Dynamic Competition of Real Estate Developers: Lesson on Counter-cycle Policy

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Abstract

Counter-cycle policy, with a shorter implementation period than universal/acyclical policy,[1] might appear to cause a smaller impact to the market also. However, once competition over time is taken into consideration, the impact is not necessarily smaller. Utilizing a unique transaction-level dataset, I study the impact of state-based/counter-cycle policy by structurally estimating the dynamic competition of the Hong Kong real estate primary market with the extended Oblivious Equilibrium. It is shown that the policy intended goal is only achieved when the dynamic competition is ignored. Furthermore, incorporating the anticipation of competition in the periods subject to the policy, the counterfactual analysis shows that the counter-cycle policy impact is at a similar scale as the universal/acyclical policy impact. This calls for caution against a common perception of smaller distortion from a counter-cycle measure.

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[1] Acyclical policy means policy implemented throughout the cycle.

1 Introduction

As every industry has its ups and downs, governments often consider intervention on the basis of the state of an industry. When an industry is in high demand, the government might be concerned with the sellers taking advantage of buyers (e.g. cryptocurrency, initial public offerings, masks during COVID etc.). When an industry is in low demand, the government might be concerned with the worsened business environment causing irreversible harm to the sellers (e.g. banks, utilities, airlines etc.). Recognizing the potential distortion to the functioning of market, many interventions are removed once the industry is out of those "undesired" state. These state-based interventions, essentially cyclical or counter-cyclical policies, are commonly perceived to result in smaller distortion as opposed to universal/acyclical policies. For example, papers like Lane (2003), Sutherland et al. (2010), and Aghion, Farhi & Kharroubi (2019) discussed how (counter-)cyclical fiscal policy can address the volatility in economy. While the state-based/cyclical intervention is implemented for a shorter period of time than a full-cycle intervention, its impact on market competition is not necessarily smaller. Furthermore, when the forward-looking firms anticipate the state-based intervention in the future, their strategic interaction can cause the policy impact to spill-over to the periods of no intervention. The research question for this work is to ask how cyclical policy affects an industry with dynamic competition, as compared to a universal policy.

To study how the dynamic competition is affected by cyclical policy, housing market would be the top of the candidate list. Aside from its importance to the society, housing market is often subject to various (counter-)cyclical policy in response to transient market shocks. One frequently discussed policy is the batch size restriction in phased listing. Other than a simple listing of all units at launch, many markets, from San Francisco, London, to Hong Kong and many cities in Asia,[2] adopt the practice of phased listing. Phased listing posts a batch of units for sales in each phase, until all units in the complex are posted. While phased listing helps the sellers to gauge the interest of the market and allows for raising price each phase, the governments are concerned that listing a small batch harms the consumers by extracting all potential consumer surplus, especially when the real estate market is "hot". In

[2]Although it is rare to see the phased listing in some cities such as New York and Singapore, phased listing is common in many more cities (e.g. Seattle, Vancouver, Tokyo, Taipei, Beijing, Guangzhou etc.)

response, when the market is "hot", penalizing small batch or batch size requirement in each phase is a frequent policy debate. In this work, I ask how counter-cyclical policy impacts the dynamic competition in housing market. In particular, is the policy of penalizing small batch listing effective in discouraging the behaviour under dynamic competition? Does a counter-cyclical policy in a dynamic competition imply a smaller impact than a universal policy?

Utilizing a unique transaction-level data set built from sales documents of all Hong Kong real estate developers, I model and estimate the dynamic competition of apartment sales between developers in the mass market using the extended Oblivious Equilibrium (extended OE). As an early work to apply the dynamic competition framework in the real estate market, I focus on the quantity and timing decisions by developers. In this paper, I assume the construction stage as given and the prices to follow an exogenous scheme that varies mainly by the phase and the state of market. By generalizing the original OE to a competition subject to common shocks, extended OE accounts for the evident common shock in the real estate market while approximating the result of Markov Perfect Equilibrium (MPE). Using pseudo likelihood maximization, a two-stage estimator, I perform the dynamic estimation of the underlying cost parameters. With the estimated market, I consider a counterfactual policy of raising the (re-)list cost by 10% as an equivalent monetary cost of stricter restriction of small batch listing. First counterfactual looks at the universal implementation and second counterfactual looks at the counter-cyclical implementation. The difference between the two counterfactuals is then evaluated.

The result shows that the observed empirical strategy can be recovered very well. In terms of the in-stock quantity,[3] the simulations by observed CCP lie mostly within the 95^{th}-percentile of the estimated strategy in extended OE. As for the on-market quantity,[4] the simulations of estimated strategy also cover the observed data pretty well. In both the universal counterfactual and the counter-cyclical counterfactual, the 10% higher (re-)list cost does discourage small batch (re-)list as the policy intended if the change in dynamic competition is not considered. However, the picture is completely different once the dynamic

[3] In-stock quantity is defined as the number of apartments not listed for sales, while the associated complex has emerged.

[4] On-market quantity is defined as the number of apartments listed but remaining on market for purchase.

competition is taken into account.

In the context of dynamic competition, even though the penalty still discourages (re-)list, the lower (re-)list in turn reduces the overall on-market apartments and hence eases the competition intensity. With a less competitive environment, apartments are sold faster. In equilibrium, the indirect competition effect of faster sales dominates the direct penalty effect and hence firms are more likely to (re-)enter under either regime, as compared to the market without any penalty. In the counterfactual of universal implementation, the competition softens and the on-market quantity in the long run reduces by 35%. The in-stock quantity decreases by about 20%. In the counter-cyclical implementation, the on-market quantity in the long run reduces by 60%. Apartments are sold faster and hence the in-stock quantity is about 25% lower than without the policy. Therefore, once the dynamic competition is taken into account, I find that the policy goal of reducing small batch listing cannot be achieved in either penalty implementation. Furthermore, policy implementation in fewer periods does not imply a smaller impact to the housing market.

This study contributes to two strands of literature. The first literature is the estimation of dynamic competition (e.g. Ericson & Pakes (1995), Pakes & McGuire (1994), and Doraszelski & Satterthwaite (2010)). Empirical works on oligopoly since Ryan (2012) and Collard-Wexler (2013)) have been growing steadily. Empirical works exceeding a handful of firms emerged 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)). These OE-based equilibrium concepts were proposed to approximate the MPE when there are many firms in the market. Adding to the existing empirical works using the original OE or the non-stationary OE(e.g. Qi (2013), Sweeting (2015), Saeedi (2019), Xu & Chen (2020) and Caoui (2023)), my work is the first empirical application of extended OE, a variant of OE when the industry is under common shock. In addition to the applications of non-stationary OE, my work shows that extended OE using the same (or weaker) OE assumptions also serves well in empirical application. And my work extends the empirical work of dynamic competition to a new industry that is a prominent part of the economy. This demonstrates the potential of OE framework in empirical analysis for industry dynamics. 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)). For the former taking the dynamic single-agent perspective, I contribute by taking the strategic perspective, considering the 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.

Section 2 discusses the transaction-level data and other industry details. Section 3 constructs a dynamic competition model with extended OE. Its estimation result are discussed in section 4. Section 5 evaluates the counterfactual policies and demonstrates the interesting contrast between universal and counter-cyclical policy. Section 6 concludes.

2 Data

2.1 Industry Details

Similar to many metropolises in the world, real estate in Hong Kong is highly priced for a small size unit. Indeed, Hong Kong frequently tops the world in terms of price per square foot. 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, followed by the data description.

In the housing primary market, developers in Hong Kong essentially follow a phased sales process for a complex (or a development, interchangeably), usually consisting of hundreds to thousands of apartments.[5] Pre-sale is the majority in sales arrangement, which is typically 2.5 years in advance of construction completion. Prior to an apartment complex opening for sales, a developer has to announce the date for beginning sales and distribute in advance the 1^{st} PL, indicating apartments for sale (usually part of all units) with pricing and various

[5]Given the population density in Hong Kong, most of units sold in residential market are apartments (or condominiums depending on the naming traditions in different regions). Apartment, rather than single-family house, is used to refer to the basic unit of sales in real estate market.

discounts stated on the 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 day when sales begin, many buyers would come to purchase, through the help of sales agents, at the listed price with eligible discounts. This is the first round. Depending on the sales status, typically a few days later, the developer would repeat to distribute the 2^{nd} PL to sell another batch of apartments. The process is repeated in each round until all apartments are listed for sale. On average, a developer takes less than 2 months to put all apartments on PLs for sales. The sales conclude when all listed apartments are sold.

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 customers per se, but also the fixed pool of middlemen (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. Timing and quantity choice are indeed crucial dimensions for sellers to compete on.

2.2 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 PLs as described before and the register of transactions. I use the 5-year period from 2014 to 2018.[6] PLs show all the apartments available for sales, including the price and size of each apartment. Register of transactions records the date of preliminary agreement for sale and purchase within 24 hours of signing the agreement. Since these two documents are mandated by law[7] on all residential complexes, these two can provide a transaction-level data set that captures the whole housing primary market in Hong Kong on sales.

As of 2013, the housing stock for the private housing in Hong Kong is 1.29 millions, out of all housing type at 2.41 millions units.[8] Based on my source documents, more than

[6]Data in use for this project is from 2014/01/01 to 2018/12/31, whereas the raw data are collected from 2013/04/29 to 2019/04/15.

