0166	-0.0766	0.0977
Recent Winning Experience	-0.1900***	0.0191	-0.0076	0.1095

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

The estimation outcomes of hedonic factors in Table 8 indicate that there is very little indirect influence coming from rival bids' site-specific characteristics, competition number and two rival characteristics (dummies of bid-to-win strategy and recent winning experiences).

Looking into the effect of JV variable, it could be observed that while being a part of JV have a positive direct influence on auction price, a developer is likely to bid significantly lower when they feel like they would encounter a competitor that used to be a part of land auction JV. In fact they will bid 39% lower if all other bidders adopt JV, which is 104 million less on average. The reason might lie in the fact that for the bidder themselves, adopting JV strategy means the pooling of resource and information, which would lead to a competitive bidding price. But when developers sense they are about to meet with a competitor that used to adopt JV strategy, they would not try to match up with its bidding price.

However, developers tend to be more determined when facing foreign rivals, even though their foreign competitors are proved to be more aggressive in past auctions. If all other bidders are foreign bidders, developer would bid 20% more, which is 54 million more in bid price.

For those players that has recent winning experience within a year, I found that they tend to bid lower due to financial constraint, but this feature has little spillover effect to other GLS players. The conservativeness of players have no significant impact on bid prices, either directly or indirectly.

5.5 Comparison with Binary Weight Matrix results

As mentioned above, the main results were estimated using an estimated spatial weight matrix. In Table 9 and Table 10, I present the results estimated using the binary spatial matrix $\boldsymbol{W_1}$. In $\boldsymbol{W_1}$ each element w_{1ij} takes the value 1 if the bidder of bid i competed with bidder of bid j in the past and 0 otherwise.

Table 9 Main Result (Binary Weights)

Dependent Var: ln(Bid Price)	(1) SAC	(2) SLM	(3) SEM	(4) GNSM	(5) SDM	(6) SDE	(7) SLX
ln(Gross Floor Area)	0.132***	0.135***	0.132***	0.154***	0.139***	0.137***	0.139***
	(0.0338)	(0.0338)	(0.0339)	(0.0331)	(0.0332)	(0.0333)	(0.0332)
Plot Ratio	0.588***	0.575***	0.575***	0.542***	0.590***	0.588***	0.588***
	(0.100)	(0.0998)	(0.0994)	(0.0905)	(0.0972)	(0.0968)	(0.0976)
Competition Number	-0.0217***	-0.0222***	-0.0214***	-0.0185***	-0.0209***	-0.0208***	-0.0213***
	(0.00680)	(0.00670)	(0.00667)	(0.00619)	(0.00633)	(0.00632)	(0.00634)
ln(Distance to CBD)	2.921***	2.740***	2.760***	2.469***	2.585***	2.548***	2.554***
	(0.441)	(0.418)	(0.422)	(0.361)	(0.396)	(0.400)	(0.397)
ln(Distance to CBD) squared	-0.173***	-0.162***	-0.163***	-0.147***	-0.152***	-0.150***	-0.150***
	(0.0282)	(0.0268)	(0.0271)	(0.0235)	(0.0252)	(0.0256)	(0.0253)
ln(Distance to MRT)	-0.118**	-0.118**	-0.121**	-0.0898*	-0.112**	-0.114**	-0.113**
	(0.0484)	(0.0482)	(0.0480)	(0.0464)	(0.0468)	(0.0469)	(0.0470)
JV	0.121***	0.120***	0.125***	0.117***	0.105***	0.103***	0.104***
	(0.0252)	(0.0251)	(0.0252)	(0.0243)	(0.0243)	(0.0244)	(0.0243)
Foreign Bidder	0.0522***	0.0520***	0.0532***	0.0479***	0.0466***	0.0474***	0.0476***
	(0.0128)	(0.0129)	(0.0129)	(0.0134)	(0.0135)	(0.0135)	(0.0135)
Bid-to-Win	0.0220	0.0214	0.0238	0.0172	0.0191	0.0219	0.0220
	(0.0157)	(0.0159)	(0.0157)	(0.0166)	(0.0166)	(0.0161)	(0.0161)
Recent Winning Experience	-0.191***	-0.191***	-0.193***	-0.191***	-0.194***	-0.198***	-0.197***
	(0.0196)	(0.0193)	(0.0195)	(0.0194)	(0.0191)	(0.0190)	(0.0189)
ρ.ln(Bid Price)	**0.00361****	**0.00398*****		**0.00971**	**0.00915**		

