Dynamic Competition of Real Estate Developers in Hong Kong: Lesson on Counter-cycle Policy*

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Abstract

Cyclical, or counter-cyclical, policy tends to be regarded as less disruptive to the market than universal/acyclical policy[1], but it is less certain when dynamic competition is involved. Utilizing a unique transaction-level dataset converted from sales documents, I study the impact of counter-cycle policy by structurally estimating the dynamic competition of the Hong Kong real estate primary market, in comparison with the acyclical policy. With the help of satellite images and other peripheral data, workarounds on data issues can be made. By approximating with an Extended Oblivious Equilibrium (EOE) that accommodates market shocks, this competition with many firms is feasibly estimated after drastically reducing the state space from the order of 55. The counterfactual analysis shows that counter-cycle policy indeed introduces an impact more extensive than acyclical policy in this market. This finding calls for caution against a common perception that a counter-cycle measure necessarily causes less distortion than a full-scale acyclical measure.

Cyclical policy is frequently regarded as a temporary measure to handle shocks in the economy. It is commonly perceived that cyclical policy introduces less distortion in the market than acyclical policy and is hence suitable to implement in special times. For example, many papers (e.g. Lane (2003), Sutherland et al. (2010), Aghion et al. (2010), Aghion, Hemous & Kharroubi (2014), Aghion & Roulet (2014), and Aghion, Farhi & Kharroubi (2019)) discuss how (counter-)cyclical fiscal policy can address the volatility in economy. While the policy implementation is clearly smaller in scale, its impact on competition is not necessarily smaller than acyclical policy. Furthermore, when the competition in reality involves dynamics, that is, action today affects standing or state in the future, the change and distortion brought by cyclical policy can last beyond the policy implementation period. On the methodological end, structurally evaluating the impact on dynamic competition is at the frontier of economics. Its computation burden limits most of the empirical work to oligopolistic competitions. However, many industries involve more firms than that of an oligopoly, ranging from dozens to thousands. These leave us with an obscure picture of how cyclical policy affects dynamic competition with many firms.

In this work, I structurally estimate the dynamic competition in apartment sales among Hong Kong real estate developers. I study how a counter-cyclical policy of raising entry and re-entry cost affects the competition with many sellers, relative to an acyclical/universal version of the policy in

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[1] Acyclical policy means policy implemented throughout all seasons. Counter-cycle policy means policy implemented only in the hot season with a hot season defined later.

counterfactual. Housing market is one of the markets that often consider (counter-)cyclical policy in response to market shocks. Moreover, the major dwelling units in Hong Kong - apartments, rather than single-home houses, makes Hong Kong a suitable market for competition analysis considering its higher homogeneity in goods. After accounting for the location difference and the size, the difference among apartments is limited, contrasting with the diverse difference in single home houses that dominate many other housing markets.

Also, the real estate primary market in Hong Kong is both dynamic and strategic in nature. Sellers face a significantly different cost before and after the beginning of sales (i.e. entry cost and re-entry cost, respectively). Prior to the sales of apartments, overwhelming advertisements throughout Hong Kong such as newspapers, magazines, metros, billboards of malls and various buildings, etc. would be made where the advertisement would be much less once sales started. Furthermore, the presence of rivals and their state distribution do affect the sales of a developer, as demonstrated in the empirical evidence later. Industry insiders also pointed out that attention to the potential clash of sales timing is crucial to sales outcome, especially to those clashing with large rivals. Nonetheless, like many other industries, more than a handful of firms actively compete in the Hong Kong real estate primary market. This implies the result to be not limited to merely oligopolistic competition. Therefore, studying the dynamic competition in Hong Kong real estate primary market with many firms informs the bigger picture of how cyclical policy affects competition.

Utilizing a unique transaction-level data set built from sales documents, I model and estimate the dynamic competition between Hong Kong real estate developers. With which, I evaluate the impact of counter-cycle policy relative to the acyclical policy by comparing the two respective counterfactuals. To track competitive behaviors over time, I collect all sales documents, including sales brochures, price lists detailing every apartment, and the sales record. By automating the conversion of thousands of PDFs into data, I obtain a transaction-level dataset rich enough for structural estimation. In lack of systemic public data on apartment sales approval, an assumption about potential entrants is necessitated. Together with satellite images and machine learning classification, partial records of approval across construction stages pin down the emergence date of potential entrants.

Supported by the rich data, I model the dynamic competition in apartment sales. Since there are more than 20 active sellers throughout, the curse of dimensionality implies a state-space in the order of 55 for Markov-Perfect Equilibrium (MPE). I utilize Extended Oblivious Equilibrium (EOE) to approximate the result MPE. By tracking the long-run rival distribution in the market, Oblivious Equilibrium (OE) approximates MPE without market-wide common shock. The evident cycle in the real estate market guides the adoption of EOE that extends the OE to competitions that are subject to common shocks. Using Pseudo Likelihood Maximization (PLM), a two-stage estimator, I first estimate the conditional choice probability (CCP) and the transition matrix. Then I perform the dynamic estimation of the underlying cost parameters using PLM. With the estimated market, I consider a counterfactual policy of raising the (re-)entry cost by 10%. The difference between its acyclical and its counter-cyclical implementation is then evaluated. The estimated market is also used to evaluate the impact of vacancy tax, recently proposed by the government in Hong Kong.

The result shows that PLM recovers the observed strategy very well. By simulating with the estimated strategy, both the raw data and the simulations by parametric CCP lie mostly within the 95^{th}-percentile of the estimated strategy for the total apartments not listed for sales (i.e. in-stock quantity). As for the total apartments listed but remaining on market (i.e. on-market quantity), the simulations of estimated strategy also cover the observed data, except at the outliers 3-4 times the typical level. Regarding the counterfactual policy of raising (re-)entry cost, the acyclical implementation raises the in-stock quantity by at least 30% about 1 year in due to the higher (re-)entry cost. Its on-market quantity stays lower than the simulations by parametric CCP in 3 years of implementation, but it takes over afterward due to the continuing lower sales rate. As for the counter-cyclical implementation, which is imposed in less than one-fifth of the data period, the in-stock quantity raises similarly by at least 30% about 1 year in and the on-market quantity takes over the simulations by parametric CCP in 1.5 years of implementation. The impact from lower sales rate kicks in much faster under counter-cyclical policy than that under acyclical policy. In terms of the (re-)entry probabilities, counter-cyclical policy also has lower (re-)entry probabilities than that of acyclical policy.

Further investigation reveals that the counter-cyclical regime has more competing apartments from rivals in the long-run average and hence the lower sales rate. It is potentially because the weaker entry deterrence in periods with normal (re-)entry cost, compared to acyclical policy, attracts more rival entries and the associated apartments in the long run. These show that counter-cycle policy, of a scale smaller than acyclical policy, can indeed trigger a more extensive impact on the market. This finding calls for caution against the common perception of temporary adjustment through cyclical policy. It can be a defacto long-lasting change when dynamic competition is taken into consideration. Comparison with the counterfactual result in OE shows that EOE differs from OE by catering better to the change in shocks, where OE is arguably a rough average of the different strategies across shocks in EOE. A counterfactual with vacancy tax is also evaluated, although the result is almost identical with or without the vacancy tax. This result is potentially because vacancy tax does not directly depend on the actions of sellers like other costs such as (re-)entry costs.

This study contributes to several strands of literature. The first literature is on the economic volatility and growth (e.g. Ramey & Ramey (1995), Aghion et al. (2010), Aghion, Hemous & Kharroubi (2014), and Aghion, Farhi & Kharroubi (2019)) where cyclical fiscal policy is recommended to nurture long-term growth. My work contributes by providing empirical evidence inside an industry on how cyclical policy might actually affect the competition. The second literature is on the structural analysis of housing market, either from a dynamic perspective (e.g. Bayer et al. (2016), Epple, Gordon & Sieg (2010), and Murphy (2018)) or from a search model perspective (e.g. Liberati & Loberto (2019), Huang, Leung & Tse (2018), and Zhu et al. (2017)). I contribute to the former by extending from the currently dynamic single-agent perspective to considering the strategic interaction between real estate sellers in the primary market. And to the latter, which focuses on the interaction between buyers and sellers, I contribute by providing an enriched understanding of dynamic competition among the sellers. The third literature would no doubt be dynamic game (e.g. Ericson & Pakes (1995), Pakes & McGuire (1994), and Doraszelski & Satterthwaite (2010)). Empirical works on oligopoly since Ryan (2012) and Collard-Wexler (2013)) are growing steadily. However, empirical works exceeding a handful of firms emerge only after a series of papers introducing OE and its variant forms (e.g. Weintraub, Benkard & Van Roy (2008), Weintraub, Benkard & Van Roy (2010), Weintraub et al. (2010), and Benkard, Jeziorski & Weintraub (2015)) proposed to approximate MPE when there are many firms in the market. In addition to the empirical works by Qi (2013) and Xu et al. (2008), my work extends the empirical work to a dominant industry of economy and is the first work to study OE under common shock (i.e. EOE).

Section 1 discusses the transaction-level data and other industry details. With which, I explore some model-free empirical observation in section 2. Section 3 constructs a dynamic competition model with EOE. Its estimation result, as well as some robustness checks, are discussed in section 4. Section 5 evaluates the counterfactual policies and demonstrates the interesting contrast between acyclical and counter-cyclical policy. Section 6 concludes.

1 Data

1.1 Industry Details

Similar to many metropolis in the world, real estate in Hong Kong is constantly regarded as highly priced for a small sized unit. Indeed, Hong Kong frequently top the world in terms of housing price. Behind the media attention of sky-reaching price, the residential real estate is a very sophisticated industry, especially so for the primary market. Since the empirical application is on the housing primary market in Hong Kong, industry details are first discussed and the data description to follow.

In the housing primary market, developers in Hong Kong have a set of standard practices in selling apartments[2], what I called as phased sales process. Real estate developers construct a complex (or a development, interchangeably), usually consisting of hundreds to thousand of apartments. Prior to an apartment complex opening for sales, developer has to print and distribute in advance the 1^{st} price list (PL), listing apartments available for sale (usually part of all units) with pricing and various discounts stated on PL. The developer would attract the real estate sales agents to represent and promote for the complex. This is the main channel of sales. On the selling day, many buyers would come to purchase, through the help of sales agents, at the listed price with eligible discounts. Few days later, developer would repeat to distribute the 2^{nd} PL to sell some unlisted apartments. They repeat the process until all apartments are listed for sale. The sales conclude when all listed apartments are sold.

Regarding the pricing, the phased sales process helps gauge the customer interest to set the right price. In the 1^{st} price list, apartments are sold at an intentionally lower price. With which, one can ensure transactions to happen so as to obtain information about market interest for the complex on hand. Since then, the price would be raised gradually where the sales speed would guide the size of each price raise.

From discussion with various industry insiders, timing and prices are crucial to the selling process. If a complex begins its sales the same week of another complex, the sales would be slower, especially when the rival complex is by an industry leader. It is not just about the impact on costumers per se, but also the fixed pool of middleman (sales agents) who need to be physically present at the selling site. The sales agents prioritize the size of developers and then the commission they received. Beyond the media attention on price setting, timing and quantity choice are indeed crucial dimensions for sellers to compete on.

In addition to the sales arrangement, another piece of information important for the dynamic competition is the flow of construction as it affects when the complex can become a potential entrant for competition. While the majority of complex in Hong Kong is pre-sold, which means the apartments are listed for sale before the physical buildings are constructed, pre-sale is regulated on the basis of construction flow. When developers obtain a piece of land, the land grant requires a pre-sale consent. For the land privatized before the land grant restriction is imposed, the pre-sale consent is still required before any pre-sale, but required through the legal practitioners who handle the pre-sale. Pre-sale consent can only be applied after consent for commencing general building and superstructure work. In other words, potential entrant status is closely related to the construction progress. In general, the construction includes several phases in Hong Kong, which can be reflected from the various consent they need to obtain. Developers need to get the approval for their building plans, consent for site formation, consent for foundation and consent for general building and superstructure (superstructure consent). Once the superstructure consent is obtained, developers can apply for pre-sale consent. And when the complex has finished construction, it needs to obtain the occupation permit before it can complete the transfer of apartment to the buyers.

1.2 Data Description

Data of this project are on the primary market of residential real estate in Hong Kong. The main data come from two documents, the price lists (PLs) and register of transactions (RTs), covering a 6-year period beginning in 2013[3], when real estate developers were required to provide the documents to the government[4]. PLs list out all the apartments available for sales, including the price and size of each apartment, 3 days prior to the date of sales. RTs record the date of preliminary agreement for

[2]Given the population density in Hong Kong, most of units sold in residential market are apartments (or condominiums depending on the naming norms in different places) and hence apartment is used to refer to the basic unit of sales in real estate market.

[3]Precise data period is from 2013-04-29 to 2019-04-15

[4]See Residential Properties (First-hand Sales) Ordinance Cap. 621

sale and purchase within 24 hours of signing the agreement. Since these 2 documents are mandated by law on all residential complexes, these two form a transaction-level data set that captures the whole housing primary market in Hong Kong on sales. Even though the source documents are all in PDF format and of various quality, I managed to process 7,000+ documents with the help of some automation tools.

Furthermore, permits over the construction phases are also collected. Note that the timing of entry is one important dimension the real estate developers compete on. Competition in sales does not start only when the sellers start posting their first PL, but it has started whenever the complex is ready for sales, regardless of decision to enter today or not. Permit data, therefore, are crucial in determining which complex is now a potential entrant and hence part of the competition. As mentioned in the process of construction, there are 4 documents required to communicate with the government over the construction: approval of plan, consent to commence work, notification of commencement and occupation permit. While these are reported by the Buildings Department in Monthly Digest, the challenge for systematic analysis here is the lack of structured mapping between the construction site (i.e. the basis of construction documents) and the apartment complex (i.e. the basis of PLs and RTs) in public information. While the construction sites do have addresses, the addresses either temporarily existed due to new roads built or are changed with only private communications between developers and government. To work around this empirical challenger, I exploited the fact that there are only a few, if not one, apartment construction in the area at a time. Manual matching considering address proximity and construction timing is hence adopted[5]. While the institutional setting hurdled us from ideal data collection, the collected data indeed sufficed to provide all potential entrant status in data used in structural model (i.e. after discretization).