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

[8]Hong Kong Census and Statistics Department, "Hong Kong Annual Digest of Statistics," 2019

Table 1: Descriptive Statistics: Mass Developments only

	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Apartment-level								
price (HK$ '000)	31,119	9,676	4,699	1,505	6,591	8,472	11,322	39,968
size (sq. ft.)	30,626	566.7	193.6	165	447	520	696	1,964
price/sq. ft. (HK$ '000)	31,119	17.3	5.6	8.1	12.7	16.0	21.4	47.0
days on-market	31,119	15.7	44.0	0	0	0	3	360
PL-level								
apt listed	241	129.1	118.1	1	42	89	186	548
apt sold on day 1	241	93.8	118.3	0	5	39	138	544
days from 1^{st}PL	241	54.2	83.9	0	4	13	63	344
Complex-level								
total apts	56	627.7	369.5	95	296.2	590	910.2	1,432
total PLs	56	6.3	2.0	3	4.8	7	8	10
listing duration	56	212.7	273.3	0	14.8	128.5	273	1,217

Note: "days on-market" measures the number of days that the apartment is available for sale but not sold (i.e. the difference between the transaction date and the listing date). "apt sold on day 1" measures the number of apartments sold on the first day that the price list is open for sale. "days from 1^{st} PL" measures the number of days from the 1^{st} PL to the current PL. "listing duration" measures the number of days from the first sales date of the complex and the sales date of the last PL. HK$ is pegged to US$ at a rate $HK\$7.8 = US\$1$.

50,000 private apartments can be obtained. The data clearly reveals the different positioning between mass market complex and luxury market complex.[9] Given my focus on the mass market, I exclude complexes that have more than 90% apartments above 600 sq. ft. with more than 25% apartments above 1,000 sq. ft. This mass market data are summarized in Table 1.

The primary housing market can be viewed from three levels of aggregation: apartment, PL and complex. For the top panel at the apartment-level, one can see that the price is very high with an average of roughly US$ 1.2 million or US$ 2,200/sq. ft. The apartments size is typically around 570 sq. ft. For each apartment, many are listed within 2 weeks from the sales of the 1^{st} PL. Once listed, an apartment is usually sold within several days of being on market, 3 days only even for the third quartile. The middle panel of PL-level shows that there are typically around 130 apartments in each PL and a majority of the apartments

https://www.censtatd.gov.hk/en/EIndexbySubject.html?scode=460&pcode=B1010003

[9] The complexes show a clear bi-modal distribution once considering the fraction of large apartments. Defining large apartments as those larger than 600 sq. ft., complexes concentrate at providing either less than 5% or more than 95% of large apartments. Even when changing the threshold to 1,000 sq. ft., the bi-modal pattern is similar.

(around 94) are sold on the same day.[10] Many PLs are posted within 2 months from the sales of the first PL. The bottom panel of complex-level shows that our 5-year data cover 56 mass market complexes. Each has, on average, about 600 apartment and they are sold in multiple PLs, averaging to around 6 PLs. Selling all apartments take about 7 months from the sales of the first PL on average.

Since competition begins before a firm lists its 1^{st} PL, the date of emergence is required to visualize the competition. I rely on the construction permits to construct the date of emergence based on the day difference between sales date and permit date since the pre-sale is regulated on the basis of construction flow. A developer needs to get approval for their building plans, consent for site formation, consent for foundation and consent for general building and superstructure (also referred to as consent to work in some government publications). Once the consent to work is obtained, the developer can apply for pre-sale consent. After finishing the construction, occupation permit is required before transferring the apartments to buyers. Since some of these remain undisclosed documents between the government and developers and other data issues,[11] I utilize the available information to form the date of emergence. In particular, I use consent to work and occupation permit to construct the date of emergence, where the former is the legal pre-requisite for pre-sale approval and the latter is required after pre-sale.[12]

Given the date of emergence, one can visualize the competition over time, via in-stock quantity and on-market quantity. In-stock quantity counts the apartments of an emerged complex that have not been listed on any PL. On-market quantity counts the apartments that have been listed, but not yet sold. Figure 1 depicts how the in-stock quantity (upper panel) and the on-market quantity (lower panel) evolve in the period from 2014 to 2018

[10] Note that this PL-level panel includes only observations on the listing days. On the non-listing days, the mean sales is 2.434 with a standard deviation of 7.638.

[11] While some permit information are reported by the Buildings Department in Monthly Digest, there is another challenge to systematic analysis. The structured mapping between the construction site (i.e. the basis of construction documents) and the apartment complex (i.e. the basis of transaction data) in public information is lacking. Manual matching that considers address proximity and construction timing is required to match the address of complex to the (temporary) address of construction sites.

[12] Relative to the consent to work, the earliest sales in data is on the 37^{th} day after the consent. I assume the date of emergence to be 30 days after the consent to work. When this is not available, I use occupation permit date considering the high correlation (0.897) between consent to work and occupation permit date. For complexes without consent to work, I assume the emergence date to be 790 days before occupation permits.

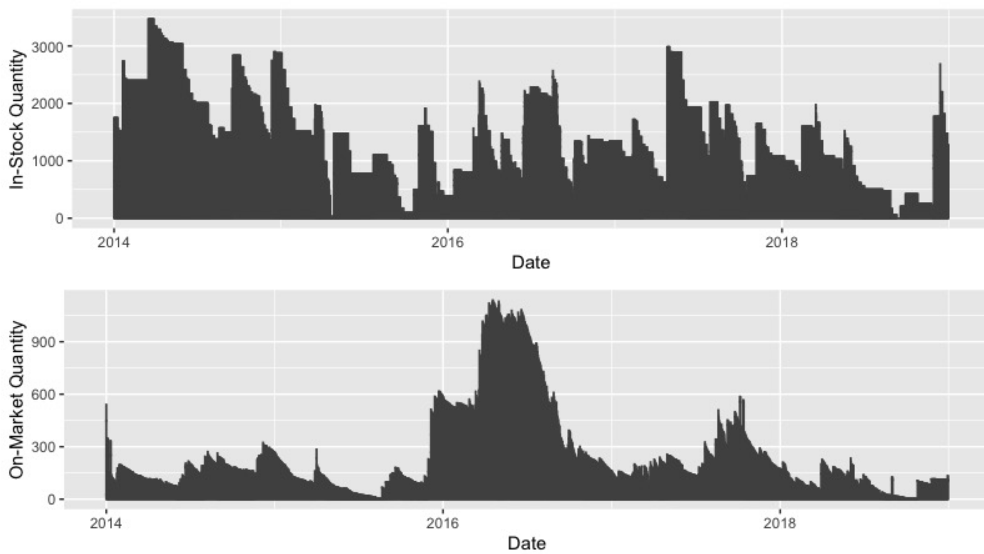

Figure 1: Raw quantities in-stock and on-market over time

for the mass market. When a complex emerges for pre-sale, the in-stock boosts before the apartments are listed. When an apartment is sold after listing, the on-market quantity reduces and hence the apartment disappears from the graph. Upper panel shows the in-stock quantity was gradually decreasing from 2014 to 2015. Then it was mostly in the range of 1,000-2,000 apartments. On-market quantities in lower panel is around 100-300 apartments most of the time. One can see year 2016 is a hard time to sell and the on-market quantity accumulates.

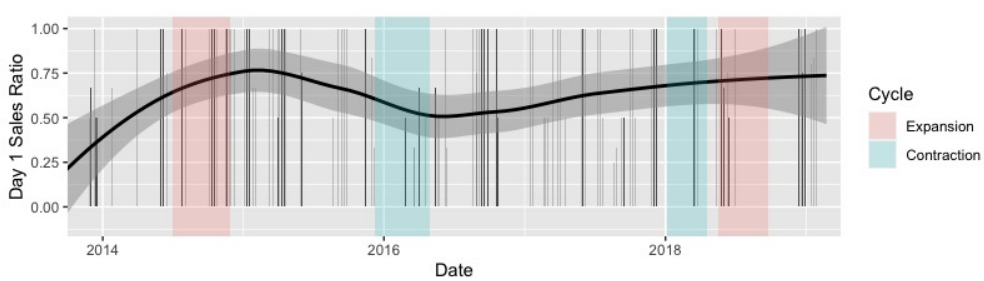

Figure 2: Cycle in Housing Market

The contrast in raw quantities across different periods naturally points to the cycle in this housing market. With the detailed data on hand, I can utilize the PL-level data to inform the cycle in market by date. Figure 2 highlights the assumption of expansion stage (red) and contraction stage (blue), based on sales ratio on day 1 of a PL. Day 1 sales ratio is defined as the quantity sold divided by the quantity available for sale on the first sales day of a PL, depicted as grey vertical lines in graph. This ratio by day is more updated than monthly or weekly indicators and is more relevant to primary housing market than secondary market indicators. Many lines are reaching 100% sales ratio at the top as it is quite common to have all apartments on a PL sold on the first day in a good time. Denser and taller lines represent a good market with high sales ratio and hence more likely an expansion stage and vice versa for a contraction stage. A local polynomial smooth line (black) is also included to visualize the trend. Based on the PL-level sales ratio, I assume that the contraction stages were the periods 2015/12/10 - 2016/04/30 and 2018/01/06 - 2018/04/20 (shaded in blue) and the expansion stages were 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 distinct patterns that further support the cycle assumption.