	(0.00154)	**(0.00153)**		**(0.00650)**	**(0.00657)**		
λ.error	0.0322		0.140*	0.103		0.133	
	(0.0955)		(0.0848)	(0.113)		(0.113)	
θ.JV				-0.441***	-0.423***	-0.435***	-0.419***
				(0.0912)	(0.0913)	(0.0908)	(0.0918)
θ.(Foreign Bidder)				0.233**	0.199**	0.223**	0.213**
				(0.101)	(0.101)	(0.0993)	(0.0997)
θ.(Bid-to-Win)				-0.138	-0.0983	-0.0133	-0.0174
				(0.107)	(0.110)	(0.0739)	(0.0750)
θ.(Recent Winning Experience)				0.00678	0.0224	0.188***	0.190***
				(0.119)	(0.120)	(0.0457)	(0.0463)
Constant	8.642***	9.264***	9.231***	9.971***	9.806***	9.976***	9.932***
	(1.705)	(1.624)	(1.640)	(1.386)	(1.524)	(1.539)	(1.527)
Observations	1,068	1,068	1,068	1,068	1,068	1,068	1,068
Pseudo R-squared	0.9575	0.9576	0.9571	0.9586	0.9588	0.9586	0.9587
Year FE	YES	YES	YES	YES	YES	YES	YES
Planning Area FE	YES	YES	YES	YES	YES	YES	YES
Land Use FE	YES	YES	YES	YES	YES	YES	YES
Year*Planning Area FE	YES	YES	YES	YES	YES	YES	YES

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

Table 10 Direct and Indirect Effect from GNSM estimation (Binary W)

	Direct		Indirect	
	dy/dx	Std.Err.	dy/dx	Std.Err.
Ln(Gross Floor Area)	0.1543***	0.0331	0.0014	0.0010
Ln(Plot Ratio)	0.5418***	0.0905	0.0048	0.0034
Competition Number	-0.0185***	0.0062	-0.0002	0.0001
Ln(Distance to CBD)	2.4688***	0.3611	0.0217	0.0152
$Ln(Distance to CBD)^2$	-0.1467***	0.0235	-0.0013	0.0009
Ln(Distance to MRT)	-0.0898*	0.0464	-0.0008	0.0007
JV	0.1170***	0.0243	-0.3987***	0.0829
Foreign Bidder	0.0479***	0.0134	0.2111**	0.0916
Bid-to-win	0.0172	0.0166	-0.1250	0.0976
Recent Winning Experience	-0.1910***	0.0194	0.0045	0.1086

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

As shown in Table 9 and Table 10, the results remain overall consistent with the one yielded using estimated weights. However, while using the binary weight matrix, LM test results in Table 11 and Table 12 indicate that the incorporation of spatial error should be included in the spatial regression, which is contradicted to the Moran's I of spatial error, and this contradiction is not affected by the inclusion of spatial-lagged independent variables. All these findings suggest that the model selection process requires further adjustment in the OLS model.

Table 11 Model Selection Diagnostics (Binary W)

Test	Statistic	df	p-value
Spatial error:			
Moran's I	0.990	1	0.322
Lagrange multiplier	1087.087	1	0.000
Robust Lagrange multiplier	1081.890	1	0.000
Spatial lag:			
Lagrange multiplier	202.141	1	0.000
Robust Lagrange multiplier	196.945	1	0.000

Table 12 Model Selection Diagnostics
(Binary W, with spatial-lagged explanatories)

Test	Statistic	df	p-value
Spatial error:			
Moran's I	0.990	1	0.322
Lagrange multiplier	877.753	1	0.000
Robust Lagrange multiplier	873.173	1	0.000
Spatial lag:			
Lagrange multiplier	194.270	1	0.000
Robust Lagrange multiplier	189.689	1	0.000

The cause of this issue probably lies in the lack of first stage regression, which could eliminate a large part of unobservables that drive bids to co-agglomerate in the space of land auctions.