1.3 Descriptive Statistics

Based on the source documents (Price List and Register of Transaction), 50,000+ apartments can be obtained. To gain a better picture with the primary housing market, the sales process alone can be viewed from 3 levels of aggregation: apartment, price list (which has hundred of apartments) and complex. In table 1, from the top panel at apartment level, one can see that the price is very high with an average of USD 1.3 million or USD 2,326 per squared feet. The apartments size is typically around 600 sq. ft. For each apartment, it is usually sold within 10 days of listing as reflected in the quartiles, although some unsold outliers drove the average to a somewhat misleading number.

Table 1: Descriptive Statistics

	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Apartment level							
price (HKD)	50,999	10,224,427.000	5,927,652.000	1,505,000	6,437,000	11,765,000	39,997,000
size(sq. ft.)	45,526	567.138	244.517	157.000	405.000	700.000	2,116.000
price/sq.ft.(HKD)	50,999	18,206.020	6,056.908	7,583	13,226	22,482	49,849
days available	50,999	23.705	57.980	0	0	9	364
Price List level							
apt listing	615	82.27	98.04	1	16	107	548
apt sold	615	54.52	90.63	0	3	60	544
Complex level							
total apts	210	300.34	339.08	1	50	416	1,432
total PLs	210	4.44	2.67	1	2	7	10

Note: HKD is pegged to USD at a rate $HKD7.8 = USD1$.

The middle panel of PL level shows that there are typically around 100 apartments in each PL

[5] For the permit with the highest availability, occupation permit, this allowed to match slightly above 80% of complex, while the rest can only match 37%-57% of the complex.

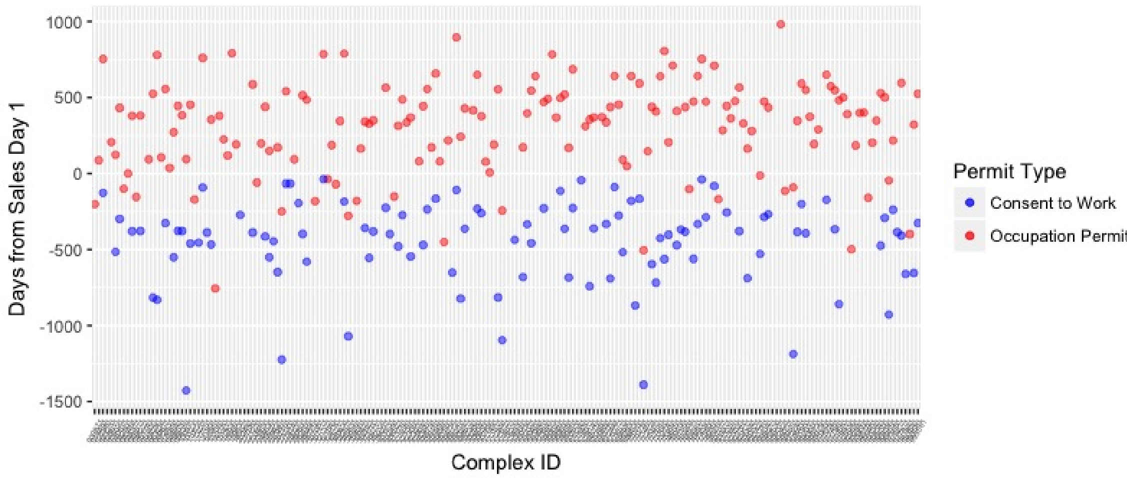


Figure 1: Difference between Sales Date and CW/OP Date

and a majority of them (around 60%) are sold on the same day. This panel includes only observations with some non-zero listings because days of zero listing and a few sales would otherwise overwhelm the summary. The bottom panel of complex level shows that our 6-year data cover 210 complexes. Each has, on average, 300 apartment and they are frequently sold in multiple PLs (even the 1^{st} quartile has 2 PLs), averaging to around 4 PLs.

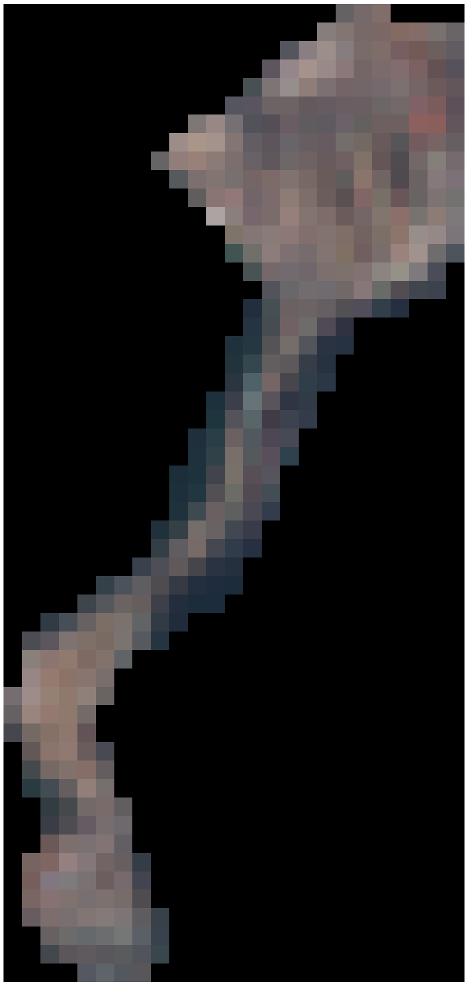
Although I have all the listing and transaction records, note that competition begins as a potential entrant, prior to even its first listing. The date of emergence, as a potential entrant, is hence required to form the picture of competition. Since sales arrangement did not provide information when the complex is allowed for pre-sale, I utilized the permit data, in particular Consent to Work (CW) and Occupation Permit (OP), to construct the date of emergence. CW is the legal pre-requisite for pre-sale approval where OP is after pre-sale. Among the collected permits, table 2 shows the earliest sales is on day 37 after obtaining CW with a median of 387 days. Visualizing the CW days (blue) and the OP days (red) in figure 1 demonstrates a relative stable difference in CW days and OP days across different complex. Hence, when CW is not available, OP can provide reasonable information of the date of CW. Referring back to table 2, the median difference of CW days and OP days is about 760[6]. As guided by these empirical observations, I assumed the date of emergence to be 30 days after CW. When CW date is not available, I relied on OP date to define CW date as 760 days earlier and another 30 days earlier for the emergence date.

Table 2: Difference between Sales Date and CW/OP Date

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
CW days	107	−449	281	−1,428	−559	−387	−270	−37
OP Days	162	310	303	−757	146	368	510	981

Given the importance of emergence date, an alternative approach utilizing satellite images is also considered. Note that construction sites are mostly outdoor and uncovered, especially when building of 30+ levels is the norm in Hong Kong, they are exposed to the lens of satellite cameras. Indeed, it would not be too different from how rivals can evaluate the construction progress and

[6]Difference in medians of CW days and OP days is $387 + 368 = 755$,



(a) Sentinel 2 on 2018-11-06

(b) Google Earth on 2018-10

Figure 2: Sources of Satellite Images at Varying Resolution

hence entry potential either. Using the part of data labelled with the CW date, a machine learning algorithm can be built for this straightforward classification task using the satellite image of each site and applied to the other part of data without CW date. For image classification task, transfer learning of pre-trained deep neural network can be conveniently adopted to reduce computation burden. There are various sources of satellite images, which vary by image resolution as one can see in figure 2. The only public data is from the Sentinel 2 project, where the satellite visits the same place every few days which provides a continuous stream of information about the construction site. Although the resolution is relatively low to bare eyes per our use case, it is still useful for classification because machine interprets images by the numbers behind. Even when the pixels look almost the same to human, machine can distinguish them well. The current training accuracy of classification is not high enough for reliable prediction[7]. Once this alternative definition of emergence date is established, one can check whether the dynamic competition model estimated is sensitive to the fixed days assumption of emergence.

[7]The current specification for image classification adopts transfer learning from ResNet18 and yielding a training accuracy about 70-80%.

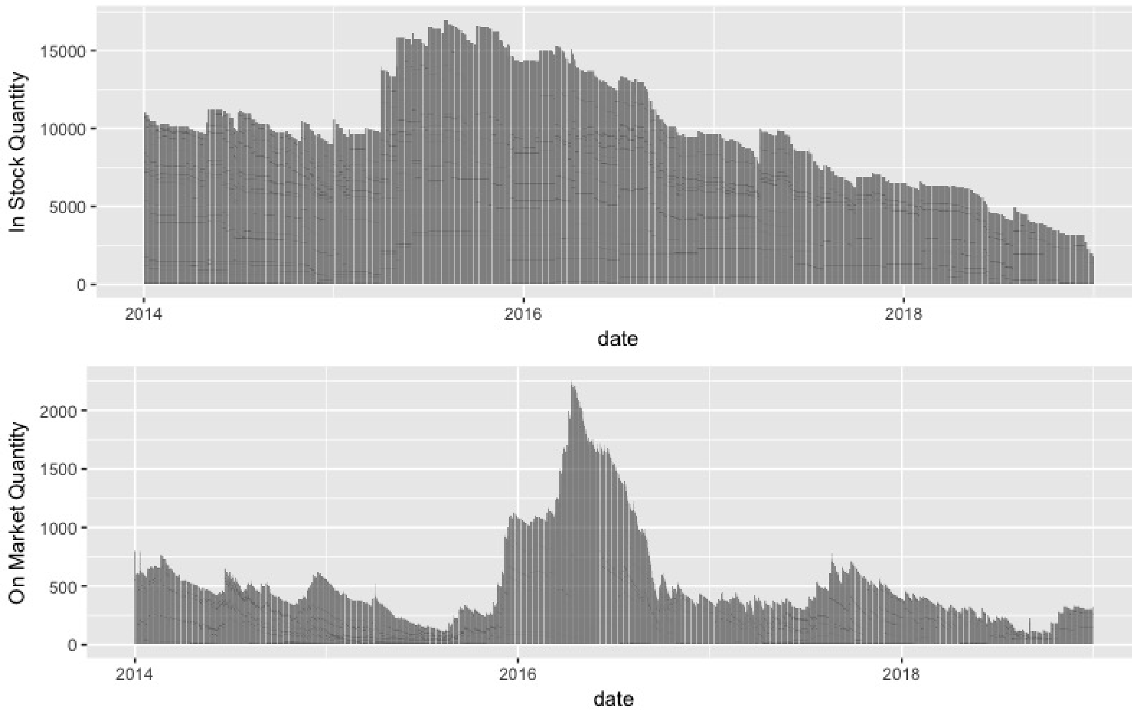


Figure 3: Raw quantities in-stock and on-market over time

Given the date of emergence, one can see how the competition presents itself over time. Figure 3 depicts how the in-stock quantity (upper panel) and the on-market quantity (lower panel) evolve in the period 2014 - 2018. When complex emerges for pre-sale, the in-stock accumulates when they are not listed. Upper panel shows the in-stock quantity was around 10,000 apartments from 2014 to 2016 and accumulates since mid-2016. It gradually goes down since late 2016. On-market quantities in lower panel is more response to the sales speed as there are much fewer apartments on-market at any day. One can see year 2016 is a hard time to sell as the on-market quantity accumulates. For the remaining periods, the on-market quantity fluctuated around 500 apartments.

The contrast in raw quantities across different periods naturally questions the suitability of assuming no seasonality in this housing market at all. With the transaction-level data on hand, I can let the data to inform the seasonality in market. Figure 4 highlights the assumption of high and low season, based on sales ratio in data (upper panel) and the Centa-City Index (CCI, lower panel). Sales ratio is defined as the quantity sold divided by the quantity available for sale on that day. The grey step function sketched the sales ratio for complex on days with new listing. Since it is quite common to have all sold once listed in a good time, I can use this new listing day sales ratio to determine seasonality. To facilitate visualizing the trend, a local polynomial smooth line (black) and the 45-day moving average (green)[8] are added. The monthly index CCI, typically used by media to gauge the trend in market, is sketched in lower panel. As guided by the sales ratio, it is assumed that the low seasons are the periods 2015-12-10 - 2016-04-30 and 2018-01-06 - 2018-04-20 (shaded in blue) and the high seasons are the periods 2014-07-01 - 2014-11-29 and 2018-05-18 - 2018-09-25 (shaded in red). As shown in sales probability later, these periods do have distinguishing pattern that further support the seasonality assumption.