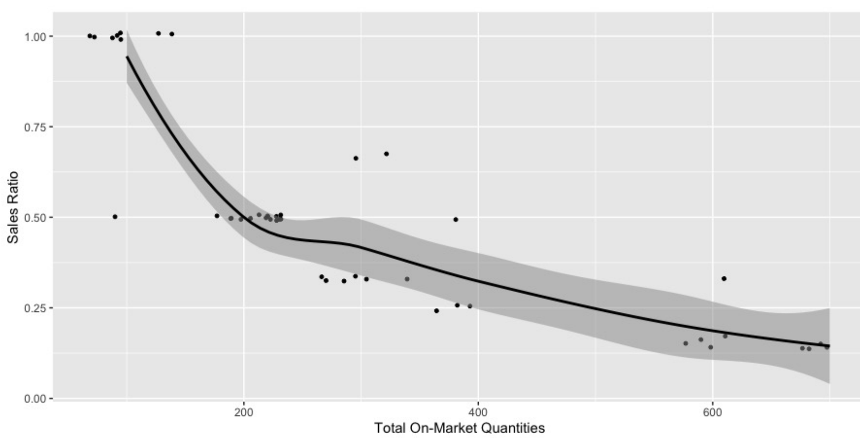

Figure 3: Competition Impact on Sales in Non-Listing Days

There is also a clear pattern on how the sales is related to the competition between the available units on market. Figure 3 shows a pattern close to an exponential decay pattern between the sales ratio of on-market apartments and the total number of apartments on-market in days without new listings. This motivates our modeling assumption that the number of apartments on-market affects the sales speed in the model as described later.[13] Some further empirical observations about pricing and competition are discussed in the

[13]Non-linear least square regression with an exponential decay function $r = \alpha n^{\gamma}$ is estimated. Complex with and without new listings are estimated separately as the sales ratios are significantly different.
Complex in Non-Listing Days: $\alpha = 47.26408$ and $\gamma = -0.85073$
Complex in Listing Days: $\alpha = 1.0913$ and $\gamma = -0.1061$

appendix section A.1.

3 Model

In order to analyse the competition among real estate developers, I specify a dynamic competition model that captures both the dynamic incentive and the strategic consideration in equilibrium.

Each seller j has a stock of n apartments to sell (i.e. in-stock apartments). Throughout the estimation, each complex is modelled as one seller. This is because joint ownership is present in close to 40% of complexes and the joint structure varies complex by complex. I assume that each complex acts as one maximizing unit, rather than grouping firms that worked together as one unit.[14] In each period t, which is one day in my estimation, seller j chooses a units of apartments to list for sales. When $a > 0$, the seller j decides on listing (or re-listing if j has listed before). Hence, action a reflects both the binary action of (re-)list and the size of (re-)list. The round of PL, denoted by k, increases by 1 whenever the seller chooses $a > 0$ and $k = 0$ is a seller yet to list the 1^{st} PL. On-market apartments that are listed but not yet sold is denoted by o. Hence, the triplet (n, o, k) represents the individual state of a seller. The number of apartments are discretized into increments of 100s. Since the data have as many as about 1500 apartments for a seller, the stock level is assumed to have at most 1500 apartments. Listing, a, and apartments on-market, o, can be 500 apartments at most. The discretized data has at most 6 PLs[15] across all complexes (i.e. $k <= 6$). When $k = 6$ is reached, the seller can only wait for the apartments to be sold on-market (i.e. $a = 0$). There is also a a state variable common to all sellers, the cycle. Denoted by z, cycle has 3 potential stages: contraction, normal, and expansion stage. Stage transition is assumed to be independent of individual state transition and the stage in cycle only transits to the immediate stage. A complete state for a seller at any time is represented by a quadruplet, (n, o, k, z).

[14] A more sophisticated ownership structure requires modeling another decision layer of whether to jointly develop a complex, before deciding on the optimal choice of apartment listing. This, however, would be beyond the scope of this research.

[15] Although the raw data has 6.3 PLs on average, discretized data has fewer PLs because the increments of 100 apartments reduces the rounds of PL.

In the beginning of each period, sellers with different stock level emerge according to the emergence sequence in reality. The existing sellers and emerging sellers simultaneously decide their action a_j $\forall j$. Sales to buyers then occur under the influence of competition between the available units on market. Individual states of sellers are then updated and payoffs are received. The market transits to next period with a potentially different stage.

3.1 Payoff

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

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

where p_{jt} is price,[16] q_{jt} is the quantity sold, c_e and c_r are for the list cost and the re-list cost respectively, c_h is the holding cost incurred as long as the seller has emerged but the apartment is not sold yet and hence $h_{jt} \equiv n_{jt} + o_{jt}$ represents the quantity holding on hand, c_o is the time-on-market (TOM) impact suffered when an apartment is listed but not sold yet[17] and ϵ_{ajt} is the action-specific idiosyncratic shock which follows type-1 extreme value distribution.

Denote β as the discount factor and G as the transition probability. 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).[18]

[16] Since this paper focuses on the quantity competition among many firms, price is assumed to vary by states (e.g. the round of PLs and cycle) only. While endogenous pricing would be theoretically more appealing, it is beyond the scope of current paper.

[17] Speculation of flaws as inferred from TOM has been discussed in the literature such as Taylor (1999). In particular, Tucker, Zhang & Zhu (2013) showed sales price is lower when resetting the days on market is banned in house sales.

[18] The primitives of model are bounded. List cost and re-list 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

3.2 Extended Oblivious Equilibrium

Since the number of sellers increases the state space quickly for Markov Perfect Equilibrium (MPE), this primary housing market with above 20 sellers is infeasible to have MPE computed.[19] Oblivious Equilibrium (OE), proposed by Weintraub, Benkard & Van Roy (2008), is adopted to approximate MPE for this housing market, where optimal strategies in OE condition on the long run industry average state distribution of rivals. The "light-tail" condition[20] for good approximation rules out "big" firms that can cause big change to payoff of their rivals. In application to my case, rival impact on profit depends on the number of apartments on market, which is limited to 500.[21] Even for the number of stock, there are not many complexes with more than 1,000 apartments. Hence it is reasonable to regard "light-tail" condition to be satisfied.

Nonetheless, OE cannot accommodate cycle directly. Two OE modifications in the literature are relevant in accommodating the differences across periods: non-stationary OE by Weintraub et al. (2010) and extended OE by Weintraub, Benkard & Van Roy (2010). Non-stationary OE has been previously adopted in some empirical works (e.g. Qi (2013), Caoui (2023) etc.).[22] If adopted in my application, I would need to assume the beginning of data period to be the commonly observed period and no other observable periods in addition. Extended OE modifies the original OE by allowing for common shocks to all firms, nesting the original OE as a special case of an invariant common shock throughout. No additional assumptions would be needed on top of the original OE assumptions. As there is

changes the state and payoff function directly. Discount factor is strictly less than one. These suffice to ensure existence of pure strategy Markov-perfect equilibrium.

[19]The MPE concerns 20 firms where each has $(16 * 6 * 6 + 15) * 3 = 1773$ states. Assuming anonymity across firms, the state space is in the order of 46.

[20]"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. In other words, "Light-tail" condition requires the expectation of maximum percentage change to profit, due to a change in state distribution, to be small. See assumption 5.2 of Weintraub, Benkard & Van Roy (2008) for the formal definition of "light-tail" condition.

[21]Note that the impact on payoff increases with rival's state , which is rival's quality level in Weintraub, Benkard & Van Roy (2008). In my case, this "tail" should refer to states with large number of apartment on market for a rival as this is what lowers the payoff.

[22]While non-stationary OE additionally requires that (1) the actual industry state in the initial period is commonly observed by all firms and (2) the industry converges to the oblivious equilibrium at a terminal period $\bar{T}$, this, in return, allows firms to optimize against a deterministic evolution of aggregate state and hence time-varying common shocks.

not a period where firms have more information than other periods, extended OE is more appropriate for my setting.

In the extended OE, denote $\tilde{s}$ as the long run average market state where σ represents the optimal oblivious strategy adopted by all sellers. Formally, instantaneous payoff and value function become

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

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

Given the optimal oblivious strategy σ, $\tilde{s}_\sigma$ is defined as $\tilde{s}_\sigma \equiv \sum_{t=0}^{\infty} P_\sigma(s_t)$, 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 (Aguirregabiria & Mira (2002) and Aguirregabiria & Mira (2007)) 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. The estimations of transition matrix, stage transition in cycle and CCP are discussed in details in the appendix. Pricing at various states also needs to be estimated as the dynamic model regards the goods as homogeneous. Step 1 estimation result is include in the appendix section 4.2. 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.

4.2 Step 1 Estimation

Considering the sparsity in my daily data is over 98% of the state space of transition matrix, 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 stages, only quantity sold is needed to estimate from data to construct a transition matrix without stage transition.

$$logit(P(q_{jt} < q|a_{jt} = 0)) = \eta_0 + \eta_1 o_{jt} + \eta_2 k_{jt} + \eta_3 z_{jt},$$

and

$$\begin{aligned} logit(P(q_{jt} < q|a_{jt} > 0)) =& \xi_0 + \xi_1 I(o_{jt} = 0) + \xi_2 I(o_{jt} \geq 200) + \xi_3 (a_{jt} + o_{jt}) \\ &+ \xi_4 k_{jt} + \xi_5 I(k = 0) + \xi_6 z_{jt}, \end{aligned}$$

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

Table 2 shows that transition on non-listing days significantly depends on the number of apartments on-market. As for listing days, even when the sample size is around 98% smaller, the number of apartments added dominates the sales and later PLs indeed sell fewer. Both show cycle 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 when adding no new apartment and 100 apartments (Table 3, 4 and 5) are shown below.

In a complete state transition, the stage can also change. Based on cycle criteria above, transition of stages can be estimated as a 3×3 matrix. The estimated matrix suggests stage is relatively persistent with less than 1% probability in changing.[23] Given the independence of stage transit, complete state transit is the previous stage-constant transition matrix multiplying the stage transit matrix. Table 6 shows an excerpt of the full transition matrix,

[23] Starting from Contraction stage, the stage transits to Normal stage with 0.8% probability. From Normal stage, transition to Contraction or Expansion stage are both 0.1% probability. From Expansion stage, transition to Normal stage is 0.6% probability.