6. Robustness Check

In this section, we altered the spatial weight matrix in two ways to check for robustness: (1) setting different influential time window; (2) keeping only frequent players' spillover effect.

6.1 Results with Different Influential Time Window

In the Main Result section, the influential time window of bid record is set to 3 years and history prices are considered to have no influence on developers' current price formation process if they take place out of the window. The assumption is made to mimic developers' decision-making mindset in real life. Due to the cost of data collection, rival records from distant past might not be developers' major concern. It is also highly possible that developers' influential power is not consistent overtime.

As the 3-year time window is set arbitrarily, here I present the estimation results generated using different time windows for comparison. The regression outcomes of all GNSM estimation using different time windows are presented in Table 13.

In general, it could be overserved when the influential window is longer than 3 years, the pseudo R^2 is smaller. This pattern indicates that including too much history information in analysis is inefficient. In fact, the 3-year window could be considered as an efficient one.

Comparing effect analysis results in Table 14 and Table 7, I found that the significance of the indirect effects of JV and foreign bidder dummy decreased after the whole sample period is included in analysis. This shows that aside from increasing the cost of collecting information, adding too much history information could bias the estimation.

Table 13 GNSM Results of Different Time-Window

Dependent Var: ln(Bid Price)	(1) 3m	(2) 6m	(3) 1y	(4) 3y	(5) 5y	(6) all
ln(Gross Floor Area)	0.1403***	0.1303***	0.1363***	0.1357***	0.1260***	0.1786***
	(0.0321)	(0.0319)	(0.0323)	(0.0327)	(0.0337)	(0.0392)
Plot Ratio	0.2288***	0.2490***	0.2377***	0.2223***	0.2519***	0.1385***
	(0.0365)	(0.0372)	(0.0376)	(0.0348)	(0.0351)	(0.0337)
Competition Number	-0.0223***	-0.0193***	-0.0188***	-0.0170***	-0.0133*	-0.0220***
	(0.0059)	(0.0061)	(0.0064)	(0.0064)	(0.0069)	(0.0061)
ln(Distance to CBD)	2.0700***	3.1694***	3.2586***	3.0125***	4.1943***	1.3068***
	(0.2980)	(0.4390)	(0.4967)	(0.4579)	(0.6097)	(0.4197)
ln(Distance to CBD) Squared	-0.1190***	-0.1879***	-0.1943***	-0.1801***	-0.2530***	-0.0761***
	(0.0194)	(0.0280)	(0.0316)	(0.0294)	(0.0389)	(0.0283)
ln(Distance to MRT)	-0.1434***	-0.1328***	-0.1103**	-0.0973**	-0.1167**	-0.0794
	(0.0472)	(0.0463)	(0.0470)	(0.0467)	(0.0514)	(0.0595)
JV	0.1207***	0.1069***	0.1079***	0.1017***	0.1031***	0.1430***
	(0.0238)	(0.0233)	(0.0238)	(0.0239)	(0.0245)	(0.0280)
Foreign Bidder	0.0438***	0.0456***	0.0449***	0.0482***	0.0470***	0.0568***
	(0.0131)	(0.0133)	(0.0134)	(0.0135)	(0.0138)	(0.0136)
Bid-to-Win	0.0126	0.0169	0.0181	0.0189	0.0139	0.0277
	(0.0164)	(0.0167)	(0.0170)	(0.0166)	(0.0172)	(0.0174)
Recent Winning Experience	-0.1956***	-0.1895***	-0.1851***	-0.1900***	-0.1840***	-0.2030***
	(0.0184)	(0.0186)	(0.0190)	(0.0191)	(0.0198)	(0.0193)
ρ.ln(Bid Price)	**0.0500*****	**0.0501***	**0.0156***	**0.0098**	**0.0242***	**0.0054**
	(0.0082)	**(0.0090)**	**(0.0060)**	**(0.0065)**	**(0.0090)**	**(0.0098)**
λ.error	-0.1657*	-0.2629**	-0.2378*	0.1087	0.0892	0.0841
	(0.0949)	(0.1167)	(0.1416)	(0.1141)	(0.1210)	(0.1029)