[8]Yellow line is the 45-day moving average for sales ratio on non-listing days. Since the sales there is at a much lower percentage, the yellow line is close to the x-axis

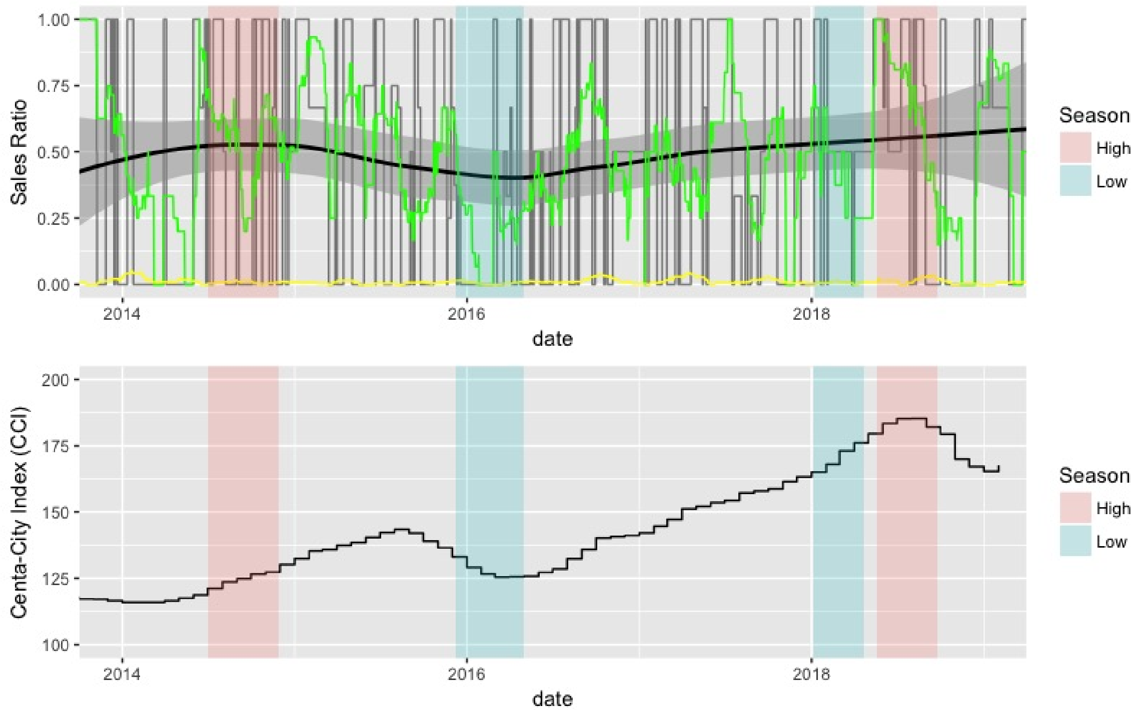


Figure 4: Seasonality in Housing Market

2 Model-free Evidence

More insights about the market can be obtained by discussing some model-free empirical evidence. These empirical observations point to the need of a more sophisticated competition model for analysis and, in turn, drive the model development in later sections. Note that the focus here would be on the prominent dimensions: pricing, entry and quantities, even though the rich data allowed us to understand the market from numerous other perspectives as well.

While the sky-high price tends to draw the most attention in media, the price variation across each apartment is rather limited. Much variation can be accounted for using variables readily observed. As table 3 shows, the adjusted R-squared achieves 86% using just apartment size and fixed effects like apartment floor, block, developer, year of sales and district. The coefficient means that 1 sq. ft. larger is associated with HKD 2.062 higher in price per sq. ft. Therefore, it doesn't seem there is much scope for sellers to autonomously choose the selling price regardless of situation.

When the pricing residuals from table 3 are analysed further, one can see that there is a clear trend the price increases as the price list releases in order. Figure 5 shows a boxplot of price residuals across PLs. The median price residual for apartments in their 1^{st} PL is negative. For the very rare[9] case of 9^{th} PL, the median price residual alone can reach about HKD 3,000 more per sq. ft. given the apartment characteristics. This matches well with the interviews on industry insiders. They described that the sellers tend to lower the price at the beginning and raise the price in every following PL. This implies the most profitable trades are those from later PLs and hence sales decision is important to sellers. In addition to the majority of multi-PL complex, some sellers chose to sell all in one single PL and these are indicated by the red boxplot. Note that for this 1^{st} (and only) PL, the median is back to zero, which provides another empirical evidence of the increasing prices in multi-PL complex.

[9]Number of observations for each PL is reflected in the width of each box.

Table 3: Regression on Price per Sq. ft.

	Dependent variable:
	Price/Sq. ft. (HKD)
Size(sq. ft.)	2.062***
	(0.057)
Constant	13,446.530***
	(1,267.206)
Floor FE	Yes
Block FE	Yes
Developer FE	Yes
Sales Year FE	Yes
District FE	Yes
Observations	45,242
R^2	0.864
Adjusted R^2	0.863
Residual Std. Error	2,147.845 (df = 45027)
F Statistic	1,337.243*** (df = 214; 45027)

*p<0.1; **p<0.05; ***p<0.01

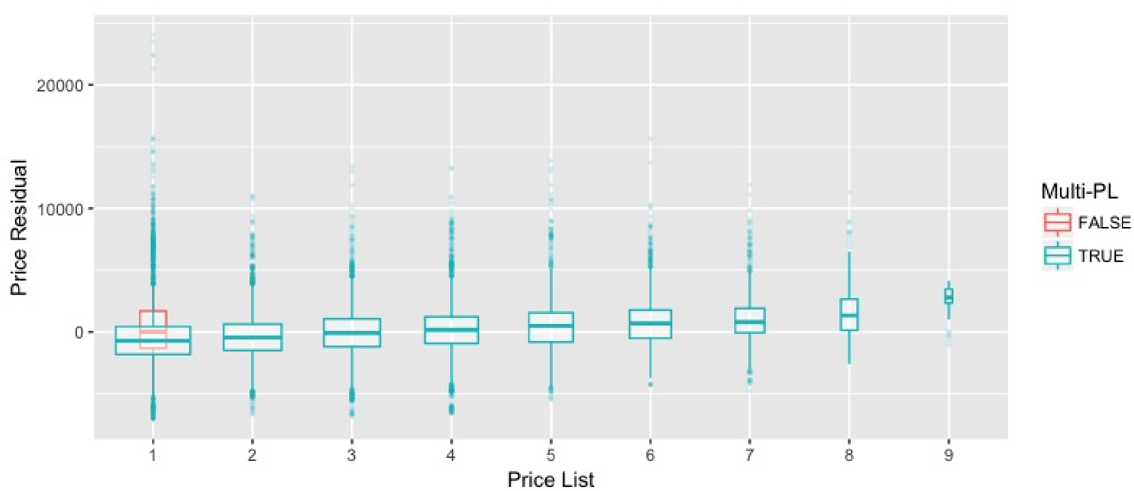


Figure 5: Price Residual across Price Lists

To achieve optimal gain, quantity is another important dimension of choice and the seller indeed has more autonomy as this is much less dictated by the apartment characteristics. Since quantity choice is simultaneously deciding the timing of (re)entry and the listing quantity, table 4 shows the (re)entry logit (column 1) and the listing quantity ordinary least square (OLS, column 3) for richer discussion. The (re)entry probability is lowered, statistically significant, under competition as measured by the number of on-market apartments and the number of complex entered. Seller is more likely to (re)enter if it has already entered or it has fewer on-market apartments unsold. As for the listing quantity, competition as measured by the number of entered complex reduces the quantity while the previous month Centa-City Index (CCI), a monthly price index for secondary market, increases the quantity, potentially due to the signal of a prosperous market for sales. Sellers tend to list more when it has more in-stock or fewer on-market as well. While quantities are significantly affected by the market competition, price response is not as obvious when similar regression is performed. Column 5 of table 4 shows the price is lower when it has more in-stock or on-market, but no statistical significant impact from any competition measures.

Table 4: Regression with Aggregate Competition Measures

	Dependent variable:					
	(re)entry		a_i		price resid.	
	logistic		*OLS*		*OLS*	*OLS*
	(1)	(2)	(3)	(4)	(5)	(6)
agg. in-stock	0.0001	−0.0002	−0.012	−0.0001	0.430	−0.344
	(0.0002)	(0.0002)	(0.008)	(0.0001)	(0.376)	(0.438)
agg. on-mkt	-0.004^{***}	-0.003^{***}	−0.071	0.0001	−2.407	0.310
	(0.001)	(0.001)	(0.045)	(0.0005)	(2.180)	(1.398)
entered rivals	-0.075^{***}	-0.085^{*}	-1.331^{*}	−0.025	32.342	−11.780
	(0.019)	(0.046)	(0.682)	(0.018)	(32.672)	(55.920)
self entered	1.833^{***}	1.814^{***}				
	(0.157)	(0.237)				
mkt avg. price resid.			−0.010	−0.0002	−0.311	0.226
			(0.018)	(0.0002)	(0.793)	(0.652)
CCI lag1			0.381^{**}	0.004	−4.344	7.332
			(0.167)	(0.002)	(8.127)	(7.017)
self PL			−1.304	−0.010	90.189	292.298^{***}
			(1.449)	(0.032)	(69.806)	(94.758)
self in-stock	−0.0002	−0.0003	0.316^{***}	0.002^{***}	-2.547^{***}	0.007
	(0.0003)	(0.0004)	(0.018)	(0.0003)	(0.833)	(0.848)
self on-mkt	-0.006^{***}	-0.006^{***}	-0.211^{***}	-0.003^{***}	-8.340^{**}	−1.113
	(0.002)	(0.002)	(0.078)	(0.001)	(3.514)	(2.837)
agg. on-mkt:entered rivals	0.0002^{***}	0.0002^{***}	0.003^{*}	0.00001	0.064	0.005
	(0.00004)	(0.0001)	(0.002)	(0.00003)	(0.089)	(0.078)
self entered:self in-stock	0.003^{***}	0.003^{***}				
	(0.0004)	(0.001)				
mkt avg. price resid.:CCI lag1			0.0001	0.00000	0.003	−0.001
			(0.0001)	(0.00000)	(0.005)	(0.005)
self PL:self in-stock			0.019^{**}	0.0002	0.327	−0.149
			(0.007)	(0.0001)	(0.334)	(0.332)
Constant	-4.367^{***}	-4.158^{***}	6.248	0.557	1,101.422	−1,741.750
	(0.437)	(0.798)	(29.698)	(0.478)	(1,451.741)	(1,523.907)
Observations	61,140	40,928	537	260	471	233
R^2			0.684	0.575	0.084	0.100
Adjusted R^2			0.678	0.556	0.062	0.055
Log Likelihood	−2,079.620	−1,120.347				
Akaike Inf. Crit.	4,177.240	2,258.693				
Residual Std. Error			55.329 (df = 525)	0.601 (df = 248)	2,450.660 (df = 459)	1,688.903 (df = 221)
F Statistic			103.377^{***} (df = 11; 525)	30.478^{***} (df = 11; 248)	3.812^{***} (df = 11; 459)	2.222^{**} (df = 11; 221)

Note: Raw data on odd columns and discretized data on even columns. *p<0.1; **p<0.05; ***p<0.01

While regressions highlight the influence from competition, it is, on one hand, reasonable to wonder whether the competition is indeed sophisticated enough to justify performing a dynamic structural analysis. On the other hand, others might question whether the regression result can reveal deeper understanding of competition. A good news is that this data allow us to observe the presence of competition at a much more granular level than simply some aggregate competition measures.

One approach for deeper investigation is to look at the distribution of rival's respective in-stock and on-market quantities, rather than just the overall sum. For regression analysis, I can introduce dummies for each unique distribution. Since dummies for continuous variable like quantities in raw data are infeasibly numerous, discretization on quantities is hence required. Since the average for each PL is around 80, the apartment quantities are all discretized into increments of 100s[10]. I further take only the top 20 frequent rival state distributions into regression. If any of these rival state dummies has significant impact to the choices (entry, quantity and price), even after sufficiently controlling the aggregate competition measures, it provides suggestive evidence that the sellers do consider the rival distribution beyond just the aggregate measures. Table 5 show that even though aggregate competition measures are controlled up to cubic terms and various interaction terms, there are always some top 20 rival states that show statistically significant effect on the choices. Therefore, pure regression analysis might over-simplify the competition at work in reality. Next section would develop a structural model to aid a deeper analysis for competition.

3 Model

In order to analyse the competition among real estate developers in primary housing market, I specify a dynamic competition model that captures both the dynamic incentive and the strategic consideration in equilibrium. This model is also computationally feasible to be used in real data.

Denote J as the number of sellers. Each seller $j \in J$ has a stock of apartments to sell, i. In each period t, seller j chooses a units of apartments to list for sales. When $a > 0$, the seller j decides on entry or re-entry, depending on whether it has entered before. Hence, action a determines both the binary action of (re-)entry and the size of (re-)entry. The number of price list (PL) keeps track of how many times the seller has added apartments for sale. In other words, the number of PL, denoted as k, increases by 1 whenever the seller chooses $a > 0$ and an un-entered seller can then be represented by $k = 0$. The individual state of seller j can be described by a triplet of apartments in-stock, apartments on-market (unsold) and the number of PL, denoted by (i, o, k). To achieve computation feasibility in estimation, raw data are discretized. The number of apartments are discretized into increments of 100s as in earlier section. Since the data have as many as about 1500 apartments for a seller, the stock level is assumed to have at most 1500 apartments. Actions, a, and apartments on-market, o, can be 500 apartments at most. There can only be 6 PLs (i.e. $k <= 6$). When $k = 6$, the seller can only wait for the apartments to be sold on-market (i.e. $a = 0$). Therefore, the state space for (i, o, k) is the states after entry plus the states before entry, $16 * 6 * 6 + 15 = 591$.

In the beginning of each period, sellers with different stock level emerges according to an exogenous schedule[11]. The existing sellers and emerging sellers simultaneously decide their action $a_j \forall j \in J$. Sales to buyers then occur under the influence of competition. While one would expect competition to be related to the number of sellers or apartments on market, the data point to the total on-market apartments. Figure 6 shows clearly that sales speed of on-market apartments is affected by the total number of apartments on-market.

Hence, the number of apartments on-market (i.e. the newly added and those unsold from last period) affects the sales speed in the model[12]. Individual state of sellers are then updated and

[10] Instead of strict cutoff at 50, data are discretized by a draw weighted by the remainder of division by 100 (i.e. increment unit). This preserves variations within the same discretized level in repeated discretization. Table 4 column 2, 4, 6 present the same regressions except using discretized data. These provide evidence that the discretization did not change the fundamental properties of raw data, although the number of observation is clearly trimmed.

[11] Estimation uses the emergence sequence in reality.

[12] Non-linear least square regression with an expoential decay function $r = \alpha n^{\gamma}$ is estimated. Complex with and without new listings are estimated separately as the sales ratios are significantly different.