Table 2: Ordered Logistic Regression for Sales

	Dependent variable:	
	qty sold	
	(1)	(2)
on-market	0.008	
	(0.002)	
sold-out		2.290
		(0.560)
on-market 200+		−19.971
		(0.519)
PL	−0.053	−0.368
	(0.110)	(0.202)
not entered		−0.748
		(0.510)
z	0.460	0.923
	(0.268)	(0.363)
Control for apts available	No	Yes
Observations	2,807	147

Note: Specification (1) & (2) is for non-listing & listing days respectively. Variable "sold-out" indicates whether all available apartments are sold. "on-market 200+" measures whether the number of apartment available for sale but not sold is larger than or equal to 200. "not entered" equals 1 when the development has not listed their first PL in the market.

accommodating stage transit at once.

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

Table 3: 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	0.013	0.987	0	0	0	0
100 200 1 1	0.003	0.026	0.972	0	0	0
100 300 1 1	0	0.005	0.054	0.94	0	0
100 400 1 1	0	0	0.012	0.11	0.878	0
100 500 1 1	0	0	0	0.026	0.207	0.767

Table 4: 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	0.254	0.746	0	0	0	0	0	0	0	0	0	0
100 0 4 1	0	0	0.33	0.67	0	0	0	0	0	0	0	0
100 0 3 1	0	0	0	0	0.416	0.584	0	0	0	0	0	0
100 0 2 1	0	0	0	0	0	0	0.507	0.493	0	0	0	0
100 0 1 1	0	0	0	0	0	0	0	0	0.598	0.402	0	0
100 0 0 1	0	0	0	0	0	0	0	0	0	0	0.504	0.496

Table 5: Transition matrix excerpt when a = 100 at different Stages

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	0.371	0.629	0	0	0	0
100 0 1 1	0	0	0.598	0.402	0	0
100 0 1 2	0	0	0	0	0.789	0.211

Table 6: Full transition matrix excerpt (with stage 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	0.368	0.624	0.003	0.005	0	0
100 0 1 1	0.001	0	0.596	0.402	0.001	0
100 0 1 2	0	0	0.004	0.001	0.785	0.21

200. Without assuming the order of dependent variable, multinomial logit would be a more appropriate functional form. Table 7 presents the result for the estimated choice probability.

As for pricing estimation, although I have pricing data for every apartment, my model considers selling decision of homogeneous goods at the PL-level. 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 the 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 $R^2 > 90\%$) is accounted for by the fixed effects of district, floor and time as discussed in the appendix and shown in Table 11. Price residual would likely capture the relevant scope the sellers can control in terms of pricing. Table 8 shows the estimation result

Table 7: Multinomial Logit on Quantity to List

	Dependent variable:				
	100	200	300	400	500
	(1)	(2)	(3)	(4)	(5)
in-stock	−0.002	0.0004	0.002	0.002	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
on-market	−0.002	−0.005	−0.079	−0.056	−1.863
	(0.004)	(0.008)	(0.008)	(0.011)	(0.000)
sold-out	−1.567	−1.696	−5.789	−4.788	−5.249
	(0.318)	(0.597)	(0.410)	(0.601)	(0.878)
entered	0.381	0.510	3.764	3.139	1.901
	(0.337)	(0.606)	(0.456)	(0.557)	(1.217)
PL	−0.430	−0.711	−0.752	−0.977	−0.213
	(0.137)	(0.242)	(0.449)	(0.596)	(1.101)
z	0.347	−0.123	−0.031	−0.899	−0.624
	(0.263)	(0.361)	(0.513)	(0.758)	(1.160)
sold-out:entered	1.949	2.695	−1.052	0.961	−0.317
	(0.337)	(0.612)	(0.456)	(0.557)	(1.217)
Constant	−3.134	−3.881	−0.973	−2.611	−3.031
	(0.370)	(0.634)	(0.410)	(0.601)	(0.878)
McFadden R^2			0.079		

Note: Dependent variable refers to the number of apartments to list. Variable "sold-out" indicates whether all on-market apartments are sold. "entered" equals 1 when the development has listed their first PL in the market.

of a linear regression on the price/sq. ft. residual.

Conditional on the homogeneous good assumption, the estimation regards all apartments of the same state charge the same. The only variations comes from the state. I construct the representative price as average price/sq. ft. times average sq. ft., which is HK$ 9.165 million per apartment. Combining the two, I have the pricing for model estimation. Some excerpts (Table 9 and 10) of the 1773×6 matrix are shown below.

Some features of the pricing are worth mentioning. It has an increasing trend as later PLs are posted (Table 9). 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

Table 8: Linear regression on Residual of Price/sq. ft.

	Dependent variable:
	price resid
PL	374.681
	(202.463)
z	210.843
	(430.334)
Single PL Complex	736.773
	(431.013)
PL:z	−68.789
	(188.367)
Constant	−892.213
	(475.615)
Observations	136
R^2	0.134
Adjusted R^2	0.107
Residual Std. Error	980.291 (df = 131)
F Statistic	5.058 (df = 4; 131)

Note: Variable "single-PL complex" indicates whether the development list all apartments in one PL.

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.

4.3 Main result

Given the full transition matrix with stage transition, 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 list cost (c_e), re-list cost (c_r) and TOM impact (c_o), one would need to know the value of choice $a = 0$ and hence the holding cost need to be pinned down. Together with the discount factor, β, there are 2 parameters (i.e. c_h, β) that need to be assumed in order to identify and estimate the list cost, c_e, re-list cost, c_r and TOM impact c_o. I assume $\beta = 0.9994$ and $c_h = 20$.

Note that the discrete choice here is directly associated with the price in data. The price

Table 9: Price across PLs

	100	200	300	400	500	0
100 0 6 1						9.96
100 0 5 1	9.96					9.801
100 0 4 1	9.801					9.642
100 0 3 1	9.642					9.483
100 0 2 1	9.483					9.324
100 0 1 1	9.324					9.165

Table 10: Price across different In-Stock

	100	200	300	400	500	0
100 0 0 1	9.548					9.165
200 0 0 1	9.165	9.548				9.165
300 0 0 1	9.165	9.165	9.548			9.165
400 0 0 1	9.165	9.165	9.165	9.548		9.165
500 0 0 1	9.165	9.165	9.165	9.165	9.548	9.165

needs to be normalized to reconcile with the observed choice probability across options, which results from the type 1 extreme value private shock in the model. Therefore, an additional normalization parameter is also estimated.

While the ex-ante value can be calculated with the transition matrix and CCP, their sparsity necessitates assumptions to handle the states that are never visited. I fix the ex-ante value of unvisited states to be worth HK$ 3 million per apartment. For apartments unsold by the 6^{th} PL, I make the same assumption to limit the influence from the empirically unobserved situation on the estimation result.

With the list cost and re-list cost estimated for each of 1773 states through PML, an extended OE can be computed. Comparing simulations from the estimated extended OE and simulations from the step 1 CCP, figure 4 shows that the extended OE (i.e. 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, extended OE can reasonably generate the raw data the same way as the empirical CCP can generate. In figure 4, the colored lines represent simulations by the empirical CCP (blue) and the estimated extended OE (red). Solid lines mean the average of simulations and the dotted lines represent the 5^{th} and 95^{th}

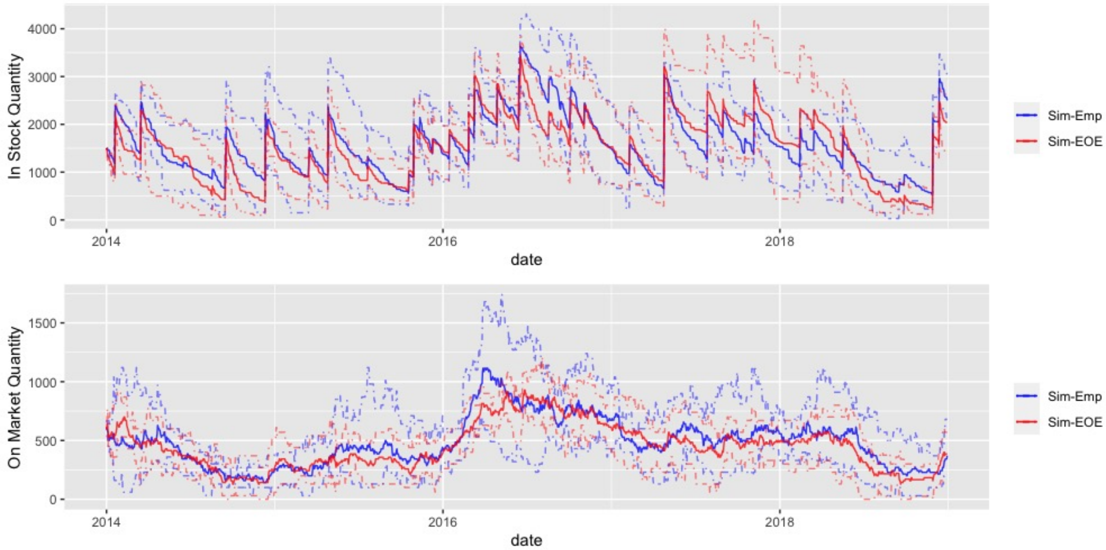

Figure 4: Simulations of Estimated Extended OE

percentiles.

As shown in the appendix section A.2, the list and re-list probabilities of extended OE closely resemble those of empirical CCP. Even though the re-list probabilities in normal stage show that a slightly larger difference in numbers, the relative probabilities across choices are maintained. This indeed suggests re-list plays a smaller role than list does in reality, which is why the overall picture in simulation is still very close.