θ.JV	-0.1252**	-0.1904***	-0.2504***	-0.4224***	-0.3576***	-0.2419**
	(0.0596)	(0.0635)	(0.0861)	(0.0918)	(0.0938)	(0.1048)
θ.(Foreign Bidder)	-0.0345	0.0164	0.0253	0.2209**	0.0916	0.2217**
	(0.0674)	(0.0699)	(0.0935)	(0.1006)	(0.0972)	(0.0968)
θ.(Bid-to-Win)	-0.2657***	-0.1566*	-0.1212	-0.0836	-0.1614	0.1447
	(0.0987)	(0.0828)	(0.0824)	(0.1060)	(0.1139)	(0.1280)
θ.(Recent Winning Experience)	-0.8507***	-0.8477***	-0.1373	-0.0064	-0.2910*	-0.0368
	(0.1546)	(0.1754)	(0.1132)	(0.1181)	(0.1708)	(0.1880)
Constant	11.7787***	7.8004***	7.4033***	8.3658***	4.3410*	13.8602***
	(1.2291)	(1.6778)	(1.8886)	(1.7287)	(2.2171)	(1.9054)
Observations	1,068	1,068	1,068	1,068	1,068	1,068
Pseudo R2	0.9586	0.9591	0.9583	0.9585	0.9571	0.9560
Year FE	YES	YES	YES	YES	YES	YES
Planning Area FE	YES	YES	YES	YES	YES	YES
Land Use FE	YES	YES	YES	YES	YES	YES
Year*Planning Area FE	YES	YES	YES	YES	YES	YES

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

Table 14 Direct and Indirect Effect from GNSM estimation (15 years)

	Direct		Indirect	
	dy/dx	Std.Err.	dy/dx	Std.Err.
Ln(Gross Floor Area)	0.1786***	0.0392	0.0009	0.0017
Ln(Plot Ratio)	0.1385***	0.0337	0.0007	0.0013
Competition Number	-0.0220***	0.0061	-0.0001	0.0002
Ln(Distance to CBD)	1.3068***	0.4197	0.0065	0.0123
Ln(Distance to CBD)^2	-0.0761***	0.0283	-0.0004	0.0007
Ln(Distance to MRT)	-0.0794	0.0595	-0.0004	0.0007
JV	0.1430***	0.0280	-0.2206**	0.0960
Foreign Bidder	0.0568***	0.0136	0.2031**	0.0885
Bid-to-win	0.0277	0.0174	0.1325	0.1161
Recent Winning Experience	-0.2030***	0.0193	-0.0347	0.1741

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

6.2 Results with No Spillover from Infrequent Players

In this test, while the infrequent players are still considered influenced by frequent players' previous actions, I removed the spillover of infrequent players by setting their bids' spatial weight zero. Infrequent players are defined as GLS participants that have played less than ten times or have no winning experience during the fifteen-year sample period.

The intuition of this check is to reflect the key player policy in network games. (Ballester et al., 2006; Lee et al., 2020). As shown in Table A1, 68.44% of the bids were placed by frequent players. It is highly possible that instead of every possible competitor, developers only study the behavior pattern of the major players.

It is worth noticing that lower GLS participation does not necessarily indicates a weaker market position or a smaller market share. However, it does imply that the developer has little interest in GLS sites or competition. This differences in preference and strategy would further lead major players to pay less attention to the infrequent players' behavior since they either barely show up or never won even once.

Results presented in Table 15 and Table 16 are considered robust with the main results. Both the direction and magnitude of coefficients are considered consistent with the ones listed in Table 5 and 6.