Table 5: Regression with Top 20 Rival State Distribution with Controls

	Dependent variable:		
	(re)entry	a_i	price resid.
	logistic	*OLS*	*OLS*
	(1)	(2)	(3)
top s_{-j}#4	-14.413	-0.200	$-3{,}655.819^{***}$
	(1,137.402)	(0.428)	(1,220.674)
top s_{-j}#6	-14.378	-0.319	$2{,}119.733^{*}$
	(1,393.028)	(0.422)	(1,193.889)
top s_{-j}#7	1.198	-0.716	$-2{,}577.139^{**}$
	(1.034)	(0.448)	(1,289.770)
top s_{-j}#9	1.608^{**}	-0.387	-381.305
	(0.740)	(0.417)	(1,180.886)
top s_{-j}#13	-14.268	0.523	$2{,}880.778^{**}$
	(1,543.231)	(0.468)	(1,366.676)
top s_{-j}#14	-14.385	0.891^{**}	1,523.493
	(1,579.547)	(0.438)	(1,254.286)
top s_{-j}#15	1.614	1.403^{***}	310.011
	(1.047)	(0.455)	(1,318.309)
top s_{-j}#19	-14.784	-1.058^{**}	1,581.119
	(1,675.267)	(0.448)	(1,272.316)
control agg. measures up to cubics	Yes	Yes	Yes
Observations	40,928	260	233
R^2		0.669	0.309
Adjusted R^2		0.598	0.138
Log Likelihood	$-1{,}097.028$		
Akaike Inf. Crit.	2,286.056		
Residual Std. Error		0.572 (df = 213)	1,612.411 (df = 186)
F Statistic		9.361^{***} (df = 46; 213)	1.810^{***} (df = 46; 186)

*p<0.1; **p<0.05; ***p<0.01

Note: All controls in table 4 are used while adding all aggregate competition measures (e.g. agg. on-mkt, entered rivals) up to cubic terms.

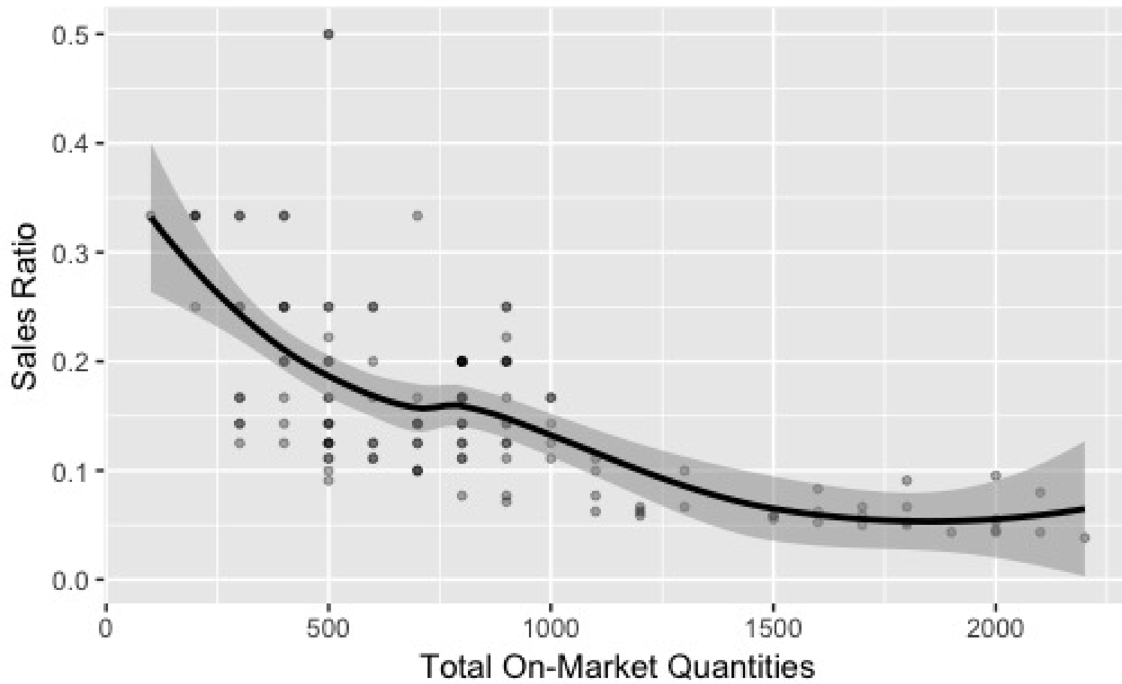


Figure 6: Competition Impact on Sales in Non-Listing Days

Table 6: Seasonality transit

	Low	Normal	High
Low	1 - pr_{01}	pr_{01}	0
Normal	pr_{10}	1 - $\text{pr}_{10} - pr_{12}$	pr_{12}
High	0	pr_{21}	1 - pr_{21}

payoffs are received. The market transits to next period.

As shown in the earlier section, seasonality is another important feature of primary housing market. It impacts both the sales speed and prices. However, unlike the other 3 state variables, seasonality is a state variable common to all sellers in the same period. Seasonality has 3 potential level, low, normal and high. Seasonality transit is assumed to be independent to individual state transit and to move to the immediate period only. Table 6 shows the 3x3 transition matrix. Adding seasonality, denoted z, to the individual state, a complete state for a seller at any time is represented by a quadruplet, (i, o, k, z).

3.1 Payoff

Payoff to seller j depends on not just his own action, but also the rivals' action and sales outcome. Instantaneous payoff is:

$$\begin{aligned}\pi(a_{jt}, a_{-jt}, s_{jt}, s_{-jt}) = pq(a_{jt}, a_{-jt}, s_{jt}, s_{-jt}) - c_e I(a_{jt} > 0 | k = 0) \\ - c_r I(a_{jt} > 0 | k > 0) - c_h h_{jt} - c_o o_{jt} + \epsilon_{ajt}\end{aligned} \tag{1}$$

Complex in Non-Listing Days: $\alpha = 3.85640^*$ and $\gamma = -0.48900^{***}$
Complex in Listing Days: $\alpha = 1.71702$ and $\gamma = -0.19410^*$

where p is price[13], q_{jt} is the quantity sold, c_e and c_r for the entry cost and reentry cost respectively, c_h is the holding cost that incurs as long as the seller emerged but the apartment is not sold yet and hence $h_{jt} \equiv i_{jt} + o_{jt}$ represents the quantity holding on hand, c_o is the TOM impact that incurs when an apartment is listed but not sold yet and ϵ_{ajt} is the action-specific idiosyncratic shock which follows type-1 extreme value distribution.

Denote β as the discount rate and G as the transition matrix. Value function is :

$$V(s_t, \epsilon_{ajt}) = \max_{a_{jt}} \pi(a_{jt}, a_{-jt}, s_t) + \beta \sum_{s_{t+1}} \bar{V}(s_{t+1}) G(s_{t+1}|s_t, a_t) \tag{2}$$

where $s_t \equiv (s_{jt}, s_{-jt})$ and $a_t \equiv (a_{jt}, a_{-jt})$ with subscript $-j$ representing all sellers except seller j.

I can ensure the equilibrium existence following Doraszelski & Satterthwaite (2010). First, the primitives of model are bounded. Entry cost and re-entry cost are random and private given the presence of idiosyncratic ϵ_{ajt}. State space and profits are finite, and my model has no "investment" decision that changes the state and payoff function directly. Discount rate is strictly less than one. Second, transit function is continuous to the industry state. These suffice to ensure existence of pure strategy equilibrium. Intuitively, the need for mixed strategy in equilibrium is circumvented by the presence of private cost.

3.2 Extended Oblivious Equilibrium

While the proposed specification above is parsimonious in capturing the essential features observed in the market, computation capability constraint nowadays necessitates further modifications to limit the quick scaling of dimensionality in dynamic competition model. Since the number of sellers increases the state space exponentially for Markov Perfect Equilibrium (MPE), commonly used in dynamic oligopoly literature, this primary housing market with 20-60 sellers is infeasible to have MPE computed[14].

Oblivious Equilibrium (OE), proposed by Weintraub, Benkard & Van Roy (2008), can approximate MPE for this housing market. Unlike MPE that conditions on the current state of each rival, optimal strategies in OE condition on the long run industry average state distribution of rivals. This approximation builds on the intuition that when there are many firms in an industry, the number of entry cancels out with the number of exit that leaves the state distribution largely unchanged over time. Therefore, as long as this small difference in state distribution does not change much of the rival's impact on payoff, the payoff from OE is close to that from MPE. Hence, Weintraub, Benkard & Van Roy (2008) shows that satisfying a "light-tail" condition[15] is sufficient for OE to approximate MPE well. Intuitively, "light-tail" condition requires the expectation of maximum percentage change to profit, due to a change in state distribution, to be small. In application to our case, rival impact on profit depends on the number of apartments on market.[16] Since the number of apartments on market is limited to 500 in data, the expectation of maximum percentage change to profit is small because for any states with larger than 500 on-market has zero probability in the state distribution. Even for the number of stock, there are less 5% of complex with 1,000 or more

[13] Since this paper focuses on the quantity competition among many firms, price is assumed to follow a mechanical scheme that depends on states (e.g. the number of PLs). While endougenous pricing would be theoretically more appealing, it is beyond the scope of current paper

[14] The state space of MPE with 20 firms in current specification is $((16*6*6+15)^{20})*3$, which is in the order of 55.

[15] "Light-tail" condition essentially states that there exists z such that $E[g(\tilde{x})1_{\tilde{x}>z}] < \epsilon$ for all $\epsilon > 0$ with $g(\tilde{x}) = sup_y|\frac{dln\pi(y,f)}{df(\tilde{x})}|$ where $\tilde{x}$ is the (rival's) quality draw from the invariant state distribution of OE, f. See assumption 5.2 of Weintraub, Benkard & Van Roy (2008) for the formal definition of "light-tail" condition.

[16] Note that the impact on payoff increases with rival's state (that is rival's quality level) in Weintraub, Benkard & Van Roy (2008) as it modeled in the Ericson-Pakes framework where profit is lower with higher rival quality. Hence, the 'tail' in the condition naming refers to the rival states that have larger impact on payoff. In our case, this "tail" should refer to states with large number of apartment on market for a rival as this is what lowers the payoff.

apartments. Hence it is reasonable to regard "light-tail" condition to be satisfied. Nonetheless, OE cannot accommodate seasonality directly. Extended oblivious equilibrium (EOE), suggested in Weintraub, Benkard & Van Roy (2010), is called for as EOE allows for common shocks to all firms (e.g. seasonality in a market). By adopting EOE, the state space reduces from that of MPE in the order of 55 to $(16 * 6 * 6 + 15) * 3 = 1773$, a computationally manageable size.

Therefore, in the extended oblivious equilibrium framework, sellers no longer keep track of each rival in each time period. Rather, it regards the competitive environment as the average market state distribution in the long run. Denote $\tilde{s}$ as the long run average market state where σ represents the optimal strategy adopted by all sellers. Formally, payoff becomes

$$\begin{aligned}\pi(a_{jt}, s_{jt}, \tilde{s}_{\sigma}) = pq(a_{jt}, s_{jt}, \tilde{s}_{\sigma}) - c_e I(a_{jt} > 0|k = 0) \\ - c_r I(a_{jt} > 0|k > 0) - c_h h_{jt} - c_o o_{jt} + \epsilon_{ajt}\end{aligned} \tag{3}$$

And the value function keeps track of long run average market state only.

$$V(s_{jt}, \epsilon_{ajt}, \tilde{s}_{\sigma}) = \max_{a_{jt}} \pi(a_{jt}, s_{jt}, \tilde{s}_{\sigma}) + \beta \sum_{s_{t+1}} \bar{V}(s_{j(t+1)}, \tilde{s}_{\sigma}) G(s_{j(t+1)}|s_{jt}, a_{jt}, \tilde{s}_{\sigma}) \tag{4}$$

Given the optimal oblivious strategy σ, $\tilde{s}_{\sigma}$ is defined as

$$\tilde{s}_{\sigma} \equiv \sum_{t=0}^{\infty} P_{\sigma}(s_t) \tag{5}$$

where $P_{\sigma}(s_t)$ represents the transition to new states given original state s_t while all sellers adopt oblivious strategy σ.

4 Estimation

4.1 Methodology

Pseudo Maximum Likelihood (PML) estimation is adopted to estimate the underlying cost parameters. PML is a two-step estimator. In the first stage, it estimates the policy function (i.e. conditional choice probability, CCP) and transition matrix. In the second stage, given the first stage estimates and the model parameters, PML evaluates the choice likelihood under different values of cost parameters and hence the likelihood of observing the collected data. Its estimates of cost parameters would be the parameters that gives the maximum likelihood of the observed data. One advantage for using PML is the choice likelihood it generates in estimation. Given the large state space even with EOE, the choice likelihood adds transparency to the process that would help gauge the appropriateness of the estimated equilibrium.

4.2 Step 1 and result

First step to implement PML is to estimate transition matrix and seasonality, conditional choice probability, as well as pricing at various state. In our EOE framework, transit would be represented by a 1773 by 1773 matrix. Note that even our daily data for all sellers (i.e. (active) seller-day) only has less than 2% of the state space. The transition matrix based on raw data is not just sparse, but also missing some transitions had the observed data been realized again. Therefore, a complete non-parametric estimation is not ideal. Ordered logistic regression on the quantity sold is adopted to extract information from the order of discrete outcome. Since the promotion and sales arrangements are significantly different on the listing days (i.e. on period t given $a_t > 0$) and the non-listing days, two ordered logistic regressions are estimated separately. Given the independent transit in seasons, only quantity sold is needed to estimate from data to construct a transition matrix without season transition.

$$logit(P(q_{jt} < q|a_{jt} = 0)) = \eta_0 + \eta_1 o_{jt} + \eta_2 k_{jt} + \eta_3 z_{jt} \tag{6}$$
$$logit(P(q_{jt} < q|a_{jt} > 0)) = \xi_0 + \xi_1 a_{jt} o_{jt} + \xi_2 k_{jt} + \xi_3 I(k = 0) + \xi_4 z_{jt} \tag{7}$$

where $q_0, q_1 \in \{0, 100, 200, 300, 400, 500\}$.