Cost estimates show that cycle does matter. For any given individual state (i.e. keeping (n, o, k) fixed), the cost decreases by around 30% when the stage changes from normal to contraction stage. The cost increases by 40% changing from normal to expansion stage. This is reasonable because list and re-list cost advertising, soliciting real estate agents, attracting media reporters and occupying the sales venue constitute a major part of the cost. And these are subject to increase as the competition intensifies and vice versa. Also, the re-list cost is lower than the list cost. This is consistent with the higher list cost to initiate the beginning of sales phases. Cost estimate excerpts are included in the appendix section A.2.

5 Counterfactual Policy

5.1 Counter-cyclical and Universal Phased Sales Penalty

A policy commonly considered in the real estate sales 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 round of PLs in phased sales.

Counterfactual policy I consider here is to penalize the seller whenever they add only part of the apartments on hand. I model the penalty as an additional charge equivalent to 10% of the (re-)list cost whenever the sellers do so. Specifically, I raise 10% of their (re-)list cost as long as they are not listing all apartments on hand when they have 500 apartments or less. For those with more than 500 apartments, the (re-)list costs increases by 10% as long as they are not adding 500 apartments when listing. While this serves the purpose to encourage sellers providing more apartments when they list, it also satisfies the state space constraint.

In the counterfactual, I consider both a universal implementation and a counter-cyclical implementation of the penalty. While it is reasonable to implement the penalty throughout all market situations for policy consistency, various factors might render the implementation specific to a certain part of cycle. Government might regard the policy as hampering the healthy operation of market, so they intentionally impose it only in the expansion stage, when they deem the market to be too hot. Or, the lobbying from the sellers for removing penalty could be stronger in the contraction stage given the worse business prospect. Hence, evaluating a stage-specific policy should weigh in as a potential policy choice or simply an inevitable compromise. The alternative to universal implementation is to impose the penalty only in the expansion stages. Our extended OE model is indeed well-suited to discuss the difference between universal implementation and counter-cyclical implementation, if there is any.

5.1.1 Implementation in Whole Cycle

In the universal implementation, the penalty does not differentiate by expansion or contraction stage. It implies that once the policy is adopted, it is maintained regardless of the common shock realized.

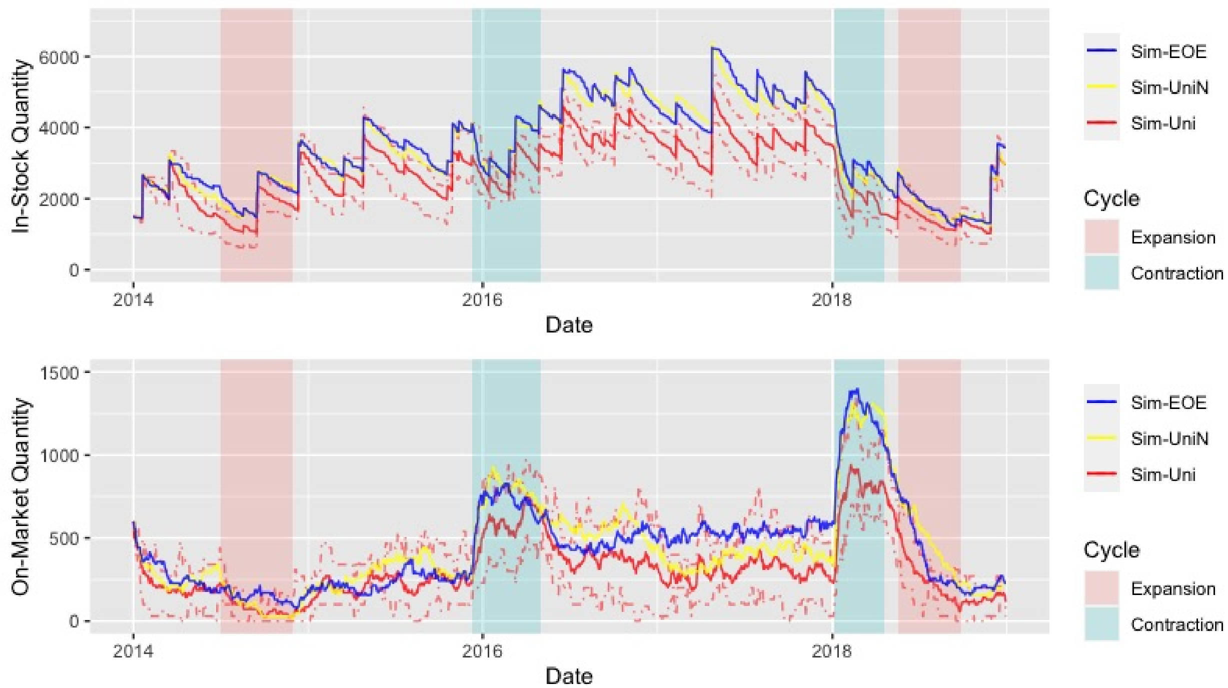

Figure 5: Simulations under Universal Phased Sales Penalty

This intervention of penalizing small batch impacts the competition. By simulating the market with the new strategy, Figure 5 shows the market under the 3 schemes: without penalty, naive response with penalty and counterfactual with penalty. Naive response refers to those accounting for only the penalty, but not the associated competitive environment change. It can be shown that the policy goal is only achieved when competition environment change is not taken into consideration. Firms respond to the penalty by listing more each batch. This naive response (yellow) yields a similar result as the market without the penalty (blue) for both in-stock quantity (upper panel) and on-market quantity (lower panel).

In reality, the competition environment does change once the behavior of individual firm changes. The quantities in-stock (upper panel) are consistently lower throughout most of the period. However, since every firm tends to sell smaller batches than without policy, it is easier to sell. As observed from the apartments available on-market (lower panel), the market with the penalty has consistently fewer apartments on-market. This implies a less competitive environment of fewer competing apartments on market that speeds up the sales. As a result, the universal penalty leads to smaller listing batches and faster sales. Therefore, the universal policy would not eliminate the undesired behavior of small batch listing. It fails the policy intended goal in this counterfactual.

The appendix section A.3 provides further analysis of the optimal strategy under the naive response and the counterfactual. In the former case, if one ignores the fact that the competition environment would change, the small list is discouraged, especially apparent when the stock level is high. This would be aligned with the policy intended goal for larger list. In the latter case of counterfactual, the competition environment changes resulting from the individual behavior change. Firms now incline more to enter with small batches. Firstly, the penalty can discourage apartment listing. Secondly, the firms tend to enter with smaller batches when they are entering, counter to the policy intended goal. This results from the competition environment change, reducing about 480 apartment on market in the long run average to around 310 apartments once the penalty is imposed. This eases the sales of the listed units. In view of this, the optimal response by the firms is to list small batches so as to take advantage of the higher prices in later batches, rather than just listing larger batches as the policy intends.

5.1.2 Implementation in Expansion Stage Only

Counterfactual policy considered here is to raise (re-)list cost by 10% only when the market is in expansion stage. Once the market moves back to normal or contraction stage, the penalty is removed and (re-)list cost is back to the original level. Hence, the penalty is de facto imposed less than 1/3 of the time.

A comprehensive picture of the changed strategy can be demonstrated in simulations. Figure 6 shows the market under the 3 schemes: without penalty, naive response with penalty and counterfactual with penalty. Similar to the case of universal implementation, the policy goal is only achieved when competition environment change is not taken into

Figure 6: Simulations under Counter-cyclical Phased Sales Penalty

account (yellow). The simulations using the optimal strategy under counter-cyclical policy is in red. Overall, while one might expect the impact of such an counter-cyclical policy to the market should be smaller, the impact looks similar to the universal policy. The quantity in-stock (upper panel) is lower than that without the penalty. Furthermore, in the contraction stage of early 2016 and the normal stage before, one can see a larger drop of stock in upper panel than that under universal policy. When penalty is not charged in normal and contraction stage, firms would seize the time to list the apartments in these stages. This highlights the fact that, even though penalty is restricted to expansion stage only, when the dynamic incentive is considered, it introduces an impact not necessarily smaller. Taking the competitive environment into account, one might regard this limited penalty causing a bigger impact given the fewer apartments on market in the long run average.

The appendix section A.4 analyses the strategies further. In the naive strategy, it is evident that only the firms in expansion stage are affected, but not other stages. Especially for firms with more stocks, small batch list is discouraged. As for the counterfactual with penalty, an impact of similar size unfolds via anticipation. When the penalty is imposed in expansion stage (i.e. $z = 2$), sellers are discouraged to enter. In the expansion stage, the list is discouraged, and slight more so than that under universal penalty. As for the other stages without penalty in counter-cyclical policy, both list and re-list have much higher (re-)entering probabilities. Expecting the higher (re-)list cost in expansion stage, the counter-cyclical penalty raises incentive for the firms to (re-)enter in normal or contraction stage. This points to the fact that the strategies under counter-cyclical policy are not just affected by the penalty itself directly, but by the future stages with penalty. Regarding the competitive environment, the long run average reduces from around 480 apartments to around 280 apartments on market. This implies a similar change as that of a full-cycle penalty, if not a bigger change. Hence, counter-cyclical penalty affects states not subject to penalty indirectly through the long run market state.

6 Conclusion

While the state-based policy might be adopted to intend for a smaller impact, dynamic competition renders the actual market outcome to be more complicated. With the help of extended OE, this study looks into the dynamic competition among real estate developers in Hong Kong. How counterfactual policies intending to discourage small batch listing, with universal and counter-cyclical implementation, affect the competition and market outcome is evaluated. It can be shown that both universal and counter-cyclical policy only achieve the policy goal when their associated competition changes are not taken into consideration. Counterfactual policy analysis further shows that the counter-cycle policy actually introduces an impact larger or comparable to the universal/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 universal measure.