Table 15 Estimation Result with Only Frequent Players' Spillover

Dependent Var: ln(Bid Price)	(1) SAC	(2) SLM	(3) SEM	(4) GNSM	(5) SDM	(6) SDE	(7) SLX
ln(Gross Floor Area)	0.1453***	0.1367***	0.1318***	0.1205***	0.1391***	0.1401***	0.1424***
	(0.0331)	(0.0329)	(0.0330)	(0.0331)	(0.0322)	(0.0323)	(0.0322)
Plot Ratio	0.2007***	0.2164***	0.2204***	0.2695***	0.2352***	0.2264***	0.2249***
	(0.0361)	(0.0377)	(0.0370)	(0.0398)	(0.0360)	(0.0355)	(0.0359)
Competition Number	-0.0203***	-0.0194***	-0.0182***	-0.0154**	-0.0179***	-0.0179***	-0.0187***
	(0.0063)	(0.0065)	(0.0065)	(0.0067)	(0.0063)	(0.0062)	(0.0062)
ln(Distance to CBD)	2.2948***	2.8673***	3.0291***	4.0207***	3.1004***	2.8036***	2.8055***
	(0.3161)	(0.4382)	(0.4590)	(0.7106)	(0.4729)	(0.4343)	(0.4324)
ln(Distance to CBD) squared	-0.1350***	-0.1705***	-0.1804***	-0.2414***	-0.1853***	-0.1670***	-0.1673***
	(0.0209)	(0.0282)	(0.0295)	(0.0447)	(0.0301)	(0.0279)	(0.0277)
ln(Distance to MRT)	-0.1064**	-0.1124**	-0.1138**	-0.1145**	-0.0991**	-0.0985**	-0.0968**
	(0.0500)	(0.0477)	(0.0476)	(0.0480)	(0.0467)	(0.0465)	(0.0468)
JV	0.1326***	0.1219***	0.1255***	0.0941***	0.1033***	0.1027***	0.1044***
	(0.0250)	(0.0247)	(0.0248)	(0.0238)	(0.0236)	(0.0236)	(0.0236)
Foreign Bidder	0.0534***	0.0531***	0.0540***	0.0445***	0.0469***	0.0473***	0.0477***
	(0.0128)	(0.0130)	(0.0129)	(0.0136)	(0.0135)	(0.0134)	(0.0135)
Bid-to-Win	0.0219	0.0211	0.0232	0.0135	0.0163	0.0193	0.0192
	(0.0158)	(0.0160)	(0.0156)	(0.0168)	(0.0167)	(0.0163)	(0.0164)
Recent Winning Experience	-0.1912***	-0.1906***	-0.1906***	-0.1882***	-0.1866***	-0.1888***	-0.1891***
	(0.0192)	(0.0191)	(0.0192)	(0.0195)	(0.0191)	(0.0191)	(0.0189)
ρ.ln(Bid Price)	**0.0027***	**0.0038****		**0.0106**	**0.0116**		
	(0.0016)	**(0.0015)**		**(0.0073)**	**(0.0075)**		
λ.error	0.1943**		0.2701***	0.2584**		0.2652***	
	(0.0768)		(0.0747)	(0.1113)		(0.1022)	
θ.JV				-0.4584***	-0.4852***	-0.5207***	-0.5051***
				(0.1067)	(0.1087)	(0.1081)	(0.1106)

θ.(Foreign Bidder)				0.2668**	0.2807**	0.3245***	0.3119***
				(0.1184)	(0.1200)	(0.1179)	(0.1197)
θ.(Bid-to-Win)				-0.1163	-0.1036	-0.0114	-0.0216
				(0.0974)	(0.1016)	(0.0812)	(0.0807)
θ.(Recent Winning Experience)				-0.0099	-0.0128	0.1996***	0.2098***
				(0.1383)	(0.1406)	(0.0479)	(0.0484)
Constant	10.6726***	8.7984***	8.2530***	4.7685*	7.9557***	9.0355***	9.0013***
	(1.3132)	(1.7205)	(1.7863)	(2.6301)	(1.8002)	(1.6738)	(1.6640)
Observations	1,068	1,068	1,068	1,068	1,068	1,068	1,068
Pseudo R-squared	0.9569	0.9574	0.9569	0.9577	0.9587	0.9584	0.9586
Year FE	YES	YES	YES	YES	YES	YES	YES
Planning Area FE	YES	YES	YES	YES	YES	YES	YES
Land Use FE	YES	YES	YES	YES	YES	YES	YES
Year*Planning Area FE	YES	YES	YES	YES	YES	YES	YES