Table 7: Ordered Logistic Regression for Sales

	Dependent variable:	
	qty sold	
	(1)	(2)
qty list		2.570***
		(0.233)
on-mkt	0.874***	−0.478
	(0.138)	(0.754)
PL	0.134**	−0.266
	(0.060)	(0.171)
not entered		−0.408
		(0.402)
z	0.352**	0.712***
	(0.158)	(0.247)
qty list:on-mkt		0.478
		(0.501)
Observations	12,782	273

*p<0.1; **p<0.05; ***p<0.01

Note: Column 1 is for non-listing days while column 2 is for listing days.

Table 7 shows that transit on non-listing days significantly depends on the number of apartments on-market and later PLs associates with a larger sales. As for listing days, even when the sample size is 98% smaller, the number of apartments added dominates the sales and later PLs indeed sell fewer. Both show seasonality has positive association with the sales. Projecting the ordered logistic result to the 6 transition matrices (one for each action) of size $1773 * 1773$, excerpts (table 8, 9 and 10) when adding no new apartment and 100 apartments are shown below.

In a complete state transition, the season can also change. Based on seasonality criteria above, transition of seasons can be estimated as a $3 * 3$ matrix. The estimated matrix (table 11) suggests season is relatively persistent with less than 1% probability in changing. Given the independence of season transit, complete state transit is the previous season-constant transition matrix multiplying the season transit matrix. Table 12 shows an excerpt of the full transition matrix, accommodating season transit at once.

Table 8: Transition matrix excerpt when a = 0

t \ $t+1$	100 0 1 1	100 100 1 1	100 200 1 1	100 300 1 1	100 400 1 1	100 500 1 1
100 0 1 1	1	0	0	0	0	0
100 100 1 1	0.008	0.992	0	0	0	0
100 200 1 1	0	0.018	0.982	0	0	0
100 300 1 1	0	0.001	0.042	0.957	0	0
100 400 1 1	0	0	0.002	0.094	0.904	0
100 500 1 1	0	0	0	0.005	0.199	0.796

Table 9: Transition matrix excerpt when a = 100 across PLs

t \ $t+1$	0 0 6 1	0 100 6 1	0 0 5 1	0 100 5 1	0 0 4 1	0 100 4 1	0 0 3 1	0 100 3 1	0 0 2 1	0 100 2 1	0 0 1 1	0 100 1 1
100 0 5 1	0.186	0.814	0	0	0	0	0	0	0	0	0	0
100 0 4 1	0	0	0.23	0.77	0	0	0	0	0	0	0	0
100 0 3 1	0	0	0	0	0.28	0.72	0	0	0	0	0	0
100 0 2 1	0	0	0	0	0	0	0.337	0.663	0	0	0	0
100 0 1 1	0	0	0	0	0	0	0	0	0.398	0.602	0	0
100 0 0 1	0	0	0	0	0	0	0	0	0	0	0.365	0.635

Table 10: Transition matrix excerpt when a = 100 at different Season

t \ $t+1$	0 0 2 0	0 100 2 0	0 0 2 1	0 100 2 1	0 0 2 2	0 100 2 2
100 0 1 0	0.245	0.755	0	0	0	0
100 0 1 1	0	0	0.398	0.602	0	0
100 0 1 2	0	0	0	0	0.574	0.426

Table 11: Seasonality transit

	Low	Normal	High
Low	0.992	0.008	0
Normal	0.002	0.997	0.002
High	0	0.007	0.993

Table 12: Full transition matrix excerpt (with season change)

t \ $t+1$	0 0 2 0	0 100 2 0	0 0 2 1	0 100 2 1	0 0 2 2	0 100 2 2
100 0 1 0	0.243	0.749	0.002	0.006	0	0
100 0 1 1	0.001	0.001	0.397	0.6	0.001	0.001
100 0 1 2	0	0	0.004	0.003	0.57	0.423

Conditional choice probability (CCP) would be represented by a $1773 * 6$ matrix. Similar to the transition matrix, complete non-parametric estimation is not ideal. There are only about 300 observations choosing $a > 0$, which is about 2.5% of matrix size. Parametric estimation would be needed. Ordered logit is not chosen here because the order in a might not contain strictly useful information. Over 90% of observations choose $a = 0$ and hence the difference between choosing 0 and 100 would not be the same as that between 100 and 200. Without assuming the order of dependent variable, multinomial logit would be a more appropriate functional form. Table 13 presents the result for the estimated choice probability.

Table 13: Multinomial Logit on Quantity to List

	Dependent variable:				
	100	200	300	400	500
	(1)	(2)	(3)	(4)	(5)
in-stock	-0.002^{***}	0.001^{***}	0.003^{***}	0.003^{***}	0.004^{***}
	(0.001)	(0.0004)	(0.0005)	(0.001)	(0.001)
on-mkt	-0.006	-0.012	-0.056^{***}	-58.846	-59.909^{***}
	(0.004)	(0.009)	(0.007)		(0.000)
on-mkt sold out	-2.653^{***}	-3.554^{***}	-6.364^{***}	-5.015^{***}	-5.742^{***}
	(0.281)	(0.563)	(0.300)	(0.508)	(0.817)
entered	0.904^{***}	0.784	3.301^{***}	2.216^{***}	-1.084^{***}
	(0.304)	(0.611)	(0.400)	(0.774)	(0.0003)
PL	-0.203^{**}	-0.200	-0.580	-0.959	-2.262^{***}
	(0.095)	(0.180)	(0.398)	(0.992)	(0.0004)
z	0.422^{***}	0.648^{**}	0.343	-0.453	0.035
	(0.158)	(0.256)	(0.392)	(0.732)	(1.110)
on-mkt sold out:entered	2.283^{***}	2.509^{***}	0.399	2.623^{***}	-0.666^{***}
	(0.300)	(0.589)	(0.400)	(0.774)	(0.0003)
Constant	-4.032^{***}	-5.279^{***}	-3.462^{***}	-5.423^{***}	-6.159^{***}
	(0.319)	(0.619)	(0.300)	(0.508)	(0.817)
Akaike Inf. Crit.	3,699.754	3,699.754	3,699.754	3,699.754	3,699.754

*p<0.1; **p<0.05; ***p<0.01

As for pricing estimation, although I have pricing data for every apartment, my model makes decision on a PL-level to sell homogeneous goods. The pricing relevant for model estimation should be aggregated to PL-level and uniform prices in the same PL. Simple average of apartments listed do not work for two reasons. One is that the payoff function, $\pi(a_{jt}, s_{jt})$, would no longer be anonymous to seller identity. Sellers of the same state can add 100 apartments of different average price in raw data. The other reason is that homogeneous good assumption abstracts away from which apartments to be added/removed when listing decision changes and hence simple average can no longer be computed. Instead, I propose estimating the pricing residual for each state and using the sum of estimated residual and a representative price as the price at the corresponding state. Note that even in raw data where price varies apartment-by-apartment, much of the variations ($adjusted R^2 > 85\%$) is accounted for by the fixed effects of district, floor time. Price residual would likely capture the relevant scope the sellers can control in terms of pricing. Table 14 shows the estimation result of a linear regression on the price per sq. ft. residual.

Table 14: Linear regression on Residual of Price per sq. ft.

	Dependent variable:
	price resid
PL	347.610*
	(184.218)
z	4.050
	(417.427)
Single PL Complex	79.889
	(397.977)
PL:z	56.867
	(156.393)
Constant	−857.678*
	(492.584)
Observations	191
R^2	0.153
Adjusted R^2	0.135
Residual Std. Error	1,234.713 (df = 186)
F Statistic	8.418*** (df = 4; 186)
Note:	*p<0.1; **p<0.05; ***p<0.01

Given the homogeneous good assumption, all apartments should charge the same, other than the variations by state. I construct the representative price as average price per sq. ft. times average sq. ft., which is HKD 9.36 million per apartment. Combining the two, I have the pricing for model estimation. Some excerpts (table 15 and 16) of the $1773 * 6$ matrix are shown below.

Table 15: Price across PLs

	100	200	300	400	500	0
100 0 6 1						10.178
100 0 5 1	10.178					9.968
100 0 4 1	9.968					9.757
100 0 3 1	9.757					9.547
100 0 2 1	9.547					9.337
100 0 1 1	9.337					9.126

Note: in millions HKD

Some features of the pricing are worth mentioning. It has an increasing trend as later PLs post (table 15). This is an important payoff feature in the industry as described before. Industry participants would take this capability of charging high price in later PLs to gauge sales performance of a seller. Another feature is that the pricing for listing all apartments at once is higher than that for listing partially. This is another dominant feature in data, which trades off the opportunity of charging higher price in later PLs. Also, when there is no apartments newly added, the pricing remains the same as its previous PL. This implies when apartments are sold on non-listing days, their price remains at the latest PL level. This is also a norm in the industry as described before.

Table 16: Price across different In-Stock

	100	200	300	400	500	0
100 0 0 1	9.168					9.126
200 0 0 1	9.126	9.168				9.126
300 0 0 1	9.126	9.126	9.168			9.126
400 0 0 1	9.126	9.126	9.126	9.168		9.126
500 0 0 1	9.126	9.126	9.126	9.126	9.168	9.126

Note: in millions HKD

4.3 Main result

Given the full transition matrix with season transit, CCP and pricing, the instantaneous payoff can be computed up to the 4 cost parameters, (c_e, c_r, c_h, c_o). Since only the difference in value matters in discrete choice model, one needs to first pin down one of the choices. In order to estimate entry cost (c_e) and re-entry cost (c_r), one would need to know the value of choice $a = 0$ and hence the holding cost and TOM impact need to be pinned down. Together with the discount factor, β, there are 3 parameters (i.e. c_h, c_o, β) that need to be assumed in order to identify and estimate the entry cost, c_e, and reentry cost, c_r.

With the entry cost and re-entry cost estimated for each of 1773 states through PML, an Extended Oblivious Equilibrium (EOE) can be computed. Comparing simulations from the estimated EOE and simulations from the step 1 CCP, figure 7 shows that the EOE recovers the simulated data generated by the empirical CCP pretty well. While the raw data are only one realization of its data generation process, EOE can reasonably generate the raw data the same way as the empirical CCP can generate. In figure 7, the grey area shows the raw data and the colored lines represent simulations by the empirical CCP (blue) and the estimated EOE (red). Solid lines mean the average of simulations and the dotted lines represent the 5^{th} and 95^{th} percentiles.

Taking a closer look at the estimated EOE, one can compare the entry and reentry probabilities of EOE with those of empirical CCP. In the excerpts below (i.e. table 18 & 19), the EOE entry probabilities for 500 or less apartments in-stock, across all seasons, are quite close. As for table 20 & 21, the excerpts for reentry probabilities in normal season show that although the differences are slightly larger numerically, the relative probabilities across choices are maintained. Also, note that PML relies on data to influence the weights across all likelihood differences in estimation. The larger difference in reentry probabilities might suggest reentry plays a smaller role than entry does in reality. This is indeed consistent with the earlier simulation result, where EOE, as it is, generates data close to what empirical CCP generates.

Cost estimates show that seasonality does matter. Table 22 shows an excerpt of entry cost across seasons. For any given individual state (i.e. keeping (i, o, k) fixed), the cost increases by more than 6% when the season changes from low to normal or from normal to high. This is reasonable because

Table 17: Parameters of choice

β	0.99
c_h(in HKD)	20
c_o(in HKD)	20,000

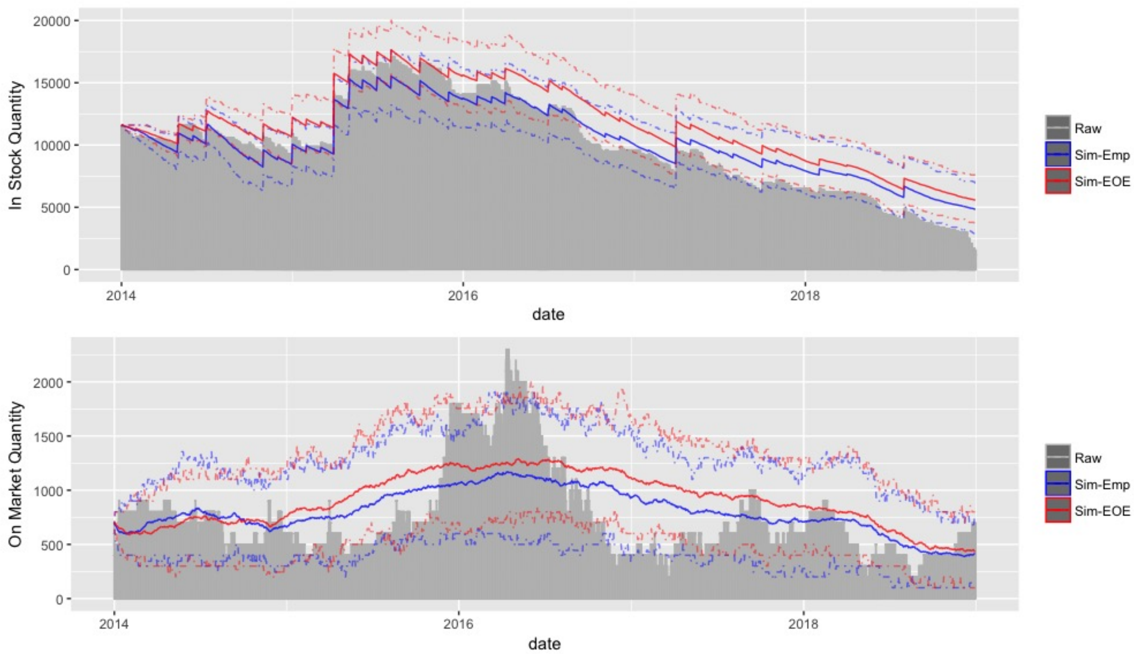


Figure 7: Simulations of Estimated EOE

Table 18: Empirical Entry Probability

	100	200	300	400	500	0
100 0 0 0	0.0013	0	0	0	0	0.9987
200 0 0 0	8e-04	3e-04	0	0	0	0.9988
300 0 0 0	7e-04	2e-04	2e-04	0	0	0.9989
400 0 0 0	6e-04	2e-04	2e-04	1e-04	0	0.9989
500 0 0 0	5e-04	3e-04	2e-04	1e-04	0	0.9989
100 0 0 1	0.002	0	0	0	0	0.998
200 0 0 1	0.0013	5e-04	0	0	0	0.9982
300 0 0 1	0.001	4e-04	2e-04	0	0	0.9983
400 0 0 1	8e-04	5e-04	2e-04	1e-04	0	0.9984
500 0 0 1	7e-04	5e-04	3e-04	1e-04	0	0.9984
100 0 0 2	0.0031	0	0	0	0	0.9969
200 0 0 2	0.0019	9e-04	0	0	0	0.9972
300 0 0 2	0.0016	8e-04	3e-04	0	0	0.9973
400 0 0 2	0.0013	9e-04	3e-04	1e-04	0	0.9974
500 0 0 2	0.0011	0.001	4e-04	1e-04	0	0.9974