With the estimated extended OE, counterfactual policies (i.e. phased sales penalty) of different stage implementation can be evaluated. Once dynamic competition is considered, penalty on phased sales raises the (re-)list probability and does not achieve the policy goal. What might be even more surprising is that the counter-cyclical implementation indeed causes a bigger/similar impact to the universal one. By discouraging (re-)list in expansion stage and allowing (re-)list in other stages, the counter-cycle penalty reduced the long run average industry state drastically in net. Even firms not at the penalized states respond to the change in long run state due to the change in competitive environment. As a result, a state-based policy that implements in only one-fifth periods still causes an impact of a similar size as the full-scale universal policy. While this is just one application, it does call for further work on the implication of state-based policy on competition 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.

A Appendix

A.1 Further Descriptive Evidence

More insights about this real estate primary market can be obtained by discussing some descriptive evidence. These empirical observations point to the need of a more sophisticated competition model for analysis and, in turn, motivate the model setup. Note that the focus here would be on the prominent dimensions: pricing, list and quantities, even though the rich data allowed us to understand the market from numerous other perspectives as well.

Table 11: Regression on Price/sq. ft.

	Dependent variable:				
	Price/sq. ft. (HK$)				
	(1)	(2)	(3)	(4)	(5)
Size(sq. ft.)	−2.821	1.612	2.063	−2.776	−4.904
	(0.165)	(0.074)	(0.059)	(0.253)	(0.762)
Size(sq. ft.)-square				3.510e-03	6.657e-03
				(1.783e-04)	(1.078e-03)
Size(sq. ft.)-cube					−1.410e-06
					(4.762e-07)
Constant	18,907.400	12,823.410	16,477.340	17,778.440	18,204.360
	(98.528)	(96.273)	(220.126)	(228.513)	(269.997)
Sales Year FE	No	Yes	Yes	Yes	Yes
District FE	No	Yes	Yes	Yes	Yes
Floor FE	No	No	Yes	Yes	Yes
Block FE	No	No	Yes	Yes	Yes
Developer FE	No	No	Yes	Yes	Yes
Observations	30,626	30,626	30,626	30,626	30,626
Adjusted R^2	0.009	0.847	0.924	0.925	0.925
F Statistic	293.958	8,465.749	2,462.452	2,479.909	2,464.491
df	1; 30624	20; 30605	152; 30473	153; 30472	154; 30471

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. Table 11 shows that including the sales year and the geographic district fixed effect can account for 84.7% variation as shown in specification (2). The adjusted R-squared achieves 92% when fixed effects like apartment floor, block and developer are added in specification (3). As for the relationship between size and price/sq. ft., whether including it linearly or in a polynomial form up to the cube does not affect the adjusted R-squared

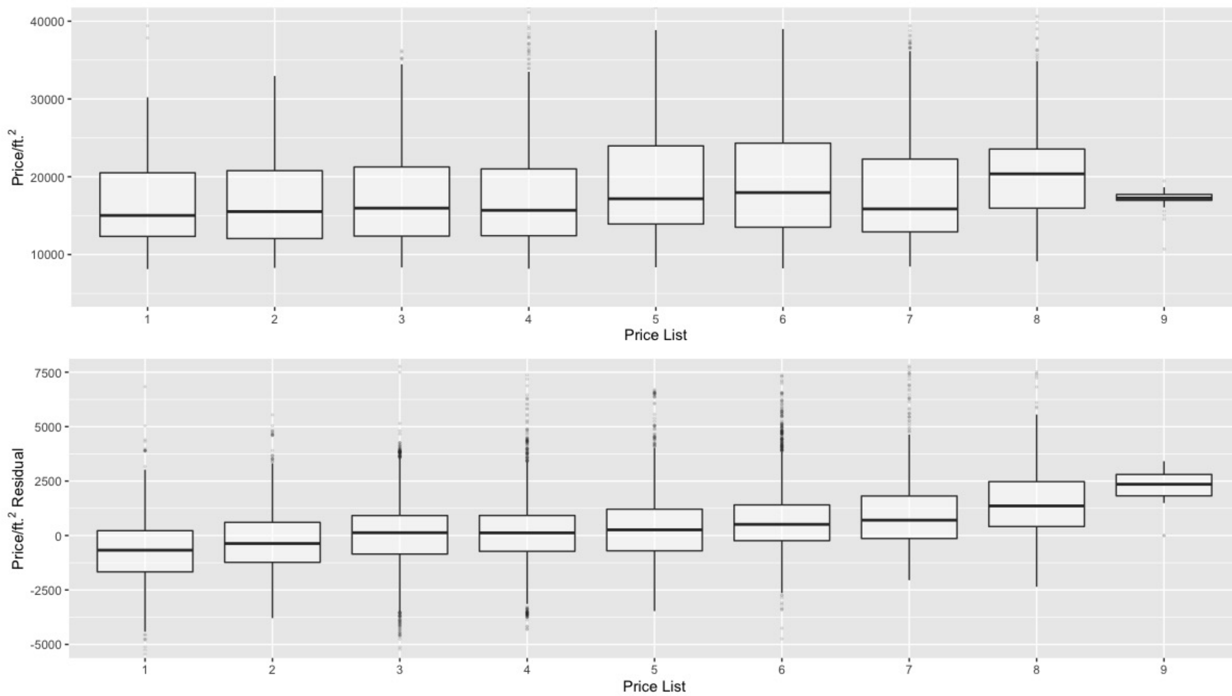

Figure 7: Price (top) and Price Residual (bottom) across PLs

much. I take the specification (3) as the benchmark specification for pricing regression. Since the fixed effect factors are beyond sellers control at the time of pricing decision, it doesn't seem there is much scope for sellers to autonomously choose the selling price regardless of situation. For the current model, I assume that sellers can only affect the pricing residual but not other factors.

When the pricing residuals from Table 11 specification (3) are analysed further, one can see that there is a clear trend the price increases as the PL releases in order. Figure 7 shows the boxplots of price and price residuals across PLs. While the price in the upper plot does not show a clear trend across PLs, the price residual in the lower plot has an unambiguous increasing trend as PL increases. The median price residual for apartments in their 1^{st} PL is negative. For the case of 9^{th} PL, the median price residual alone can reach about HK$ 1,500/sq. ft. given the apartment characteristics. This matches the interviews with industry insiders well. 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.

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-)list and the listing quantity, Table 12 shows both the list (specification (1)) or re-list (specification (2)) logit and the listing quantity ordinary least square (OLS, specification (3)) for richer discussion. The list probability is lowered, statistically significant, under competition as measured by the number of complex entered. Seller is more likely to re-list if it has fewer on-market apartments unsold. As for the listing quantity, competition as measured by the number of in-stock apartments reduces the quantity while the previous month CCI, the 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 as well. While quantities are significantly affected by the market competition, price response is not as obvious when a similar regression is performed. Specification (4) of Table 12 shows the price is lower when it has more on-market, but no statistical significant impact from any competition measures.[24]

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 solely 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 100, the apartment quantities are all discretized into increments of 100s.[25] The discretized version of Table 12 shows similar result, which supports that the discretization did not change the fundamental properties of raw data, although the number of observation would clearly be trimmed. With the discretized

[24]While these measurements might appear related, all pairwise correlations are less than 0.63, where only 6 pairs have correlation above 0.5.

[25]Instead of strict cutoff at 50, data are discretized by a draw weighted by the remainder of division by 100 (i.e. the increment unit). This preserves variations within the same discretized level in repeated discretization.

Table 12: Regression with Aggregate Competition Measures

	Dependent variable:			
	List	Re-list	Qty to list	Price resid.
	logistic		*OLS*	*OLS*
	(1)	(2)	(3)	(4)
Agg. in-stock	−0.0001	0.001	−0.055	0.184
	(0.001)	(0.0003)	(0.022)	(0.414)
Agg. on-mkt	0.001	−0.0001	0.019	−0.599
	(0.001)	(0.0004)	(0.023)	(0.442)
Entered rivals	−0.137	0.061	−0.255	−11.533
	(0.075)	(0.046)	(1.972)	(37.507)
CCI lag	−0.008	−0.006	0.646	1.894
	(0.013)	(0.008)	(0.293)	(5.667)
Thur-Sat	1.672	0.811	−0.748	57.630
	(0.397)	(0.181)	(9.653)	(185.492)
Self PL			0.853	224.234
			(2.987)	(57.124)
Self in-stock	−0.0002	0.003	0.319	−0.717
	(0.0005)	(0.0004)	(0.028)	(0.533)
Self on-mkt		−0.005	−0.166	−5.892
		(0.002)	(0.110)	(2.116)
Self PL:Self in-stock			0.007	−0.008
			(0.010)	(0.184)
Constant	−2.863	−4.168	−43.264	−334.192
	(2.260)	(1.416)	(44.621)	(854.633)
Observations	1,816	5,512	240	236
R^2			0.681	0.213
Adjusted R^2			0.668	0.182
Residual Std. Error			68.163	1,293.957
F Statistic			54.473	6.802
df			9; 230	9; 226

Note: "Agg. in-stock" and "Self in-stock" measures, on that day, all in-stock apartments and own in-stock apartments respectively. Similarly for "Agg. on-mkt" and "Self on-mkt". "Entered rivals" measure the number of rival complexes that have listed their 1^{st} PL and still in-stock apartments unsold, excluding self. "CCI lag" is the Centa-City index of previous month. "Thur-Sat" is a dummy for whether or not the day falls on Thursday to Saturday. "Self PL" is the current round of PL at listing. The last two specifications are conditional on the days this complex has decided to list and hence much fewer observations than days deciding whether to list.

data, I can take the top 20 frequent rival state distributions into regression. If any of these rival state dummies has significant impact to the choices (list, 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 13 shows 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. These motivate the structural model to aid a deeper analysis for competition.