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

Table 16 Direct and Indirect Effect from GNSM estimation
(Only Frequent Players)

	Direct		**Indirect**	
	dy/dx	Std.Err.	dy/dx	Std.Err.
Ln(Gross Floor Area)	0.1205***	0.0331	0.0012	0.0009
Ln(Plot Ratio)	0.2695***	0.0398	0.0026	0.0019
Competition Number	-0.0154**	0.0067	-0.0001	0.0001
Ln(Distance to CBD)	4.0207***	0.7106	0.0391	0.0285
Ln(Distance to CBD)^2	-0.2414***	0.0447	-0.0023	0.0017
Ln(Distance to MRT)	-0.1145**	0.0480	-0.0011	0.0009
JV	0.0941***	0.0238	-0.4185***	0.0980
Foreign Bidder	0.0445***	0.0136	0.2445**	0.1082
Bid-to-win	0.0135	0.0168	-0.1063	0.0896
Recent Winning Experience	-0.1882***	0.0195	-0.0109	0.1278

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

Comparing the estimation outcomes and pseudo R^2 reported in Table 15 and Table 5, I could draw a conclusion that eliminating the infrequent players spatial spillover does not have a significant impact on either the numeric outcomes or the model's explanation power.

Table 16 presents the effect analysis outcomes of GNSM model using the data of frequent players. Comparing with the results in Table 6, indirect effects of JV and foreign in Table 16 is slightly larger, which is consistent with previous empirical findings concerning key player policy (Lee et al., 2020). Overall, the results are considered robust with the main findings.

7. On the Competitive Environment of Singapore Land Market

In this section we discuss this chapter's implication on the future development of Singapore land market with a focus on the competition environment.

In Singapore, property developments are closely monitored by the government to maintain a healthy real estate market. Over the years, Singapore government has carried out several measures to ensure that housing prices in private residential market move in line with economic fundamentals. The ultimate goal is to keep the property market sustainable and resilient to external shocks like recessions. Under this background, the aggressive bidding strategies of foreign bidders attracts attention. Specifically, people are curious about two things: would high land prices lead to higher property price, and would the aggressive foreign player crowd out local developers.

There are certainly many complaints toward aggressive foreign bidders, especially the ones from mainland China. It is shown in Figure A2 that Chinese players started to win more and more GLS sites since 2009. In fact, more than 20% of GLS sites released in 2017 were won by Chinese players. However, would they harm the sustainability of property market?

The answer lies in the rationale behind those aggressive bids. The premium paid by foreign bidders may be explained by two hypotheses: 1) Information asymmetry, as foreign developers new to Singapore lack knowledge of local market; 2) Foreign developers have acquired enough experience in their country on how to reduce marginal cost. (Coulson et al., 2018) In the first case, the price gap between foreign and local bidders would narrow over time. In the second case, higher land cost does not necessarily lead to higher housing prices as foreign developers' better know-how enables them to remain profitable even when land costs are high. In fact, this point is supported by the data provided in Chua and Sing's commentary article.[3] They found that, controlling for hedonic factors and transaction time, the price of new residential property launched by Chinese developers is 3% lower than those launched by local developers.

Therefore, the first question is answered. The influx of foreign developers may have benefitted average home buyers in Singapore. But what about local developers?

As stated in the previous chapter, competition is not necessarily a bad thing. On the contrary, local rivalry is highly motivating. Intimidated by foreign players, executives in local firms would be stimulated to outdo their rivals. This is supported by the empirical findings in this chapter as I found firms tend to match the offers made by their foreign rivals. In addition, being in the same market also makes it easier for all market participants to compare performances of each other. Local developers could thus acquire knowledge spillover from productive foreign developers and enhance their own performance. If the government simply protect local companies from global competition,

[3] Sing Tien Foo & Chia Liu Ee, 11 AUG, 2019, "Commentary: Did aggressive land bidding by Chinese developers push up Singapore property prices?", CNA https://www.channelnewsasia.com/news/commentary/land-bidding-chinese-developers-singapore-property-rising-cost-11764932

innovation and industry upgrade in property market would be hindered. (Porter, 1998).