Table 19: EOE Entry Probability

	100	200	300	400	500	0
100 0 0 0	0.0012					0.9988
200 0 0 0	7e-04	2e-04				0.9991
300 0 0 0	8e-04	2e-04	2e-04			0.9989
400 0 0 0	9e-04	2e-04	1e-04	1e-04		0.9987
500 0 0 0	9e-04	3e-04	2e-04	1e-04	7e-04	0.9977
100 0 0 1	0.0024					0.9976
200 0 0 1	0.0018	5e-04				0.9977
300 0 0 1	0.002	5e-04	2e-04			0.9973
400 0 0 1	0.0022	6e-04	2e-04	1e-04		0.9968
500 0 0 1	0.0023	9e-04	4e-04	1e-04	4e-04	0.9959
100 0 0 2	0.0041					0.9959
200 0 0 2	0.0034	5e-04				0.996
300 0 0 2	0.0034	6e-04	1e-04			0.9959
400 0 0 2	0.0034	7e-04	1e-04	0		0.9957
500 0 0 2	0.0033	0.001	2e-04	0	0	0.9954

Table 20: Empirical Re-entry Probability

	100	200	300	400	500	0
100 0 1 1	0.0397	0	0	0	0	0.9603
200 0 1 1	0.0243	0.0121	0	0	0	0.9636
300 0 1 1	0.0198	0.0089	0.0057	0	0	0.9655
400 0 1 1	0.0162	0.0102	0.0047	0.0028	0	0.9661
500 0 1 1	0.0132	0.0117	0.0061	0.0037	0	0.9652

Table 21: EOE Re-entry Probability

	100	200	300	400	500	0
100 0 1 1	0.0145					0.9855
200 0 1 1	0.0089	0.0053				0.9858
300 0 1 1	0.0083	0.0035	0.0023			0.9859
400 0 1 1	0.0087	0.0037	0.0017	6e-04		0.9853
500 0 1 1	0.0093	0.0044	0.002	5e-04	0.0018	0.982

entry and reentry cost advertising, soliciting real estate agents, attracting media reporters and sales venue constitute a major part of . And these are subject to increase as the competition intensifies and vice versa. In addition to the different sales probability across season incorporated into the transition matrix, the data reveal that there are also entry/reentry cost differences across seasons.

Table 22: Estimated Entry Cost

	100	200	300	400	500	0
100 0 0 0	10.292					0
200 0 0 0	10.094	20.188				0
300 0 0 0	9.896	19.792	29.688			0
400 0 0 0	9.698	19.396	29.094	38.792		0
500 0 0 0	9.5	19	28.499	37.999	47.499	0
100 0 0 1	10.936					0
200 0 0 1	10.726	21.451				0
300 0 0 1	10.515	21.031	31.546			0
400 0 0 1	10.305	20.61	30.914	41.219		0
500 0 0 1	10.094	20.189	30.283	40.377	50.471	0
100 0 0 2	11.787					0
200 0 0 2	12.716	23.121				0
300 0 0 2	12.467	24.934	34.001			0
400 0 0 2	12.217	24.435	36.652	44.427		0
500 0 0 2	11.968	23.936	35.903	47.871	54.399	0

Table 23: Estimated Re-entry Cost

	100	200	300	400	500	0
100 0 1 1	10.017					0
100 100 1 1	12.553					0
100 200 1 1	14.499					0
100 300 1 1	15.855					0
100 400 1 1	16.621					0
100 500 1 1						0
200 0 1 1	10.021	20.042				0
200 100 1 1	12.557	25.115				0
200 200 1 1	14.503	29.007				0
200 300 1 1	15.86	31.719				0
200 400 1 1	16.626					0
200 500 1 1						0

In the reentry cost, one would also notice that the cost for the seller increases drastically when its own apartments on-market increase, as high as 25% for every 100 apartments more on market (see the excerpt in table 23. This cost surge reflects the difficulty described by industry participants. Whenever the apartments of a complex are not (nearly) all cleared, it is very difficult to motivate the real estate agents to promote the apartments. As such, the sellers would need to provide a much higher commission rate for the agents had they want to add more apartments before previous apartments are (mostly) cleared. This is also consistent with the data. All actions to add new apartments are taken when the apartments on-market are less than or equal to 200 (i.e. $o \leq 200$)

and 98% are taken when $o \leq 100$.

While one might incline to interpret the cost estimates as in millions HKD the same way as the prices, note that the estimated entry cost and reentry cost are not directly interpretable. On one hand, this is because the standard logistic distribution assumption in the discrete choice models necessitates payoff difference across choices, say the highest probability being 0.99999, to be within a range of 10[17]. When there are more than 2 choices, prices at a higher numerical scale (e.g. in hundreds or in millions) can easily throw some choices to have a difference larger than 10 from other choices, which makes degenerate strategy likely. Therefore, price needs to scale low enough to apply discrete choice model. On the other hand, the scaled price makes the saving from waiting smaller in absolute terms. This makes entry cost and re-entry cost take up a larger role in encouraging the seller to wait since only the absolute difference matters in logistic framework. Hence, the need of standard logistic distribution and the concern in the saving by waiting render the cost estimates cannot be directly interpreted. This would be an inevitable feature under the constraints of discrete choice framework in the latest literature. The estimates, however, are still valid given the current model set-up. While this limits what the data can tell us about the entry and reentry cost, the estimated equilibrium can be used to evaluate various counterfactual policy that are of practical use.

4.4 Robustness Check

The current specification of estimation to construct CCP, tansit matrix and pricing is kept simple for transparency. It is reasonable to consider, however, whether there is big impact when other specifications of those functions are used instead and hence the estimation result driven by parametric form. Therefore, I consider other specifications and their implication to the stage 1 result on CCP, transition matrix and pricing here.

For CCP, alternative to what table 13 suggested, I consider multinomial logit up to square terms with the following specification.

$$\begin{aligned} a_{jt} = &\zeta_0 + \zeta_1 i_{jt} + \zeta_2 i_{jt}^2 + \zeta_3 o_{jt} + \zeta_4 o_{jt}^2 \\ &+ \zeta_5 soldout_{jt} + \zeta_6 entered_{jt} + \zeta_7 PL_{jt} + \zeta_8 PL_{jt}^2 \\ &+ \zeta_9 z_{jt} + \zeta_{10} soldout_{jt} * entered_{jt} \end{aligned}$$

Comparing with the original CCP, the CCP constructed based on the multinomial logit above differs by $-1.240e^{-6}$ on average[18] with a median $2.761e^{-4}$. The 1^{st} quartile and the 3^{rd} quartile of their differences are $-2.395e^{-3}$ and $2.533e^{-3}$ respectively. By changing the parametric form, CCP doesn't change much from the one I used in the structural estimation.

For transition matrix, since parametric form is needed due to small proportion of states observed (only $> 2\%$ of $1773 * 1773$ state space) as discussed before, I combine the ordered logit and the independent season transit, to form the transition matrix. However, the specifications of ordered logit can consider an alternative form for robustness check. I considered the alternative form as shown below.

$$\begin{aligned} logit(P(q_{jt} < q | a_{jt} = 0)) = &\eta_0 + \eta_1 o_{jt} + \eta_2 k_{jt} + \eta_3 z_{jt} + \eta_4 o_{jt}^2 + \eta_5 k_{jt}^2 \\ logit(P(q_{jt} < q | a_{jt} > 0)) = &\xi_0 + \xi_1 a_{jt} o_{jt} + \xi_2 k_{jt} + \xi_3 I(k = 0) + \xi_4 z_{jt} \\ &+ \xi_5 o_{jt}^2 + \xi_6 k_{jt}^2 \end{aligned}$$

Constructing an alternative transition matrix of $1773 * 1773$ by 6 potential actions (i.e. $a \in (100, ..., 500, 0)$) based on the above, one can see the difference is not much even when specifica-

[17] For example, in a binary choice of values for 10 and 0, the probability for choosing value=10 is 0.9999546.

[18] Note that the 0s and 1s in CCP due to model assumption are not included as the difference would be zero by construction.

tion changed. Table 24 shows that the difference for each potential action has a median difference[19] to be in the order of -3 to -7, with the 1^{st} quartile and 3^{rd} quartile less than 0.1.

Table 24: Difference in Transition Matrix by Action

a	1^{st} Quartile	Median	Mean	3^{rd} Quartile
100	-0.0270917	$9.4870e-3$	$1.925e-18$	0.0808123
200	-0.0366667	$1.579e-3$	$-1.295e-18$	0.0424968
300	-0.0133411	$-4.084e-4$	$9.278e-19$	0.0114992
400	-0.0034778	$5.740e-7$	$-8.735e-19$	0.0023588
500	-0.0026873	$-1.003e-5$	$-1.635e-18$	0.0008090
0	-0.0029763	$-1.148e-6$	0	0.0027198

For pricing, other than the linear regression used in table 14, I attempt to estimate by considering the second order.

$$PriceResidual_{jt} = PL_{jt} + z_{jt} + SinglePLComplex_{jt} + PL_{jt} * z_{jt} + PL_{jt}^2$$

With this alternative specification, the pricing calculated from the estimated coefficients differs from the pricing in benchmark case from -8% to 2% with a mean difference at -0.5%. Hence, the pricing residual regression is not significantly restricted by the generic formulation in table 14.

5 Counterfactual Policy

5.1 Vacancy tax

Government in Hong Kong announced on 29 June 2018 to introduce vacancy tax for unoccupied apartments in the primary market. The claimed policy goal is to encourage real estate developers "to expedite the supply of first-hand private residential units in completed projects". The proposal was put before Legislative Council by 11 September 2019. Even though the discussion was discontinued on 23 June 2020 as it exceeded the LegCo term, it was widely discussed back then and recently mentioned again as COVID-19 situation gradually settled in Hong Kong.

While it sounds plausible that sellers would put out more goods to sell as the holding cost increases, it is not necessary the equilibrium outcome. When more goods are on-market, the competition makes the goods harder to sell and suffer more from the Time-On-Market impact, or even larger holding cost still. Therefore, to analyse whether the market will respond to the policy as intended, a model incorporating competition would be required for policy analysis.

5.1.1 Counterfactual Implementation

To implement the vacancy tax, government proposed to charge "Special Rates" on units remain unsold and not rented out for more than 6 months over the past 12 months with its occupational permit issued. The "Special Rates", usually known as vacancy tax, are equivalent to 200% of the rateable value of the apartment.

In terms of our competition model, the vacancy tax would simply be raising the holding cost. Although the time dependency of the policy proposed would be difficult for any Markov-based model including the EOE model, one can consider a variant that shall shed light on how competition might change. I will evaluate the same vacancy tax except it is collected on all apartments after emerging.

[19] Note that the 0s and 1s in transition matrix due to model assumption are not included as the difference would be zero by construction.

In addition to its feasibility for all Markov-based models, this variant form pursues the same intention of raising the holding cost to encourage earlier supply, albeit the larger scale of intervention. Since it is also possible that the actual proposed policy might not change the competition equilibrium, if this variant policy of larger scale doesn't change its competition equilibrium, it suggests that the actual proposed policy, which intervenes the market at smaller scale, might not change either.

Table 25: EOE Entry Probability under Vacancy Tax

	100	200	300	400	500	0
100 0 0 0	0.0012					0.9988
200 0 0 0	0.0018	2e-04				0.998
300 0 0 0	0.0023	3e-04	1e-04			0.9973
400 0 0 0	0.0027	5e-04	3e-04	1e-04		0.9965
500 0 0 0	0.003	7e-04	5e-04	2e-04	5e-04	0.9952
100 0 0 1	0.0024					0.9976
200 0 0 1	0.004	4e-04				0.9956
300 0 0 1	0.0053	8e-04	1e-04			0.9938
400 0 0 1	0.0063	0.0014	3e-04	0		0.992
500 0 0 1	0.0069	0.002	7e-04	1e-04	2e-04	0.9901
100 0 0 2	0.0041					0.9959
200 0 0 2	0.0074	4e-04				0.9922
300 0 0 2	0.01	9e-04	1e-04			0.989
400 0 0 2	0.012	0.0016	2e-04	0		0.9862
500 0 0 2	0.0135	0.0024	4e-04	0	0	0.9837

Table 26: EOE Re-entry Probability under Vacancy Tax

	100	200	300	400	500	0
100 0 1 1	0.0069					0.9931
200 0 1 1	0.0083	0.0022				0.9896
300 0 1 1	0.0087	0.003	9e-04			0.9874
400 0 1 1	0.0089	0.0034	0.0013	2e-04		0.9861
500 0 1 1	0.0089	0.0036	0.0016	3e-04	6e-04	0.9851

The rateable value is at 5% of rental value of an apartment. Given the model assumption of representative apartment, the rateable value is about HKD 33 per day. The holding cost, c_h, is now at $20 + 33 * 2 = 86$ in Hong Kong Dollars.