Table 13: Regression with Top 20 Rival State (s_{-j}) Distribution with Controls

	Dependent variable:			
	List	Re-list	Qty to list	Price resid.
	logistic		*OLS*	*OLS*
	(1)	(2)	(3)	(4)
Top s_{-j}#3	-15.297		0.121	987.534*
	(2,317.635)		(0.555)	(555.534)
Top s_{-j}#4	-3.411*		-0.086	$-1{,}090.938$
	(1.770)		(0.677)	(693.447)
Top s_{-j}#5	-15.145	-12.292	-0.717	$-1{,}351.895$*
	(5,752.425)	(2,115.383)	(0.694)	(694.895)
Top s_{-j}#8		3.573*	0.182	-585.117
		(1.869)	(0.841)	(849.116)
Top s_{-j}#11		-16.460	-1.625**	936.577
		(6,208.832)	(0.679)	(707.977)
Top s_{-j}#17	29.690		0.279	$-2{,}821.534$***
	(4,591.166)		(1.024)	(1,022.640)
Top s_{-j}#20		-16.059	1.867**	$-1{,}109.069$
		(7,604.236)	(0.743)	(965.260)
Observations	1,054	1,456	104	100
R^2			0.660	0.647
Adjusted R^2			0.406	0.365
Residual Std. Error			0.837	835.407
F Statistic			2.598	2.295
df			44; 59	44; 55

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

Note: All controls in Table 12 are used while adding all aggregate competition measures (e.g. agg. on-mkt, entered rivals) up to cubic terms.

A.2 Discussion on Estimation Result

In the section, I include multiple excerpts on (re-)list probabilities for the estimated extended OE and the empirical CCP, as well as the cost estimates across states. Taking a closer look at the estimated extended OE, one can compare the list and re-list probabilities of extended OE with those of empirical CCP. In Table 14 & 15, the extended OE list probabilities for 500 or less apartments in-stock, throughout the cycle, are quite close. As for Table 16 & 17, the excerpts for re-list probabilities in normal stage 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 re-list probabilities suggest re-list plays a smaller role than list does in reality. This is indeed consistent with the earlier simulation result, where extended OE generates data close to what empirical CCP generates.

Table 14: Empirical List Probability

	100	200	300	400	500	0
300 0 0 0	0.0053	0.0042	0.0036	0	0	0.9868
400 0 0 0	0.0044	0.0043	0.0022	0.0022	0	0.9866
500 0 0 0	0.0037	0.0045	0.0026	0.0019	0.001	0.9861
100 0 0 1	0.0158	0	0	0	0	0.9842
200 0 0 1	0.0089	0.0057	0	0	0	0.9854
300 0 0 1	0.0074	0.0037	0.0026	0	0	0.9862
400 0 0 1	0.0062	0.0038	0.0022	0.001	0	0.9867
500 0 0 1	0.0052	0.004	0.0025	8e-04	5e-04	0.9869
100 0 0 2	0.0194	0	0	0	0	0.9806
200 0 0 2	0.0125	0.0049	0	0	0	0.9826

Cost estimates show that cycle does matter. Table 18 shows an excerpt of list cost across expansion and contraction stages. For any given individual state (i.e. keeping (n, o, k) fixed), the cost decreases by around 30% when the stage changes from normal to contraction stage. The cost increases by 40% changing from normal to expansion stage. This is reasonable because list and re-list cost advertising, soliciting real estate agents, attracting media reporters and occupying the sales venue constitute a major part of the cost. And these are subject to increase as the competition intensifies and vice versa. In addition to the different sales

Table 15: Extended OE List Probability

	100	200	300	400	500	0
300 0 0 0	0.0034	0.0018	7e-04			0.9942
400 0 0 0	0.0027	0.0016	0.0016	6e-04		0.9935
500 0 0 0	0.0022	0.0016	0.0018	0.0016	6e-04	0.9923
100 0 0 1	0.0065					0.9935
200 0 0 1	0.0078	0.001				0.9912
300 0 0 1	0.0052	0.0022	5e-04			0.9921
400 0 0 1	0.0042	0.002	0.0016	3e-04		0.9919
500 0 0 1	0.0038	0.0019	0.002	0.001	2e-04	0.991
100 0 0 2	0.0077					0.9923
200 0 0 2	0.0082	8e-04				0.991

Table 16: Empirical Re-list Probability

	100	200	300	400	500	0
100 0 1 1	0.116	0	0	0	0	0.884
200 0 1 1	0.0536	0.0574	0	0	0	0.889
300 0 1 1	0.045	0.0404	0.0228	0	0	0.8918
400 0 1 1	0.0377	0.042	0.0138	0.014	0	0.8924
500 0 1 1	0.0316	0.0435	0.0163	0.0158	0.0018	0.891

Table 17: Extended OE Re-list Probability

	100	200	300	400	500	0
100 0 1 1	0.0436					0.9564
200 0 1 1	0.0282	0.0161				0.9556
300 0 1 1	0.0177	0.0126	0.0123			0.9574
400 0 1 1	0.0161	0.0098	0.0124	0.0086		0.9532
500 0 1 1	0.0149	0.0096	0.0107	0.0092	0.0065	0.9491

probability across stage incorporated into the transition matrix, the data reveal that there are also list/re-list cost differences across expansion and contraction stage. Comparing to the list cost, one can see in Table 19 in the appendix that the re-list cost is lower. This is consistent with the higher list cost to initiate the beginning of sales phases.

Table 18: Estimated List Cost

	100	200	300	400	500	0
100 0 0 0	3.954	7.908	11.862	15.816	19.77	0
200 0 0 0	3.954	7.908	11.862	15.816	19.77	0
300 0 0 0	3.954	7.908	11.862	15.816	19.77	0
400 0 0 0	3.954	7.908	11.862	15.816	19.77	0
500 0 0 0	3.954	7.908	11.862	15.816	19.77	0
100 0 0 1	5.528	11.056	16.584	22.112	27.639	0
200 0 0 1	5.528	11.056	16.584	22.112	27.639	0
300 0 0 1	5.528	11.056	16.584	22.112	27.639	0
400 0 0 1	5.528	11.056	16.584	22.112	27.639	0
500 0 0 1	5.528	11.056	16.584	22.112	27.639	0
100 0 0 2	7.742	15.483	23.225	30.966	38.708	0
200 0 0 2	7.742	15.483	23.225	30.966	38.708	0
300 0 0 2	7.742	15.483	23.225	30.966	38.708	0
400 0 0 2	7.742	15.483	23.225	30.966	38.708	0
500 0 0 2	7.742	15.483	23.225	30.966	38.708	0

Table 19: Estimated Re-list Cost

	100	200	300	400	500	0
100 0 1 1	5.382	10.764	16.146	21.528	26.91	0
100 100 1 1	5.382	10.764	16.146	21.528	26.91	0
100 200 1 1	5.382	10.764	16.146	21.528	26.91	0
100 300 1 1	5.382	10.764	16.146	21.528	26.91	0
100 400 1 1	5.382	10.764	16.146	21.528	26.91	0
100 500 1 1	5.382	10.764	16.146	21.528	26.91	0
200 0 1 1	5.382	10.764	16.146	21.528	26.91	0
200 100 1 1	5.382	10.764	16.146	21.528	26.91	0
200 200 1 1	5.382	10.764	16.146	21.528	26.91	0
200 300 1 1	5.382	10.764	16.146	21.528	26.91	0
200 400 1 1	5.382	10.764	16.146	21.528	26.91	0
200 500 1 1	5.382	10.764	16.146	21.528	26.91	0

A.3 Discussion on Counterfactual under Whole Cycle Penalty

This section provides further analysis of the optimal strategy under the naive response and the counterfactual. In the former case, if one ignores the fact that the competition environment would change, both Table 20 and Table 21 show that the small list is discouraged, especially apparent when the stock level is high. For stock with above 1000 apartments, no firms choose to enter with less than 300 apartments. This would be aligned with the policy intended goal for larger list. In the latter case of counterfactual, the competition environment changes resulting from the individual behavior change.