To sum up, welcoming foreign competitors could do more good than harm for both local homeowners and local developers.

8. Conclusion

This paper investigated the empirical evidence of the spatial strategic interaction between rivals in a framework of repeated simultaneous games using Singapore GLS data.

Comparing the results yielded from different SAR model specifications, I find consistent evidence of rival spillover: In an oligopolistic land market, developers' bidding price formation process is significantly correlated with their potential competitors' past bidding records, both through bid prices and their own strategy and features.

Overall, developers tend to bid more aggressively when they have a higher probability to encounter a competitive rival. Specifically, they also tend to bid higher when they are a part of JV, but exhibit lower level of aggressiveness when their potential rival used to be a part of joint venture. Foreign players tend to bid higher and their participation stimulate local competitors to bid higher as well.

The results of robustness checks also provide interesting insights. Comparing the results yielded using different influential time windows, I found that rival spillover is not homogenous across time. 3-year is an efficient time window to capture rival influence. What's more, the SAR results remain robust when there is only spatial spillover from frequent players in the game structure, which indicates that players have different perception and reaction pattern toward different rivals. This finding highlights the need to differentiate players in a context of repeated oligopoly.

Aside from providing reference for competitive strategy between land auction participants, this study also has profound methodological implications as it extends the application range of spatial econometrics to game contexts. Though previous work has mentioned the possibility of applying spatial econometrics in game structure, little attempt has been made empirically to realize the potential. This study explored this potential by applying SAR regressions in the analysis of spatial strategic interaction in repeated simultaneous land auctions. Although it is argued that endogeneity would appear while using spatial econometrics in non-geographical context, the GMM procedure I followed would make its effect under control. Altogether, the findings suggest the possibility of estimation bias in traditional OLS estimation, which further confirms the need to incorporate the spatial connectivity weight matrix in auction price analysis.

The findings concerning the interaction in oligopolistic land market could also provide interesting insights on the analysis of oligopolistic housing market. As the interaction pattern between rivals has been proved to have a significant influence on land price formation, it is highly possible that a competitive environment itself would drive up the winning prices of land auctions, as shown in Figure A1.2. Therefore, the winner might bear a competition premium in their land cost and this would further lead to higher financial risk. This phenomenon, commonly referred as “winners’ curse”, is proved in previous studies to have a strong influence on developers’ product pricing scheme. (Ong et al., 2003) The profound influence of land price formation on housing market could be an interesting area worthy of further exploration.

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Appendix

Table A1 Top Developers' Winning Experience

Rank	Developer	Frequency
1	Far East Organization	11
2	Frasers Centrepoint Limited (FCL)	6
2	City Developments Limited (CDL)	6
2	MCL Land	6
5	CEL Development	5
5	CapitaLand	5
5	UOL Group Limited	5
5	WingTai	5
9	Hong Leong Investment Holdings (HLIH)	4
9	HoiHup	4
9	Keppel Land	4
9	SimLian	4
9	SingLand	4
9	Sunway	4
Number of auction won by top developers		66
Total number of auction		120
Percentage of auction won by top developers		55%