5.1.2 Counterfactual Equilibrium

Table 25 and 26 showed the excerpts of updated equilibrium, as compared to the original equilibrium in table 22. At first glance, one can see there is almost no difference in the excerpts. Regarding the whole $1773 * 6$ probability matrix, there is a tiny difference ranging from $-5e-4$ to $5e-4$. Based on the equilibrium result, one can see that the impact of vacancy tax is tiny.

To visualize the difference, I used the EOE under vacancy tax to simulate again. One can see from figure 8 that the simulated markets with and without the vacancy tax are very similar. This illustrates the fact that the two equilibrium strategies are very close and hence suggesting the

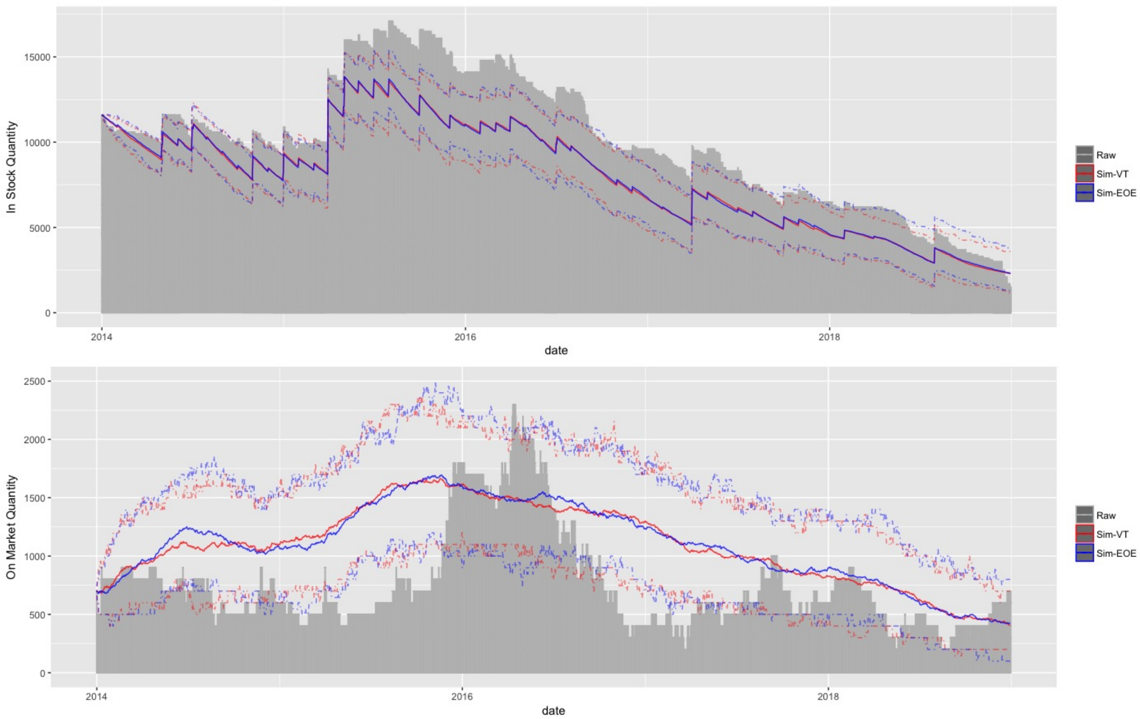


Figure 8: Simulations of Counterfactual EOE under Vacancy Tax

competition is insensitive to imposing vacancy tax[20]. In light of the competition model in EOE, the proposed vacancy tax has minimal impact to the behaviors of sellers.

5.2 Counter-cyclical and Acyclical Phased Sales Penalty

In addition to vacancy tax, another kind of policy commonly considered is Phased Sales Penalty. Given the price raise for each new PL, multiple PLs are frequently scrutinized as the tool of seller to extract all the benefits from buyers, or ”tooth-paste squeezing” in local language. Therefore, government is potentially considering some forms of regulation to restrict the number of PLs in phased sales.

Counterfactual policy I consider here is to penalize the seller whenever they add new apartment without adding all apartments on hand. These sellers would be charged a fee equivalent to 10% of the (re)entry cost whenever they do so.

In addition to acyclical/universal implementation, government frequently considers interventions as counter-cyclical measures. Since they recognize interventions as dampening the healthy operation in market, they tend to impose these regulations only in high season. Our EOE model is indeed well-suited to discuss the difference, if any, between universal implementation and seasonal implementation.

[20]Heavier vacancy tax has also been considered. For example, same procedure has been applied to a vacancy tax that collects 900%, instead of 200% in government proposal, more of the rateable value of the apartment. However, the resulting EOE strategy still stays very close to the strategy without vacancy tax.

5.2.1 Implementation in All Seasons

To implement the penalty to discourage sellers from listing small batches, I raised 10% of their (re)entry cost as long as they are not listing all apartments on hand when they have 500 apartments or less. In data, 80% of sellers have 500 apartments or less to sell in total. For those with more than 500 apartments, the (re)entry costs increases by 10% as long as they are not adding 500 apartments when adding. While this serves the purpose to encourage sellers providing more options when they list, it also satisfies the state space concern given the computational constraints. The penalty doesn't differentiate by seasons. It implies once the policy is adopted, it is maintained regardless of the season realized.

Relative to vacancy tax, this intervention of penalizing small entry has a more significant impact to the competition. The excerpts for entry (Table 27) and reentry (Table 28) strategy show the 10% penalty deter them from entering with small batches. For example, Table 28 shows that the probabilities of re-entering by adding 100 apartment with more 100 apartments in-stock (i.e. row 2 - 4) drops from 0.8% to 0.4%. Some small batch probabilities even drop to zero under the penalty. Interestingly, if I take a closer look, the probabilities of adding all apartments on hand do not change much. For example, the entry probabilities in Table 27 for sellers with 200 apartments across all 3 seasons stay at $2e-4$, $5e-4$ and $5e-4$, very close to the probabilities without penalty (i.e. $2e-4$, $4e-4$ and $4e-4$). Since the LR state distribution of the market has changed under the counterfactual policy, even states without direct change in cost can have a different strategic response. The results here suggest that the market state change is not enough to drive much difference when they're listing all they have. As we will see later, this does not always hold.

Table 27: EOE Entry Prob under Acyclical Penalty

	100	200	300	400	500	0
100 0 0 0	0.0012					0.9988
200 0 0 0	7e-04	2e-04				0.999
300 0 0 0	9e-04	1e-04	2e-04			0.9989
400 0 0 0	0.001	1e-04	0	1e-04		0.9988
500 0 0 0	0.0012	1e-04	0	0	7e-04	0.998
100 0 0 1	0.0024					0.9976
200 0 0 1	0.0017	5e-04				0.9978
300 0 0 1	0.002	1e-04	2e-04			0.9977
400 0 0 1	0.0023	2e-04	0	1e-04		0.9974
500 0 0 1	0.0026	3e-04	0	0	3e-04	0.9967
100 0 0 2	0.0041					0.9959
200 0 0 2	0.0032	5e-04				0.9963
300 0 0 2	0.0037	2e-04	1e-04			0.996
400 0 0 2	0.0043	2e-04	0	0		0.9955
500 0 0 2	0.0049	3e-04	0	0	0	0.9947

By simulating the market with the new strategy, Figure 9 shows the market would look drastically different from what we currently observe. Once the policy is in place, the quantities in-stock (upper panel) starts accumulating and there would be about 10,000 more apartments in-stock by the end of data period. This is a natural outcome as sellers are discouraged to list apartments in general. As for the apartments available on-market (lower panel), it has fewer apartments on-market given the overall lower (re)entry. Later, the apartments on-market accumulates due to 2 major forces. One is the larger batch sellers now list. This implies there is higher proportion of apartment not sold on the first day. Another force is the LR market state change. There are more apartments on-market

Table 28: EOE Re-entry Prob under Acyclical Penalty

	100	200	300	400	500	0
100 0 1 1	0.007					0.993
200 0 1 1	0.0042	0.0031				0.9928
300 0 1 1	0.0043	7e-04	0.0016			0.9933
400 0 1 1	0.0045	7e-04	1e-04	5e-04		0.9942
500 0 1 1	0.004	7e-04	1e-04	0	0.0013	0.9938

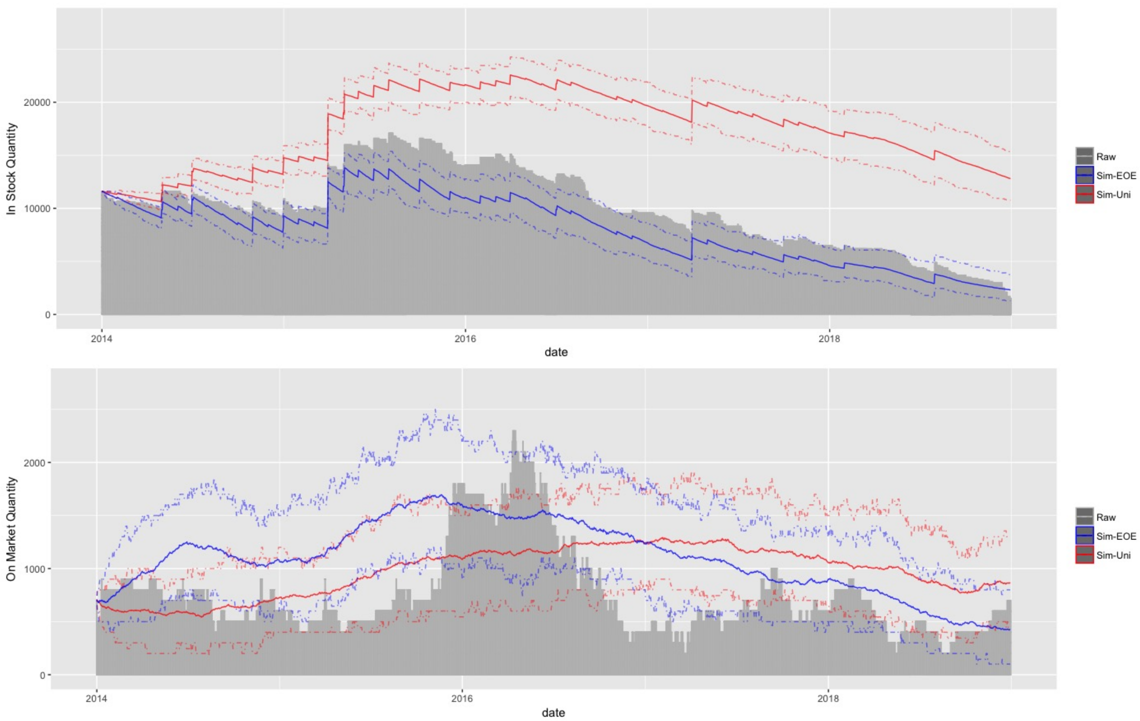


Figure 9: Simulations under Acyclical Phased Sales Penalty

in LR which means the competition to successfully sell an apartment is more intense. These effect dominate the lower (re)entry in the quantity on-market in about 3 years after penalty imposed.

5.2.2 Implementation in High Season Only

While it is reasonable to implement the penalty throughout all market situations for policy consistency, various factors might render the implementation season specific. Government might regard the policy as hampering the healthy operation of market, so they intentionally only impose it in high season, when they deem the market to be too hot. Or, the lobbying for removing penalty from the sellers could be stronger in the low season since the return from their primary business would be relatively lower by then. Hence, evaluating a season-specific policy should weigh in as a potential policy choice or simply an inevitable compromised reality.

Counterfactual policy considered here is to raise (re)entry cost by 10% when the market is in high season. Once the market moves back to normal or low season, the penalty is removed and (re)entry cost is back to the original estimated level. Hence, the penalty is de facto imposed 1/3 of the time or less given the lower probability for normal season to transit to high season.

While one might expect the impact of such an counter-cyclical policy to the market should be smaller, comparing to the acyclical policy, excerpts of entry and reentry strategy in table 29 & 30 show a different story. When the penalty is imposed in high season (i.e. $z = 2$), sellers are discouraged to enter. The probability of not entering in Table 29 increased from the range of 0.985-0.995 to be above 0.997 (i.e. the bottom 5 rows). Even if compared to the acyclical penalty in Table 27 which is around 0.995, the counter-cyclical penalty still has a stronger discouraging impact. As for the other seasons without penalty in counter-cyclical policy, a relevant comparison with acyclical penalty would be comparing with those all-in actions because these are similarly not subject to penalty. Recall that under acyclical penalty, these actions adding all apartments on hand for sale do not change much. In comparison, however, the strategy in non-penalized seasons (i.e. normal and low season) under counter-cyclical policy change drastically. Both entry and reentry have much lower (re)entering probabilities. Furthermore, notice that when some entry probabilities drop to zero in univeral penalty, it is usually those larger but still partial listing (e.g. adding 400 with a stock of 500). All-in listings tend to still have some positive probabilities, simply because they are not penalized. As for counter-cyclical policy, it tends to have zero probabilities for larger listings, regardless of full listing or not. These two observations, impact to non-high seasons and zero probabilities for all-in actions, point to the fact that the strategies under counter-cyclical policy are not just affected by the penalty itself directly, but some other factors. As it'd be shown later, it is because the penalty causing a significant change in the LR market state, which implies a stronger competition across all seasons and individual states. Hence, counter-cyclical penalty affects states not subject to penalty indirectly through the LR market state.