Table 20: Naive Extended OE List Prob under Universal Penalty

	100	200	300	400	500	0
300 0 0 0	7e-04	1e-04	0			0.9992
400 0 0 0	0.0036	4e-04	1e-04	0		0.996
500 0 0 0	2e-04	7e-04	1e-04	0	0	0.999
600 0 0 0	7e-04	1e-04	8e-04	2e-04	0	0.9982
800 0 0 0	1e-04	2e-04	8e-04	3e-04	0.0026	0.9959
100 0 0 1	0.0026					0.9974
200 0 0 1	0.0061	1e-04				0.9938
300 0 0 1	0.0072	5e-04	0			0.9923
400 0 0 1	0.005	0.0033	5e-04	0		0.9912
500 0 0 1	0.0091	5e-04	7e-04	1e-04	0	0.9896
600 0 0 1	0.006	0.0037	4e-04	4e-04	1e-04	0.9894
700 0 0 1	0.0014	0.0041	0.0054	4e-04	8e-04	0.9878
800 0 0 1	0.0035	6e-04	0.0053	0.0043	7e-04	0.9855
900 0 0 1	1e-04	0.0021	0.0017	0.0048	0.0091	0.9822
1000 0 0 1	0	1e-04	0.0047	0.0013	0.0134	0.9806
1100 0 0 1	0	0	3e-04	0.0102	0.0094	0.98
1200 0 0 1	0	0	1e-04	2e-04	0.0174	0.9824
1400 0 0 1	0	0	0.0061	0.0012	0.0114	0.9812
100 0 0 2	0.0027					0.9973
200 0 0 2	0.0047	1e-04				0.9953
600 0 0 2	0.0022	0.0045	0	1e-04	0	0.9931
700 0 0 2	1e-04	0.001	0.0041	0	2e-04	0.9946

Table 21: Naive Extended OE Re-list Prob under Universal Penalty

	100	200	300	400	500	0
100 0 1 1	0.004					0.996
200 0 1 1	0.0063	4e-04				0.9933
300 0 1 1	0.0015	0.0047	6e-04			0.9932
400 0 1 1	0.0092	1e-04	6e-04	1e-04		0.99
500 0 1 1	0.0048	0.0054	1e-04	5e-04	1e-04	0.9892

The excerpts for list (Table 22) and re-list (Table 23) strategy show that firms now incline more to enter with small batches. First, the last column that presents the probability of listing no apartments is larger than without the penalty, which suggests the penalty can discourage apartment listing. Second, the actions of listing all are now smaller or even zero suggesting the firms tend to enter with smaller batches when they are entering, counter to the policy intended goal. This results from the change in the competition environment. Without the penalty, the long run average has about 480 apartment on market. Once the penalty is imposed, the discouraged firms keep to around 310 apartments on market in the long run average. This eases the sales of the listed units. In view of this, the optimal response by the firms is to list small batches so as to take advantage of the higher prices in later batches, rather than just listing larger batches as the policy intends.

Table 22: Extended OE List Prob under Universal Penalty

	100	200	300	400	500	0
300 0 0 0	0.002	2e-04	0			0.9977
400 0 0 0	0.0082	7e-04	1e-04	0		0.991
500 0 0 0	0.0023	0.0016	2e-04	0	0	0.9959
600 0 0 0	0.003	0.0011	0.0011	1e-04	0	0.9947
800 0 0 0	0.0035	0.0053	0.0016	7e-04	0.0011	0.9877
100 0 0 1	0.0039					0.9961
200 0 0 1	0.0078	1e-04				0.9922
300 0 0 1	0.0092	6e-04	0			0.9902
400 0 0 1	0.0072	0.0034	3e-04	0		0.9891
500 0 0 1	0.0125	5e-04	3e-04	0	0	0.9866
600 0 0 1	0.0099	0.0036	2e-04	1e-04	0	0.9861
700 0 0 1	0.0069	0.0054	0.003	1e-04	2e-04	0.9844
800 0 0 1	0.0062	0.0042	0.0051	0.0019	2e-04	0.9824
900 0 0 1	0.0014	0.0049	0.0052	0.0041	0.0044	0.9801
1000 0 0 1	6e-04	0.0012	0.0058	0.0041	0.0097	0.9787
1100 0 0 1	3e-04	7e-04	0.0017	0.0064	0.0135	0.9774
1200 0 0 1	9e-04	3e-04	7e-04	0.0016	0.0159	0.9806
1400 0 0 1	1e-04	3e-04	0.0086	0.0026	0.0135	0.9749
100 0 0 2	0.0037					0.9963
200 0 0 2	0.0062	0				0.9938
600 0 0 2	0.0044	0.0028	0	0	0	0.9927
700 0 0 2	1e-04	0.0021	0.0021	0	1e-04	0.9956

Table 23: Extended OE Re-list Prob under Universal Penalty

	100	200	300	400	500	0
100 0 1 1	0.0053					0.9947
200 0 1 1	0.0079	4e-04				0.9917
300 0 1 1	0.0038	0.0045	4e-04			0.9913
400 0 1 1	0.0116	2e-04	3e-04	0		0.9879
500 0 1 1	0.0087	0.0046	1e-04	1e-04	0	0.9865

A.4 Discussion on Counterfactual under Expansion Stage Penalty

The appendix allows for further analysis of the strategies under expansion stage penalty. When one looks at the naive strategy assuming the competition environment does not change, it is evident from Table 24 and 25 that only the firms in expansion stage are affected, but not other stages. Especially for firms with more stocks, small batch list is discouraged.

Table 24: Naive Extended OE List Prob under Counter-cyclical Penalty

	100	200	300	400	500	0
300 0 0 0	7e-04	1e-04	0			0.9992
400 0 0 0	0.0036	4e-04	1e-04	0		0.996
500 0 0 0	2e-04	6e-04	1e-04	0	0	0.9991
600 0 0 0	7e-04	1e-04	7e-04	1e-04	0	0.9983
800 0 0 0	1e-04	3e-04	9e-04	3e-04	0.0015	0.997
100 0 0 1	0.0026					0.9974
200 0 0 1	0.0063	1e-04				0.9936
300 0 0 1	0.0074	5e-04	0			0.992
400 0 0 1	0.0052	0.0035	5e-04	0		0.9908
500 0 0 1	0.0099	5e-04	7e-04	1e-04	0	0.9889
600 0 0 1	0.0066	0.004	4e-04	4e-04	0	0.9887
700 0 0 1	0.0017	0.0046	0.0061	4e-04	4e-04	0.9869
800 0 0 1	0.0039	7e-04	0.0061	0.0048	3e-04	0.9842
900 0 0 1	1e-04	0.003	0.0025	0.0069	0.0063	0.9812
1000 0 0 1	0	1e-04	0.0075	0.0022	0.0106	0.9796
1100 0 0 1	0	1e-04	6e-04	0.0141	0.0066	0.9786
1200 0 0 1	1e-04	0	2e-04	4e-04	0.0174	0.982
1400 0 0 1	0	1e-04	0.0076	0.0024	0.0106	0.9792
100 0 0 2	0.0027					0.9973
200 0 0 2	0.0044	1e-04				0.9955
600 0 0 2	0.0021	0.004	0	0	0	0.9939
700 0 0 2	0	8e-04	0.0034	0	1e-04	0.9956

Table 25: Naive Extended OE Re-list Prob under Counter-cyclical Penalty

	100	200	300	400	500	0
100 0 1 1	0.004					0.996
200 0 1 1	0.0066	3e-04				0.9931
300 0 1 1	0.0017	0.005	5e-04			0.9928
400 0 1 1	0.01	1e-04	5e-04	0		0.9893
500 0 1 1	0.0054	0.0057	1e-04	4e-04	0	0.9884

Albeit the much shorter implementation period compared to the full-cycle policy, excerpts of list and re-list strategy in Table 26 & 27 show how the similar impact comes about. When the penalty is imposed in expansion stage (i.e. $z = 2$), sellers are discouraged to enter. In the expansion stage, the list is discouraged, and slight more so than that under universal penalty. As for the other stages without penalty in counter-cyclical policy, the strategy in normal and contraction stage change. Both list and re-list have much higher (re-)entering probabilities as shown in Table 26 and 27. Expecting the higher (re-)list cost in expansion stage, the counter-cyclical penalty raises incentive for the firms to (re-)enter in normal or contraction stage. This points to the fact that the strategies under counter-cyclical policy are not just affected by the penalty itself directly, but by the future stages with penalty. Regarding the competitive environment, even though the counter-cyclical policy is implemented in less than 1/3 of the period, it reduces the long run average from around 480 apartments on market without penalty to around 280 apartments on market. This implies a similar change as that of a full-cycle penalty, if not a bigger change. Hence, counter-cyclical penalty affects states not subject to penalty indirectly through the long run market state.

Table 26: Extended OE List Prob under Counter-cyclical Penalty

	100	200	300	400	500	0
300 0 0 0	0.002	3e-04	0			0.9977
400 0 0 0	0.0088	6e-04	1e-04	0		0.9904
500 0 0 0	0.0021	0.0015	1e-04	0	0	0.9963
600 0 0 0	0.0029	9e-04	9e-04	1e-04	0	0.9952
800 0 0 0	0.0039	0.0061	0.0014	5e-04	5e-04	0.9877
100 0 0 1	0.004					0.996
200 0 0 1	0.008	1e-04				0.9919
300 0 0 1	0.0097	6e-04	0			0.9897
400 0 0 1	0.0076	0.0036	3e-04	0		0.9885
500 0 0 1	0.0139	4e-04	3e-04	0	0	0.9855
600 0 0 1	0.0111	0.0037	1e-04	1e-04	0	0.985
700 0 0 1	0.0078	0.0061	0.003	1e-04	1e-04	0.9829
800 0 0 1	0.007	0.0049	0.0056	0.0019	1e-04	0.9806
900 0 0 1	0.002	0.0062	0.0063	0.0049	0.0023	0.9782
1000 0 0 1	0.001	0.002	0.008	0.0058	0.0064	0.9768
1100 0 0 1	7e-04	0.0013	0.0031	0.0097	0.0097	0.9755
1200 0 0 1	0.0014	7e-04	0.0016	0.0033	0.0134	0.9796
1400 0 0 1	2e-04	6e-04	0.0103	0.0048	0.0119	0.9723
100 0 0 2	0.0036					0.9964
200 0 0 2	0.0058	0				0.9942
600 0 0 2	0.0041	0.0023	0	0	0	0.9936
700 0 0 2	1e-04	0.0017	0.0015	0	0	0.9967

Table 27: Extended OE Re-list Prob under Counter-cyclical Penalty

	100	200	300	400	500	0
100 0 1 1	0.0053					0.9947
200 0 1 1	0.0082	4e-04				0.9914
300 0 1 1	0.0042	0.0047	3e-04			0.9908
400 0 1 1	0.0128	1e-04	2e-04	0		0.9869
500 0 1 1	0.01	0.0046	1e-04	1e-04	0	0.9852

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