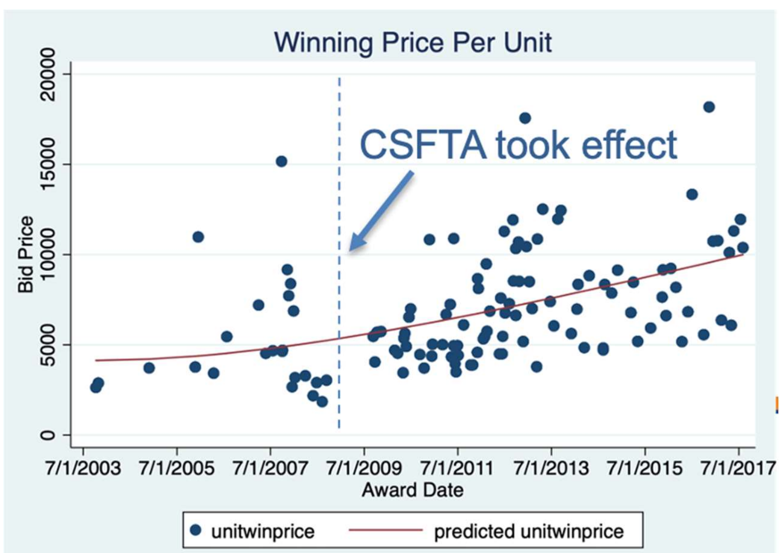

Figure A1 Winning Price Per Unit, 2003-2017

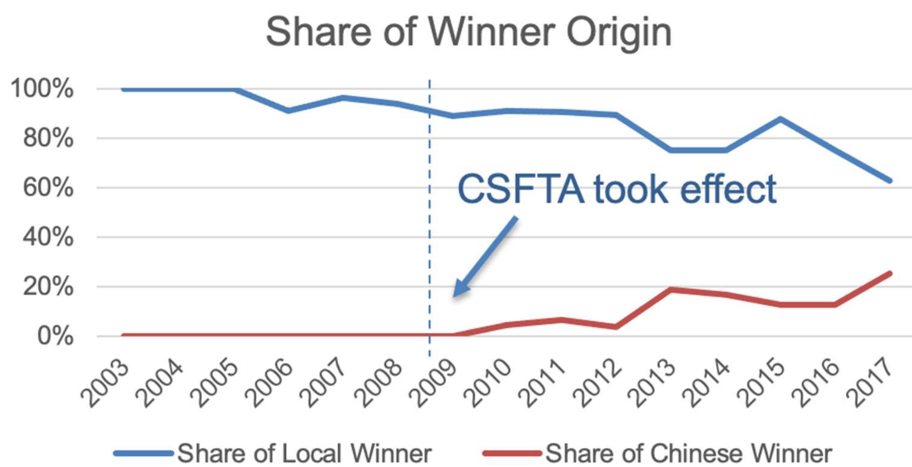

Figure A2 Share of Winner Origin

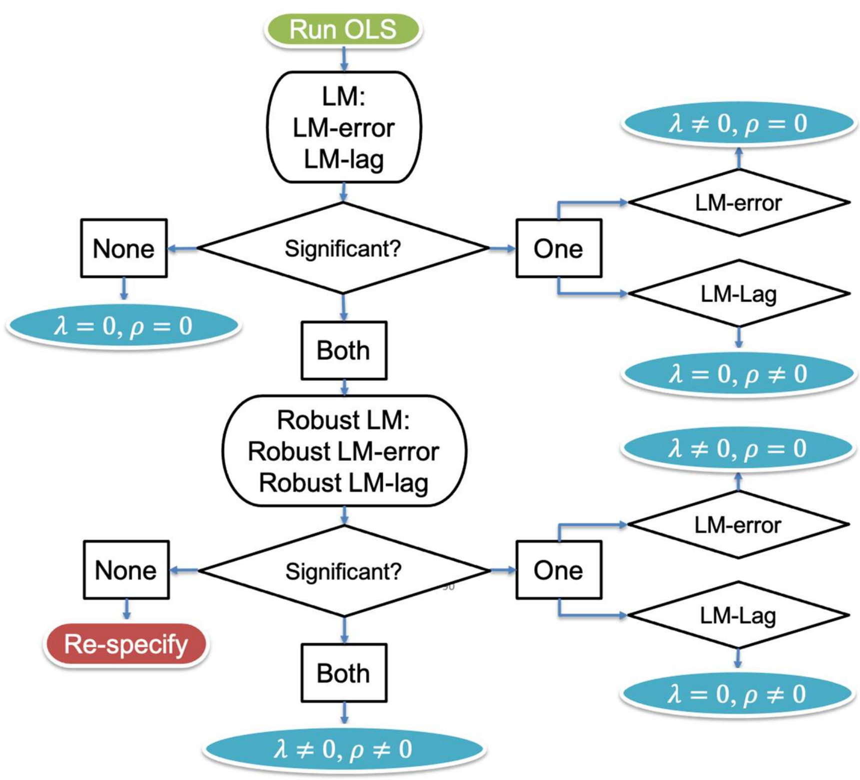

Figure A3 LM Test Procedure