Table 29: EOE Entry Prob under Counter-cyclical Penalty

	100	200	300	400	500	0
100 0 0 0	6e-04					0.9994
200 0 0 0	9e-04	1e-04				0.9991
300 0 0 0	0.0011	1e-04	0			0.9988
400 0 0 0	0.0013	1e-04	0	0		0.9985
500 0 0 0	0.0015	2e-04	1e-04	0	1e-04	0.9981
100 0 0 1	0.0013					0.9987
200 0 0 1	0.002	1e-04				0.9979
300 0 0 1	0.0025	2e-04	0			0.9973
400 0 0 1	0.0029	4e-04	1e-04	0		0.9966
500 0 0 1	0.0034	5e-04	1e-04	0	0	0.9959
100 0 0 2	0.0023					0.9977
200 0 0 2	0.0014	2e-04				0.9985
300 0 0 2	0.0016	0	0			0.9984
400 0 0 2	0.0019	1e-04	0	0		0.998
500 0 0 2	0.0023	1e-04	0	0	0	0.9976

A more comprehensive picture of the changed strategy can be demonstrated in simulations. Figure 10 is the simulations using the optimal strategy under counter-cyclical policy (red). Similar to the case of acyclical policy, the quantity in-stock (upper panel) accumulates since the policy is imposed since the (re)entry probabilities are now lower. And the stock difference between the strategy under counter-cyclical policy and the empirical strategy increases to about 10,000 apartments by the end of data period. As for the quantity on-market (lower panel), the story is quite different from that of acyclical policy. While the quantity on-market start off lower due to fewer entries, it soon accumulates because there are more apartments on-market in the long run. The sellers face a more

Table 30: EOE Re-entry Prob under Counter-cyclical Penalty

	100	200	300	400	500	0
100 0 1 1	0.0043					0.9957
200 0 1 1	0.0051	9e-04				0.994
300 0 1 1	0.0052	0.0011	3e-04			0.9934
400 0 1 1	0.0052	0.0012	4e-04	1e-04		0.9932
500 0 1 1	0.0052	0.0012	4e-04	1e-04	1e-04	0.993

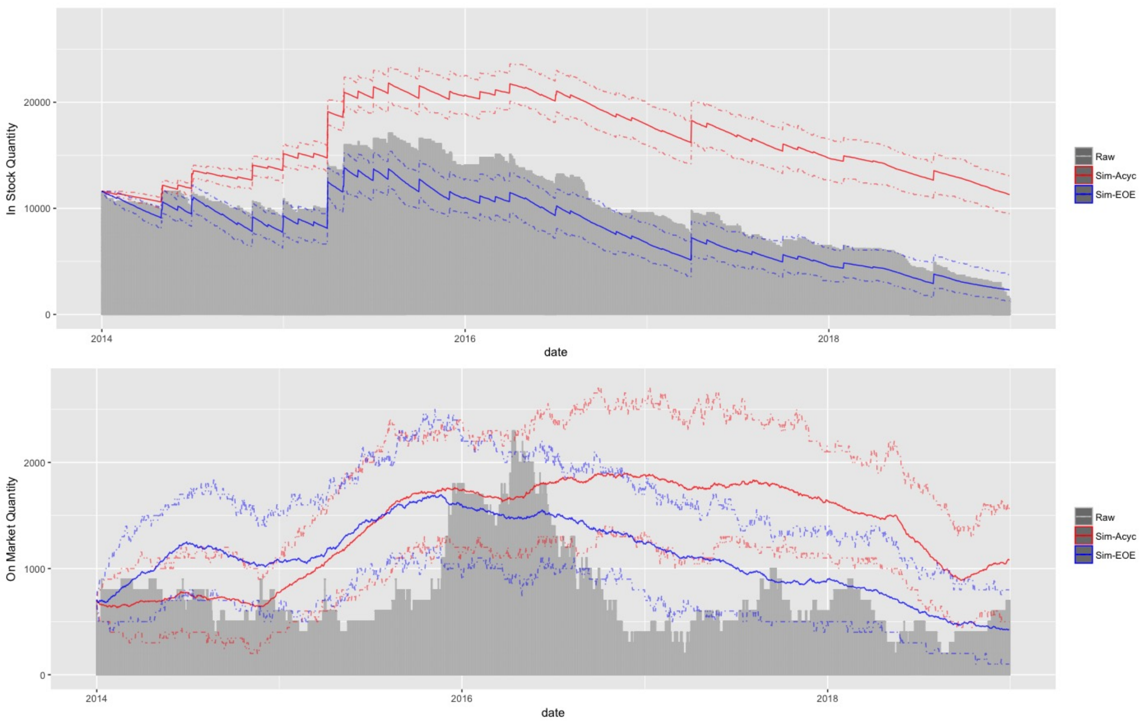


Figure 10: Simulations under Counter-cyclical Phased Sales Penalty

severe competition in getting their apartments to be sold. As a result, more are stuck on-market. The counter-cyclical penalty caused the quantity on-market to be higher than without penalty in less than 2 years, much earlier than under the counterfactual policy of acyclical penalty.

5.2.3 Discussion on Acyclical and Counter-cyclical Penalty

The contrast in the resulting markets from acyclical policy and counter-cyclical policy can be quite puzzling. Since the scale of counter-cyclical policy is absolutely smaller than that of acyclical policy with the same magnitude of penalty, a common expectation would be the impact to the market being smaller, regardless of what the impact is. The comparison yet says a very different, if not exact opposite, story. When the penalty is imposed only in the high season, the change in the quantity on-market and the change in the optimal strategy are both much larger than that of acyclical penalty. As I dig deeper into the markets under two counterfactual policies, I can see the difference roots in the policy implication to the LR market state. Counter-cyclical policy leads to a much higher number of apartments on-market in the long run. This implies a much more intense selling competition.

The lower selling rate in turn accounts for both the feature of more apartments on-market and the lower (re)entry probabilities even in seasons without penalty.

As to the further insight on why counter-cyclical policy reaches the oblivious equilibrium with a higher number of apartments on-market, it is potentially because counter-cyclical policy weakens one of the counteracting forces. Under acyclical penalty, there can be more apartments on-market because sellers are likely to list a bigger batch every time, but this is counteracted by the lower probability for sellers to list. The former force dominates as reflected from the higher quantity on-market in the long run. As for counter-cyclical penalty, although it has the same mechanics happening in high season, the other seasons no longer face the penalty that discourages them from (re)entering. This suggests that sellers has additional motivation to (re)enter in other seasons in anticipation of penalty in high season. This is a consequence of competition that cannot be easily captured had I not have a dynamic competition model. As a whole, high season penalty induces more apartments on-market and other seasons seize the chance to enter without penalty. From the long run perspective where both high and other season can be realized in expectation, these two factors contribute to a bigger dynamic competition response. Therefore, policy of a smaller scale, such as counter-cyclical policy in this case, can actually entail a bigger impact to the market once the dynamic competition is taken into account.

5.3 Comparison of EOE and OE

Since EOE is an extension that has yet to be applied in literature, one might consider the difference between EOE and OE in the counterfactual scenarios. Therefore, counterfactual simulations using OE estimation were also performed to gauge the potential differences.

Similar to the EOE estimation, I first estimated the CCP and transition matrix in OE, then I estimated the underlying cost and simulated the countefactuals based on estimations from previous steps. Regarding the differences, they mainly result from the different state space. For CCP, the states across different seasons are now exact same in OE and hence a $1773*3$ matrix can be compactly represented by a $591*3$ matrix. For transition matrix, other than compactly representing $1773*1773$ by $591*591$, the absence of seasonality also implied there is no transition of season. Once the state space adjustment has been made, the same evaluation of counterfactuals can be performed.

Figure 11 compares the OE counterfactual under the vacancy tax scenario. In the upper panel, simulations of OE under vacancy tax scenario (green) are very close to that of EOE (red) and hence both are close to the scenario without vacancy tax, similar to earlier finding. The difference would be more in the on market quantity (lower panel), which is about 200 apartment max around the end of 2014 and the early 2015.

As for counterfactual under phased sales penalty, note that one can only compare the EOE and OE under acyclical phased sales penalty because OE does not distinguish cycle that accomodates counter-cycle policy. Under acyclical phased sales penalty, figure 12 clearly demonstrates the difference between with and without season in equilibrium. By focusing on the counterfactual path for the in-stock, the upper panel shows that OE counterfactual (green) can over-estimate as many as 1000 apartments, around the time of late 2017. Also, notice that for the periods before 1^{st} high season and that between 2 low seasons, the OE counterfactual (green) almost exactly replicates the EOE counterfactual (red). As time progresses, the divergence emerges only since high season and converges back after a low season of similar length and then it diverges again since the 2^{nd} low season and converges again after the 2^{nd} high season of similar length. These contrasting observations are indeed consistent with the difference between EOE.

When the market reaches a high season in EOE, firms in EOE tend to sell more than before as the apartments are now sold faster, but the firms in OE do not distinguish and hence sell less in this period. And vice versa is also true for low season. As a result, the in-stock quantity tend to be lower in EOE (red) and be higher in OE (green) for a high season, and vice versa for a low season. Since the time spent in either high or low season is similar in our case, it is reasonable that whenever both

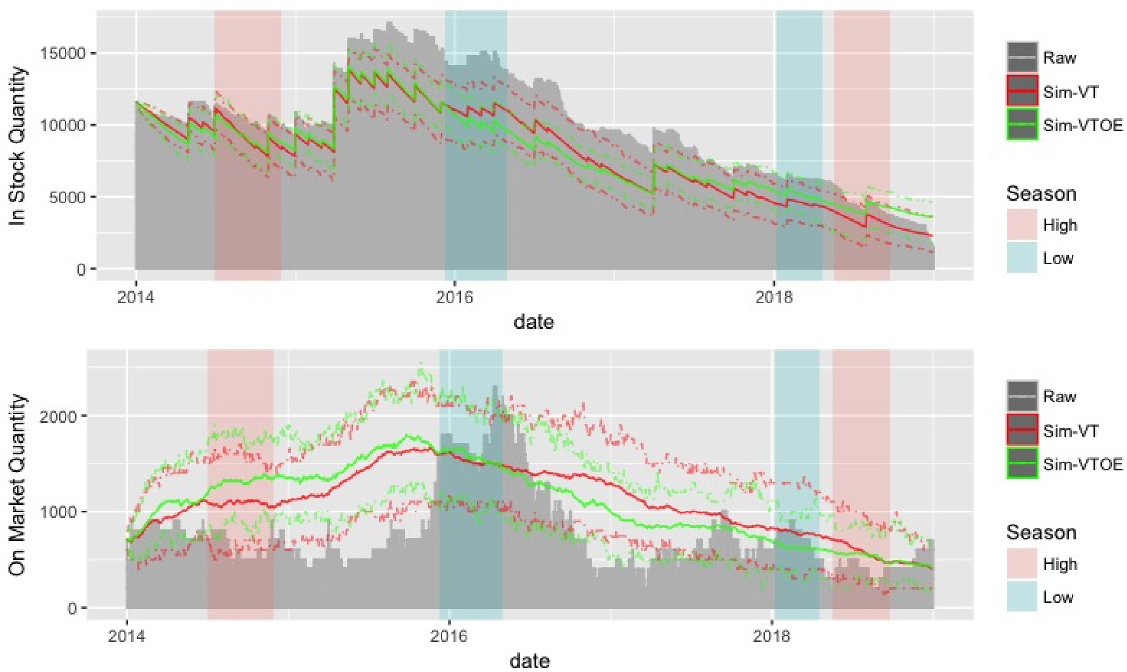


Figure 11: Simulations of Counterfactual under Vacancy Tax: EOE vs OE

high and low season are passed once, convergence becomes divergence in the middle and goes back to convergence. Indeed, the fact that 1^{st} divergence has OE (green) higher and the 2^{nd} divergence has EOE (red) higher can also be explained by the same mechanism. This comparison suggests that even though OE can be regarded as a rough average of EOE over whole period in our case, the OE would still diverge from the EOE when the high or low season occurs. While this comparison simply realizes the theoretical design that EOE is more appropriate for market with seasonality, it also highlights that the time span between high and low season matters to the duration for how long an OE remains inappropriate for a seasonal market.

6 Conclusion

This study looks into the dynamic competition among real estate developers in Hong Kong and evaluate how counterfactual policy, acyclical and counter-cycle, affect the competition and market outcome. Counterfactual policy analysis shows that counter-cycle policy actually introduce an impact bigger than acyclical policy in this market. This calls for caution against a common perception that counter-cycle measures necessarily cause less distortion than a full-scale acyclical measure.

Similar to many industries, this primary housing market has more than a handful of competitors throughout and there are dozens of them in our case. If adopting MPE as typical in dynamic game literature, the state space quickly scales to the order of 55 and beyond. While the current computation power implies that this is infeasible to estimate, it fits pretty well with the OE framework addressing industries with many firms. Condition on firms of states with big payoff impact unlikely emerging[21], OE approximates MPE by tracking the long run industry state distribution, rather than each rival's state in every period. Taking into account the seasonality in housing market, EOE, an extension that accommodates common shock to all firms, is adopted for estimation. The state

[21] That is satisfying "light-tail" condition.

Figure 12: Simulations of Counterfactual under Vacancy Tax: EOE vs OE

space reduced to 1773 where each firm monitors its own states, the market season and the long run industry state. Implementing the EOE estimation by Pseudo Likelihood Maximization, entry and re-entry cost can be recovered. Simulation shows that the estimated can well replicate the observed market.

With the estimated EOE, counterfactual policies (i.e. vacancy tax and phased sales penalty) of different seasonal implementation can be evaluated. Vacancy tax, although widely discussed by government, has minimal impact in our competition model. This is apparently because quantity decision is insensitive to holding cost that everyone faces. In contrast, penalty on phased sales clearly reduces the (re)entry probability. What is more surprising is that the counter-cyclical implementation indeed causes a bigger impact than the acyclical one. While the acyclical implementation does discourage firms at penalized states from (re)entering, the counter-cyclical penalty discourage all firms, even those not at penalized states. By discouraging (re)entry in high season and allowing (re)entry in other seasons, the counter-cycle penalty raised the long run average industry state drastically in net. Even firms not at penalized states respond the change in long run state. As a result, a counter-intuitive outcome that seasonal policy causes a bigger change emerges. While this is just one application, it does call for further work on the implication of seasonal policy, relative to universal policy, using the dynamic competition framework. As this discrete choice modeling tool advances, we can have better grasp on policies, especially when policies tend to have implication over a longer term.

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